Data-driven strategic decision-making in SMEs

A study on the current state of DA in SMEs, perceived barriers & opportunities

Master thesis

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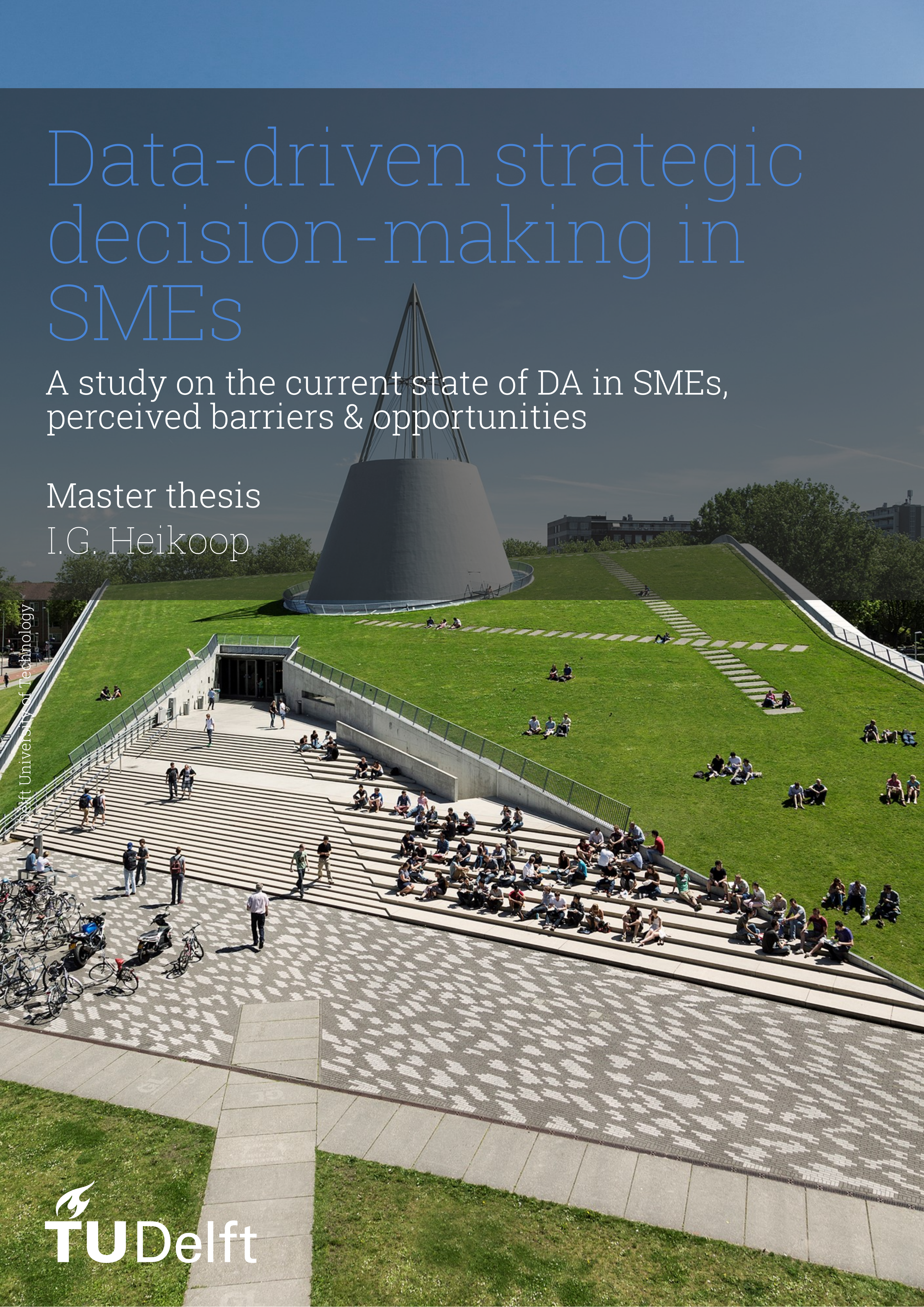

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by

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Preface

In front of you lies my master thesis, *Data-driven strategic decision-making in SMEs*, written for the Master of Science Complex Systems Engineering & Management (CoSEM) of TU Delft.

CoSEM teaches students to think beyond the technical aspects of technology application, using systems thinking and multidisciplinary problem-solving approaches. Throughout my academic career, I have always been interested in business science in collaboration with the appliance of the technology TU Delft is so famous for. During my last CoSEM courses, the idea of researching data analytics in smaller enterprises emerged.

I would like to thank my first supervisor, Dr. Smit for giving me the opportunity to research this subject to complete my studies here in Delft. I would like to thank him for the extensive discussions that ultimately led to the thesis you are reading right now. He guided me through my first experience of designing, performing and discussing qualitative research. My second supervisor, dr. De Bruijne was always available for questions and provided me with detailed feedback during the writing process, which I am thankful for.

I would also like to thank all the participants for the extensive conversations. Without their participation, I would not have been able to write this thesis. In their busy lives, running the businesses they are so proud of, they took the time to answer my questions, discuss their perspectives and explain their motivations.

Finally, i would like to thank my friends and family for being there for me and always being ready to help.

I hope you, the reader, enjoys reading this thesis.

I.G. Heikoop
Delft, August 2024

Executive summary

The ability of data analytics (DA) to improve strategic decision-making (SDM) by analyzing large volumes of data has been well documented in larger enterprises. In Small- and Medium-sized Enterprises (SMEs), the importance of DA is increasingly acknowledged. However, most of the SME-specific research has focused on DA use in non-strategic contexts. This research focuses on the current usage and adoption of DA in the SDM of SMEs.

The primary objective of this research is to understand how decision-makers in SMEs use DA in SDM, and to identify the perceived barriers and opportunities for its usage. This study addresses the main research question: "How do decision-makers in Small- and Medium-sized Enterprises utilize data analytics in strategic decision-making, and what are the perceived opportunities and barriers associated with its application?" By addressing this question, this study contributes to the existing literature by providing an understanding of the current state of DA usage in SMEs and identifying SDM-SME-specific barriers and opportunities.

Three sub-questions guide this research question:

1. How and in what SDM use cases do SME decision-makers use DA?
2. What barriers do decision-makers in SMEs encounter when utilizing DA in SDM?
3. What opportunities do decision-makers in SMEs perceive regarding further implementation of DA into their SDM processes?

This research is of qualitative nature, conducted with data gathered through semi-structured interviews with 13 decision-makers from various SMEs. Through thematic analysis of the interviews in the context of the existing literature, the research concluded on the usage of DA in five cases within the SDM of SMEs:

SMEs use DA to support decisions regarding market positioning, by analyzing market trends and competitors. SDMs regarding market responsiveness are also supported by DA, by supporting SDM by conducting procurement and sales analysis and resource planning. Furthermore, DA supports SDMs regarding customer relations, value proposition improvements and the improvement of their organization. Some early adopter SMEs use predictive and prescriptive techniques in their SDMs. The usage of more sophisticated predictive and prescriptive techniques in SDM is not widespread yet under SMEs.

Despite these usages within the SDM of SMEs, several barriers were observed to hinder the implementation of DA in SDM. Technical barriers to adoption are lacking analysis quality and missing data. The costs and insufficient benefits of DA in SDM are both technological and organizational barriers. The organizational barriers further include the sentiment of the decision-maker, the knowledge in the SME, the SME size, internal resistance, and having no time or set priority for DA.

The research also highlights several opportunities for SMEs to further implement DA in their SDM. These opportunities include possible collaborations among SMEs or governmental institutions, and the cost of DA going down with technological advancements.

Given the potential benefits, it is recommended for decision-makers in SME to explore partnerships with other businesses or public institutions. This could initiate shared resources, reduced costs, and enhanced DA capabilities. Collaborative efforts can facilitate access to higher-quality data and advanced analytics tools that might be otherwise inaccessible.

Furthermore, as technological advancements make DA tools more affordable, SMEs should prioritize investments in scalable solutions that align with their growth objectives. A phased approach, starting with basic analytics and gradually integrating more advanced techniques, can help manage costs while building internal expertise.

To overcome organizational barriers, SMEs should invest in training and development to build internal DA expertise. Upskilling existing employees and hiring DA professionals can bridge knowledge gaps and foster a data-driven culture.

It is recommended that the SMEs try to utilize these opportunities. Considering the added value of DA to SDM, it is also recommended for governing bodies to investigate the possibilities for supporting the further adoption of DA in the SDM of SMEs.

Contents

Nomenclature

Abbreviations

Abbreviation	Definition
CoSEM	Complex systems Engineering & Management
DA	Data analytics
DOI	Diffusion of Innovation
IT	Information Technology
SME	Small and Medium Enterprise
SDM	Strategic decision-making
TAM	Technology Acceptance Model
TOE	Technology, Organization & Environment

1
Introduction

In this chapter, the research is introduced. Section 1.1 describes the research context, introducing the concepts of data analytics and strategic decision-making. Section 1.2 further describes the problem at hand. Section 1.3 describes the research objective and introduces the research question and sub-questions. Section 1.4 describes the relevance to the study program this research was conducted for. Section 1.5 describes the practical relevance of the research, and section 1.6 provides a reading guide for this thesis.

1.1. Research context

The business landscape of Small- and Medium Enterprises (SMEs) is characterized by ever-changing technology usage, shifting market conditions and evolving customer expectations (Rashidirad & Salimian, 2020). In this dynamic, competitive business landscape, the strategic decision-making (SDM) of SMEs is crucial to the success of these SMEs (Rashidirad & Salimian, 2020; Schoemaker et al., 2018).

Next to this, innovation and the adoption of new technological capabilities is recognized as beneficial to the performance of SMEs (Rashidirad & Salimian, 2020; Yasin et al., 2014). Data analytics (DA) is one of these important technological capabilities. DA is the collection, analysis, use and interpretation of data to gain actionable insights, create value and establish a competitive advantage (Akter & Wamba, 2016).

DA is so valuable for businesses because it serves as a basis for improved and better-informed decision-making (Bianchini & Michalkova, 2019; Ghasemaghaei et al., 2018). It has the potential to provide insights during decision-making that were previously inaccessible (Adaga et al., 2024). In day-to-day operations, DA usage has been proven to enable higher operational efficiency (Bianchini & Michalkova, 2019). Next to improving efficiency, long-term, important decisions are also improved by DA usage (LaValle et al., 2010).

DA usage is a differentiator for success amongst the top performing enterprises (LaValle et al., 2010). Top performers, defined by LaValle et al. (2010, p. 6), are enterprises that "*substantially outperform industry peers*". In these enterprises, DA is not only used in day-to-day operations but also in "larger", more important decisions. Top performers were found twice as likely to use DA to guide future strategies opposed to lower performers, again underscoring the importance of well-informed SDM.

SDM is the process through which organizations formulate and implement decisions that are critical to achieving long-term goals and maintaining competitive advantage. This process is characterized by its complexity, uncertainty, and the high stakes involved, as strategic decisions often have far-reaching implications for the entire organization (Eisenhardt & Zbaracki, 1992; Harrison, 1996). These decisions involve resource allocation, market positioning, competitive strategy, and overall business direction (Mintzberg, 1994). Strategy should be free to "appear" at any time, at any place in the organization (Mintzberg, 1994). This also applies to SMEs, like Schoemaker et al. (2018) explains; strategic decisions are constantly made and a range of strategic decision categories exist.

The article of LaValle et al. (2010) focused on DA and firm performance larger enterprises. More recently, the importance and value of DA for SMEs is increasingly acknowledged (Bhardwaj, 2022; Bianchini &

Michalkova, 2019). Recent studies have observed increased usage and attractiveness of DA in SMEs (Ragazou et al., 2023). In certain sectors such as such as retail and manufacturing in particular, SMEs, have shown to be able to adopt DA (Gavrila & de Lucas Ancillo, 2021; Sargut, 2019). In 2018, Bianchini and Michalkova (2019) observed the percentage of SMEs using DA to be in a slightly upward trend, with 12% of SMEs in the European Union using DA, a opposed to 10% in 2016 (Bianchini & Michalkova, 2019, p. 17). Whilst usage is on the rise, SMEs overall have struggled with adoption (Coleman et al., 2016).

Initially, DA posed a technical challenge for all organizations, centered around the storage and processing of large volumes of data. Larger enterprises have overcome these challenges (Adaga et al., 2024; Olaniyi et al., 2023). This has led to the transformation of DA into a strategic tool that that drives (strategic) business decisions regarding innovation, efficiency, and competitiveness (Adaga et al., 2024).

In contrast with larger enterprises, SMEs can struggle with DA usage (Bhardwaj, 2022; Bianchini & Michalkova, 2019; Coleman et al., 2016; Maroufkhani et al., 2020), as SMEs are often restrained by challenges unique to them compared to larger enterprises. These challenges can be of technical, managerial or operational nature (Bhardwaj, 2022). Technical challenges can include a lack of understanding, knowledge and experience. Managerial challenges can include the insufficient resources to take data-driven decisions, or weak strategic orientation. Operational challenges can include a lack of skilled workforce, insufficient funds, organisational culture or a disparity between teams of an SME (Bhardwaj, 2022).

The main objective of DA usage is to enhance decision-making (Choo, 1996). Many studies on DA in SMEs have focused on using DA to improve operational efficiency (Bhardwaj, 2022). This is a logical first step in analyzing the DA usage of SMEs, due to the potential to improve operational efficiency using insights based on DA. After all, this yields direct results in efficiency and thus revenue of SMEs. However, as LaValle et al. (2010) described, DA usage can also be valuable in strategic decisions trough improved guidance to decision-makers. Improving operational efficiency is valuable, but the strategy of SMEs is particularly crucial to SMEs as they are under pressure of fierce competition (Rashidirad & Salimian, 2020). Still, there is a lack of studies focusing on the usage on SMEs usage of DA in the SDM of SMEs (Bhardwaj, 2022).

The distinction between SDM and decisions aimed at improving operational efficiency is not always easy to make. Strategic decisions as described above focus on long-term goals and vision, have high impact on the entire organization and are made by top management (CEOs, business owners, senior executives) (Mintzberg, 1994). Decisions regarding operational efficiency can be strategic, as they can also focus on long term goals and fit the other aforementioned requirements. This can make the distinction between the two a bit convoluted. To make the distinction clearer, we can look at the definition of "operations management" of Slack et al. (2010, p. 4): "*The activity of managing the resources which produce and deliver products and services.*". Managing operations is fundamentally different to making strategic decisions. Strategic decisions can also include some aspects of operations, but operations management, to improve operational efficiency, can be non-strategic.

Effective DA usage in SDM can lead to important decisions being made based on empirical evidence, rather than intuition of the decision-maker (Adaga et al., 2024). If DA are leveraged in decision-making across the enterprise, an SME can benefit from increased profitability and productivity (Justy et al., 2023; Mosbah et al., 2023; Seseni & Mbohwa, 2021), due to this improved decision-making. Insights regarding customer behaviour, market trends and operations can lead to better decisions (Sarker, 2021).

In describing DA usage, the distinction can be made between descriptive, predictive and prescriptive DA. Especially predictive DA, looking forwards instead of backwards like in descriptive DA, can be helpful in improving decision making in strategic decisions, resulting in better long-term business performance (Ragazou et al., 2023; Szukits & Móricz, 2023). The question rises, if, and, if so, how DA are used in the SDM of SMEs.

1.2. Problem statement

In the past two decades, both academia and business practices have frequently touted phrases like "data is the new oil" and "data knows everything". Despite the present widespread availability of extensive data (Pittenger et al., 2023), decision-makers in SMEs often struggle to use DA effectively in their SDM.

It would be beneficial for SMEs to be able to use DA in their SME. However, to fully enable improved long-term SME performance from data analytics, a deeper understanding of the role of DA in the SDM of SMEs is required (Bhardwaj, 2022). When decisions are made using DA, a sound collaboration is required between the data, DA tools, and decision-makers (Elgendy et al., 2022). This can ultimately lead to better-informed and genuinely data-driven decisions (Elgendy et al., 2022).

Analysing this collaboration in detail for SDM in SMEs is complex, because the high variability among SMEs often requires a consideration of specific context in analysis approaches regarding SMEs (de Mattos et al., 2023; Zamani, 2022). While research has focused on the technological aspects of DA, (Ferraris et al., 2019; Maroufkhani et al., 2020; Wang & Wang, 2020), or solely on improvements of operational efficiency (Bhardwaj, 2022), there is a critical gap in understanding how DA is used in the SDM of SMEs. At this moment, we do not know how SMEs use DA in their SDM. Furthermore, it is known SMEs face some barriers in DA adoption, but specifically for SDM, these barriers have not been researched or specified.

Davenport (2018) describes how enterprises were increasingly recognizing the strategic value of DA, leading to more widespread implementation. In 2012, Durst and Edvardsson (2012) described how some SMEs were adopting advanced DA tools, while others lacked behind due to resource constraints or lack of expertise. Due to advancements in DA technologies however, it has possibly been easier for SMEs to adopt these tools, providing access to data-driven insights that were previously only accessible to larger enterprises (Wamba et al., 2015). This raises the question, how and in what strategic decisions are these tools utilized by SME decision-makers right now? What holds (further) adoption back, and what opportunities can SME owners take on?

DA is instrumental in informing or prescribing decisions, highlighting its value in the strategic decision-making process (Lorkowski & Kreinovich, 2018). These decisions are crucial as they shape the commitment and scope of enterprises (Khalifa, 2021; Shivakumar, 2014). Additionally, the dynamic and often unpredictable nature of SME environments means that decision-makers must be agile and responsive, making the integration of DA both a challenge and a necessity (Azevedo & Almeida, 2021).

Like explained in 1.1, SMEs vary significantly from one another (de Mattos et al., 2023; Zamani, 2022), but many SMEs have in common that they are are often highly competitive, entrepreneurial and dynamic (Pereira et al., 2020; Rashidirad & Salimian, 2020). This could make us further believe that some interesting insights are to be made regarding DA usage in SDM. To further add to the motivation of this research, it has been observed that much of the research has focused on building capabilities in SMEs from a technological perspective (Ferraris et al., 2019; Maroufkhani et al., 2020; Wang & Wang, 2020), but an understanding of how DA is used in the SDM of SMEs is missing.

The personal views and experiences of SME entrepreneurs significantly influence strategic decisions, as SME leaders often rely on their intuition and past experiences (Antoncic et al., 2018). This makes the perceptions on DA and experiences with it of SME entrepreneurs, or SME decision-makers important in analyzing the adoption of DA in SDM. Understanding these perceptions can provide insights into the factors that facilitate or hinder effective data-driven SDM. Entrepreneurs' attitudes toward risk, innovation, and change are particularly influential, affecting how readily they adopt new technologies and data-driven approaches (Mazzarol, 2015).

Researching the uses and use cases of DA in the SDM of SMEs can help fill the knowledge gap regarding DA in SDM, and shed light on the complex implementation of such an important facilitator of informed decision-making. Researching what decision-makers in SMEs perceive as barriers and opportunities considering adopting DA into their SDM can help with further adoption and thus usage.

1.3. Research objective and research question

The goal of this research is to develop a better understanding of the usage of data analytics (DA) in the strategic decision-making (SDM) of SMEs. By developing this understanding, we can discuss how we can help decision-makers in SMEs adopt DA in their SDM. Furthermore, we can then discuss what next steps they could take in their journey of DA adoption.

Usage of DA by strategic decision-makers can be the next step to better strategic decisions. How do SMEs, considering their unique challenges, competitive, entrepreneurial and dynamic nature, utilize DA in their SDM? And, considering the importance of the personal perceptions of decision makers in

SME SDM, what do the decision-makers in place perceive as opportunities and barriers to DA usage in SDM? This leads to our research question:

"How do decision-makers in Small- and Medium-sized Enterprises (SMEs) utilize data analytics (DA) in strategic decision-making (SDM), and what are perceived barriers and opportunities associated with its application?"

This research question can be answered using three sub-questions:

1. "How and in what SDM use cases do SME decision-makers use DA?

   Understanding the specific use cases, methods and approaches used by decision-makers in SMEs to apply data analytics will provide insights into the practical implementation of DA. This exploration will provide knowledge about the ways in which SMEs leverage DA in specific strategic decisions, offering potential insights into best practices and innovative approaches.
2. "What barriers do decision-makers in SMEs encounter when utilizing DA in SDM?

   Identifying the barriers and concerns encountered by decision-makers in SMEs when utilizing data analytics in strategic decision-making will aid in understanding the barriers to effective implementation and utilization of data-driven strategies. By examining these barriers, this sub-question seeks to provide insights into the practical constraints and obstacles that SMEs face in harnessing the full potential of DA in SDM. This understanding can inform strategies to address these challenges and improve the effectiveness of data analytics initiatives in SMEs.
3. "What opportunities do decision-makers in SMEs perceive regarding further implementation of DA into their SDM?"

   Exploring the perceived opportunities and benefits associated with the integration of DA into SDM processes provides insights into the motivations behind SMEs' adoption of data-driven SDM. Understanding these perceived benefits can provide insights into the strategic rationale and motivations guiding SMEs' (potential) commitment to DA, thereby contributing to a broader understanding of the role of data-driven SDM in SMEs.

1.4. Relevance to study program

This thesis is written for the Master of Science Complex Systems Engineering & Management (CoSEM) of the TU Delft. CoSEM teaches to let students to think beyond mere technical innovation, and deal with human aspects such as stakeholder interests, culture and behavior (TU Delft, 2024). This study and its socio-technical components make for a CoSEM thesis.

1.5. Practical relevance

The practical relevance of this research lies in its potential to enhance the SDM processes within SMEs. In today's dynamic business environment, the ability to effectively utilize DA can provide SMEs with a competitive edge, enabling them to make more informed, timely, and strategic decisions. By understanding how SMEs use DA in their SDM, other SMEs can benefit by attempting to apply what is relevant to them. This research aims to bridge the gap between theoretical insights and practical application, offering tangible benefits to SME decision-makers.

Identifying and addressing barriers that SMEs face when trying to utilize DA in their SDM can help overcoming them and make it easier to overcome them. This can be of value for decision-makers in SMEs. Next to the academic knowledge gap this research aims to fill, it is written to help SME decision-makers that are struggling to adopt DA into their SDM. Exploring the opportunities decision-makers perceive can shed light on missed chances in the industry and help SMEs navigate the complexities of DA usage.

1.6. Reading guide

Chapter 2 of this thesis describes the conceptual background to this research. Chapter 3 contains the research approach and methodology. Chapter 4 describes the results from and analysis of the gathered data. Lastly, chapter 5 contains the discussion of the results and conclusions to the sub-questions and research question. Chapter 5 also discusses the scientific and practical implications of this research.

2

Conceptual background

In chapter 1, the potential benefits of the usage of data analytics (DA) in the strategic decision-making (SDM) for Small- and Medium-sized Enterprises (SMEs) were described. However, it is unclear how decision-makers in SMEs use DA in their SDM. And how can we enable more decision-makers in SMEs to use DA in their SDM? This led to the research question for this research: "How do decision-makers in Small- and Medium-sized Enterprises (SMEs) utilize data analytics (DA) in strategic decision-making (SDM), and what are perceived barriers and opportunities associated with its application?"

The first objective of this chapter is to place the research question within the broader context of existing knowledge and theories. In 2.1 and 2.2, DA are placed in SDM context. In 2.3, the current state of DA in SMEs is described along with factors determining DA adoption. The second objective of this chapter is to synthesize this conceptual background into theoretical frameworks. These are presented at the end of 2.2 and 2.3.

2.1. Data analytics: General definition and typology

In chapter 1, sub-question 1 was introduced: "*How and in what SDM use cases do SME decision-makers use DA?* " To build a theoretical framework for this sub-question, the concepts of DA, SDM, and DA specifically in SDM context are discussed.

Performing DA is applying a variety of methods for efficiently analyzing large volumes of data from both structured and unstructured sources (Bianchini & Michalkova, 2019). The primary objective of DA is to improve decision-making (Choo, 1996). It has the potential to be an important factor in enhancing enterprise competitiveness (Bianchini & Michalkova, 2019). In line with this, as mentioned in section 1.1, the importance and value of DA in SMEs is increasingly acknowledged (Bhardwaj, 2022; Bianchini & Michalkova, 2019).

Generally (for example, by LaValle et al. (2010), a distinction is made between different kinds of DA. Each type serves a distinct purpose and offers different levels of complexity and insight:

- Descriptive analytics: provides a retrospective or real-time overview of data, enabling users to comprehend past trends and patterns effectively.
- Predictive analytics: employs statistical algorithms to forecast future outcomes based on historical data, aiding in proactive decision-making.
- Prescriptive analytics: recommends optimal actions to achieve desired outcomes, guiding decision-makers towards the most effective strategies.

Descriptive analytics are at the heart of most DA systems (Cochran, 2018). They are the most simple form of analytics, because they only describe what has happened in the past, or in the case of real-time analysis, what is happening right now (Cochran, 2018). They describe the world as it is (or as it was) (Cochran, 2018). Predictive analytics are more sophisticated than descriptive analytics, as they require an extra step beyond just describing. A good predictive model requires detailed knowledge and the right assumptions (Cochran, 2018). Prescriptive analytics are the most sophisticated and best suited to "prescribe" predictive decision-making, but are harder to implement because of the even more complex models and technical requirements (Menezes et al., 2019).

Sometimes, for example by Igulu et al. (2023), a distinction is made between descriptive and diagnostic analytics. Diagnostic analytics would then be analytics "*which are primarily concerned with determining why something has occurred*" (Igulu et al., 2023). In this research, this distinction is not made, and diagnostic analytics are considered descriptive, as they are descriptive in nature with a different thought process of the decision-maker.

Five dimensions of data are traditionally mentioned as factors that make analytics complicated to perform. These dimensions, referred to as five Vs (Mucci & Stryker, 2024), are:

- Volume: The scale and sheer volume of data often poses a challenge, making it difficult to warehouse and process.
- Variety: Large volumes of data are often not consistent nor follow specific templates or formats.
- Velocity: A high rate of data inflow can make managing or integrating (new) data in an existing database challenging.
- Veracity: Coping with biases, doubts and other issues of mistrust can pose a large challenge.
- Volatility: Refers to how quickly and unpredictably data changes over time. Volatility complicates DA, requiring real-time processing and adaptive algorithms to effectively handle the constantly evolving information.

Sivarajah et al. (2017) discussed DA adoption theory (which is further discussed in detail in section 2.3) and adds a sixth V:

- Variability: the meanings of data and specific data points can be constantly changing, posing a challenge.

These dimensions pose a challenge for DA usage in SMEs, as the complexity of analytics can be a barrier to SMEs, which is further explained in 2.3. This typology informs the rest of the research and highlights the need for a tailored approach to data analytics in SMEs, depending on their specific strategic needs and resources. But to further delve into the barriers to adopting DA usage in SDM, SDM must first be further explained.

2.2. Strategic decision-making: General definition and DA context

Eisenhardt and Zbaracki (1992) defined strategic decisions as "*important, in terms of the actions taken, the resources committed, or the precedents set*". They are seen as "*large, expensive, and precedent setting*" (Nutt & Wilson, 2010). When analyzing SDM, the focus should be on the decisions made by the top leaders of an organization, that affect health and survival (Eisenhardt & Zbaracki, 1992).

Generally, decision making follows four main steps (Celona, 2016; Petrovsky, 2023; Thakkar, 2021). Problem identification is the first step, involving the decision problem and structuring it. Generating options follows, to generate alternatives with characteristics to evaluate. After this, evaluation of the alternatives takes place. This is where DA is traditionally most easily applicable. The selection of the alternative is the last step of decision-making, which is where the decision maker selects the, in his perception, best alternative, and develops recommendations or implementations.

2.2.1. Differences in SDM between SMEs and large corporations

In SMEs, the SDM process is often very centralized due to their size and general centralized steering (Hang & Wang, 2012). This leads to the decisions made, often by the founder or owner, being influenced by their entrepreneurial vision. This also results in the SDM becoming heavily reliant on the abilities of the individual decision-maker (Hang & Wang, 2012). This might influence the barriers to DA in SDM, which are discussed in 2.3. First, we discuss the potential of DA in SDM.

2.2.2. The potential of DA in SDM

DA impacts SDM processes by integrating advanced analytics and machine learning algorithms, developing structured decision-making frameworks, and enhancing the overall quality of decisions (Adaga et al., 2024). It enables businesses to make (strategic) decisions based on empirical evidence rather than intuition, resulting in more accurate and effective strategies (Jahan & Sazu, 2022). In larger corporations, DA are already used in SDM and its improvements during SDM are observable (Hendstein & Katsu, 2022). They found that predictive modelling "*revolutionalized strategic control*" (Hendstein & Katsu, 2022, p. 149). In their study, global trade forecasting was beneficial to the SDM of a corporation. In SMEs, it is not known yet how DA are used in SDM.

To be able to investigate this, we can investigate how DA adds value in SDM, not specifically in SMEs, and take this as a starting point for the research. Gregor et al. (2006) proposed a framework that describes where Information Technology (IT) adds value in organizations. DA, which is IT, could be analysed using this framework. He divided the benefits of adopting IT in four categories: informational, transactional, strategic, and transformational.

Whilst these benefits all have underlying relations to each other (Gregor et al., 2006) (for example, having better access to information will support strategic decisions), the division guides us to what benefits can be made in terms of strategy and SDM, as is framework has two levels and we can now look at what strategic benefits they identified. The by Gregor et al. (2006) identified strategic benefits received from IT are: creation of competitive advantage, establishing useful links with other organizations, enabling quicker response to change, improving customer relations, and providing better products or services to customers.

Elia et al. (2020) proposed a more specific framework on use cases of added value of DA in businesses. They categorized the value creation of DA in the same categories as Gregor et al. (2006) did, informational, transactional, strategic, and transformational, but then list use cases specific for DA in strategy (Elia et al., 2020). In the following sections, the use cases from Elia et al. (2020) are discussed in the the context of literature relevant to the research, so we can construct an as complete as possible overview as foundation for the rest of the research.

Market positioning

The first case where DA can add value in strategy is in market positioning (Elia et al., 2020). Market positioning is the process of establishing the business in the market, in the minds of customers or against competitors (Kotler & Keller, 2016, p. 297). During the determining of the market positioning of a business, decision-makers make strategic decisions in how they will cater to customers' needs, building a competitive advantage towards competitors and how they will act when monitoring their current market position.

The usage of DA can be valuable in market positioning of the business (Elia et al., 2020). DA usage provides new knowledge on customer needs and competitor behavior, as explained by Elia et al. (2020). Furthermore, DA can be of value in monitoring the market, selecting target markets, combining marketing elements and observing the market and competitors (Bahrami et al., 2012; Wamba et al., 2015).

Market responsiveness

Supporting market responsiveness is the second use case of DA in strategy identified by Elia et al. (2020). Market responsiveness is about the ability of an enterprise to respond to changes in the market such as fluctuations in customer or supplier demand (Elia et al., 2020). DA is valuable in this, supporting the identification of opportunities and threats of organizations, enabling "agility", quicker response to change (Barlette & Baillette, 2022), and enabling businesses to adapt to changing market circumstances and evolving customer needs (Elia et al., 2020; Jahan & Sazu, 2022).

Agile organizations have resources, in this case access to DA in SDM, that can be swiftly mobilized in the context of expected changes (Verdú & Gómez-Gras, 2009). DA can help identify and mitigate risks (Oliveros-Torresy et al., 2014), helping with agility, agile organizations deploy quantitative techniques provide to assess and manage threats or risks (McNeil et al., 2005).

Customer relations
The third case where DA can add value in strategy is in maintaining or improving customer relations (Elia et al., 2020). Firms can benefit from performing DA on their customer data (Erevelles et al., 2016). For example, in their literature review, Elia et al. (2020) explained how DA can help with maintaining or improving customer relations. They can do so by predicting customer behaviour and by defining customer-oriented value propositions using data, and by customizing advertising messages based on analytics. In these ways, businesses can provide goods or services better tailored to their customer base. Successful DA usage in customer relationship management can lead to innovations in the business and value proposition, due to the ability to create a better overview of specific customer demands (Anshari et al., 2019).

Value proposition
The fourth use case in strategy where DA can add value is in the value proposition of the business. By examining the above customer data and market trends, businesses can identify opportunities for new products and services, driving innovation (Elia et al., 2020). DA usage provides businesses with the insights necessary to align innovations with new customer demands and preferences (Jahan & Sazu, 2022).

Recently, literature has introduced the concept of data-driven business model innovation (Wiener et al., 2020). Data-driven business models are business models which focus on value creation leveraging data (Guggenberger et al., 2020). Businesses can leverage DA processes and summarize internal data to improve innovations in their value creation (Sorescu, 2017; Wiener et al., 2020). Furthermore, Goldstein (2022) discusses how data-driven business model innovation can improve competitiveness and resilience in SMEs, sometimes requiring decoupling of new business models from established ones.

Organizational benefits
The fifth use case in strategy, this one being formulated by synthesising literature instead of taken from the framework of Elia et al. (2020) and then contextualized, are organizational benefits.

DA can add value to strategic decisions made with the incentive to improve the organization. Like Elia et al. (2020) explained, DA can help enhance operations, sustain organizational performance, and improve overall firm performance.

Instead of the term "organizational benefits", Elia et al. (2020) placed the component "skill development" under strategy. However, if we take the literature on strategy (in section 2.1) into consideration, taking this component to a higher abstraction level is better suited for this research. Examples of developing skills in Elia's framework are the hiring of big data experts, developing teams involved with DA, and the development of innovative projects within the enterprise. The component "organzational benefits" also takes these skill developments into account, but aligns better in abstraction level to the other components of SDM discussed in the sections above.

DA can support SDMs regarding organizational benefits in multiple ways; Lang (2022) explores how data management improves financial enterprise management efficiency and viability, emphasizing the role of emerging technologies in alleviating financing issues. Artificial Intelligence (AI, advanced DA) can be valuable when making financial decisions for organizations (Zhou et al., 2023) and improve operational efficiency (Brynjolfsson & McAfee, 2017) and organizational innovations (Tawil et al., 2023; Wamba et al., 2015).

Tawil et al. (2023) and Wamba et al. (2015) highlight how DA can support in productivity, innovation, and job creation. Machine learning and Artificial Intelligence systems (advanced forms of predictive and/or prescriptive analytics) have been proven to be able to solve operational problems (Brynjolfsson & McAfee, 2017).

The long-term benefits of better (strategic) decisions regarding internal improvements by using DA and synthesizing these into the component "organizational benefits" lets us take this into our framework, which is discussed in the next section.

2.2.3. Framework for sub-question 1

In 2.1, it was described how DA usage can be split into three categories: Descriptive, predictive and prescriptive analysis. In 2.2, five main categories were DA can potentially add value in the SDM of SMEs were identified: Market positioning, market responsiveness, customer relations, value proposition, and organizational benefits.

To be able to answer sub-question 1, a framework was built to support the investigation of what techniques were used in which categories of strategic decisions. The outline for this framework is displayed in table 2.1 below.

Table 2.1: Framework for SQ 1

SDMs regarding | Analytics used	Market positioning	Market responsiveness	Customer relations	Value proposition	Organizational benefits
Descriptive					
Predictive					
Prescriptive					

2.3. Current state and barriers to DA in SMEs

As described in section 2.2 and the literature, DA are often wrongly viewed as separate organisational information systems, but, when implemented correctly they can integrate organisation-wide (Janssen & van der Voort, 2016; Melchert et al., 2004). Despite the aforementioned potential benefits, SMEs face barriers in adopting DA, including limited financial resources, lack of skilled personnel, and inadequate technological infrastructure (Bianchini & Michalkova, 2019).

Numerous authors elaborate on the difficulties of DA in practice. For example, in a literature review, Sivarajah et al. (2017) argues why there are very limited examples of good prescriptive analytics in the real world. The analysis from such data often provides partial insights into a complex business problem, thus being limited by what is included and the characteristics of the data. Xu et al. (2014) explain how predictive analytics in decision-making is difficult to realize, because the processing of the large amount of data required is often slow. However, recent developments and broader adoption of cloud analytics in SMEs has helped overcome this barrier (Gui et al., 2021). Alam and Marwah (2023) proposes a cloud computing strategy tailored for SMEs, allowing scalable and secure data storage that accommodates business growth. The state and adoption of DA in SMEs in constantly evolving.

Studies have found the adoption rate for (big) DA in SMEs to be as low as around 12% (Bianchini & Michalkova, 2019; Willets et al., 2022). Despite the aforementioned potential, the adoption of DA for SMEs remains a complex process and is thus limited in adoption (Bianchini & Michalkova, 2019).

The second sub-question, introduced in chapter 1 is: "*What barriers do decision-makers in SMEs encounter when utilizing DA in SDM?* ". The third sub-question is: *What opportunities do decision-makers in SMEs perceive regarding further implementation of DA into their SDM?* . Given the current limited adoption of DA, the barriers that hinder its use and the opportunities that are perceived will be investigated. To answer these sub-questions, a theoretical framework will be constructed. To be able construct this framework, the factors influencing adoption are discussed in this section.

2.3.1. Adoption theory: TOE for DA adoption, barriers and opportunities

To analyze complex processes of adoption, theoretical frameworks can be used and be of help with understanding the nature of adoption processes. A foundational framework in technology adoption literature is the Technology-Organization-Environment (TOE) framework by (Tornatzky & Fleischer, 1990).

Compared to other widely accepted technology adoption models, like the Diffusion Of Innovation (DOI) theory of Rogers (2003) or the Technology Acceptance Model (TAM) of Venkatesh et al. (2003), the TOE-framework provides the best view for this study. It overcomes the focus on the technology of the DOI (Rui, 2007, p. 7), and introduces the environmental context, which is not present in the DOI theory, and is not solely focused on the organization (Rogers, 2003). Next to this, TAM focuses on lower-level user acceptance, whilst TOE focuses on organizations (Bryan & Zuva, 2021). The TOE-framework is most suitable for studying barriers and opportunities of DA adoption in the SDM of SMEs.

The TOE-framework, displayed in figure 2.1 below, allows for systematic evaluation of how factors (like opportunities and barriers from sub-question 2 and 3) affect technology adoption of organizations. After the introduction of the TOE-framework, many studies on adoption of technologies have used it to evaluate adoption.

The technological context addresses the existing technologies relevant to the firm, both currently in use and those available for adoption. The organizational context considers the characteristics and resources of the firm. The environmental context includes external factors such as industry characteristics and general environment. (Tornatzky & Fleischer, 1990)

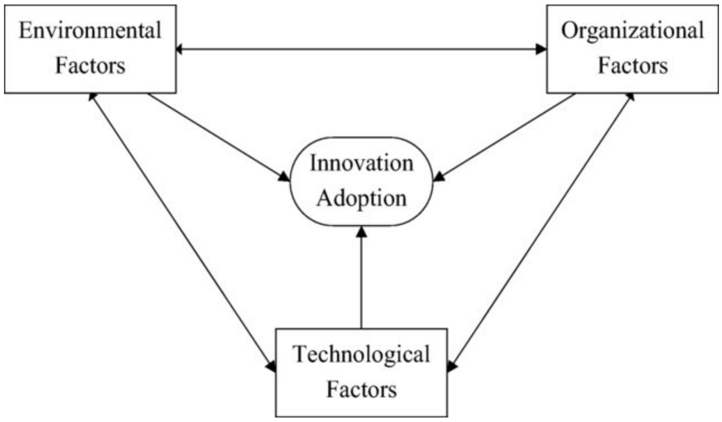

Figure 2.1: Technology-Organization-Environment Framework (Tornatzky & Fleischer, 1990)

In the context of this study, it is possible to identify a number of factors for adoption and place these in the context of the TOE-framework and its components. These factors can be barriers, because they could all influence and thus hinder the adoption of DA. The sections below describe the possible technological, organizational and environmental barriers to DA adoption in SMEs.

2.3.2. Technological factors

Literature on DA adoption indicates the main technological factors for adoption in organizations are complexity, compatibility of the techniques, and IT infrastructure (Ramanathan et al., 2012; Verma & Bhattacharyya, 2017).

Complexity of DA techniques

Rogers (2003) defined complexity in technological context as "*the degree to which an innovation is perceived as relatively difficult to understand and use*" (Rogers, 2003, p. 230). Compatibility could affect adoption of DA in firms, due to certain technologies being more suitable for the existing infrastructure of specific firms (Ramanathan et al., 2012).

The chosen tools and methods used impact the insights, speed and efficiency of the process (Mosbah et al., 2023). The technology and tools involved in predictive or prescriptive DA involve a variety of methods such as machine learning and modelling (Mohanty & Vijayakumar, 2019). Excel, SPSS, MATLAB, R and Python are commonly used, but require specific expertise (Goundar et al., 2021) and are often expensive to use (Mosbah et al., 2023). Technology constantly evolves. For instance, a relatively new technology, cloud DA, could in comparison to regular DA tools, potentially be more attractive and of better use to small(er) businesses. They require less technical expertise and facilities, and being more cost-effective (Naous et al., 2017; Ragazou et al., 2023). The complexity of DA techniques, based on the properties of those techniques can be a barrier for DA usage.

Data compatibility to organization

The type, quality and quantity of data available can impact the effectiveness of DA (Mosbah et al., 2023). Organizations often encounter issues regarding data quality when attempting DA (Gong & Janssen, 2021). Data can be difficult to work with, and challenges concerning data (quality) often relate to its characteristics and the challenges associated with the six Vs (described in section 2.1).

Sivarajah et al. (2017) name the IT architecture of a business to be a potential hurdle for DA adoption. Next to the data being of high quality, it is important that the IT architecture is suitable for analytics (Coleman et al., 2016). Coleman et al. (2016) composed a reference architecture for DA in his article on DA in SMEs. The complexity of this architecture poses a challenge for SMEs (Coleman et al., 2016), it requires sound hardware and networking, data storage, processing, analytics and integration, and requires tools for reporting and security. This complex infrastructure not being up to standard poses issues for organizations trying to adopt DA (Gong & Janssen, 2021).

2.3.3. Organizational factors

The organizational context contains factors that stem from the characteristics of the organizations (Tornatzky & Fleischer, 1990). Three factors were identified in the literature.

Managerial attitude towards DA

Strong leadership and support from top management are essential for successful technology adoption. Horani et al. (2023) and Verma and Bhattacharyya (2017) noted that top management's commitment to allocating resources and fostering a supportive culture are essential in DA adoption. The attitude towards DA from the decision-makers in the enterprise can be a barrier for adoption (Verma & Bhattacharyya, 2017). The perceived benefits of the decision-maker are an important factor in choosing to adopt DA in decision-making (Chen & Nath, 2018). The skills and knowledge within the organization are also important (Tawil et al., 2023).

The strategies, policies and procedures around DA are influential to its usage. The process component involves the internal application of DA. It relates to a series of "how" questions: how to: capture the data, integrate the data, transform the data, select the right model and provide the results (Gong & Janssen, 2021). Furthermore, it includes the vision, objectives, strategies, policies and procedures required to govern DA activities such as data collection storage, analysis and utilization (Mosbah et al., 2023).

Available budget

According to literature, financial investment or the available budget is a barrier to the adoption of DA. The implementation of DA requires significant financial resources, including costs for data storage, real-time processing, and analysis tools. Many SMEs and even larger organizations often struggle to allocate sufficient budget for these technologies due to their high initial investment requirements. For instance, Bruintjies and Njenga (2024) identified finances as a barrier for government organizations, which typically have large overall budgets. Willets et al. (2022) found financial barriers to be a significant in usage of DA in operational contexts in SMEs.

Knowledge in the organization

The skills and expertise of individuals within an SME are important for effectively using DA. Data scientists play a key role by applying their technical knowledge to handle and analyze data. Their ability to choose the right methods and tools is essential for gaining useful insights from data. Without their expertise, it can be difficult for an SME to fully benefit from DA, as the quality of the analysis relies on the accuracy of their work (Mosbah et al., 2023; Power et al., 2018).

It is important that data scientists, managers and decision makers are able to make the right decisions in adopting DA and picking the right techniques (Mosbah et al., 2023). They need to understand DA well enough to make informed choices about which tools and techniques to use.

2.3.4. Environmental factors

The environmental includes elements beyond the organization's control but that significantly affect its operations, opportunities, and constraints (Tornatzky & Fleischer, 1990). Two factors were identified in the literature.

External pressure

External pressure can be a factor influencing DA adoption (Verma & Bhattacharyya, 2017). Musawa and Wahab (2012) identify two primary drivers of external pressure: pressure from business partners and competitive pressure. Business partner pressure is the potential influence of business partners of the firm to encourage or discourage IT adoption. Competitive pressure is caused by the industry and the firm's competitors adopting technology. This may influence the adoption choices of DA in the SDM of SMEs.

Regulatory environment
The regulatory environment, requirements and compliance standards can also compel organizations to adopt DA (Salleh & Janczewski, 2016; Tawil et al., 2023). Regulations often compel organizations to adhere to strict guidelines to ensure data security and privacy. These are important to keep in mind during whole analysis process and especially when dealing with large amounts of data, as it can be difficult to navigate the regulatory environment when data volume and complexity rises (Salleh & Janczewski, 2016).

The challenge of ensuring compliance with privacy regulations in a big data environment can significantly deter organizations from adopting DA. The complicated nature of these regulations, coupled with the high stakes of non-compliance such as legal penalties, financial losses, and reputational damage can lead organizations to hesitate in fully exploiting DA (Salleh & Janczewski, 2016).

2.3.5. Complexity and interdepency

As explained by Tornatzky and Fleischer (1990), it is important to keep the complexity and interdependencies of the TOE-factors in mind when discussing the components individually. Looking critically at the contextual elaboration of the components above, relations exist between the factors. For example, the characteristics of DA will influence the perceived benefits, the external pressure from the environment, This is a key property of the TOE-Framework (Tornatzky & Fleischer, 1990), and should be kept in mind when researching DA in the SDM of SMEs.

2.3.6. Framework for sub-questions 2 & 3

In section 2.3, key factors for the adoption of DA were described using the TOE-framework. We can take these factors as a starting point for barriers and opportunities for DA adoption. We can go from factors to barriers because the factors that influence DA adoption point to specific challenges or obstacles that could hinder its successful adoption. However, it is not yet clear whether all these factors are applicable to the SDM of SMEs. In this research, these identified barriers serve as a starting point to further explore their relevance to SDM processes in SMEs.

To support the research, a framework was built to provide an overview of the identified barriers. This framework is displayed in table 2.2 below.

Table 2.2: Literature framework of barriers to DA adoption

Type*	Barrier or opportunity for improvement	Source
T	Complexity of DA techniques	(Coleman et al., 2016; Mosbah et al., 2023; Ramanathan et al., 2012; Verma & Bhattacharyya, 2017)
	Data compatibility to organization	(Mosbah et al., 2023; Verma & Bhattacharyya, 2017)
O	Managerial attitude towards DA	(Chen & Nath, 2018; Horani et al., 2023; Verma & Bhattacharyya, 2017)
	Available budget	(Bruintjies & Njenga, 2024; Verma & Bhattacharyya, 2017; Willets et al., 2022)
	Knowledge in the organization	(Mosbah et al., 2023)
E	External pressure	(Musawa & Wahab, 2012; Verma & Bhattacharyya, 2017)
	Regulatory environment	(Salleh & Janczewski, 2016; Tawil et al., 2023)

*Type: Technological, organizational, environmental.

This framework and the framework from section 2.2.3 provide structure for the research and research approach. Chapter 3 describes the research approach.

3
Research approach

The research question for the proposed research is "How do decision-makers in Small- and Medium-sized Enterprises (SMEs) utilize data analytics (DA) in strategic decision-making (SDM), and what are perceived barriers and opportunities associated with its application?". The frameworks to use in this research are displayed in sections 2.2 and 2.3. In this chapter, the research approach and methods, which were used to further develop this framework, are described.

Section 3.1 provides an overview of the research design. Section 3.2 describes the data collection method. 3.3 describes the materials for analysis and analysis methods. 3.4 describes ethical considerations and 3.5 displays the research planning.

3.1. Research design overview & flow diagram

Table 3.1 below displays an overview of the research design. The components to display an overview of the design were established by Saunders et al. (2019).

Table 3.1: Research design overview

Component	**Description**
Research goals	Building the frameworks and theory applicable to SMEs from chapter 2.
Nature of the data	Qualitative data
Data collection strategy	Semi-structured interviews
Research setting	In person in-office or by exception online video call
Research subjects	SME Decision-makers (managers, owners)
Temporal orientation	Cross-sectional

The goal of this research was to develop a better understanding of DA in the SDM of SMEs. To achieve this, the frameworks displayed in chapter 2 were built upon, using the results of analysis of qualitative data. This data was gathered using semi-structured interviews with decision-makers of SMEs, such as managers or owners. The temporal orientation of the study is cross-sectional, due to the duration of the research and nature of the research question.

The data gathering and framework development can be visualised as displayed in figure 3.1 below. This research flow diagram displays the iterative process of interview design and framework development.

The data analysis was carried out in-between the interviews, to improve the effectiveness of the following interviews, and finalized after the last interview.

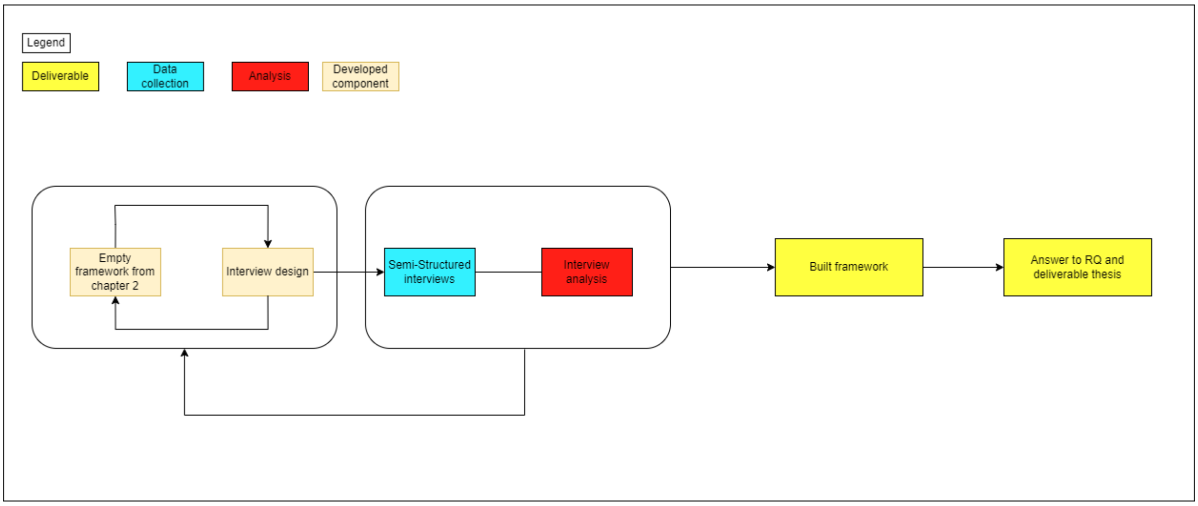

Figure 3.1: Research Flow Diagram

3.2. Data collection

Semi-structured interviews have been conducted to gather insights about the usage of DA in the strategic decision making of SMEs. They provide in-depth information and evidence from interviewees, whilst maintaining focus on the scope of the study and allowing flexibility and adaptability compared to a structured interview (Mashuri et al., 2022). This method also allows for reflection after each interview, to reflect on the content of the guideline, including potential biases, wrong assumptions, and on the general experience of the interview (Roberts, 2020).

An objective of the data collection using interviews was to achieve data saturation, which is when no new information is gathered from new interviews (Morse, 1995; Rahimi & khatooni, 2024). When conducting interviews, saturation generally occurs somewhere between 9 to 17 interviews (Hennink & Kaiser, 2022).

3.2.1. Approaching participants and interview setting

Potential participants were contacted though e-mail or a phone call. Some participants in the hospitality and retail sector were approached in their corresponding businesses. Each participant was told an interview was expected to last approximately 60 minutes, allowing for in-depth discussions.

Most interviews have taken place in-person, which was the preference of the researcher. Two participants asked specifically for a video-call, for which exceptions were made. When arranging interviews, the participants were told the interviewer was willing to travel to the participant to take an in-person interview.

3.2.2. Subjects & sampling strategy

To gain insights about DA in decision making in SMEs, a criterion for interview participants was to be close to the SDM of an SME. Whilst the definition of an SME can vary depending on context (Berisha & Pula, 2015), the European Commission has standardized the term in the Union, and states that SMEs have less than 250 staff members and under or equal to €50 million turnover (European Commission, 2003). This definition of SMEs was used to select participants.

Thirteen interviews with decision-makers in these SMEs were conducted. As the research has taken place in the Netherlands, all interviews were held with Dutch SMEs. In the Dutch SME space, several sectors are significantly larger than others:

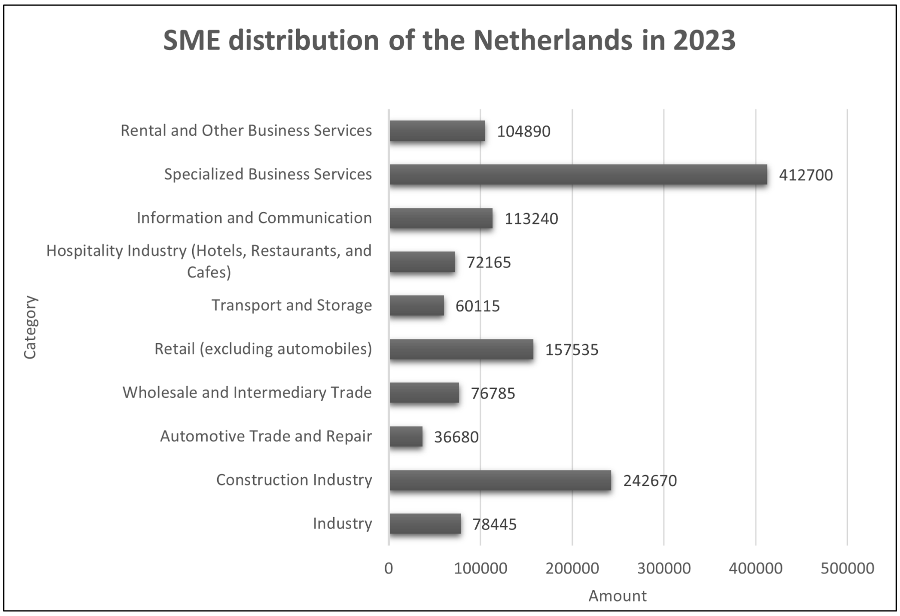

Figure 3.2: SME Distribution according to data from MKB Statline, 2024

The most prevalent sectors in the Netherlands are specialized business services (30%), construction industry (17%), retail (12%) and IT (8%). To be able to answer the research question, which encompasses the entire SME sector, maximum variety sampling across the SME distribution was used. If the widest range of perspectives is caught in the data collection, and themes still emerge from the analysis, these themes are applicable across SME sectors. Table 3.2 displays the participants, their sector, specific business type and roles in their SME.

Table 3.2: Participant characteristics

	Sector	**Business**	**Role of participant**
Alpha	Specialized Business services	Business economics consultancy	Owner - manager
Bravo	Specialized Business services	SME Consultancy	Business partner
Charlie	Specialized Business services	Software consultant	Owner - manager
Delta	Specialized business services	Software consultant	Owner - manager
Echo	Specialized business services / Industry	Energy consultant	Manager
Foxtrot	Healthcare	Specialized healthcare provider	Owner - developer
Golf	Construction industry	Contractor	Controller
Hotel	Retail	Store	Owner - manager
India	Wholesale and Intermediary trade	Food producer and wholesaler	Owner - manager
Juliet	Industry	Metal working	Owner – manager
Kilo	Industry	Industrial specialized equipment development	Owner - manager
Lima	Industry	Clothes printer	Owner - manager
Mike	Hospitality	Ice cream shop	Owner - manager

3.2.3. Interview procedure

The interviews were recorded using the phone of the researcher.

During the interviews, an interview guideline was used. In Appendix A, the guideline is displayed. An interview guideline enables researchers to maintain focus on topics, without constraining to a particular format and thus keeping the advantages of semi-structured interviewing, such as increased depth of the method (Mashuri et al., 2022). Because the interviews were held in Dutch, a Dutch translation was used during the interviews. This semi-structured interview guideline served as a guide during the interviews, ensuring that relevant topics are discussed. Sometimes, a brief discussion before the start of the recording took place. When this occurred, on some occasions the first question was different due to continuation on that current subject. The interviews were not bound to the questions and themes in the guideline, which allowed for further depth when deemed necessary by the researcher.

During the duration of the research, the interview guideline was revised multiple times. The version in the appendix is the latest and final version.

In the framework for sub question 1, potential use cases where DA can add value in SDM are listed. In the (final version of) interview guideline, decision makers are asked to describe an example of where DA helps in their SDM when following the guideline for the interviews. They are then asked, about what holds them back in further adoption. This is aimed at the second framework, which identified potential barriers for DA adoption in SDM. The prompts and next questions in the guideline in the guideline are aimed at deeper questioning or asking to provide other examples, to ensure rich qualitative data for analysis.

3.3. Materials and analysis

The interview recordings were transcribed by listening to the recording and typing out the contents of the interviews.

As interview content translation might compromise validity of the results and introduce unnecessary biases, the interviews were be transcribed in Dutch. The transcripts can be found in Appendix C. During the qualitative analysis, the codes were composed in English. Having translation take place in the coding phase was consciously chosen for, to minimize content translation bias in the analysis. For readability purposes, quotes have been translated in Chapter 4: Results. To ensure traceability of the results, each quote has a reference attached mentioning the transcript it was translated from and which lines in that transcript.

As explained by (Miles et al., 2019), the first step to qualitative analysis is data reduction. Using the literature frameworks, the (highest level-) themes were SDM types, type of analytics, barriers and opportunities. The starting point for the sub themes were determined using the frameworks of chapter 2.

After determining these basic themes, an abdudctive approach was taken during the analysis of the data. An abductive approach goes back and forth between data and theory, instead of choosing for a one-way approach (Saunders et al., 2019; Suddaby, 2006). This allows for flexibility and iterative improvements in theory development (Saunders et al., 2019).

This iterative process involved coding the transcripts, organizing codes into themes, and interpreting the findings in relation to the research objectives. This analysis was conducted using ATLAS.ti, software specifically designed for qualitative analysis. The methods and best practices described by Miles et al. (2019) served as a guide during coding.

During coding, an initial code book, which was solely based on the frameworks, was further developed, specified and changed where deemed necessary by the researcher. For example, the barriers in the framework 2.3 were taken as a starting point, and then specified specified to what was found regarding SMEs during the data analysis, which led to the themes discussed in chapter 4.

In the discussion in chapter 5, a comparison is made between what we saw in the literature as barriers to DA usage, and what we specifically saw as barriers for DA usage in the SDM of SMEs.

Conducting the interview analysis and connecting the results to the framework allowed for conclusions on how DA are used in the SDM of SMEs. The detailed results from the analysis are described in chapter 4, discussion and conclusion of these results is stated in chapter 5.

3.4. Ethical considerations and confidentiality

This research has adhered to with GDPR and TU Delft Human Research Ethics (HREC) guidelines. Prior to participation, participants have been provided with information regarding the purpose, objectives, and interview procedure. Participants have been offered the opportunity to ask questions to clarify any concerns.

Due to the competitive nature of the SME space and potential strategic advantages to using DA, confidentiality has been important throughout the research. All data collected was treated with respect and the identity of participants was protected. Participants have been informed of their right to withdraw from the study at any time without any negative consequences, and have signed an informed consent form. This form can be found in appendix D.

4
Results

In this chapter, the results of the qualitative analysis are described. The transcripts of the interviews are displayed in Appendix B (confidential in publication version). Following the thematic analysis, carried out as described in section 3.3, this results section was written.

Section 4.1 displays the observed themes based on the frameworks from chapter 2. Section 4.2 describes the results regarding discussed DA in SDM. Section 4.3 describes the observed perceived barriers of decision-makers. Section 4.4 describes the observed perceived opportunities of decision-makers.

4.1. Themes, sub themes and definitions

Table 4.1 displays the themes that emerged from the thematic analysis, along with their definitions and grounding. Under grounding, the first number displays the amount of mentions, the second number (in brackets) displays the amount of participants these mentions are across.

Table 4.1: Themes

Theme	Sub theme	Definition	Exemplary quote	Grounding
SDM Types	Market positioning	Quotations regarding DA in the market positioning of the business	*"(…) from a market perspective, we have used all the data from CBS. So, we have used all data of what businesses, what type of businesses, what organizations exist (…)"* (transcript Delta, line 241-244)	26 (11)
	Market responsiveness	Quotations regarding DA used for enabling market responsiveness, or agility of the business	*"(…) what is your occupancy rate on one (machine), what is your occupancy rate on the other, what is the revenue per order on one and what is your revenue per order on the other. Right now we use this almost monthly to set course."* (transcript Juliet, line 41-44)	16 (8)
	Customer relations	Quotations regarding DA adding value in customer relations	*"a percentage of customers were interested in a specific service... so we decided to offer it as a service"* (transcript Charlie, line 13-17)	6 (6)
	Value proposition	Quotations regarding DA used in improving the value proposition or supporting innovations	*"We have data from the feedback of people we work with to develop our product."* (transcript Delta, line 282-283)	5 (4)
	Organizational benefits	Quotations regarding DA used in internal enhancements structuring the business, processes or finances	*"(…) always keep your team a bit diverse, so that they can learn from each other, then it is not a good idea to do all the signaling in one place anyway. But this kind of (financial) data helps make the choice."* (transcript Charlie, line 140-142)	22 (9)

Analytics type	Descriptive analytics	Quotations regarding descriptive analytics	*"A relationship is made between turnover and personnel costs. These are of course just costs that you have control over, so to speak. I do make that relationship, from day to day actually."* (transcript Mike, line 100-102)	83 (13)
	Predictive analytics	Quotations regarding predictive analytics	*"You have this inventory now, we predict that this is going to be the decrease based on what you have done in the past (…) so with the current delivery time, you need to order now."* (transcript Juliet, line 145-151)	23 (10)
	Prescriptive analytics	Quotations regarding prescriptive analytics	*"It already exists in theory, you just need companies that actually implement it. The technology has been around for a long time."* (transcript Juliet , line 534-536)	26 (7)
Barriers	Organizational issues	Quotations regarding the people or organizational structure of SMEs being a barrier to DA usage in SDM.	*"(..) because we're such a small team, very informal and non-hierarchical, a lot of issues actually get picked up and addressed along the way."* (transcript Echo, line 319-321)	47 (10)
	Cost-benefit balance	Quotations regarding cost-benefit as a barrier to DA usage in SDM	*"Look, it is a cost-benefit story (…)"* (transcript Lima, line 234)	16 (9)
	Technical DA issues	Quotations regarding technical issues as a barrier to DA usage in SDM	*"That data is simply not collected or not yet used."* (transcript Bravo, line 79)	44 (10)
Opportunities	Technical advancements	Quotations regarding technology advancement opportunities	*"You also see it change per day, that direction, but you can't say, okay what if I throw this in, what do I end up with? We're not there yet."* (transcript Charlie, line 75-76)	27 (9)
	Collaboration	Quotations regarding collaboration opportunities, with other enterprises or central organs.	*"You really need to have a central body that initiates these kinds of things"* (transcript Juliet, line 417-418)	6 (5)
	Organizational advancements	Quotations regarding internal organizational opportunities	*"Someone needs to delve into it and figure out how we want to do that (…)"* (transcript Echo, line 111-112)	3 (3)

4.2. DA in SDM

The first objective of the interviews was to investigate the usage of DA in the SDM of the participants. In this section, the observations regarding the usage of DA in SDM are discussed. They are presented on the basis of the identified themes, which correspond with the use cases of the framework of section 2.2.

Descriptive - predictive - prescriptive

When asked about what analytics were used in decision-making, most participants described examples of descriptive analytics. Figure 4.1 below displays the distribution of applied DA methods, and how much they co-occurred during the interviews.

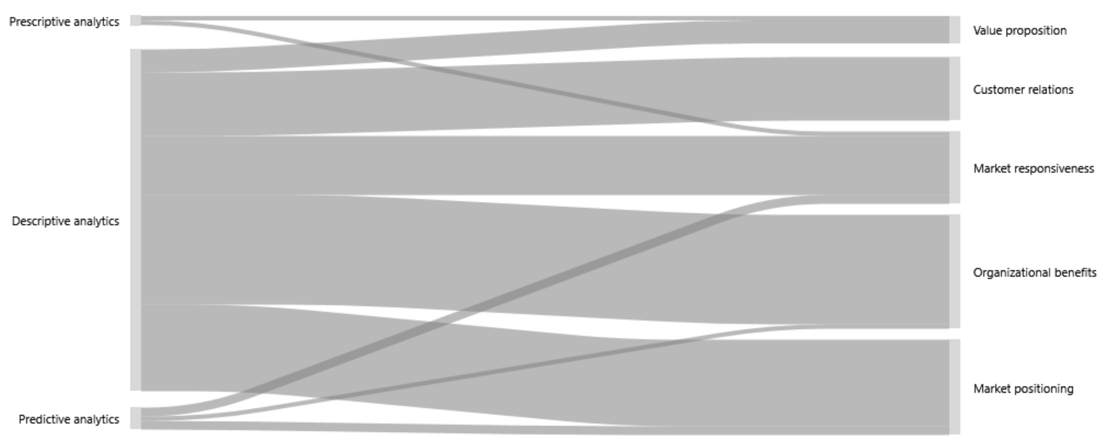

Figure 4.1: Co-occurrences forms of analytics in SDM

As can be seen in figure 4.1, descriptive analytics were the most discussed type, with participants highlighting its role in understanding past performance informing strategic decisions. For example, one participant described the importance of descriptive analytics in their sales strategy: "*At the end of each year, I look back at my assortment to see what we have sold in various gradations, a critical look to, what did we sell, and sometimes you get to the conclusion that you should stop selling something"* (transcript November, line 73-74). In the next sections, the specific use cases and how much which methods were observed are further discussed.

Predictive analytics were rarely talked about in applied cases of SDM, and often only described in potential cases (which are not shown in figure 4.1, but described in section 4.3. Opportunities), with participants noting its potential in forecasting and improving decision-making. The potential was often recognized, but not deployed in their SDM. The barriers explain this. In two SDM processes, prescriptive analytics were used in decisions regarding the value proposition and market responsiveness, both by participant Juliet.

Prescriptive analytics were, just like predictive analytics, less frequently discussed in applied cases of DA usage in SDM, indicating that SMEs may still be in the early stages of adopting more advanced forms of DA in their SDM. Some predictive analytics are used in market responsiveness and positioning, and some internally (for organizational benefits).

In the next sections, the results per theme (use case of DA) are presented.

4.2.1. Market positioning

The use of DA in the process market positioning was frequently discussed by the participants. Market positioning in this context mostly meant analyzing (external) market trends and analyzing competitors. The most discussed forms of analytics in this context were descriptive techniques. In the analysis, a distinction was made between two sub-themes:

Market trend analysis

In 10 out of the 13 SMEs interviewed, decision-makers described some form of DA used in the strategic orientation in the market they operate in. For example, a participant described how they use sectoral data from a central organization: "*And of course there are industry data, we can look at a CBS for data on the sector.*" (transcript Hotel, line 82-84). This was mentioned by other participants as well. For market trend analysis, descriptive analytics prove valuable for SMEs.

Next to simply determining position using industry data, determining market potential was described as an important aspect of market trend analysis. SMEs map data across regions, such as the Benelux, to gauge market potential. For example, this was explained explicitly by a participant: "*And we have mapped the data of the entire Benelux. So we know the enormous market potential, which is also very important for investors*" (transcript Delta, line 267-269). This mapping helps decision-makers identify target demographics and geographic areas for strategic focus.

Competitor analysis

Five participants explicitly mentioned they analyzed competitors and their market positioning compared to their own. For example, a participant explained how they benchmark their pricing compared to competitors: "*Yes, what is realistic? So, we benchmark every now and then, for sure.*" (transcript Charlie, line 157-158). Another participant explained: "*(...) we look at our competitors. We know the market, and we can actually determine, which competitors are present, how big is that market, what contracts are available, how are those assignments actually divided into which works? So we have a little overview of what's going on in the market. Using this, we try to form a vision to focus on.*" (transcript Golf, line 86-90). SMEs compare themselves in pricing and production to their competition using DA.

Customer analysis

The use of DA in SDMs regarding customer strategy was mentioned across eight interviews. Participants explained how they try to understand customer behavior, and integrate these insights into their SDM.

They track their customer base in varying ways, allowing for improvement of their customer relations. For example, participants ask through which channel customers found them: "*(...) the first question to customers was, how did you reach us?*" (transcript Juliet, line 334).

Customer behaviour and segmentation was sometimes used by the participating SMEs to segment their customer base into distinct groups, or work with feedback data or purchasing patterns.

4.2.2. Market responsiveness

Participants explained how they try to respond to the behavior of the market using DA. In the thematic analysis, a distinction was made between two sub-themes of market responsiveness.

Procurement and sales optimizations

Firstly, it was explained by the participants how they use DA in their procurement and sales decisions. They try to be more agile using DA, using the results of analysis to quickly respond to changes. For example, a participant explained, "*We continuously monitor market demand, and when we see a decline, we quickly adjust our prices*" (Transcript Juliet, line 56-58).

Descriptive DA are not solely used for agility, but also for understanding short-term and long-term sales patterns. For example, one participant first described how they analyze customer behaviour regarding their sales: "*I'm just saying, peak run, if you look on an annual basis, we first go on an annual basis, when am I busy, towards autumn. After summer, leading up to autumn. Christmas less busy. Less busy, and then at some point between Christmas and New Year's, it gets busy again, holidays, people buy products, and then after New Year's, not busy anymore*" (transcript India, line 257-262). When he is then asked if he bases his procurement based on this analysis, he says: "*Yes. I base my procurement on that.*" (transcript India, line 279). This case shows how SMEs analyze sales patterns over longer periods of time, to anticipate busy periods and then make their procurement decisions accordingly. Similar optimizations regarding procurement and sales were explained by the other participants.

There are also unique instances where SMEs have implemented predictive or even prescriptive analytics to optimize purchasing and sales. One participant explained: "*Predictive, yes in inventory* (...) *and what it then does is it says okay, you now have this inventory, we predict that this will be the demand based on what you've done in the past, so with the current delivery time you need to order now*" (Transcript Kilo, line 145-151). So, next to just descriptive analytics, some SMEs have gone a step further and are leveraging predictive or prescriptive analytics and adjust their inventory and ordering processes accordingly.

Enterprise Resource Planning (ERP)

Secondly, it was observed that in several sectors such as industry, retail and food wholesale, SMEs have adopted Enterprise Resource Planning (ERP) systems. They use these to optimize or gain insights about business processes. ERP systems differ in their user experience and sophistication: "*I work with Exact Online (...) in which I can, for example, involve procurement, utilities, rent, insurances, and make an overall picture. (...) what does that* [product] *cost me to make?*" (transcript Mike, line 120-117). The analyses these programs provide can inform decision-makers by being able to keep track of and easily display procurement and sales.

These systems are used to a varying degree and with different purposes. Participant Golf explained they were changing provider, because they were aspiring to make more informed decisions, but were not satisfied with the user experience and sophistication of the one they were using before (transcript Golf, line 188-191). SMEs are actively looking to improve their decision-making by being more informed of what is happening with their resources. Another participant explained how they were using an ERP system, but mostly to make internal optimizations (transcript Kilo, line 397-399). These systems are used and give insights to improve overall efficiency and agility. Participants Alpha, Bravo, Charlie and Delta all did not mention this component or anything regarding operational efficiency when asked about DA usage in their SDM.

4.2.3. Customer relations

The use of DA in SDMs regarding relationships emerged as a theme from the data. Participant Echo highlighted the importance of customer satisfaction surveys, where DA is used to measure and analyze client feedback on various services. These results are integral to SDM, guiding decision-makers in refining their strategies. Echo notes that when a service scores lower than expected, the team "looks into what is happening and how we can improve it," demonstrating a commitment to continuous improvement in customer relations.

Participant Charlie emphasized how DA can uncover emerging customer needs by analyzing data from a small group of active clients. By identifying that "*a percentage of customers were interested in a specific service... so we decided to offer it as a service*," (transcript Charlie, line 13-17) businesses can proactively expand their offerings to better meet client demands, thereby strengthening customer relationships and satisfaction. This proactive, data-driven approach is important for both retaining existing customers and by anticipating and fulfilling client needs.

Lastly, participant Delta underscores the value of feedback data in understanding customer experiences. They mention that "*we have data from the feedback of people we work with*," (transcript Delta, line 282-283) which is important for making informed decisions that align with customer expectations. The insights gained from DA in these contexts underscore its role in shaping customer relations strategies, enabling businesses to be more effective in their engagements.

4.2.4. Value proposition

Some SMEs actively leverage feedback mechanisms and data analysis to drive product development and refine their services. For example, one firm utilizes feedback from system users and developers based in India to continuously improve their offerings: "*Feedback from system users and developers in India is continuously used to improve the offerings.*" (transcript Delta, line 231-233). This approach demonstrates how SMEs are using DA to not only maintain but also elevate the quality of their products and services by incorporating data input from stakeholders.

Value proposition SDMs being supported by DA was less often observed than the other SDM types. This indicates that while many SMEs recognize the importance of customer feedback and analytics in day-to-day operations, fewer are systematically integrating these insights into broader strategic decisions about their overall market positioning and value offerings.

In the realm of service and product innovation, the strategic use of DA is more evident among SMEs that are actively responding to market demands and technological advancements. One participant described this approach by stating "*We have data of the feedback of the people we work with which we use to develop our product*" (transcript Delta, 282-283). Whilst this leans a bit towards market analysis, it also shows us how some SMEs are using DA to not only refine products but also to guide the development of new offerings and aligning them with customer needs.

4.2.5. Organizational benefits

SMEs rely on descriptive analytics to gain insights from their financial data, which helps them understand their current situation and guide decision-making. For instance, one participant described how analyzing financial data can illuminate key aspects of their business: "*You can know things, but when you see things in front of you, only then it becomes really clear (...) So, it works enlightening, but sometimes confirmatory too.* (transcript Kilo, line 293-294) This statement highlights how descriptive analytics not only provides clarity but also reinforces existing perceptions, thereby supporting strategic decisions based on historical data.

Despite the clear value of descriptive analytics, the participant expressed an interest in exploring predictive analytics to guide future decisions. However, they acknowledged that while they see the potential of predictive analytics, they have not yet implemented it in their processes: *I am definitely looking into that, absolutely. But if you're asking me right now what I'm specifically doing with it, I honestly can't answer that, no.*" (transcript Kilo, line 307-308). This reflects a recognition of the benefits of predictive analytics but also an acknowledgment of the current gap in its practical application.

Financial management and BI tools enable SMEs to make SDMs based on financial insights. participants highlighted the use of (descriptive) financial reporting and analysis to assess costs, profitability per project, and overall financial performance, for example: "*Yes, in Excel. And I also share something about it every now and then, during that New Year's coffee. (...) most years I just pick something out and then I go into it a bit more in depth, for example the average size of a contract.*" (transcript Alpha, line 483-486)

Risk management emerged as a less emphasized theme among the participants, with only one participant discussing its integration into SDM. The following citation illustrates how this participant utilized DA to assess risk and justify investments: "*I came to the conclusion very quickly that if I buy a large format printer, I will probably earn it back within 1.5 years. And that is without any additional business, that is purely existing* *business. Well, the business is on the rise, plus if you have a printer, you also have smaller parties that come to buy from you. Well, that is an example of data analysis that I have done. So I did not look from my head, I just looked from my head, what exactly is in it, what comes out and based on that we said, okay, we will buy the thing.*" (transcript Lima, line 111-119).

4.3. Barriers

The second objective of the interviews was to identify what barriers decision-makers were encountering when attempting to implement DA in their SDM. Three themes were identified throughout the interviews regarding barriers. Figure 4.3 displays the identified barriers. The classification of the individual barriers is also displayed.

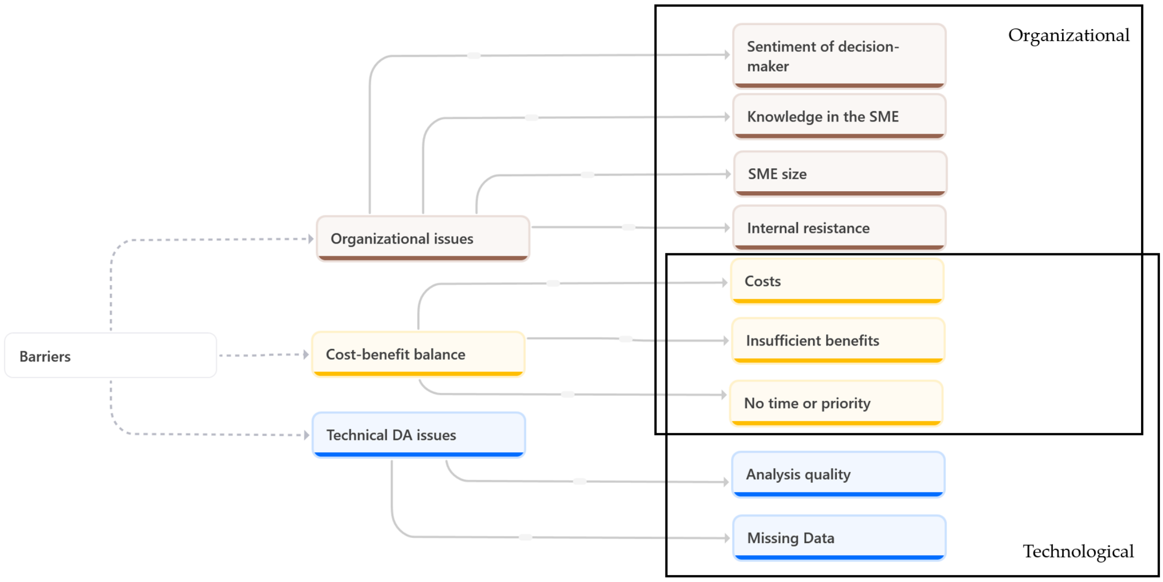

Figure 4.2: Barriers

Figure 4.2 shows how organizational issues, cost-benefit balance and technical DA issues were the themes resulting from the qualitative analysis. These are further described below. The cost-benefit balance barrier can not be classified as purely technical or organizational, and is thus classified as both. In the discussion in chapter 5, this and the placement in the framework of the other barriers in will be further discussed.

Interestingly, no purely environmental barriers were described during by the participants during the interviews. This will also be discussed further in chapter 5. First, the themes are described below.

4.3.1. Organizational issues

The data implied that issues related to the characteristics of their organizations or individuals in these organizations form barriers for DA adoption in SDM. The following sub-themes were identified regarding these issues.

Sentiment of decision-maker

Decision-makers in SMEs exhibited a mixed sentiment towards relying on DA in SDM, or on using DA as a whole. 8 out of 13 participants mentioned some kind of personal sentiment withholding them from trusting DA in their SDM.

For instance, in one interview, it was discussed if a decision-maker would fully trust a prescriptive analysis when making a significant investment, stating: "*I must honestly say that I'm not sure if I have enough trust in software to make such an investment based on it*" (transcript Lima, line 142-143). Similar expressions of hesitation were articulated by other participants. Bravo even called fear of analytics as something he sees "*Yes, I think that fear is one of the most important aspects why data is not used*" (transcript Bravo, line 238-239). He explained how many owners of SMEs are opposed to using analytics because they think it will bring their work in jeopardy. SDMs seem to be considered so important, that a somewhat conservative approach is taken as to changing the processes around it.

Skill or knowledge
Participants explained in many cases how they would like to use DA more in their SDM, but do not possess the knowledge or skills to use DA to its potential.

They voiced concerns about their own limitations or those of their teams in understanding and applying DA tools. For instance, Participant Hotel admitted: "*I think you need some knowledge about that. I think that I could not do enough with that data to really use it in a purposeful way.*". This statement underscores a common issue: while decision-makers may have access to data, they often lack the analytical skills required to extract meaningful insights from it. Without these skills, the data remains underutilized, and the full potential of DA in enhancing decision-making processes is not realized.

Moreover, the challenge of skill and knowledge gaps extends beyond individual decision-makers to the broader organizational context. Some participants reflected not only on their own abilities but also on the general capabilities within their organizations or the SMEs they are familiar with. For example, a participant noted: "*(...) technologically, it is all possible, but you need people who have trained those models.*" (transcript Foxtrot, line 335-336). They explained in a more broad sense that they believe skills or knowledge are an issue when SMEs try to adopt DA in SDM.

This lack of expertise creates a barrier. SMEs may be equipped with the necessary technological infrastructure, but without the right skills, they cannot leverage DA to its potential.

SME size
Some participants mentioned how the scale of their SME makes their decision-making manageable without using DA. One explained how they simply do not feel the need for adoption yet: "*It is still possible to oversee it*". (transcript Charlie, line 282), where "*it*" refers to the strategic problems they encounter. Decision-makers are still able to make strategic decisions without much DA, because the scale of his enterprise makes him able to know what is going on, throughout the whole enterprise.

One participant emphasized the advantage of a small team environment characterized by low hierarchy and informal problem-solving. They described how this setup enables proactive adjustments and prevents major crises from escalating: "*But actually, because we're such a small team, very informal and non-hierarchical, a lot of issues actually get picked up and addressed along the way. (...) By the time things could potentially go really wrong, we've already adjusted course because we sit next to each other and we're constantly in dialogue.* "(Transcript Foxtrot, line 319-324). When strategic issues are discussed this informally, these SMEs do not get the chance, nor feel urgency to do a thorough analysis.

Participants Bravo and Delta specifically mentioned the stages of the Greiner growth model by Greiner (1972) and its different crises as a reason for why a lot of SMEs are not ready for DA adoption in SDM yet. These participants both consult SMEs, their observations are based on expertise and experience. They explained how many SMEs are experiencing "*growth-pain*" (transcript Bravo, line 157), and not in the right phase of the Greiner growth model, to prioritize DA integration in SDM yet. SME decision-makers have other priorities or concerns, and can be stubborn, as Delta explains: "*You should Google the Greiner growth model. Each organization has it's own crisis. (...) many directors think, let me go my own way (...) but if we make clear agreements and know what information we need, we can digitize well.* " (transcript Delta, line 68-74).

The insights from participants Bravo and Delta highlight the relevance of the Greiner growth model in understanding why many SMEs are not yet prepared to adopt DA in SDM. These crises typically involve issues like leadership struggles, a need for clearer structures, or resistance to change, which can overshadow the urgency of adopting new technologies like DA. Consequently, for many SMEs, the focus remains on resolving their current organizational crises rather than on pursuing DA integration, which they may not see as an immediate necessity.

Internal resistance

A single participant explained how it was difficult to gather data because his colleagues, who had to deliver the data based on their work, were not capable or willing to submit enough data for analysis. He wanted to do more thorough financial analysis, but it was very difficult to gather enough electronic data, because the colleagues were used to and wanted to submit their worked hours on paper: "*(...) and that is really a difficult and long trajectory to get through.*" (transcript Golf, line 205-206). This was not explicitly mentioned by other participants.

4.3.2. Cost-benefit balance

Participants expressed concerns about the high costs associated with advanced analytics tools and the difficulty in justifying these expenses. One participant explained, "*For this type of business, these investments are still very difficult to recoup*" (transcript Hotel, line 133-144). The cost-benefit barrier can be divided in three sub-themes.

Costs

Multiple participants mentioned the perceived high cost of implementing DA in general use and in SDM as a barrier for further use or implementation. It appears that cost is a major concern when considering or attempting DA adoption for informed decision-making. For example, participant Lima described this in a very concrete way:

"*Look, it's kind of a cost-benefit story. My thought has always been, I can invest 20,000 euros in something, that should then give something back to me. But, to get that, net 20.000 euros back in earnings, I have to sell so much more for that that, I sincerely wonder to what extent that is realistic. And the downside of software is, it's also not like if I write it now, it's done after that.*" (transcript Lima, line 141-146),

and he further continues about the required time and cost investment:

"*There are really tens of thousands of dollars just walking away because, you're not giving it the attention it should have. And that scares me a little bit. It's a compound or confluence of a lot of factors that I say okay, I sincerely, 100%, see the point of it, but I look up to the cost enormously.*" (transcript Lima, line 358-361)

The SMEs that described this as an issue have a limited budget and every investment is a significant one, especially to something supportive like DA, that does not necessarily pay out directly. This is closely related to the next factor. The potential benefits being insufficient can also be a barrier.

Insufficient benefits

Not just the costs, but the data implies how the estimated benefits of DA usage can also be a barrier for adoption. Participants highlighted the challenge of justifying the investment in DA, given those high costs. These businesses often operate with limited resources and overhead, making every investment decision critical to their sustainability and growth. For example, participant Golf described this: "*(...) but how can I set it up effectively and so that it simply helps us, but also does not require such investment costs for people who have to come, that is the constant balance.*" (transcript Golf, line 172-175).

Participants in the study underscored the difficulty of justifying investments in DA, especially when the benefits are not immediately clear or quantifiable. This statement reflects a broader sentiment among SMEs, where decision-makers must balance the need for advanced analytical tools with the financial constraints they face. The difficulty lies in the absence of direct and concrete benefits that can be immediately observed or measured. Many SMEs have limited overhead, and no direct concrete benefits can make it difficult to justify the expenses of (advanced) DA usage in SDM.

No time or priority

Participants also explained how they simply do not have the time or can not give implementing DA priority in their schedules. "*I think, in every business in their starting phase, the bookkeeping comes last. "Whatever".*" (transcript Mike, line 147-148). Another explained they would like to explore DA possibilities further, but: "*(...) time is what we have the least of (...)*" (transcript Echo, line 114-115). Time investments are a barrier for SMEs further implementing DA.

4.3.3. Technical DA issues

The data implied that issues regarding technical concerns of DA are barriers to further adoption in SDM. The following two sub-themes form this barrier:

Missing data

Without proper data, it is tough to build accurate predictive models or make well-informed decisions. This is a problem for some SMEs. For instance, one respondent highlighted that *"data is simply not being collected or used yet"* (transcript Bravo, line 79) in their context. Missing data was explained by participants as a barrier to DA usage in their decisions.

Analysis quality

Missing could potentially be related to the next sub-theme in this barrier, lacking analysis quality. This issue was brought up multiple times in the interviews, indicating a worry among SMEs about the reliability and accuracy of their data analysis efforts.

This concern was expressed through different knowledge levels of SME decision-maker. For example, participant Golf, who is an expert on the topic of DA, noted "*What holds it back? Very simple: no trust in the source, so that's more on trust and then related to that is, how do you generate the response, so to speak.* (...) *Trust and transparency, and the quality, that's all tied together* (transcript Golf, line 397-399). Participant Foxtrot, who has no specific expertise in DA also has concerns about analysis quality: *we find it very important that it is not speculative, and I'm very easily afraid of that* (transcript Foxtrot, line 254-255).

4.4. Opportunities

The third objective of the interviews was to identify the opportunities that decision-makers perceive in the adoption and integration of DA in SDM. Despite the numerous barriers discussed earlier, participants also highlighted several potential opportunities and possibilities that could still be leveraged in the adoption of DA.

4.4.1. Collaboration

The first opportunity identified during the analysis lies in fostering collaboration among SMEs. It is an understanding among decision-makers that there are overarching strategies and challenges that are shared across the sector. This suggests that pooling resources and knowledge could lead to substantial benefits. For instance, one participant noted the why the opportunity exists, stating: "*If you zoom out a bit, you will see that companies in those sectors actually do more or less the same thing, only the emphasis is different*" (transcipt Bravo, line 188-190) This highlights a key aspect of the opportunity: despite varying focuses, there is a significant overlap in the fundamental activities of these companies, which can be leveraged for collective advantage.

Participants further discussed the potential benefits of working with other SMEs or industry associations to leverage collective data and insights. One participant suggested that the trade association they are required to join could play a role in initiating such collaborative efforts. "*It would be great if the trade association, where we are obliged to participate in, initiated this, and we could join in and contribute*" (Transcript Juliet, line 417-419). This indicates a desire for more structured and facilitated collaboration through established industry bodies, which could serve as a platform for sharing insights and resources.

Another participant provided a concrete suggestion on how to enhance this collaboration. They proposed that increased government subsidies could support innovative projects and data utilization: "*If you really want to do something with data and perhaps further innovate, it might be that there should be better subsidies for that, maybe from the government. You have certain subsidies, of course, for research and development. Maybe you need to make that more accessible.*" (Transcript Lima, line 314-319). This underscores the importance of external support in enabling SMEs to engage in meaningful collaborative activities and innovations.

The feedback from participants reflects a mutual understanding of the benefits of collaboration and the importance of structural and financial support in facilitating it. They envision a collaborative ecosystem where industry associations and government subsidies play roles in enabling joint efforts. This approach not only enhances the sharing of data and insights but also drives overcoming of numerous barriers like the costs and SME size constraints, making it an opportunitity for the SMEs.

4.4.2. Organizational advancements

Three participants mentioned how their DA usage in SDM could improve through organizational advancements.

Organizational advancements present an opportunity for improving the use of DA in SDM. The insights from the interviews reveal that while barriers such as cost, technical challenges, and internal resistance exist, there are also clear pathways for overcoming these obstacles through targeted organizational advancements. These advancements can be understood in two main areas: the availability of budget and the enhancement of understanding and knowledge within the organization.

Budget available

While cost is often cited as a major barrier to DA adoption, the data suggests that in some cases, the challenge is not the absolute lack of funds but rather the prioritization and allocation of these resources. For example, Participant Echo explicitly mentioned that budget constraints are not a primary concern for their organization, stating: "*(...) we are prepared to pay for it, that is not the problem*" (transcript Echo, line 110-111). This indicates that there is budget available, providing an opportunity for investment. Others apart from participant Echo did not explicitly explain this. However, SMEs might have budget available, it is just that the organization has to realize it has to leverage that opportunity.

Understanding could improve

Other participants expressed how they perceived a possible better understanding of the implications of analytics as an opportunity for SMEs to adopt it in their decision making. For example, "*(...) like you do not have it in your own control. But people do not understand, that it is not the choice that is being made for you*" (transcript Juliet, line 545-546). An opportunity lies in the fact that individuals (decision-makers) in organizations can improve their understanding of DA, to enable further adoption of DA in their SDM.

4.4.3. Technical advancements

Two themes regarding potential technical advancements were identified in the analysis. This opportunity tells us how decision-makers feel like opportunities lie in technological advancements they have not leveraged yet, or that DA will advance further in the future and thus will be better suited to them. This twofold resulted in two sub-themes that were identified in the analysis.

Potential technology integrations

Decision-makers described opportunities regarding both predictive and descriptive analytics regarding technical advancements. One participant emphasized the advancements in descriptive analytics they could make: "*Yes, you could certainly do more with data in that respect. Making decisions about which channels to pursue, whether or not to attend events, adjusting our activity within our own network, understanding conversion rates, and analyzing the origin of appointments. What is the percentage that that ultimately converts into customers?*" (transcript Charlie, line 331-334). Another participant emphasized the potential of predictive analytics: "*in terms of prediction, I would like to know much more about where the market needs lie*" (transcript Bravo, line 325-326).

Some participants were more specific in their opportunities regarding technological advancements in their SDM. They were often aware of what is possible, and talked about integrating dashboards, forecasting, real-time (prescriptive) AI assistants, simulating strategies.

Cost of analysis will go down

Participants Juliet and Foxtrot linked technical advancements to a potential lower cost of DA usage in SDM in the future. Juliet explained, "*But I do believe that in a very short period of time, you can go to a point where if a programmer normally spends 40 hours on it, then he will only spend 5 hours on it. And then everything becomes interesting, right?*" (transcript Juliet, line 236-238). This indicates that the decision-makers are aware that DA-technology is constantly evolving, and that this might result in lower cost in the future.

4.5. Concluding remarks on results

This chapter has provided an examination of how DA is utilized in SDM within SMEs. The findings indicate that SMEs are predominantly using descriptive analytics to review past performance and to guide decisions related to market positioning, market responsiveness, customer relations, value proposition and organizational benefits. However, it appears that the adoption of more advanced analytics, such as predictive and prescriptive models, remains limited. This suggests that while SMEs recognize the value of these tools, they are still in the early stages of integrating them into their decision-making processes.

The integration of DA into SDM is particularly evident in areas such as market positioning, customer relations, and organizational performance. These areas benefit from DA by enhancing the accuracy and relevance of decisions. However, significant barriers persist, including organizational issues, cost-benefit issues, data analysis quality issues and concerns about privacy.

Despite these challenges, the research highlights opportunities for SMEs to enhance their use of DA in SDM, particularly through collaborative efforts and the development of in-house capabilities. These findings illustrate the opportunities that are still unexploited in SMEs, and possibly can help with overcoming the barriers. The upcoming discussion will further delve into the usage, barriers and opportunities, and will offering recommendations for how SMEs can better harness the power of DA in their strategic decision-making processes.

5 Discussion and conclusions

In this chapter, the results are discussed and the conclusions to the research question and sub-questions are stated.

In section 5.1, the findings regarding the integration of DA in SDM are discussed, and sub-question 1 is answered. In section 5.2, the barriers to DA adoption for SMEs are discussed, and sub-question 2 is answered. In section 5.3, The opportunities in DA adoption for SMEs are discussed, and sub-question 3 is answered. In 5.4, the main research question is answered. In section 5.5, scientific implications of the research are discussed. In 5.6, the practical implications and recommendations are discussed.

The objective of this research was to develop a better understanding of the usage of data analytics (DA) in the strategic decision-making (SDM) of SMEs. To answer the research question, "How do decision-makers in Small- and Medium-sized Enterprises (SMEs) utilize data analytics (DA) in strategic decision-making (SDM), and what are perceived opportunities and barriers associated with its application?", thematic analysis of the data following 13 semi-structured interviews with decision-makers in SMEs was conducted.

5.1. DA in the SDM of SMEs

The ability of DA to improve decision-making by analyzing large volumes of data has been well documented in larger enterprises (Bianchini & Michalkova, 2019). Despite the potential added value in strategic decisions (Elia et al., 2020), most of the research on DA in SMEs lacked strategic perspectives (Mosbah et al., 2023).

To research the DA usage in the SDM of SMEs, the framework regarding the added value of DA by Elia et al. (2020), was discussed in chapter 2, which led to the following categories of use cases for DA in SDM: Market positioning, market responsiveness, customer relations, value proposition, and organizational benefits.

Using the framework from chapter 2, the usage of DA in the SDM of SMEs can now be stated in table 5.1:

Table 5.1: Framework for SQ 1

SDMs regarding | Analytics used	Market positioning	Market responsiveness	Customer relations	Value proposition	Organizational benefits
Descriptive	Yes, widely used	Yes, widely used	Yes, widely used	Yes, somewhat used	Yes, widely used
Predictive	Used by early-adopter SMEs	Used by early-adopter SMEs	Used by early-adopter SMEs	Used by early-adopter SMEs	Used by early-adopter SMEs
Prescriptive	Not observed	Used by early-adopter SMEs	Not observed	Used by early-adopter SMEs	Not observed

The findings showed that DA is utilized in the SDM of SMEs. It plays a role in enhancing market positioning, responsiveness, customer relations, overall value proposition, and organizations. The results show how descriptive analytics are the most prevalent form of DA in the SDM of SMEs, primarily used for reporting and performance monitoring, enabling more informed strategic decisions. This aligns with the literature discussed in chapter 2, which suggests SMEs often start with simpler forms of analytics due to the unique barriers they encounter (Bianchini & Michalkova, 2019). It does show that considering DA in SDM, we are still at this "start" for SMEs.

To classify the usage of DA in the different types of SDM, the term "early adopters" has been used in table 5.1. This term stems from the Diffusion of Innovation (DOI) theory by Rogers (2003). Whilst the interviews and approach were not necessarily built to be supported by this theory, the wide range of adoption of DA in the different use cases makes this theory suitable to provide a basis for answering the research questions.

The DOI theory provides a framework for understanding how new technologies and innovations spread within sectors or society. According to the DOI theory, the adoption of technology follows a curve that includes innovators, early adopters, early majority, late majority, and laggards. Figure 5.1 displays this curve:

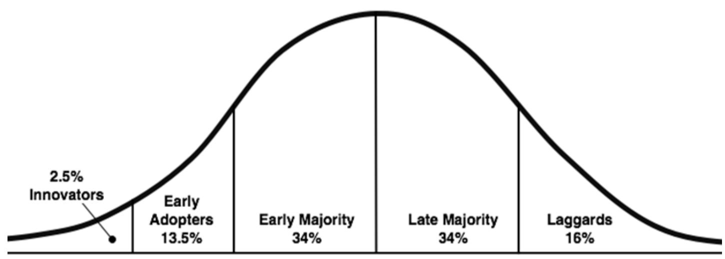

Figure 5.1: DOI-curve (Rogers, 2003)

The DOI-theory is now relevant because our findings reveal varying levels of DA usage in the SDM of SMEs. With some SMEs adopting predictive and prescriptive analytics early on, while others lag behind, the DOI-theory provides a framework for understanding these differences. It helps to explain why some SMEs, categorized as innovators and early adopters, are leading the way in DA usage, while others are still hesitant or facing barriers.

If we place the results in context of the DOI-theory, it appears that we are still at the start of the curve considering predictive and prescriptive DA usage in the SDM of SMEs. This appears to be the case because the data explains how adopters exist, but a lot of SMEs still have not placed DA into their SDM processes. SMEs that do use these techniques appear to be unique. This aligns with the literature, such as Sivarajah et al. (2017) and Coleman et al. (2016) in which it is stated that many SMEs face difficulties adopting DA. The innovators and early adopters do however, in combination with the evidence of added value in the literature, prove concept for DA usage in the SDM of SMEs. These experiences can help to reduce the barriers for other SMEs, encouraging broader adoption.

In the DOI-theory, innovators are the first individuals or organizations to adopt a new technology or innovation. They are typically risk-takers and are willing to experiment with new ideas, even if there is uncertainty about the outcomes. In the context of DA usage in SMEs, innovators would be those businesses that have integrated predictive and prescriptive analytics into their SDM processes very early on, despite potential challenges or a lack of proven success within their industry.

Early adopters are the next group to embrace new technologies. They are more cautious than innovators but are still open to new ideas and willing to adopt them after seeing initial evidence of success. In the case of SMEs using DA in SDM, early adopters would be those businesses that have started using these techniques after seeing the benefits demonstrated by the innovators, even though DA is not yet widespread among SMEs.

When we say that many SMEs are still at the start of the adoption curve for DA in SDM, we mean that only a small number of businesses (the innovators and early adopters) have started using these techniques, while the majority are still hesitant or facing barriers. Understanding these categories helps to explain why DA adoption is still limited and emphasizes the potential for broader uptake as more SMEs observe the success of the early adopters and innovators.

Looking back at table 5.1, we see how DA is widely used in the market positioning of SMEs. Using market trend analysis, competitor analysis and customer analysis SMEs try to position themselves as competitively as possible opposed to the market. Literature highlights the competitiveness of SMEs (Schoemaker et al., 2018), and how DA can add value the market positioning for it (Elia et al., 2020). It was observed in practice that DA is indeed used in SDMs regarding market positioning of SMEs. This is in line with what Bianchini and Michalkova (2019) explains, how DA enables SMEs to identify strategic opportunities and threats, to improve competitive positioning. SMEs value knowing where they stand in their corresponding market, and use DA in this strategic component by analyzing open industry data, mapping their market potential, or analyzing competitors and "benchmarking" themselves. It can be noted that these analyses are achieved by performing descriptive DA, which is what SMEs mostly use for market positioning. Predictive or prescriptive DA are rarely used yet, indicating barriers possibly hinder adoption here.

Considering the dynamic business landscape of SMEs, described by Bianchini and Michalkova (2019) as characterized by ever-changing technology usage, shifting conditions and evolving customer expectations, it is no surprise that SMEs use DA for descriptive analytics to improve their market responsiveness. In the results, some rare use cases of predictive and prescriptive analytics were applied for better market responsiveness.

DA can, according to the literature, help improve customer relations, by allowing businesses to spot opportunities for innovative products and services, with DA aligning these innovations with customer needs (Elia et al., 2020). The results show us how in practice, DA is being applied in SDMs regarding customer relations. Customer behaviour is analyzed and customer groups are segmented, indeed allowing for increased competitiveness and increased innovation. As seen in the results, this is also mostly done by using descriptive analytics.

The literature suggests that DA can support decisions regarding value proposition improvements (Elia et al., 2020; Jahan & Sazu, 2022). Whilst the findings support this, they also reveal that SMEs primarily support this using descriptive analytics based on customer or developer feedback or market data. Recent studies highlight data-driven business model innovation, where businesses use DA and internal data to enhance value creation, improving competitiveness (Goldstein, 2022; Guggenberger et al., 2020; Sorescu, 2017; Wiener et al., 2020). True data-driven business model innovation, where DA supports fundamental changes in the business, was not directly observed and appears to be limited in practice for SMEs. It appears that a lot of SMEs innovate based on the entrepreneurial feeling of the decision-maker, in most cases the owner of the SME.

In this research, SDM has been conceptualized and presented in segments where DA could be used. However, the findings show how many aspects of SDM are interconnected and often overlap. For example, analysis on customers might improve the ability to perform data-driven value proposition changes, or better data on the current market positioning might support decisions regarding procurement and sales, which was segmented under market responsiveness. This overlap suggests that both DA tools and strategic decisions are often multidimensional, affecting multiple areas of SDM simultaneously rather than in isolation.

The results show that DA is used in strategic decisions concerning organizational benefits in SMEs. The confirmatory nature of descriptive DA helps in improving the confidence of the decision-maker in strategic decisions for organizational improvements. While participants acknowledged the potential of DA for predictive or prescriptive analytics, they also expressed uncertainty about how to realize this potential.

5.1.1. Conclusion: sub-question 1

Sub-question 1 was: "How and in what SDM use cases do SME decision-makers use DA?"

The findings indicate a range of integration levels in the different use cases of DA in SDM among SMEs. Ultimately, usage seems to depend greatly on the individual SME. This variation is possibly influenced by the barriers and opportunities associated with DA usage in SDM. The level of DA usage in the SDM of SMEs varies, and depends on the individual SME and its characteristics.

DA is used in the SDM of SMEs regarding market positioning, market responsiveness, customer relations, value proposition, and organizational benefits. Decision-makers in SMEs employ mostly descriptive methods of DA in their SDM. Some SMEs are early adopters of predictive and, or, prescriptive analytics. These are outliers, most forms of DA that was observed in the SDM of SMEs was descriptive.

5.2. Barriers to DA usage in the SDM of SMEs

This section discusses the identified barriers to DA usage in the SDM of SMEs and discusses their placement and relation to the literature.

5.2.1. Barriers in TOE-context

In Figure 5.2, the identified barriers are displayed within the TOE-context to provide an overview of their distribution across technological, organizational, and environmental dimensions. However, it is important to note that these placements are not definitive, as the factors within each TOE component are inherently interrelated. This means that while barriers may be categorized under one specific TOE component, they can still influence and interact with factors in other components, reflecting the complex and interconnected nature of DA adoption challenges.

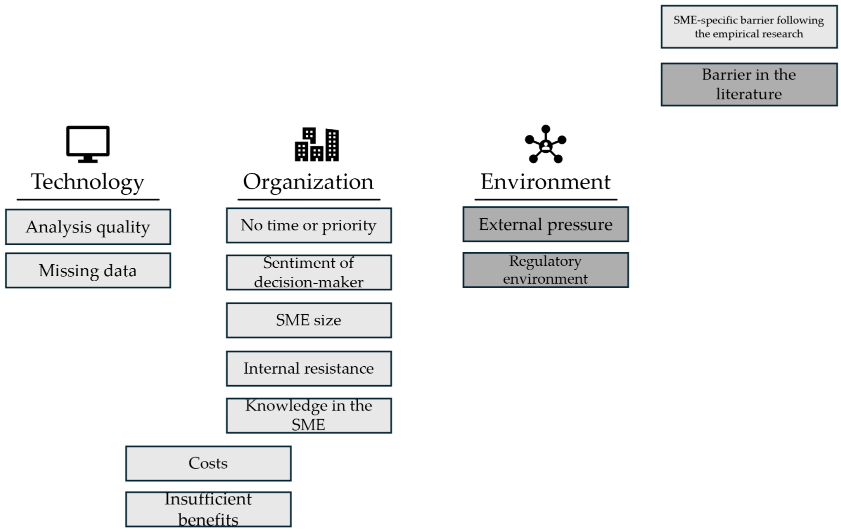

Figure 5.2: SME-specific barriers in TOE-framework

Technological barriers
One of the primary technological barriers emerging from the analysis is the analysis quality of the performed DA. Sivarajah et al. (2017) names the complexity of DA techniques as a barrier for its usage. Gong and Janssen (2021) already explained how enterprises often face challenges regarding data quality.

Another technological barrier is the issue of missing data. If the organization is not ready for DA yet, this can be a barrier (Mosbah et al., 2023; Verma & Bhattacharyya, 2017). If the organization is not ready, which is apparently the case for a number of SMEs, missing data can form a barrier to DA usage in SDM.

Considering the importance of SDM in the organization (Mintzberg, 1994), it is understandable that the analysis quality and data present for analysis are sound before DA is conducted in the SDM of SMEs.

In figure 5.4, the barriers "cost" and "insufficient benefits" are categorized as in-between technology and organization. This aims to show the dependence on both components for these barriers. Costs is traditionally a technological barrier, but due to the properties of SMEs such as the knowledge and size, they are categorized as in-between. The same applies to the barrier "insufficient benefits".

Environmental barriers
Unexpectedly, environmental barriers were missing in the interview data. As can be seen in figure 5.2, external pressure and the regulatory environment (pressure from business partners or competition and rules, requirements or compliance standards (Musawa & Wahab, 2012)) were not observed in practice. This absence may suggest that SME decision-makers are not necessarily concerned with these as a barrier. This could be because they are primarily encountering the other barriers. This will be further discussed in the next section, "organizational barriers". Another possible explanation is that external pressure is simply not felt, because adoption barriers mainly concern predictive or prescriptive techniques, and most that are using these techniques are still innovators or early adopters (as explained in section 5.1).

Environmental barriers to DA usage in enterprises can be external pressures (Musawa & Wahab, 2012; Verma & Bhattacharyya, 2017) and the regulatory environment (Salleh & Janczewski, 2016; Tawil et al., 2023). Interestingly, these barriers were not observed in practice among SMEs. However, this does not mean they do not exist, as they were not necessarily stated as not present by the participants. Possibly, these barriers exist, but decision-makers do not explicitly mention them yet, because the other barriers are more prevalent. The barriers are described in the literature, but are not explicitly debunked in the results, so they are listed with a side note in the framework in 5.2.

Organizational barriers

As explained by Horani et al. (2023) and Verma and Bhattacharyya (2017), leadership commitment and support are essential for successful technology adoption. Some participants indicated that they do not trust the analyses enough, or do not want to be an analysis driven business. Following these results, the personal sentiment to DA of the decision-maker seems to influence the usage and adoption of DA in SDM. This is in line with the literature, as Hang and Wang (2012) argued that SDM in SMEs is heavily reliant on the characteristics of the decision maker. A sentiment change amongst decision-makers could be needed for further DA adoption in the SDM of SMEs.

As explained in the section about environmental barriers above, SME decision-makers did not express concern over pressures from business partners or compliance standards. Possibly, this is the case because they are primarily encountering other barriers. Adoption barriers might mainly concern predictive or prescriptive techniques, and most SMEs using these techniques are still innovators or early adopters. This leads to a focus on immediate operational tasks and firefighting, leaving little room for strategic initiatives such as DA implementation. For instance, the thesis mentions that bookkeeping and similar administrative tasks often take a backseat due to more pressing business activities. This, and the other organizational barriers can be seen in the context of a growth model.

An effect of the size or growth of SMEs was described by two participants. Some participants stated that it is too early in their current stage of business development to let strategic decisions to be driven by DA. Two participants, Bravo and Delta, explicitly mentioned the Model of the five stages of organizational growth by Greiner (1972). These participants, next to decision-makers, are both consulting other SMEs in their strategic decisions, and Delta additionally consults on DA integration. Their explanation for a lot of SMEs not fully embracing DA in their SDM yet, is how they are not in the right stage of organizational growth. Most SMEs are still in their second or first phase of growth, as was explained by participant Bravo. The Greiner Growth model is displayed in figure 5.3:

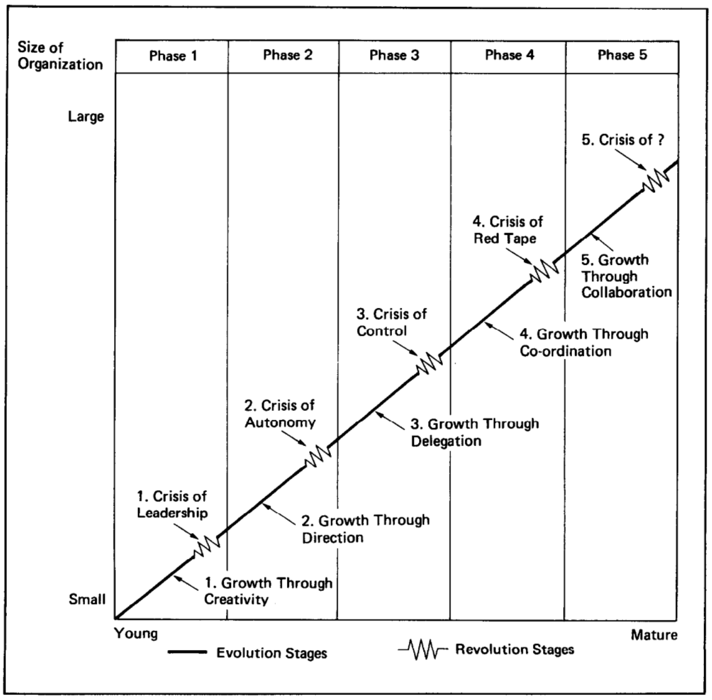

Figure 5.3: The Greiner Model of the five stages of growth (Greiner, 1972)

Many SMEs, as indicated by participants in the research, are still in the early phases (Creativity or Direction) of this model. In these stages, the focus is predominantly on survival, establishing market presence, and creating basic operational structures (Greiner, 1972), rather than on leveraging advanced DA for SDM. The barriers in line with this observation include no time or priority, the SME size, knowledge in the SME, costs, and insufficient benefits. The decision-makers of these SMEs are concerned with other problems than advanced technology integration.

Interconnectedness of the barriers
Connections can also be hypothesized between the empirical barriers themselves. For example, quality issues in data analysis can arise from organizational issues (also stated by (Mosbah et al., 2023)), and poor data practices could lead to privacy issues. If an organization faces resistance to change or lacks skilled personnel, the cost of training and change management increases. Furthermore, the size of an SME is almost certainly directly related to other barriers, such as available knowledge and insufficient benefits.

Whilst these are both barriers, they could also be discussed as consequences of the firm size. The interconnectedness of the barriers are what makes DA adoption so complex. This also confirms that we can look at the barriers in a TOE-framework-fashion, in the TOE-framework, the factors of adoption all influence each other (Tornatzky & Fleischer, 1990).

5.2.2. Relation to literature framework

This section aims to explain how we moved from the literature framework to the overview that was displayed figure 5.2. Compared to the barriers identified in the literature, using the data from the empirical research, the barriers were specified in the thematic analysis for SMEs.

In figure 5.1 below, the barriers from the literature framework are displayed on the left.

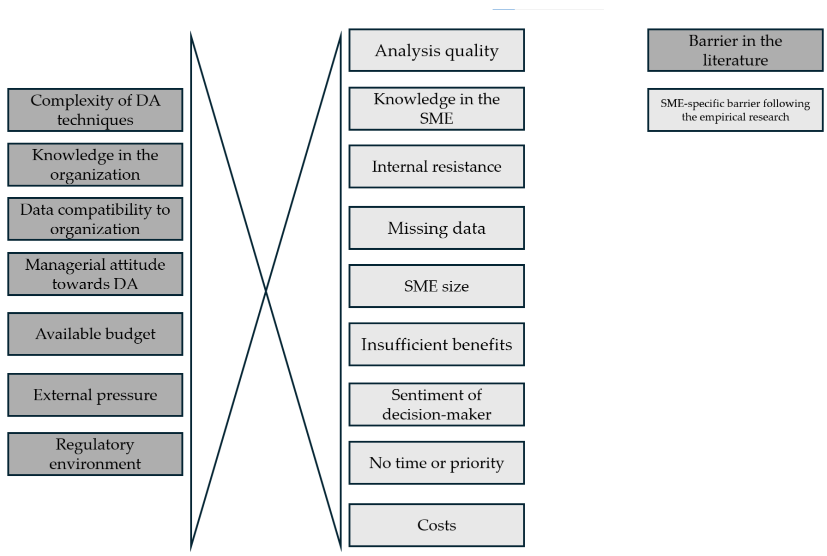

Figure 5.4: Interconnected relation to the literature

The figure aims to provide an overview of the barriers from the literature opposed to the identified barriers from the empirical research. The flow icon in the middle illustrates the interconnectedness and complexity of the relation between "left" and "right". The figure explains how the barriers to DA adoption, as identified in the literature, are not isolated challenges but are interconnected with the empirical barriers uncovered in this research. We could formulate relations from "literature" barrier to each "empirical" barrier.

To further illustrate this, we can take an example and walk through the relationships. Let us take the complexity of DA techniques, a barrier of Coleman et al. (2016), Mosbah et al. (2023), Ramanathan et al. (2012), and Verma and Bhattacharyya (2017). This barrier could relate to knowledge in the SME: the more complex the DA techniques, the greater the knowledge required to implement them effectively. SMEs often lack this expertise, leading to poor utilization of DA tools and techniques. But also analysis quality: when DA techniques are complex, the quality of analysis can suffer if those using the tools are not adequately trained. This can lead to incorrect insights, further discouraging the use of DA. Furthermore, we can relate to SME Size or the costs of DA: smaller SMEs with limited resources may find complex DA tools overwhelming, both in terms of the investment needed to understand and use them, and the infrastructure required to support them. This can lead to a perception that DA is beyond their reach, reinforcing the barrier of insufficient perceived benefits. This is just an example, and describing these relations could go on for every literature barrier in relation to every empirical barrier.

This is is not an unexpected nuance when placing the empirical findings in the literature, as the interconnections between factors is inherent to theory building on the Technology-Organization-Environment Framework (TOE-framework (Tornatzky & Fleischer, 1990)). After all, in this framework, technology, organization and environment are stated to be interconnected and the complexity theory behind it says the same about the underlying factors.

Still, the idea behind using the TOE-framework is to bring clarity to a complex situation. The barriers can still be categorized into the three components, which helps to formulate discussion and recommendations. In the conclusion, we will still categorize using the TOE-framework.

5.2.3. Conclusion: sub-question 2

Sub-question 2 was: "What challenges and concerns do decision makers in SMEs encounter when utilizing DA in strategic decision-making?"

This research identified several barriers to further DA usage in the SDM of SMEs, which were categorized using the TOE-framework:

1. Technological barriers: Challenges related to analysis quality and missing data. SMEs often struggle with ensuring data accuracy, completeness, and reliability of analysis.
2. Organizational barriers: Internal factors within SMEs that hinder DA adoption, including having no time or not assigning priority to DA, the scale of the SME, cost-benefit considerations, and the personal sentiment of decision-makers towards DA. Many SMEs are in early stages of development, focusing on survival and basic operations, which makes DA seem less relevant or feasible.
3. Environmental barriers: External pressure and the regulatory environment, whilst described in the literature, were not mentioned by the SME participants as barriers to their adoption of DA in SDM. Still, no direct evidence was found that this is fundamentally wrong to describe as a barrier, so these barriers are possibly still applicable.

In this conclusion, it is important to note that the TOE context provides an overview and classification, but it is important to recognize that these placements are not absolute. The factors are interconnected, and barriers in one TOE component can influence and interact with factors in others. This makes the adoption of DA in SDM highly complex, as attempting to tackle one barrier could influence another.

5.3. Opportunities for DA usage in SDM of SMEs

Three main opportunities were perceived by decision-makers in SMEs.

Collaborations

SMEs can leverage support from central organizations such as industry associations, which can offer training, resources, and platforms for sharing best practices. Such collaborations can help SMEs overcome knowledge and skill barriers by providing access to expert guidance and collective learning opportunities.

By collaborating with other SMEs, companies can share data, insights, and DA tools. This pooling of resources can lower individual costs and enhance the quality of data analysis, making DA more accessible and effective. This can help overcome the barriers in both technological and organizational context, as the quality could be enhanced, data enriched, and size and cost issues be relieved.

Organizational advancements

Organizational advancements in training and development are not just about filling knowledge gaps but about transforming the organizational culture towards one that is data-driven. The emphasis on continuous learning and adaptation ensures that employees at all levels are not only proficient in DA tools but are also equipped to apply these tools in innovative ways that drive strategic decisions. The impact of this approach is twofold: it builds internal capacity for sophisticated data analysis, and it creates a mindset that values data as a key asset in decision-making.

Technical advancements
The evolution of DA technologies represents an opportunity for SMEs, as the decreasing costs and increasing accessibility of these tools mitigate one of the primary barriers to DA adoption. The ongoing advancements in machine learning, real-time processing, and analytics platforms mean that SMEs can now access sophisticated tools that were previously out of reach. The implication here is profound: as these technologies become more affordable and user-friendly, SMEs can integrate them into their SDM processes without the previously associated high costs and technical hurdles. Better availability following technical advancements of DA tools is likely to lead to broader adoption across the SME sector, enabling even smaller enterprises to harness the power of data-driven decision-making. In turn, this can lead to more informed, strategic decisions that enhance competitiveness.

5.3.1. Conclusion: sub-question 3

Sub-question 3 was: "What benefits and opportunities do decision-makers in SMEs perceive regarding the integration of DA into their strategic decision-making processes?"

The research identified several opportunities for increasing DA usage in SDM among SMEs. These include enhancing collaboration with central organizations and other SMEs, improving employee understanding and training, and leveraging emerging and cost-effective DA technologies. By capitalizing on these opportunities, SMEs can possibly overcome existing barriers and integrate DA more effectively into their SDM processes.

5.4. Main research question

The main research question to this research was: "How do decision-makers in Small- and Medium-sized Enterprises (SMEs) utilize data analytics (DA) in strategic decision-making (SDM), and what are perceived barriers and opportunities associated with its application?"

Decision makers in SMEs use DA in various SDM use cases. In the SDM process, descriptive analytics are mostly used when attempting to make more informed strategic decisions. Predictive and prescriptive analytics are mostly used by early adopters of the technology, but can be valuable for improving long-term business performance. SMEs use DA to make better decisions on market positioning, market responsiveness, customer relations, value proposition and organizational issues.

SMEs encounter barriers that can be categorized using the TOE-framework. These barriers vary per SME, resulting in the varying usages of DA in the SDM of SMEs. SMEs encounter instances where they have not gathered the data. The analysis quality of their performed analyses can be lacking. They encounter a broad range of organizational barriers, ranging from having no time, looking up to the costs of DA, or they judge that integrating DA into their current SDM processes, considering the scale of their business, would not yield enough benefits to justify the cost.

Possibly, technological advancements, collaborations or improving the organizational infrastructure of the SMEs can help overcome these barriers.

5.5. Scientific implications

This research aims to provide a scientific contribution by expanding the knowledge on the utilization of DA in the SDM of SMEs. The study contributes to the existing body of knowledge on DA by providing (albeit exploratory) empirical evidence on its application in SMEs. It achieves this through examination and analysis of empirical data from interviews with SMEs. By directly capturing the experiences of DA usage by SME decision makers across a wide range of sectors, it offers a view that goes beyond what was already known about DA usage in the SDM of SMEs.

The findings reveal that SMEs, despite multiple barriers, can leverage DA in their SDM. This challenges the prevailing, but somewhat old-fashioned, notion that DA capabilities are exclusive to larger corporations. However, DA solutions do need tailoring to accommodate the unique needs and limitations of SMEs.

Table 5.1, which details the specific applications and benefits of DA in SMEs, is particularly significant. This table not only highlights the practical utility of DA across various strategic domains, such as market positioning and customer relations, but also serves as a foundational reference for future academic inquiries. It provides an overview that future researchers can build upon, further exploring how DA contributes to strategic outcomes in SMEs.

Furthermore, by analyzing the barriers faced by SMEs in adopting and integrating DA into their SDM, this study aims to provide specification of the already stated barriers, which was needed due to the unique characteristics of SMEs.

5.5.1. Limitations

While this study provides valuable insights into the use of DA in the SDM of SMEs, several limitations should be acknowledged.

The SMEs included in this study are only from the Netherlands. This focus may limit the applicability of the findings to SMEs in other regions or countries, especially in those with different economic characteristics and challenges.

The study involved a sample of thirteen SME decision-makers, chosen through a process of maximum variety sampling to capture diverse perspectives. While this approach aimed to cover a broad range of experiences, this (voluntary) sampling introduces a limitation. It is important to recognize that those who chose to participate may differ from those who did not. Participants might have been more inclined to engage in the study if they already had a positive attitude towards DA or were more familiar with its use. Consequently, the potential bias introduced by the voluntary sampling of SME decision-makers could have led to an overrepresentation of early adopters and those already familiar with DA, potentially under representing the challenges faced by SMEs with less experience or interest in DA.

While the study identifies cost as a barrier, it does not delve deeply into the cost-benefit analysis that SMEs perform when deciding whether to adopt DA. The lack of detailed financial analysis or comparison of investment versus return on DA initiatives could limit the understanding of why some SMEs choose not to invest in more advanced analytics.

SMEs encompass a broad range of company sizes, from micro-enterprises to larger small businesses. The findings do not differentiate how company size within this spectrum might influence DA adoption and the associated barriers. This generalization may overlook important nuances, such as resource availability or decision-making complexity, which could significantly impact the adoption of DA.

As DA is a rapidly evolving technology, with continuous advancements in methodologies, this research provides a "snapshot" in time that may cause the conclusions to, in time, be outdated. Whilst this is natural for technology research, it is still something that should be kept in mind if this research is read at a later time.

Lastly, while this study identifies significant barriers and opportunities for DA use in SMEs, it does not quantitatively assess the relative impact of these factors. Future research could further look into this.

5.5.2. Future research directions

Following the scientific implications and limitations of the research, a number of future research directions can be formulated.

Expanding the research to different regions or might give interesting insights or contributions, considering economical, cultural or regulatory differences. Furthermore, looking at specific sectors individually might enable researchers to do a more detailed analysis of SDM usage. Examining specific sectors individually allows for a more structured analysis of how DA is utilized and perceived in the SDM within different industry contexts. Sectors may face unique challenges and opportunities related to their operational environments, market dynamics, and regulatory frameworks. A detailed sector-specific analysis can reveal industry-specific patterns and requirements, offering targeted insights into how DA techniques are applied and how their adoption can be optimized. This approach not only enhances the understanding of DA usage but also helps in developing tailored strategies to address sector-specific barriers and leverage opportunities.

Future research into the usage and barriers and opportunities for further adoption of DA in the SDM of SMEs could be interesting to conduct quantitatively. Given the limitations, if the the barriers and opportunities are considered as factors for adoption, a quantitative study could be interesting to conduct, to see which factors are the most significant in DA adoption in the SDM of SMEs. Factor analysis using the data from surveys among a large quantity of SMEs could determine which barriers are more important than others.

Given the financial concerns raised by SMEs in this study regarding DA investments, future research could also focus on the cost-benefit dynamics of DA adoption. Studies could explore how SMEs can optimize their investment in DA, balancing the upfront costs with long-term strategic benefits, and identifying the most cost-effective approaches to DA implementation.

Future research could explore how the size of an SME influences its ability to adopt and effectively use DA in SDM. This research could involve a comparative analysis across different sizes of SMEs to identify distinct challenges, resource constraints, and decision-making processes that vary with company size. This research would provide a better understanding of how company size shapes DA adoption, potentially leading to size-specific strategies or support mechanisms to enhance DA utilization across the SME spectrum.

Future research could also examine the effectiveness of different approaches to building DA skills within SMEs. Considering the opportunity that lies in the training or improving knowledge of employees, this could include studies on the impact of external training programs, the role of higher education institutions in DA skill development, or the benefits of in-house training versus outsourcing DA expertise.

The impact of the potential linkage between the barriers and opportunities could be interesting to further research. The differences across sectors between, for example, the usage of DA in decisions regarding operational efficiency, which possibly is less prevalent in some sectors compared to others, could be interesting to research quantitatively.

5.6. Practical implications and recommendations

One of the opportunities was collaboration among SMEs. A recommendation for SMEs is to try to collaborate with other SMEs to overcome some of the barriers like the size of the SME and costs. If collaborations implement scalable analytics solutions that can grow with the businesses, this could allow SMEs to start with predictive analytics and gradually incorporate more advanced tools.

For SMEs to fully realize the potential of DA, they must invest in building internal (organizational) capabilities. This includes upskilling current employees and possibly hiring new talent with DA expertise. Creating a data-driven culture within the organization will be essential for overcoming organizational barriers and ensuring the sustainable integration of DA into SDM. A phased approach, starting with basic analytics and gradually integrating more advanced techniques, can help manage costs while building internal expertise and mitigating other barriers.

Considering the added value to decision-making, governments and industry bodies can consider to play a role in promoting the adoption of DA in SMEs by providing incentives and support structures. This could include subsidies for technology adoption, tax incentives for investment in data analytics infrastructure, and the creation of innovation hubs where SMEs can experiment with DA solutions.

We are just at the edge of predictive and prescriptive data analytics (and AI) enabling true data-driven strategic decision-making in SMEs. The order of the day, which gets priority in many SMEs, can hold back adoption. Decision-makers seem aware of the possibilities, but still need to overcome numerous interrelated barriers to seize the opportunities.

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A

Interview guideline

A.1. Guideline (English)

Please note that this is the guideline of a semi-structured interview. This guideline encompasses the main themes, questions and prompts to be discussed with the interviewees. The interviews could make use of further prompts that are not described here, such as "could you elaborate more on that" and "why did you make that decision".

Introduction
The interviewer first informs the participant of the research goals. The interviewer explains the concept of strategic decision making and predictive analytics, as it is crucial for the quality of the interview for the interviewee to understand what is meant by both in the context of this research. "Before the interview starts, it is made clear to the participant that answering to the questions is voluntary and should take approximately one hour. With your permission, the interview will be recorded. All responses will be kept anonymized and you and your enterprise will not be identifiable as a respondent. You have the right to withdraw from the study at any time without any consequences. Do you have any questions regarding what I just explained? May I turn on the recorder?"

The table below displays the themes to be discussed.

Theme	Question
DA in SDM	Can you give an example of where data analytics helps in making a strategic decision? **Prompts:** What exactly does that look like? Did this gradually develop, or was that a conscious decision? In addition to this example, where do you think DA add value in your SDM? What hold you back for further adopting DA in your strategic decisions? **Prompts:**Is it realistic to overcome this in the near future? What would that look like? When making strategic decisions such as the one we just discussed, can you provide an example of a case where you used data or data analytics? **Prompts:** If not, do you think this could happen? Is this unrealistic? How are you preparing for possibly more informed decision-making enabled by data?

Further into barriers	What is needed to further incorporate analytical techniques into your strategic decision-making? **Prompts:** Are there other specific barriers preventing this for you? Why are you considering it this way? Are there barriers in the business operations? If so, which ones?
Possible further topics	The interviewer concludes by asking if the respondent has any ideas or perspectives they haven't shared yet, and if there are any other things that have come to mind that haven't been discussed yet.

Thank you for your time, the information and interesting perspectives you shared.

A.2. Guideline (Dutch)

Note that this is the guideline of a semi-structured interview. This guideline encompasses the main themes, questions and prompts to be discussed with the interviewees. The interviews could make use of further prompts that are not described here, such as "could you elaborate more on that" and "why did you make that decision".

Introductie
U wordt uitgenodigd om deel te nemen aan een onderzoek genaamd Data-Driven Business Model Innovation in SMEs. Het doel van dit onderzoek is inzicht verkrijgen in het gebruik van data-analyse in de ontwikkeling van de bedrijfsvoering van het MKB. Dit gesprek zal gebruikt worden voor het formuleren van resultaten en conclusies in de scriptie. De thema's, patronen en conclusies over het MKB in Nederland zullen gepubliceerd worden, de individuele transcripten van de interviews niet. U wordt gevraagd om uw verhalen, ervaringen en perspectieven te delen tijdens het interview, ik vraag u niet naar bedrijfs- of productgeheimen.

Thema's en vragen
Het onderzoek wordt nader geïntroduceerd bij de respondent. Hierdoor kan mogelijk vanaf het eerste moment al worden afgeweken van de openingsvraag, omdat de ervaring leert dat het gesprek natuurlijk leidt tot een versie van het eerste thema.

Thema	Vraag
DA in SDM	Kun je een voorbeeld geven van waar data-analysetechniek binnen je bedrijf helpt bij het nemen van een strategisch besluit? **Voorbeelden van vervolgvragen:** Hoe ziet dat er precies uit? Is dit geleidelijk ontstaan, of is dat een bewuste keuze geweest? Is er, naast dit voorbeeld, ook een plek waar jij denkt dat dit waarde creëert i.p.v. toevoegt? Kun je nog een voorbeeld geven? Zijn er ook plaatsen, waar je eigenlijk keuzes op basis van analyse zou kunnen verwachten, maar die bij jou op gevoel gaan? Wat houdt je tegen om DA technieken verder op te nemen in je besluitvorming? **Voorbeelden van vervolgvragen:** Is het in de nabije toekomst realistisch om te overkomen? Hoe zou dat er uit zien? Hoe bereiden jullie je voor op mogelijk beter geinformeerde besluitvorming (mogelijk gemaakt door data?)
Verder in op barrières	Wat is er nodig om analysetechnieken voor jou verder op te nemen in je strategische besluitvorming? **Voorbeelden van vervolgvragen:** Zijn er andere specifieke barrières voor jou die dit tegenhouden? Waarom maak je deze overweging op deze manier? Zijn er barrieres in de bedrijfsvoering? Zo ja, welke?
Eventuele verdere onderwerpen	De interviewer sluit af door te vragen of de respondent nog ideëen of perspectieven heeft die hij nog niet heeft gedeeld, en of er nog dingen zijn waar de respondent op is gekomen die nog niet ter sprake zijn gekomen.

B
Interview transcripts

This appendix is confidential and not for publication.

C

Informed consent form

Datum: 1 mei 2024

U wordt uitgenodigd om deel te nemen aan een onderzoek genaamd Predictive analytics in SMEs. Dit onderzoek wordt uitgevoerd door I.G. Heikoop van de TU Delft, begeleid door Dr. A.C. Smit en Dr. M.L.C. De Bruijne.

Het doel van dit onderzoek is inzicht verkrijgen in het gebruik van voorspellende analyse in de besluitvorming van het MKB, en zal ongeveer 60 minuten in beslag nemen. De data zal gebruikt worden voor het formuleren van resultaten en conclusies in de masterscriptie van de heer Heikoop. De thema's, patronen en conclusies over de gehele sector zullen gepubliceerd worden, de transcripten van de interviews niet. U wordt gevraagd om uw verhalen, ervaringen en perspectieven te delen tijdens het interview..

Zoals bij elke online activiteit is het risico van een databreuk aanwezig. Wij doen ons best om uw antwoorden vertrouwelijk te houden. We minimaliseren de risico's door de transcripten van de interviews gedurende het onderzoek in een beveiligde omgeving van de TU Delft op te slaan. De transcripten zullen enkele maanden na publicatie verwijderd worden.

Door enkel patronen en concepten te benoemen in de scriptie is het niet mogelijk uw onderneming of uw persoon te identificeren aan de hand van het gepubliceerde. Wanneer toch een citaat wordt opgenomen in de gepubliceerde tekst, zal hiervoor altijd toestemming aan u worden gevraagd.

Uw deelname aan dit onderzoek is volledig vrijwillig, en u kunt zich elk moment terugtrekken zonder reden op te geven. U bent vrij om vragen niet te beantwoorden

Ivo Heikoop

06-[redacted]

Vink de vakken in de rechterkolommen aan	**Ja**	**Nee**
A: Algemene Overeenkomst - Onderzoeksdoelen, Deelnemerstaken en Vrijwillige Deelname		
1. Ik heb de informatie over het onderzoek gedateerd 01-05-2024 gelezen en begrepen, of deze is aan mij voorgelezen. Ik heb de mogelijkheid gehad om vragen te stellen over het onderzoek en mijn vragen zijn naar tevredenheid beantwoord.		
2. Ik doe vrijwillig mee aan dit onderzoek, en ik begrijp dat ik kan weigeren vragen te beantwoorden en mij op elk moment kan terugtrekken uit de studie, zonder een reden op te hoeven geven.		
3. Ik begrijp dat mijn deelname aan het onderzoek de volgende punten betekent: • Het interview wordt opgenomen en tijdelijk opgeslagen. • De opname zal worden getranscribeerd, en de door de onderzoeker gevonden conclusies als gevolg van de analyse zullen worden gepubliceerd. • De opname en het transcript zullen 3 maanden na publicatie van het onderzoek worden vernietigd.		
4. Ik begrijp dat ik in geen wijze word gecompenseerd voor mijn deelname.		
5. Ik begrijp dat de studie in de zomer van 2024 eindigt.		
B: Mogelijke risico's van deelname (inclusief gegevensbescherming)		
6. Ik begrijp dat mijn deelname de volgende risico's met zich meebreng: Mogelijk datalek. Ik begrijp dat deze risico's worden geminimaliseerd door het opslaan van de interviewdata in een beveiligde omgeving. De onderzoeker hanteert een datamanagementplan waardoor risico's op het lekken van onderzoeksdata geminimaliseerd zijn		
7. Ik begrijp dat mijn deelname betekent dat er persoonlijke identificeerbare informatie en onderzoeksdata worden verzameld, met het risico dat ik hieruit geïdentificeerd kan worden.		
8. Ik begrijp dat binnen de Algemene verordening gegevensbescherming (AVG) een deel van deze persoonlijk identificeerbare onderzoeksdata als gevoelig wordt beschouwd, namelijk strategische overwegingen van mijn handelen in het ondernemen.		
9. Ik begrijp dat de volgende stappen worden ondernomen om het risico van een databreuk te minimaliseren, en dat mijn identiteit op de volgende manieren wordt beschermd in het geval van een databreuk: Het transcript wordt spoedig na het interview geanonimiseerd. De transcripten worden in een beveiligde omgeving opgeslagen		
10. Ik begrijp dat de persoonlijke informatie die over mij verzameld wordt en mij kan identificeren, zoals bijvoorbeeld de naam van het bedrijf waar ik werkzaam/eigenaar van ben, niet gedeeld worden buiten het studieteam.		
11. Ik begrijp dat de persoonlijke data die over mij verzameld wordt, vernietigd wordt 3 maanden (verwachte termijn) na publicatie van de scriptie		
C: Onderzoekspublicatie, verspreiding en toepassing		
12. Ik begrijp dat na het onderzoek de geanonimiseerde informatie gebruikt zal worden voor publicatie van de scriptie bij opname in de TU Delft research repository. Ik begrijp dat geanonimiseerde citaten hierin voor kunnen komen, maar de transcripten hier niet in opgenomen zijn.		
13: Ik begrijp dat, indien de onderzoeker mijn antwoorden wil citeren in resulterende producten, hij deze geanonimiseerd zal invoegen.		
D: (Langdurige) Gegevensopslag, toegang en hergebruik		
16. Ik geef toestemming om de geanonimiseerde data, de resultaten van thematische analyse van de interviews, gearchiveerd worden in de TU Delft research data repository, opdat deze gebruikt kunnen worden voor toekomstig onderzoek en onderwijs.		

Signatures

Naam deelnemer Handtekening Datum

Ik, de onderzoeker, verklaar dat ik de informatie en het instemmingsformulier correct aan de potentiële deelnemer heb voorgelegd en, naar het beste van mijn vermogen, heb verzekerd dat de deelnemer begrijpt waar hij/zij vrijwillig mee instemt.

I.G. Heikoop

Naam onderzoeker Handtekening Datum

Contactgegevens van de onderzoeker voor eventuele verdere informatie: Ivo Heikoop, 06-[REDACTED], i.g.heikoop@student.tudelft.nl