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Data-Driven Lead Prioritization in Existing B2B Customer Relationships: A Microfoundations Case Study in a Finnish Digital Mobility Company

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ABSTRACT:

Asiakasdatan merkitys B2B-myynnissä on kasvanut, kun digitaaliset järjestelmät, analytiikkatyökalut ja ennakoivat mallit mahdollistavat asiakkaiden käyttäytymisen tarkemman seuraamisen. Datavetoiset työkalut voivat auttaa yrityksiä tunnistamaan esimerkiksi aktiivisia, passivoituneita, kasvavia tai asiakkuuden kehittämisen kannalta potentiaalisia asiakkaita. Pelkkä asiakassignaalien näkyväksi tekeminen ei kuitenkaan vielä selitä, miten myynnin priorisointikäytännöt muuttuvat organisaatiossa.

Tämän tutkimuksen tarkoituksena on tarkastella, miten datavetoiset työkalut muuttavat olemassa olevien B2B-asiakkaiden priorisointikäytäntöjä. Tutkimus avaa datavetoisen liidien priorisoinnin mustaa laatikkoa mikroperustojen näkökulmasta. Mikroperustojen avulla tutkimuksessa tarkastellaan, miten yksilöiden tulkinnat, roolien välinen koordinointi ja organisaation rakenteet vaikuttavat siihen, miten dataperusteiset asiakassignaalit muuttuvat käytännön myyntitoiminnaksi.

Tutkimus toteutettiin laadullisena tutkimuksena suomalaisessa digitaalisen liikkumisen yrityksessä. Ensisijainen aineisto koostuu haastatteluista, joita täydennettiin yrityksen asiakasdataa ja B2B-asiakaskäyttäytymistä kuvaavilla aineistoilla. Tutkimuksen tulokset osoittavat, että datavetoiset työkalut eivät muuta priorisointikäytäntöjä suoraan. Ne muuttavat priorisointia epäsuorasti kolmen mekanismin kautta. Ensinnäkin työkalut tekevät olemassa olevia B2B-asiakkaita näkyvämmäksi asiakassignaalien avulla. Toiseksi nämä signaalit täytyy tulkita, arvioida ja koordinoida organisaation eri roolien välillä. Kolmanneksi signaalit muuttuvat käytännön toiminnaksi vasta, kun ne kytkeytyvät rutiineihin, vastuisiin, CRM-logiikkaan ja seurantakäytäntöihin.

KEYWORDS: Data-driven B2B sales; Lead Prioritization; Microfoundations; Customer relationship management; Predictive sales analytics

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ABSTRACT:

The importance of customer data in B2B sales has increased as digital systems, analytics tools, and predictive models enable more detailed monitoring of customer behavior. Data-driven tools can help companies identify, for example, active, inactive, growing, or otherwise potentially valuable customers from the perspective of customer development. However, making customer signals visible does not alone explain how sales prioritization practices change within an organization.

The purpose of this study is to examine how data-driven tools change prioritization practices for existing B2B customers. The study opens the black box of data-driven lead prioritization from a microfoundations perspective. Through microfoundations, the study examines how individual interpretations, coordination between roles, and organizational structures influence how data-based customer signals are transformed into practical sales action.

The study was conducted as a qualitative case study in a Finnish digital mobility company. The primary empirical material consists of interviews, which were supported with company materials describing customer data and B2B customer behavior. The findings show that data-driven tools do not change prioritization practices directly. Instead, they change prioritization indirectly through three mechanisms. First, the tools make existing B2B customers more visible through customer signals. Second, these signals must be interpreted, evaluated, and coordinated across different organizational roles. Third, signals are transformed into practical action only when they are connected to routines, responsibilities, CRM logic, and follow-up practices.

KEYWORDS: Data-driven B2B sales; Lead Prioritization; Microfoundations; Customer relationship management; Predictive sales analytics

Contents

Figures

Tables

1 Introduction

Customer data is increasingly shaping how firms understand, manage, and prioritize their B2B customer relationships. Digital platforms, CRM systems, analytics dashboards, and predictive models make it possible to observe customer behavior across transactions, accounts, and service interactions. For sales organizations, this creates an important managerial opportunity: customer data can help direct limited commercial attention toward customers where action is most relevant. Analytics can strengthen sales decision-making and firm performance when firms have sufficient data quality, analytical capabilities, managerial support, and an organizational culture that supports evidence-based decisions (Germann et al., 2013; Wedel & Kannan, 2016). In B2B contexts, this issue is especially important because customer relationships are often long-term, complex, and distributed across several actors, systems, and touchpoints (Homburg et al., 2002; Payne & Frow, 2005).

The promise of data-driven tools is closely connected to lead prioritization. Predictive sales analytics can estimate sales-relevant outcomes such as churn risk, customer value, and cross-selling or upselling potential, thereby helping sales organizations allocate attention more systematically (Habel et al., 2023). Lead-scoring models can also support prioritization by ordering leads or accounts according to their estimated commercial relevance, and predictive approaches have been shown to improve on more traditional judgement-based scoring methods (Wu et al., 2024). However, this does not explain how prioritization changes inside the organization. Knowing that a tool can identify relevant customers is different from understanding how its outputs enter everyday sales and customer relationship work.

This study addresses this issue by opening the black box of data-driven lead prioritization for existing B2B customers. The central problem is not only whether analytical tools can make customer signals visible, but how those signals become meaningful and actionable in sales work. A dashboard metric may identify an inactive customer or growth opportunity with customer account, but the signals does not automatically determine what

should be done, who should act, or how follow-up should take place. Prior research on sales technology shows that performance benefits depend on adoption, managerial support, training, and integration into sales work rather than on technology availability alone (Ahearne et al., 2005; Habel et al., 2023). This makes existing-customer prioritization an organizational issue, not only a technical ranking task.
To examine this process, the thesis adopts a microfoundations perspective. Microfoundations research explains organizational capabilities and outcomes through lower-level foundations, including individuals, interactions between actors, and structural arrangements (Felin et al., 2012). This perspective is suitable for the present study because data-driven B2B sales capability cannot be understood only as technological capability. Instead, the influence of data-driven tools depends on how customer signals are interpreted, coordinated, and connected to organizational practices. The microfoundations lens therefore helps explain how analytical outputs become part of lead-prioritization capability in practice.

The empirical context of this thesis is 24Rent, a Finnish digital car-sharing company whose B2B customer management is being developed within a data-rich self-service business model. The study is conducted as a qualitative single case study. The primary empirical data consists of interviews with actors involved in commercial management, B2B sales, analytics, technical support, and business development. These interviews are supported by internal company material, including customer classifications and data views related to B2B customer behavior. This setting makes it possible to examine how customer signals are produced, interpreted, and connected to sales action in an actual organizational context.

To address this research opportunity, the study is guided by the following research question:

How do data-driven tools change lead-prioritization practices for existing B2B customers?

To answer this question, the study follows how data-driven prioritization develops from customer visibility into organizational action. It first examines how customer data and analytical tools make existing B2B customers visible through activity signals, account-level patterns, and customer classifications. It then analyzes how these signals are interpreted and coordinated by organizational actors before they can guide sales attention. Finally, the study examines how signal-based prioritization becomes connected to routines, responsibilities, and follow-up practices. Through this structure, the thesis develops a microfoundational explanation of how data-driven tools can reshape existing-customer sales capability.

The study contributes to the literature in three ways. First, it extends research on data-driven B2B sales by shifting attention from predictive tools as technical solutions to the organizational process through which their outputs become part of sales prioritization. Second, it contributes to microfoundations research by showing how data-driven sales capability develops through the translation of customer signals into coordinated and repeatable sales practices. Third, it provides practical insight for firms developing data-driven B2B customer management by showing that dashboards, customer lists, and predictive signals create value only when they are connected to clear action logic, responsibility, CRM structures, and follow-up routines.

The study includes five chapters. Following the introduction, Chapter 2 presents the theoretical background of the study. The theoretical background focuses on data-driven B2B sales and microfoundations. Also, the theoretical framework used in this study is included in the theoretical background. Chapter 3 introduces the research methodology, including the case context, data collection, and data analysis process. This is followed by Chapter 4, which presents the empirical findings and revises the theoretical framework based on the case evidence. The concluding chapter, Discussion, presents the theoretical contributions and managerial implications of the study, followed by the limitations and suggestions for future research.

2 Theoretical background

This section reviews relevant academic literature about data-driven B2B sales and microfoundations theory. The first part examines how data-driven approaches shape B2B sales, with particular focus on predictive tools, customer signals, and prioritization. The second part introduces the microfoundations as the theoretical lens of the study. The literature review ends by combining these two streams and developing the conceptual basis for analyzing how data-driven tools reshape lead-prioritization practices for existing B2B customers.

2.1 Data-driven B2B sales

B2B selling has traditionally been relationship-based work in which salespeople rely on accumulated customer knowledge, personal experience, and ongoing interpretation of the customer's situation. In many cases, effective selling has required mobilizing expertise across internal functions and coordinating contributions from different specialists, rather than executing a purely individual "seller-buyer" exchange (Steward et al., 2010). Customer relationship management (CRM) has been understood as a broader strategic and cross-functional process through which firms integrate customer information, multichannel interactions, and performance assessments across the organization (Payne & Frow, 2005). More recently, growing attention has been directed to the role of analytics in strengthening B2B sales and customer relationship management. Prior research suggests that customer big data analytics can improve customer relationship performance and sales growth, particularly when supported by suitable analytics culture (Hallikainen et al., 2020). Likewise, Zhang et al. (2020) show that the assimilation of big data analytics can enhance CRM performance in B2B firms, including through stronger mass-customization capability. These studies suggest that contemporary B2B sales performance increasingly depends on the firm's ability to combine internal coordination, customer information, and analytics-based capabilities.

Alongside broader work on data-driven selling, a distinct stream on sales analytics has emerged to examine how analytical tools support sales planning, forecasting, account development, and frontline selling. Recent reviews show that firms are increasingly adopting advanced analytics, including predictive models to support sales decisions across the customer lifecycle, but that much of this work is still at an early stage and unevenly implemented across organizations and industries (Matthews et al., 2025). At the same time, studies in predictive sales analytics suggest that such tools can support sales employees by estimating outcomes such as customer churn, and cross- or upselling potential (Habel et al., 2023). In B2B contexts, analytical models have also been studied as tools for improving customer retention decisions through more accurate identification of customers at risk of churning (De Caigny et al., 2021).

In this thesis, the outputs of data-driven tools are understood as customer signals. These signals may indicate inactivity, churn risk, customer value, growth potential, recent purchase behavior, or other customer status. Their immediate role is not to determine sales action automatically, but to make existing customers more visible for commercial attention (Habel et al., 2023; Wu et al., 2024).

Table 1 summarizes the key concepts and working definitions used in the data-driven B2B sales literature and in this study.

Table 1. Key concepts and definitions in data-driven B2B sales.

Concept	Working definition	Key sources
Customer big data analytics	Organizational capability to collect, integrate, and analyze large volumes of customer data to improve relationship management and sales outcomes.	Hallikainen et al. (2020)
Data-driven B2B sales	Sales and account management where targeting, prioritization, and interventions are systematically informed by customer/account data, analyzed with statistical or machine-learning methods, and operationalized through CRM/automation systems.	Hallikainen et al. (2020); Zhang et al. (2020)
Sales analytics	The application of analytical techniques to sales data to support decision-making in sales management and frontline selling.	Matthews et al. (2025)
Predictive sales analytics	Analytical applications that predict future sales-relevant outcomes (e.g., propensity to buy, churn risk, cross-sell potential) to inform sales actions.	Habel et al. (2023)
Lead scoring model	An analytical tool that assigns a score to a lead or account based on its likelihood of a sales-relevant outcome, such as conversion, customer value, or expansion value.	Wu et al. (2024)
Lead-management optimization	Using data-mining methods to prioritize and route leads to follow-up to improve efficiency and conversion.	Espadinha-Cruz et al. (2021)
Lead prioritization	Ordering and selecting existing B2B customers/contacts for proactive outreach based on predictive signals and relational knowledge.	Wu et al. (2024)
Customer visibility	The extent to which customer behavior, activity, and account-level patterns can be observed, compared, and used as a basis for commercial attention.	Payne & and Frow (2005); Hallikainen et al. (2020)

Data-driven customer signals	Indicators derived from customer data that make sales-relevant customer states visible, such as inactivity, churn risk, growth potential, or customer status	Habel et al. (2023); Wu et al. (2024)
Customer-linking and selling capabilities	Bundles of processes and skills that translate analytics into relationship management and selling actions, especially in turbulent environments.	Itani et al. (2024)

2.1.1 Antecedents of data-driven B2B sales

Research on data-driven B2B suggests that the development and effectiveness of analytical tools depend on a set of organizational antecedents rather than on technology alone. One important condition is the ability to integrate analytics into sales decision-making in a way that supports, rather than replaces, frontline expertise. In data-driven B2B settings, firms may benefit from hybrid decision-making approaches in which analytical models guide more than routine decisions, while sales teams retain discretion in unusual or complex cases (Karlinsky-Schichor & Netzer, 2024). However, this requires more than the introduction of the tools. Digital transformation studies in B2B sales indicate that firms often need to revise established assumptions about how selling is organized and how value is created, which places emphasis on managerial attention to change processes and role redesign rather than on system implementation alone (Mattila et al., 2021). In a similar vein, related work shows that digital transformation in B2B sales is more likely to succeed when firms develop coherent operating models that connect digital tools with sales activities, performance management, and organizational learning (Muhkopadhyay et al., 2025). These organizational conditions are closely tied to a broader question of analytics capability. Rather than being a single IT investment, analytics capability is typically understood as the firm's ability to assemble and deploy data, technology, and talent in a coordinated way (Gupta & George, 2016). In B2B customer management settings, the value of analytics also appears to depend on cultural and managerial complements, as performance benefits are stronger when the organization supports the systematic use of evidence in commercial processes (Hallikainen et al., 2020). This highlights that the challenge is not merely to process analytics resources, but to embed them into core organizational processes. Consistent with this view, Zhang et al. (2020) suggest that embedding is shaped by internal factors such as data-driven culture and by external pressures such as competition.

Data infrastructure and data quality also form an important part of the conditions under which data-driven B2B sales can function effectively. This is particularly important in existing customer settings, where the relevant unit of action is often the account rather than an individual contact. Under such conditions, predictive scoring and prioritization depend on the ability to connect customer histories, contract information, usage data, and organizational identifiers across contacts, locations, and subsidiaries. Studies of lead scoring suggest that predictive approaches depend on the availability of accurate lead and sales data, because implementation and prioritization rely on sufficiently structured information inputs (Gonzales-Flores et al., 2025). Similarly, lead-management research indicates that scoring and pipeline applications become difficult to interpret and use when data capture is inconsistent and process definitions remain unclear (Espadinha-Cruz et al., 2021). Yet the presence of structured data alone does not guarantee value creation. The usefulness of data-driven tools also depends on whether they fit the decision problems that sales organizations face and whether firms possess the capabilities needed to translate analytical output into commercial action. Itani et al. (2024) suggest that analytics contributes to financial performance indirectly through customer-linking and selling capabilities, which implies that analytical tools are most valuable when they are aligned with sales tasks and supported by routines for acting on insights. This challenge extends to technology adoption in everyday sales work. Earlier sales technology research shows that field-level uptake depends on perceived usefulness as well as organizational training and supervisory support (Schillewaert et al., 2005). More recent studies likewise suggest that the performance implications of sales technology vary according to how it is used, for example whether it supports information access, analysis, or communication, which makes training and measurement choices consequential for sustained and productive use (Hunter, 2019). At the broader organizational level, sales enablement research further indicates that implementation may weaken when different functions and hierarchy levels hold inconsistent understandings of what enablement means in practice, thereby reducing follow-through even when tools are available (Lauzi et al., 2023).

Finally, cross-functional alignment around data-driven decision-making appears to function as an enabling condition rather than merely a downstream outcome. Sales enablement research conceptualizes enablement as a cross-functional capability that aligns organizational resources to improve sales effectiveness, suggesting that data-driven tools require shared ownership beyond the sales function (Peterson et al., 2021). More generally, research on data-driven decision-making indicates that adoption and implementation are shaped by organizational factors such as executive commitment, interdepartmental dynamics, and organizational structure (Sleep et al., 2019). Taken together, the reviewed literature suggests that data-driven B2B sales is shaped by five interrelated antecedents: (1) governance that links analytical tools to selling roles and sales enablement across functions, (2) analytics capability as a coordinated bundle of data, technology, and human resources, supported by an analytics-oriented culture, (3) integrated and sufficiently credible account-level data, (4) fit between analytical tools and the commercial tasks they are intended to support, together with complementary customer-linking and selling capabilities and (5) adoption conditions that help sales employees incorporate predictive applications into everyday decision making. In combination, these antecedents define the organizational context in which predictive signals can be translated into operational inputs for lead and account prioritization.

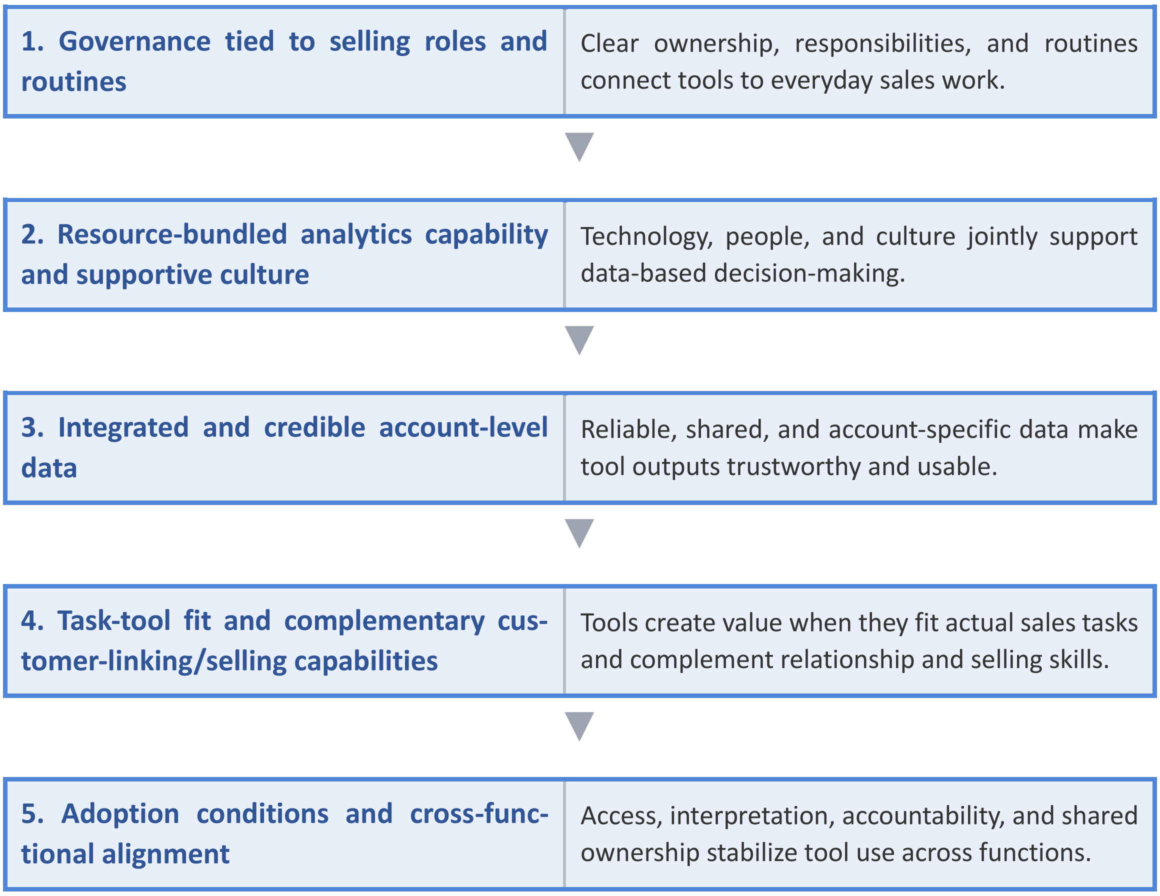

Figure 1. Antecedents enabling data-driven B2B sales.

2.1.2 Data-driven B2B sales processes

Data-driven B2B sales processes can be understood as moving from data capture and integration toward predictive analysis and operationalization in sales work. Although prior B2B analytics studies do not always describe this sequence as a single formal process model, they collectively suggest that firms seek to transform customer data into commercially useful insights through analytics and CRM-related processes (Hallikainen et al., 2020; Zhang et al., 2020). Within this broader process, lead and account scoring models serve as important analytical tools for prioritization. Wu et al. (2024) distinguish between traditional lead scoring, which relies more strongly on managerial or salesperson judgement, and predictive lead scoring, which uses data mining and machine-learning approaches to support scoring. Their review further suggests that predictive lead-scoring models tend to outperform traditional approaches in sales settings. Applied lead-management research likewise shows that data-mining based scoring can support more systematic lead evaluation and follow-up processes when firms rely on structured data and defined process logic (Espadinha-Cruz et al., 2021). This process can also be understood as a visibility process: data-driven tools translate dispersed account information into customer signals that make customers more noticeable for sales attention (Wu et al., 2024).

In existing customer contexts, similar analytical logic can be extended from prospecting to retention and account-development decisions. Predictive sales research argues that quantitative analytics models can reveal outcomes such as customer value and churn probabilities, while broader reviews show increasing organizational interest in advanced sales analytics and AI-enabled decision tools (Habel et al., 2023; Matthews et al., 2025). Related B2B marketing research also examines AI applications across customer life cycle stages, including retention, which supports the view that analytics can be used beyond new-customer acquisition alone (Moradi & Dass, 2022). At the same time, the literature increasingly emphasizes that the value of these tools depends on how they are embedded in everyday sales work. Habel et al. (2023) propose that predictive sales analytics adoption is shaped by task characteristics, fairness, and transparency perceptions, and the fit of the tool with existing routines and performance metrics. Earlier sales technology similarly shows that adoption depends on salespeople’s performance-related perceptions, user training, and supervisor expectations (Schillewaert et al., 2005), while Hunter (2019) argues that the performance implications of technology vary depending on how technology use is conceptualized and measured in B2B sales contexts. From a process perspective, data-driven B2B sales therefore involves not only building predictive models but also embedding their output into the routines through which commercial actors interpret and act on customer information. Even so, recent review work still points to important knowledge gaps in sales analytics research, which means that the micro-level translation of predictive cues into day-to-day prioritization decisions remains only partly understood (Matthews et al., 2025).

2.1.3 Outcomes of data-driven B2B sales

Empirical research generally reports positive, but often conditional outcomes of data-driven tools for B2B sales and relationship performance. At the firm level, customer big data analytics has been associated with improved customer relationship performance and sales growth in B2B firms (Hallikainen et al., 2020). Likewise, the assimilation of big data analytical intelligence has been linked to stronger CRM performance, suggesting that analytics can enhance firms' ability to manage customer relationships more effectively (Zhang et al., 2020). Related research further shows that the performance effects of big data-AI fit are indirect rather than automatic: analytics contributes to organizational financial performance through stronger customer-linking and selling capabilities, particularly in turbulent market conditions (Itani et al., 2024).

At the process level, prior studies suggest that predictive scoring and data-driven lead management can improve commercial effectiveness by supporting more systematic prioritization. Review evidence indicates that predictive lead-scoring models tend to outperform more traditional scoring approaches and are associated with better sales performance outcomes (Wu et al., 2024). Similarly, data-mining based prioritization can improve conversion effectiveness and support more structured follow-up processes when firms rely on sufficiently organized data and process logic (Espadinha-Cruz et al., 2021). In existing customer settings, the same underlying logic can be extended from new-customer acquisition to retention and account development. Predictive sales analytics research suggests that such tools can estimate outcomes such as customer churn and customer value, thereby helping firms identify where intervention may be most needed (Habel et al., 2023). Recent field evidence from B2B churn-prediction application further indicates that predictive sales analytics can generate value in existing-customer management, although realized gains depend on how effectively the tool is implemented in the sales force (Habel et al., 2024).

These outcome effects should nevertheless be interpreted with caution. Research on AI use in B2B marketing highlights important barriers related to data quality, human capital, technology, and cost, which can limit the benefits firms derive from analytics tools (Moradi & Dass, 2022). In a similar way, predictive sales analytics research argues that positive performance effects depend on whether salespeople understand and accept the application and whether the tools fit their tasks, routines, and performance context (Habel et al., 2023; Habel et al., 2024). More broadly, recent work on sales analytics suggests that the field is advancing rapidly but still contains substantial knowledge gaps, especially regarding how analytics is embedded in organizational processes and decision-making (Matthews et al., 2025). For this reason, current evidence supports the view that data-driven tools can strengthen B2B sales performance and customer relationship outcomes, but their effects are contingent on organizational capabilities, implementation conditions, and everyday use. Although customer engagement has been defined as customer behavioral manifestations beyond purchase (Ng et al., 2020), there is still limited direct evidence on how data-driven sales tools reshape engagement in ongoing B2B relationships specifically. This leaves an important opening for context-sensitive research that examines how predictive signals enter existing sales routines, how commercial actors adapt them in practice, and how these adaptations relate to customer-level outcomes such as retention, account development, and engagement.

2.2 Microfoundations

Microfoundations provide the theoretical lens for examining how organizational-level capabilities are generated, maintained, and changed through lower-level foundations. In strategic management, concepts such as routines, capabilities, and organizational performance are often discussed as firm-level phenomena. However, these concepts require explanation of the mechanisms through which they are produced. The microfoundations perspective addresses this problem by directing attention to the individuals, interactions, and structural arrangements through which collective outcomes emerge (Felin et al., 2012).

This perspective is particularly relevant for studies of organizational change because it avoids treating capabilities as properties that firms simply possess. A firm may introduce new systems, technologies, processes, or resources, but these do not automatically become organizational capability. Capability emerges only when lower-level elements are connected in ways that enable repeated and coordinated action (Abell et al., 2008). Thus, microfoundations help explain why similar formal resources or tools may produce different outcomes across organizations (Felin et al., 2012).

In this thesis, microfoundations are used to examine how changes in sales-related capability are generated through lower-level organizational mechanisms. The perspective is suitable because data-driven tools do not change sales work by themselves. Their influence depends on how actors interpret information, how roles coordinate around that information, and how organizational arrangements make certain actions possible (Felin et al., 2012). The following subsections first discuss the origins and purpose of microfoundations theory and then examine its three central levels. This provides the theoretical basis for later analyzing how data-driven lead prioritization becomes embedded in B2B sales capability.

2.2.1 Origins and purpose of microfoundations theory

Microfoundations research emerged in strategic management as a response to explanations that focused mainly on firms, routines, capabilities, and performance at the collective level. In such organization-level explanations, firms are described as if they act, learn, adapt, or possess capabilities as unified entities. Felin and Foss (2005) argue that this creates an explanatory problem, because organization-level outcomes cannot be fully understood without specifying the lower-level foundations from which they arise. Similarly, Abell et al. (2008) argue that links between routines, capabilities, and performance remain incomplete unless researchers identify the mechanisms that connect lower-level action to collective outcomes.

The purpose of microfoundations is therefore to open the black box of organizational explanation. Instead of accepting firm-level capabilities as self-explanatory, the perspective asks how they are produced through concrete foundations. Barney and Felin (2013) clarify that microfoundations should not be understood as a purely individualistic or psychological approach. Rather, microfoundations explain how macro-level phenomena are grounded in lower-level elements, including individuals, social processes, and structures (Felin et al., 2012). This distinction is important because the perspective does not deny the role of routines, institutions, or organizational design. Instead, it asks how these collective phenomena are created, reproduced, and changed.

The microfoundations perspective is especially relevant for capability research because capabilities are often conceptualized at the firm level, such as a firm's ability to innovate, adapt, sell, or use analytics. Microfoundations help explain how these collective capabilities are produced through individuals, social processes, and organizational structures (Felin et al., 2012; Teece et al., 1997). Salvato and Rerup (2011) similarly argue that routines and capabilities require multilevel analysis. Their work is useful because it shows that routines and capabilities are not only collective entities, but phenomena that can be understood by examining their parts and interrelationships. This multilevel view helps explain how collective patterns of action emerge from lower-level foundations without reducing organizational capability to individual behavior alone.

From this perspective, microfoundations theory is useful when it is necessary to understand how organizational capability is built. A firm may have resources, technologies, systems, and formal processes, but these do not automatically become capability. Capability emerges when actors use resources in coordinated and repeated ways that are supported by organizational structures (Felin et al., 2012). This point is central for this study, where data-driven tools are examined not as isolated technologies, but as part of changing lead-prioritization practices.

2.2.2 The three levels of microfoundations

Felin et al. (2012) identify three central categories of microfoundations: individuals, interactions between them, and structural arrangements. These categories provide a multilevel explanation of how routines and capabilities are built. The individual level explains how actors interpret information and make judgements. The interactional level explains how actors coordinate and align their actions with others. The structural level explains how organizational arrangements enable, constrain, and stabilize action.

At the individual level, microfoundations focuses on cognition, attention, skills, experience, motivation, and judgement. Individuals matter because organizational action depends partly on what actors notice, how they interpret situations, and how they decide to act (Felin et al., 2012). Gavetti (2005) highlights that cognition is central to capability development because managerial representations shape how organizations search for solutions and respond to strategic challenges. Helfat and Peteraf (2015) similarly emphasize managerial cognitive capabilities, including the mental activities through which managers sense, interpret, and respond to opportunities and problems. These studies support the microfoundations argument that capabilities are not produced only by routines or structures, but also by the interpretive and judgement-based activities of actors.

At the interactional level, microfoundations focus on social processes through which individual actions become coordinated organizational action. Organizational action is rarely produced by individuals alone. It depends on communication, coordination, negotiation, and alignment between people who hold different roles and forms of knowledge. Felin et al. (2012) identify processes and interactions as one of the core categories through which routines and capabilities are generated. This level is important because individual interpretation does not automatically become organizational action. Actors need to communicate their interpretations, compare alternatives, agree on priorities, and coordinate responsibilities. This kind of multilevel analysis is needed because routines and capabilities emerge from relationships between different levels of action (Salvato & Rerup, 2011). The interactional level therefore explains how individual insights become shared and coordinated activities.

At the structural level, microfoundations focuses on organizational arrangements that guide and constrain action. These arrangements include roles, responsibilities, systems, routines, incentives, and organizational design (Felin et al., 2012). They include structure as a central category of microfoundations because structures shape how individuals act and how interactions are organized. In the microfoundations explanation structure remains important, its point is not replacing structure with individuals, but to explain how structures and lower-level action are connected (Barney & Felin, 2013). They argue that structures make certain actions easier, repeated, and legitimate, while those actions may also restrict other forms of action. This makes the structural level also central for understanding how capabilities become stable over time.

The three levels are analytically distinct, but they should not be understood as separate explanations. Individual cognition is shaped by the information and roles available in the organization. Interaction depends on shared routines, responsibilities, and communication channels. Structures become meaningful only when actors enact them in practice. Thus, the value of microfoundations lies in explaining capability development as a multilevel process in which individuals, interactions, and structures jointly produce organizational outcomes (Felin et al., 2012; Salvato & Rerup, 2011).

Table 2 summarizes the three levels of microfoundations used in this study.

Table 2. Three levels of microfoundations.

Microfoundations level	Key elements	Capability-building role
Individual level	Cognition, attention, skills, experience, motivation, and judgement	Explains how actors interpret information, evaluate alternatives, and initiate action
Interactional level	Communication, coordination, negotiation, and alignment between actors	Explains how individual interpretations become shared priorities and coordinated action
Structural level	Roles, routines, systems, rules, responsibilities, and organizational design	Explains how organizational arrangements enable, constrain, and stabilize action

This three-level view provides the theoretical foundation for analyzing organizational change without reducing it either to individual decision-making or to formal systems. In the context of this thesis, it prepares the analysis of how new informational inputs become embedded in sales work. Data-driven tools may introduce new customer signals, but these signals change lead prioritization only when they affect how actors interpret customer situations, how commercial roles coordinate action, and how organizational arrangements support repeated follow-up. The next section applies this microfoundations logic to B2B sales and data-driven lead prioritization.

2.2.3 Microfoundations of B2B sales capability

The previous section 2.1. showed that data-driven B2B sales depends on organizational conditions such as analytics capabilities, credible customer data, task-tool fit, adoption support, and cross-functional alignment. These insights explain when predictive tools may become useful in sales organizations. However, they do not fully explain how sales work changes when data-driven signals enter everyday prioritization. A microfoundations perspective addresses this limitation by shifting attention from the existence of tools and capabilities to the lower-level foundations through which sales capability is enacted and changed (Felin et al., 2012).

In this thesis, lead prioritization is treated as concrete activity through which sales capability becomes visible. In existing B2B customer relationships, prioritization is not only a matter of identifying new prospects or estimating conversion probability. It concerns the allocation of limited commercial attention across an existing customer base: which customers are noticed, which signals are interpreted as meaningful, when follow-up is initiated, and who becomes responsible for action. Prior research on lead scoring shows that prioritization supports the ranking and qualification of leads and can influence how sales and marketing efforts are directed (Wu et al., 2024). This makes lead prioritization a suitable phenomenon for microfoundations analysis, because it connects customer information, human judgement, role coordination, and organizational routines, which correspond closely to the individual, social process, and structural foundations of organizational capabilities (Felin et al., 2012). B2B sales research supports the view that selling should be understood as an organizational capability rather than only as individual salesperson activity. For example, Homburg et al. (2002) argue that important customer relationships are managed through configurations of activities, actors, resources, and formalization. Similarly, Terho et al. (2012) emphasizes that commercial strategies become effective only when they are translated into sales-level activities, such as understanding the customer’s business model, developing value propositions, and communicating customer value. These studies do not directly examine data-driven lead prioritization, but they show that B2B sales outcomes depend on how organizational intentions are converted into concrete selling activities.

From a microfoundations perspective, data-driven tools change prioritization only when their outputs become meaningful for actors. A predictive score, dashboard signal, churn warning, or activity indicator does not automatically produce sales action. At the individual level, actors must notice the signal, evaluate its credibility, compare it with their customer knowledge, and judge whether it requires action. This reflects the broader microfoundations argument that cognition and judgement are important foundations of capability development (Gavetti, 2005; Helfat & Peteraf, 2015). At the interactional level, data-driven prioritization changes when individual interpretations become coordinated across roles. Existing customer sales and management often involves several commercial actors, such as salespeople, sales managers, customer success roles, marketing, or analytics-related functions. Therefore, a data-driven signal must become more than information available to one person. It must become a shared basis for deciding what the signal means, how urgent it is, what kind of customer intervention is appropriate, and who should act. This is a central element in microfoundations view that capabilities are generated through processes and interactions, not through isolated individual decisions (Felin et al., 2012; Salvato & Rerup, 2011). At the structural level, prioritization changes when organizational arrangements stabilize new ways of acting. CRM fields, dashboards, account ownership rules, reporting routines, follow-up expectations, and managerial controls shape whether predictive signals become part of normal sales work or remain passive information. Structures are therefore not merely background conditions. They influence what actors see, what they are expected to do, and how repeated action becomes legitimate. This is consistent with Barney and Felin's (2013) argument that microfoundations do not reject structure but explain how structures and lower-level action are connected.

Parallel B2B research points toward this logic but does not fully address the phenomenon studied in this thesis. Töytäri et al. (2017) for instance, adopt a microfoundations perspective in industrial value-based pricing and show that implementation barriers arise partly from individual managers and organizational conditions. This is relevant because it demonstrates that commercial change cannot be explained only through firm-level strategies or formal tools. However, pricing and value-based selling studies do not explain how predictive customer signals reshape the daily allocation of sales attention in existing B2B customer relationships. This leaves the specific gap addressed in this thesis. Prior research provides knowledge about data-driven sales, predictive analytics, sales technology use, and B2B commercial capability development. Yet less is known about how data-driven signals become embedded in everyday prioritization for existing customers. A microfoundations perspective enables this study to examine that process as a multilevel change in which predictive signals become consequential through individual interpretations, interactional coordination, and structural arrangements. This provides the basis for the theoretical framework, where data-driven tools are examined as informational inputs that reshape how commercial attention is allocated across existing B2B customers.

2.3 Theoretical framework for data-driven lead prioritization

The previous chapter provides the basis for the theoretical framework of this thesis. Section 2.1 showed that data-driven B2B sales depends on the availability of customer data, analytics capability, task-tool fit, and organizational conditions that support the use of analytical outputs in sales work. Section 2.2 introduced microfoundations as the theoretical lens for explaining how organizational capabilities are enacted and changed through individuals, interactions, and structural arrangements. Combining these streams, this thesis conceptualizes data-driven lead prioritization as a process in which predictive customer signals become consequential only when they are translated into everyday sales action.

The framework consists of four connected elements. The first element is **data-driven customer signals**. In existing B2B customer relationships, these signals may concern churn risk, inactivity, customer value, growth potential, or other indicators that make some customers more visible and valuable for commercial follow-up. Prior research suggests that such tools can support prioritization by helping firms identify where sales attention may be most valuable (Habel et al., 2023; Wu et al., 2024). However, the framework does not treat these signals as direct determinants of action. Instead, they are understood as informational inputs that enter an existing sales process.

The second element is **microfoundational translation**. This refers to the mechanisms through which data-driven signals are interpreted, coordinated, and embedded in sales work. At the individual level, actors evaluate whether the signal is credible, commercially relevant, and consistent with their customer knowledge. At the interactional level, commercial roles coordinate around the signal by deciding what it means, how urgent it is, and who should respond with action. At the structural level, systems, routines, ownership rules, reporting practices, and follow-up expectations shape whether the signal becomes part of repeated prioritization work. This element draws directly on the microfoundations view that organizational capabilities are generated through these three levels (Felin et al., 2012; Barney & Felin, 2013).

The third element is **change in lead-prioritization practices**. In this thesis, such change is examined through three analytical questions: which customers receive attention, which cues guide prioritization, and how responsibility for follow-up is organized. Data-driven tools may change prioritization by making previously overlooked customers visible, by shifting attention from reactive contact toward proactive intervention, or by creating new forms of coordination between commercial roles. The framework also allows for uneven change, because predictive signals may be ignored, questioned, selectively used, or adapted to existing routines.

The fourth element is **customer-level implications**. If data-driven signals become embedded in prioritization practices, sales attention may become more systematic, timely, and targeted. This may support retention, account development, reactivation, or customer engagement. These implications are not treated as automatic outcomes of analytics. Rather, they are examined as possible consequences of changed prioritization practices. This distinction is important because prior research shows that the effects of analytics depend on how tools are implemented and used in organizational work (Germann et al., 2013; Habel et al., 2023).

The theoretical framework guiding the empirical analysis is summarized in Figure 2.

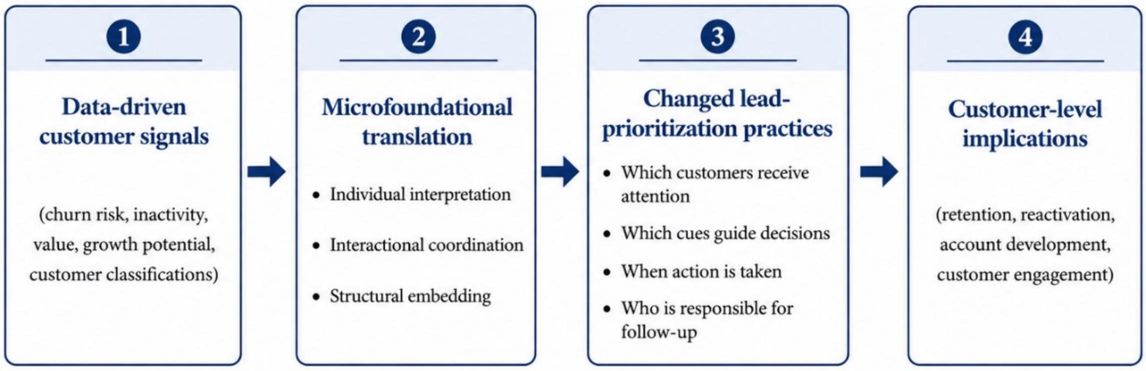

Figure 2. Theoretical framework for data-driven lead prioritization.

3 Methodology

This chapter presents the methodological choices of the thesis. The study examines how data-driven tools change lead-prioritization practices for existing B2B customers in a specific organizational context. Because the research question concerns interpretation, coordination, and organizational arrangements, the methodology must support detailed analysis of how actors understand and use data-driven customer signals in everyday work. The chapter first presents the research approach, then introduces the case company and case context, the empirical material, the data analysis process, and the quality assessment of the study.

3.1 Research approach

This thesis adopts a qualitative single case study approach. A qualitative approach is appropriate because the study seeks to understand how organizational actors interpret with data-driven tools, coordinate around customer signals, and connect those signals to sales-related action. The aim is not to measure the statistical effect of predictive tools on sales performance, but to understand the process through which such tools become embedded in lead-prioritization practices.

The study follows an interpretivist orientation. Interpretivist research is suitable when the purpose is to understand organizational phenomena through the meanings and actions of people situated in a particular context (Walsham, 1995). In this thesis, data-driven tools are not treated as purely technical objects with automatic effects. Instead, their relevance is examined through how organizational actors interpret customer signals, evaluate their credibility, coordinate follow-up, and connect them to existing routines. This position is consistent with the microfoundations perspective developed in Chapter 2, where organizational capability is understood as emerging through individuals, interactions, and structural arrangements (Felin et al., 2012).

The thesis also follows abductive logic. Abduction is suitable for case research where the researcher moves iteratively between existing theory and empirical material to refine the understanding of a phenomenon (Dubois & Gadde, 2002). In this study, the theoretical framework guided attention toward data-driven customer signals, microfoundational translation, changed prioritization practices, and customer-level implications. At the same time, the empirical material was used to specify how these elements appeared in the case company.

A single case study strategy is appropriate because the research question requires contextual depth rather than broad comparison across firms. A single case study strategy is appropriate because the research question requires contextual depth rather than broad comparison across firms. Case studies are particularly useful for developing rich, context-sensitive explanations of organizational phenomena and for building theoretical insights from empirical cases (Eisenhardt & Graebner, 2007; Gibbert et al., 2008). In this thesis, data-driven lead prioritization cannot be understood apart from the company's B2B customer work, data environment, roles, routines, and ongoing development of commercial practices. The aim is therefore analytical generalization rather than statistical generalization (Eisenhardt & Graebner, 2007).

3.2 Case company and case context

The empirical case of this thesis is 24Rent, a Finnish digital mobility company that offers self-service mobility solutions with cars, vans, and minibuses in Finland. The company's service model is strongly digital: customers reserve and use vehicles through a self-service process, and the company has developed most of its own technology to support this operating model. As a result, the customer journey and sales funnel are highly automated compared with traditional car rental services.

24Rent serves both B2C and B2B customers, but this thesis focuses only on the company's developing B2B customer segment. This boundary is important because the research question concerns lead prioritization for existing B2B customers, where customer relationships, follow-up, account development, and retention-oriented actions are more relevant than in individual consumer transactions. While the digital service model enables efficient self-service use, it also creates a managerial challenge: when the customer base is large, it is not possible to manually observe how each business customer behaves, when they buy, how often they use the service, or how their activity changes over time. This makes data-driven customer signals especially relevant in the case company. In a highly automated service environment, many B2B customers may use the service without continuous direct contact with the company. The largest B2B customer accounts have stronger relationships and receive more customized service, but this is not the case across the wider B2B customer population. Therefore, data-driven tools are needed to make customer behavior visible at scale and to help the company identify which business customers may require attention, follow-up, reactivation, or development.

The case is particularly suitable for this study because 24Rent is in a phase where B2B customer management is becoming more clearly separated from the broader customer base. As company's B2B customer segment has developed, the company has increasingly recognized the need to manage B2B customer relationships with more distinct practices from the broader customer base. This makes the case relevant for examining how data-driven tools may support more systematic prioritization of B2B customers. In the case company, B2B customers are made visible through several internal data-based views and classifications. These include customer status categories, activity indicators, recent sales development, inactivity signals, seasonality, and customer-level monitoring views. These materials show what kind of customer signals are available to organizational actors and how business customers can be categorized, monitored, and compared.

The case is not defined by one isolated tool, dashboard, or predictive model. Instead, it concerns the broader organizational setting in which customer data, internal tools, commercial judgement, automated service processes, and emerging B2B routines come together. This makes 24Rent a suitable case for studying how data-driven tools change lead-prioritization practices for existing B2B customers.

3.3 Data collection and empirical material

The primary empirical data of this thesis consists of six semi-structured interviews with organizational actors involved in B2B customer work, sales, analytics, development, and managerial decision-making. Interviews are the primary data source because the theoretical lens of the thesis requires access to individual interpretation and interactional coordination. These dimensions cannot be adequately examined through dashboards or internal documents alone. Semi-structured interviews are suitable because they allow the researcher to cover common themes across interviews while also asking follow-up questions about participants' own experiences and interpretations (Kallio et al., 2016).

The interviews were conducted during March and April 2026. The interview themes focused on B2B customer prioritization, use of customer data, interpretation of data-driven signals, coordination between roles, follow-up practices, CRM-related needs, and perceived future development of B2B customer management. The interviews lasted between 30 and 58 minutes. To protect anonymity, the participants are referred to as Interviewee 1-6.

Table 3. Table of interviews.

Interviewee	Date	Interview length
Interviewee 1	26/3/26	30 min
Interviewee 2	27/3/26	58 min
Interviewee 3	31/3/26	45 min
Interviewee 4	2/4/26	43 min
Interviewee 5	7/4/26	50 min

Interviewee 6	14/4/26	30 min

In addition to interviews, internal company material was used as secondary contextual data. This material included internal customer views, dashboards, prioritization logic, customer status classifications, activity indicators, seasonal views, and other data-based materials related to B2B customer monitoring. This material was used as secondary data to understand the structural and material environment in which prioritization takes place. These kinds of documentary and organizational materials can support qualitative case research by providing insight into formal categories, routines, and representations that shape organizational action (Bowen, 2009). Due to confidentiality, customer-level examples and identifiable company data are not included in the thesis. The internal material is discussed at the level of prioritization logic, tool categories, and organizational use.

Table 4. Empirical material.

Data source	Role in the study	Relevance to framework
Interviews	Primary empirical data	Individual interpretation, interactional coordination, routines, judgement, structures
Internal dashboards and activity indicators	Secondary contextual data	Data-driven customer signals and structural arrangements
Customer status classifications and activity indicators	Secondary contextual data	Visibility of B2B customers and activity interactions
Process-related internal material	Secondary contextual data	Follow-up logic, CRM, and structural embedding

3.4 Data analysis and data structure

The empirical material was analyzed through abductive thematic analysis supported by a Gioia-inspired data structure. The analysis was not conducted as a purely inductive Gioia study, because the thesis already had a theoretical framework based on data-driven B2B sales and microfoundations. However, the Gioia approach is useful for presenting qualitative analysis transparently through first-order observations, second-order themes, and aggregate dimensions (Gioia et al., 2013). This type of data structure has also been used in recent microfoundations research to show how interview-based observations can be connected to broader theoretical interpretation (Rabetino et al., 2025).

The first stage of the analysis consisted of repeated reading of the interview material. Initial coding focused on how interviewees describe B2B customer prioritization, customer data, signal reliability, interpretation of customer behavior, coordination between roles, follow-up practices, CRM needs, and the development of B2B customer management. These first-order concepts were kept close to the empirical material and expressed as short observations.

In the second stage, related first-order concepts were grouped into second-order themes. This stage involved a higher level of interpretation and focused on what the empirical observations revealed about data-driven lead prioritization. For example, concepts related to top customers, inactive customers, lost customers, and reservation trends were grouped under the theme of making B2B customers visible through activity signals. Similarly, concepts related to data trust, business ID problems, legacy reports, and source criticism were grouped under the theme of assessing the credibility of customer signals.

In the third stage, the second-order themes were organized into aggregate dimensions. The first aggregate dimension, data-driven customer visibility as the basis for B2B prioritization, captures how customer behavior becomes visible through activity signals, account-level data, and broader prioritization criteria. The second aggregate dimension, human and cross-functional translation of customer signals, explains how these signals are interpreted, evaluated, and coordinated across commercial, analytical, and managerial roles. The third aggregate dimension, structural embedding of signal-based prioritization into B2B sales routines, captures how data-driven prioritization depends on routines, responsibilities, CRM-related needs, automation, and the development of B2B customer management practices.

Figure 3 presents the data structure used in the analysis.

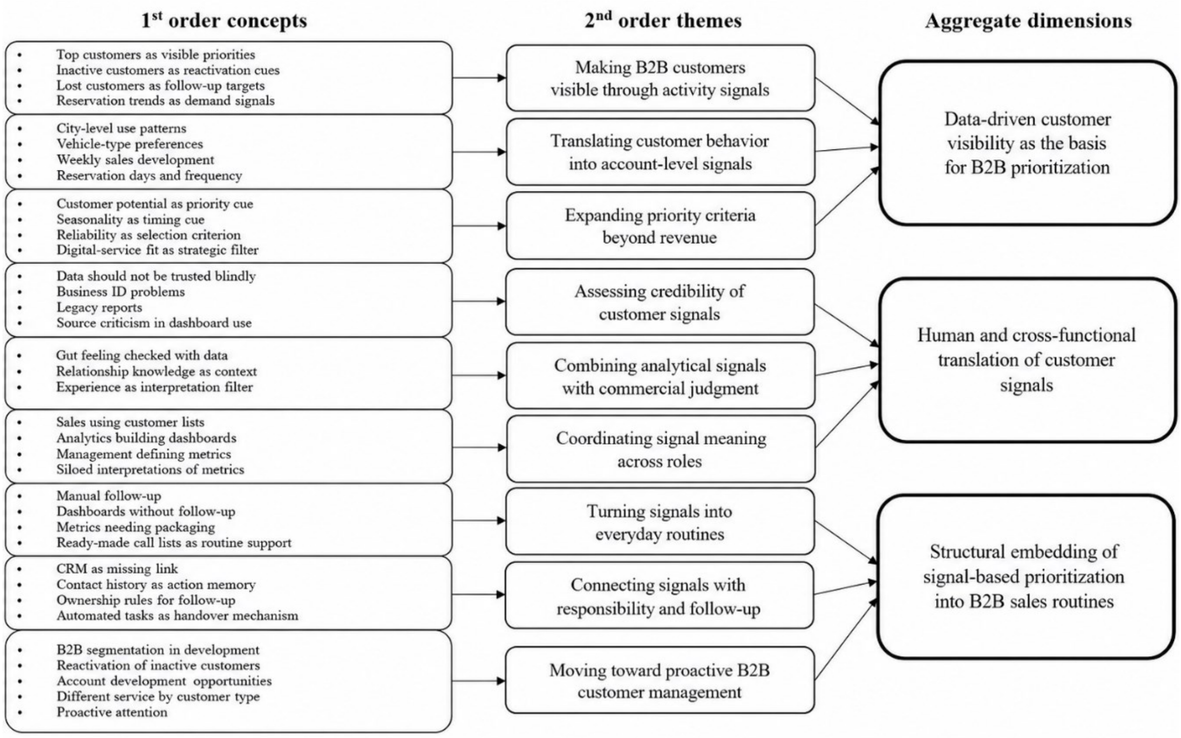

Figure 3. Data structure of data-driven lead prioritization.

This data structure also guides the next findings chapter. Instead of presenting findings by data source or individual interviewee, the findings are organized around the second-order themes and aggregate dimensions. This makes the connection between theory, empirical analysis, and findings explicit. It also supports the purpose of the study by showing how data-driven tools change lead-prioritization practices for existing B2B customers through individual interpretation, interactional coordination, and structural embedding.

3.5 Quality of the study

The quality of the study was strengthened through transparency, triangulation, reflexivity, and a clear chain of evidence. In qualitative case study research, discipline depends on showing how the research question, theoretical framework, empirical material, analysis, and findings are connected (Gibbert et al., 2008). This thesis addresses that requirement by explicitly linking the analysis to the framework developed in Section 2.3 and by presenting a data structure that shows how empirical observations were developed into themes and aggregate dimensions.

Construct validity was supported by using multiple sources of empirical material. Interviews provided access to interpretations, judgements, and coordination processes, while internal company material provided insight into the formal data environment and structural arrangements. However, the study does not treat these sources as equal. Interviews form the primary empirical basis, while internal material is used to contextualize and support the interpretation of structural conditions.

Reliability was supported by documenting the data collection and analysis process. The interview dates and durations are reported, the interviewees are anonymized, and the analysis procedure is described step by step. The use of a data structure further strengthens transparency by showing how the findings were derived from the empirical material rather than presented as isolated observations.

Internal validity was addressed through abductive movement between theory and empirical material. The theoretical framework helped guide the analysis, but the interpretation was refined through repeated engagement with the interview material and internal company context. This was important because the study examines an ongoing organizational development process rather than a completed implementation.

External validity is limited by the single case design. The findings are not intended to be statistically generalizable to all B2B sales organizations. Instead, the study aims for analytical generalization by showing how data-driven prioritization can be understood through the microfoundations of sales capability. The case is relevant because it provides a detailed example of a company developing more systematic B2B customer management within a data-rich digital mobility context.

Finally, researcher reflexivity is important because the study is conducted in a familiar organizational setting. Such proximity can provide valuable access to internal material and practical understanding, but it may also influence interpretation. To address this, the study's analysis was anchored in the theoretical framework, interview evidence, and documental internal material rather than relying only on the researcher's prior knowledge of the company.

4 Findings

This chapter presents the empirical findings of the study. The findings are based primarily on interviews with organizational actors involved in B2B customer work, analytics, development, and managerial decision making. Internal company material is used to contextualize the dashboards, customer classifications, activity indicators, and customer views discussed by the interviewees. The chapter follows the empirical themes presented in Figure 3: customer visibility, translation of customer signals, and embedding signals into B2B sales routines through microfoundations lens. The chapter ends by synthesizing the findings with the theoretical framework and research question.

4.1 Data-driven customer visibility as the basis for B2B prioritization

In case company's digital self-service model, B2B customer relationships are not continuously visible through direct interaction. Customers may make reservations, use different vehicle types, operate different cities, increase their activity, or become inactive without necessarily contacting sales or customer service. This creates a practical prioritization problem: before the company can decide which customers deserve attention, the relevant customers must first become visible.

The findings show that data-driven tools changed this visibility condition. They helped transform a broad and partly anonymous customer base into a more understandable B2B customer portfolio. However, visibility was not the same as action. The tools made customers' behavior observable, but the commercial meaning of that behavior still had to be interpreted and embedded into follow-up practices.

4.1.1 Making B2B customers visible through activity signals

The most immediate change managing B2B customers was that customer activity became easier to observe through practical signals. Interviewees described top revenue customer lists, new customer lists, inactivity indicators, lost customer classifications,

reservation trends, and sales trends as central tools for directing attention. These signals were useful because they translated customer behavior into categories that could trigger different commercial actions.
Interviewee 1 described the role of lists in everyday B2B work:

"The most useful views at the moment are the lists: top customers, news customers, and customers who seem to be disappearing". (Interviewee 1)

The same list-based logic supported different actions. Top customers represented relationship-maintenance needs, new customers created opportunities for onboarding, and disappearing customers created reasons for reactivation.

The important change was that both activity and inactivity became commercially meaningful. A customer did not need to request an offer or contact to become visible. Declining or missing activity could itself become a signal. As Interviewee 1 explained, "if a B2B customer has not booked recently, that may indicate risk of losing them or a reason to follow up".

This mattered especially for the broader B2B population beyond the largest accounts. Large customers were already visible through personal relationships and customized service. Smaller, newer, or irregular B2B customers were easier to overlook. Data-driven activity signals therefore expanded the field of possible attention beyond those customers already known by memory or direct contact.

4.1.2 Translating customer behavior into account-level signals

Customer behavior became useful for prioritization when it was translated from isolated reservations into account-level signals. In a digital car sharing business, a single reservation says relatively little about the customer relationship or opportunity. The more relevant question is whether repeated reservations, reservation count, total purchases, vehicle use, and location-specific activity reveal a pattern that should guide commercial attention.

Interviewee 2 described B2B-rentals dashboard as a central source to visibility. It showed account-level sales, reservation counts, reservation days, weekly or monthly sales development, recent purchases, and classifications such as active, declining, and lost customers. These views helped the company move from observing separate bookings toward understanding how a business customer behaves over time. The account-level interpretation mattered because B2B customers may represent different types of commercial relevance. A business customer using vans repeatedly in one city may indicate a specific local need, while a customer using different vehicles across several locations may suggest broader account-development potential. In this way, account-level signals helped actors interpret not only whether a customer was active, but what kind of relationship or opportunity the customer represented.

The usefulness of these signals depended on whether the underlying data correctly connected reservations to the same business customer. The issue was therefore not only that data existed, but whether the account-level view could be trusted as a representation of the customer’s actual behavior. When reservations, customer accounts, and company-level information were connected reliably, the data made prioritization more systematic. When this connection was uncertain, the signal required additional caution before it could guide action.

4.1.3 Expanding priority criteria beyond revenue

The findings show that data-driven prioritization was not simply a ranking of customers by revenue. Revenue obviously mattered, but interviewees emphasized that customer importance also depended on potential, seasonality, booking pattern, reliability, geographic relevance, and fit with the company’s digital service model.

Interviewee 4 summarized this logic clearly:

"It is not only about euros. It also matters whether the company makes many short reservations or fewer long reservations, what areas it uses, and whether there is potential to expand to other locations. There is no single reason why a company is important." (Interviewee 4)

This shows that data-driven tools broadened the cues used in prioritization. A customer could be important because of current sales, growth potential, local relevance, seasonal need, or strategic fit. In this sense, the tools did not only identify "large" customers. They helped reveal different types of customer relevance.

Reliability and risk management also shaped prioritization. Interviewee 1 explained that invoicing and special arrangements required attention to unpaid invoices and credit information. There was a chance that customers would be commercially attractive, but still require caution if reliability signals or information were weak. Prioritization therefore involved both opportunity selection and risk management.

The company's digital model created another filter. Interviewee 5 argued that not every customer fits the company, especially if the customer requires highly manual, non-digital service. This shifts prioritization at a strategic level from "more customers" toward "better-fitting customers".

4.2 Human and cross-functional translation of customer signals

Customer signals did not automatically determine sales action. Interviewees consistently described data as something that had to be questioned, interpreted, and connected to commercial understanding before it could guide prioritization. This makes translation the central microfoundational mechanism in the findings.

At the individual level, actors had to judge whether a signal was credible and what it meant in context. At the interactional level, different roles had to coordinate around the meaning of the signal and connect analytical views with commercial needs. These individual and interactional mechanisms explain why dashboards and lists could increase visibility without automatically changing action. Whether translated signals became stable sales practice depends further on structural embedding into routines, responsibilities, and follow-up processes, which is examined in Section 4.3.

4.2.1 Assessing credibility of customer signals

The first interpretative step was assessing whether the signal could be trusted. Interviewees did not treat data as automatically objective or actionable.

"Data should never be trusted blindly. Data and analytics should always be questioned." (Interviewee 4)

"The system contains useful new views, alongside older legacy reports that may acquire contextual interpretation. More experienced users might know which reports are reliable, but other employees might not know whether a metric could be trusted." (Interviewee 3)

This created a tension: more data was available, but the ability to evaluate its reliability was unevenly distributed. Metrics could be affected by source logic, presentation, or user interpretation. Also, customer-level aggregation was one concrete example of a credibility issue. For prioritization to work, the data had to connect reservations, user accounts, and company-level information into a reliable view of the same business customer. If this connection was incomplete or inconsistent, the customer's activity could appear fragmented, making the account seem less active, less valuable, or less strategically relevant than it was. This mattered directly for prioritization because actors needed to trust that the account-level signal represented the customer's actual behavior before using it as a basis for follow-up.

Credibility assessment therefore functioned as an individual microfoundation of prioritization. The signal did not operate as an instruction. It operated as a cue that required judgement. Before action could be taken, an actor had to decide whether the signal represented the customer accurately enough.

4.2.2 Combining analytical signals with commercial judgement

Data-driven tools changed prioritization by adding analytical cues to commercial judgement, not by replacing judgement. Interviewees described how customer signals were compared with experience, customer knowledge, reliability, and relationship context.

Interviewee 1 described cases where data and customer experience could point in different directions. A customer might have a negative mark in the data but still be a good customer overall. Alternatively, an employee might have a positive impression from direct contact, while the data suggested reliability concerns. Interviewee 1 described this as that data needs to be interpreted together with customer experience.

This shows that prioritization was a hybrid judgement practice. Inactivity might signal churn risk, but it could also reflect seasonality. High usage might indicate priority, but payment behavior or service needs could change the suitable action. A customer signal created attention, but it did not determine the response.

Interviewee 3 described the same logic in development work. When an action was proposed, they tried not to rely on intuition, but to check whether data supported the assumption. Interviewee 6 described this as a strategic level: data helped determine whether an issue was significant enough in terms of cost, opportunity, or volume.

This is central to microfoundations lens. Data changed what actors noticed and what evidence they used, but actors still had to interpret the signal. Prioritization became more evidence-informed, but not automatic.

4.2.3 Coordinating signal meaning across roles

Customer signals also had to be coordinated across roles. B2B sales used customer lists and follow-up views. Analytics developed dashboards and classifications. Commercial management defined measurement needs. Strategic and development roles shaped the broader direction of B2B customer management. Prioritization therefore emerged across roles rather than inside one tool.

Interviewee 4 emphasized that useful B2B metrics could not be built only from the technical side. The B2B side needed to define what kind of measurement was needed for everyday work and future development. This shows that customer signals become useful only when analytical capability is connected to commercial purpose.

However, coordination was still partly incomplete. Interviewee 2 described the challenge directly: “People still mostly work in their own trench.” Dashboards existed, but it was not always clear what people read from them, how they interpreted them or whether their actions changed. The issue was not lack of dashboards, but lack of shared interpretation and feedback around dashboard use. Interviewee 4 also noted that different people can understand the same metric differently. Discussion and training were therefore needed to create shared understanding of what a metric shows and how it should be used. Data-driven tools created shared objects, such as dashboards, lists, and alerts, but they did not automatically create shared meaning.

This explains why interactional coordination is central to lead prioritization. A signal becomes a priority only when actors agree what it means, who should act, and how the action should be followed up. Without this coordination, the same signal may remain unused or lead to fragmented action.

4.3 Structural embedding of signal-based prioritization into B2B sales routines

The findings show that the main challenge was not only producing better visibility of B2B-customer data but embedding that data into everyday B2B routines. Dashboards, lists, and classifications helped identify relevant customers, but their impact depended on whether signals were connected to follow-up practices, ownership, CRM logic, and automation. This represents the structural level of microfoundations lens. Data-driven prioritization became consequential only when signals were connected to repeated ways of working

4.3.1 Turning signals into everyday routines

Several interviewees described a gap between available data and everyday action. Data existed, but employees did not always know how to use it consistently or how it related to their responsibilities.

“Getting data and developing data is not our main problem. The bigger issue is how to embed it into everyday work.” (Interviewee 3)

This statement captures one of the central findings. The case company had developed dashboards, metrics, and customer views, but the harder task was routinization. Signals needed to appear in daily work in a form that employees could understand and act upon. Interviewee 5 made the same point from a systems perspective. The company had previously assumed that metrics would “speak to everyone”, but this was not the case. The effective use of dashboards requires shared guidance and practical routines so that users can apply them consistently in their work. The finding highlights the importance of involving users and supporting adoption when new dashboard views are developed.

In B2B sales, this routine-use gap appeared in follow-up practices. Employees in sales work used customer-view lists and project-tools, but those are still maintained manually.

The desired improvement was a CRM-type system or ready-made contact lists that would identify which customers should be contacted next. Thus, the case company has developed useful data views for B2B customer management, but the follow-up routine was not yet fully embedded.

4.3.2 Connecting signals with responsibility and follow-up

CRM appeared as the missing structural link between customer signals and follow-up. Interviewee 2 stated:

“I have not seen a successful implementation without a CRM-system.” (Interviewee 2)

In the case company’s context, CRM meant a system where customer information, contact history, goals, actions, communication history, advertising and reservation data were connected. This distinction is important. A dashboard can show that a customer has become inactive, but it does not automatically show whether someone has contacted the customer, what was discussed, what the next step is, or who owns the relationship and follow-up action. Without this organizational memory, prioritization remains partly dependent on individual memory and manual follow-up.

Interviewee 5 described automation to remove routine work while keeping human decision-making where it matters.

“Automation does not mean everything happens automatically. It means all the stupid routines are done automatically, and the person gets only the final decision point.” (Interviewee 5)

Applied to B2B prioritization, tools could identify relevant customers, prepare information, and create follow-up prompts, while employees would still decide how to approach the customer. Structural embedding does not remove human judgement. Instead, it creates conditions where judgement can be used at the right moment and move toward employees' time to decisions where human judgement matters.

4.3.3 Moving toward proactive B2B customer management

The findings indicate that case company's B2B customer management is moving from reactive handling toward proactive portfolio management. Interviewees described B2B section as growing but still developing. The company had taken steps in measurement, structure, working methods, and technology development, but segmentation and systematic account management were still incomplete.

Interviewee 6 argued that the next development need was broader company-level visibility of the B2B customer portfolio. Although practical B2B data was already used in some daily work, "it does not yet appear clearly in company-level metrics", such as customer statistical development, average purchases, and quarterly changes. This visibility matters because, without numbers, B2B may appear mainly as additional manual workload rather than as a source of revenue, retention, and growth.

Proactive customer management also meant differentiated service possibilities. Interviewee 6 suggested that different customer types could receive different forms of customer service, automation, or benefits. Standard customers could be handled more through automation, while customers with greater potential could receive more human attention. This would allow the company to allocate resources more consciously. Interviewee 5 framed the same issue as portfolio management. Prioritization was also risk management, and not all customers fit the company's digital model. This shifts the logic from simply gathering more B2B customers toward identifying which customers the company wants, how they should be served, and where human attention creates the most value.

4.4 Summary of findings and revised theoretical framework

This study set out to examine how data-driven tools change lead-prioritization practices for existing B2B customers. The findings show that the change is not caused by data-driven tools alone. Rather, data-driven tools reshape prioritization through a sequence of empirical mechanisms. In the case company, the starting point was a large B2B customer base in a digital self-service model, where many customers interact with the company primarily through automated service channels. This increases the importance of data-driven visibility, as customer behavior cannot be comprehensively monitored through direct contact alone.

The first mechanism is making customers visible. Data-driven tools translated customer activity into signals such as activity patterns, account-level behavior, and broader priority cues. This visibility was necessary because customers could not be prioritized before they first became visible as relevant. The findings therefore refine the original theoretical framework by showing that data-driven customer signals should be understood not only as analytical outputs, but also as visibility devices that make existing B2B customers available for commercial attention.

The second mechanism is translating signals into commercial meaning. Customer signals did not automatically determine action. Actors had to assess whether signals were credible, interpret them through commercial judgement, and coordinate their meaning across roles. This explains why the same metric or customer list could support action in one situation but remain unused in another. The findings therefore specify the microfoundational mechanism through which data-driven tools influence prioritization: signals guide action only when actors trust, interpret, and coordinate around them.

The third mechanism is embedding signals into sales routines. Even when customer signals became visible and meaningful, they did not necessarily become repeated practice.

Signals became consequential only when connected to CRM logic, ownership, follow-up, automation support, and routine use. This highlighted an important development area in the case company's B2B customer management structure. Dashboards and lists helped identify relevant customers, but prioritization remained incomplete where signals were not connected to clear responsibilities and follow-up processes were still in translational stage.

Figure 4 presents the synthesis of the theoretical framework and empirical findings. The revised framework shows that data-driven lead prioritization begins from the case-specific challenge of a large and partly hidden B2B customer base. Data-driven tools first make customers visible, then actors translate signals into commercial meaning, and finally the organization must embed these signals into sales routines. When these mechanisms operate together, lead prioritization practices change; customers' attention becomes more systematic, prioritization cues broaden beyond revenue, follow-up can be triggered earlier, role responsibility becomes more important, and human attention can be allocated more selectively.

The potential customer-level implications should be interpreted carefully. The findings suggest that improved prioritization may support retention, reactivation, account development, and engagement. However, these implications are suggested by the findings rather than causally proven. The main empirical contribution of the study is therefore not to determine direct performance outcomes, but to explain the organizational mechanism through which data-driven prioritization practices may contribute to such outcomes in existing B2B customer relationships.

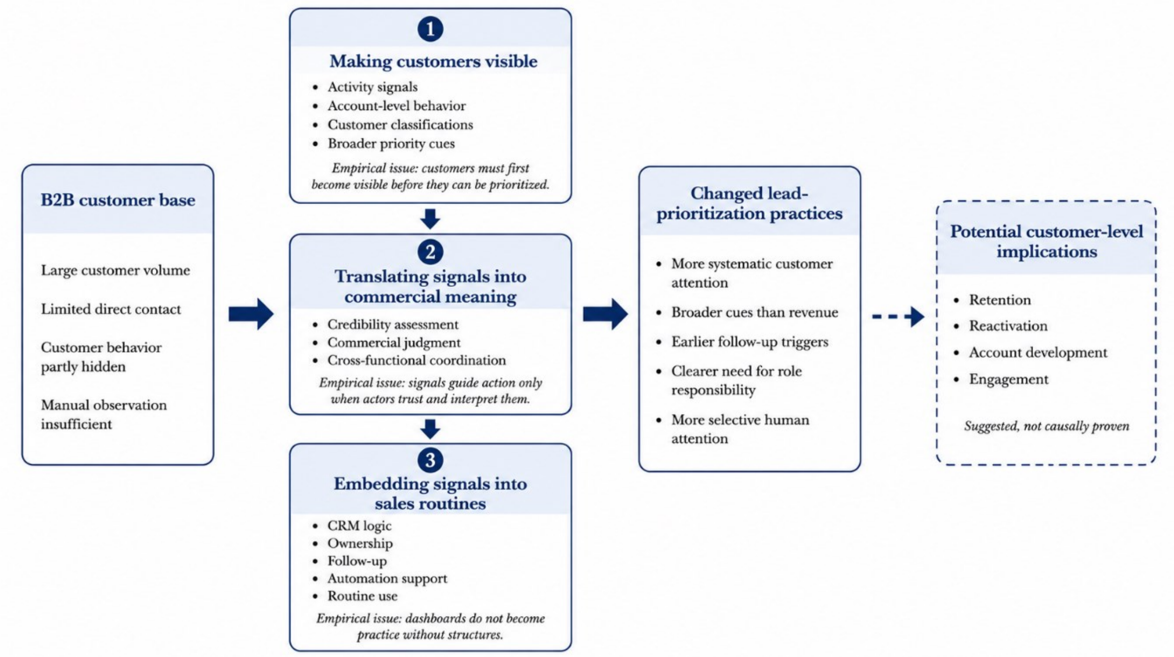

Figure 4. Synthesis of the theory and empirical findings.

5 Discussion

This chapter discusses the theoretical and managerial implications of the study. The research question asked how data-driven tools change lead-prioritization practices for existing B2B customers. The findings show that the change is indirect. Data-driven tools do not change prioritization simply by producing dashboards, customer lists, or predictive signals. They become consequential when customer signals make customers visible, when actors interpret and coordinate around those signals, and when the organization embeds them into routines, responsibilities, and follow-up practices.

The central argument of the thesis is therefore that data-driven lead prioritization is not only a technical process, but a microfoundational process of allocating commercial attention. In the case company, data-driven tools helped reveal which existing B2B customers were active, inactive, or otherwise potentially valuable. However, the findings also show that visibility alone was insufficient. Customer signals had to be trusted, interpreted with commercial judgement, coordinated across roles, and connected to CRM logic and routines before they could reshape sales work.

5.1 Theoretical contributions

The first theoretical contribution of this thesis is that it extends the discussion on data-driven B2B sales toward existing customer prioritization. Prior studies show that customer analytics and data-driven capabilities can support customer relationship performance, B2B sales performance, and CRM outcomes (Hallikainen et al., 2020; Zhang et al., 2020). Studies on sales analytics and lead scoring have also examined how predictive tools can support sales decisions and improve prioritization (Habel et al., 2023; Wu et al., 2024). This thesis adds to that literature by showing that prioritization is not only a matter of ranking new leads or predicting conversion. In existing B2B relationships, prioritization concerns how firms allocate attention across a current customer portfolio. The use of customer classifications and predictive tools helps that process significantly. This contribution shows that existing-customer prioritization differs from traditional lead scoring. In this case, the relevant question was not only which new customer is most likely to convert, but which existing customer requires follow-up, reactivation, account development, differentiated service, or risk management. Thus, the findings suggest that data-driven lead prioritization should be understood more broadly as customer attention allocation in ongoing B2B relationships.

The second contribution concerns the microfoundations of data-driven sales capability. Microfoundations research argues that organizational capabilities are built through individuals, interactions between them, and structural arrangements (Felin et al., 2012). This thesis applies that logic to data-driven B2B sales by showing how customer signals are translated into sales practice. At the individual level, actors assess whether data is credible and interpret it through customer knowledge and commercial judgement. At the interactional level, sales, analytics, development, and management roles coordinate the meaning of customer signals. At the structural level, signals become consequential only when embedded into routines, CRM logic, ownership, automation, and follow-up.

This refines the discussion on sales analytics adoption. Predictive sales analytics creates value only when tools are adopted and used in sales organizations (Habel et al., 2023). This study adds a more detailed explanation on what “use” means in practice. Use is not simply opening a dashboard or viewing a customer list. It involves interpreting the signal, deciding whether it matters, coordinating responsibility, and turning it into action.

The third contribution concerns CRM and structural embedding. Customer relationship management should be understood as a strategic and cross-functional process rather than merely a technology system (Payne & Frow, 2005). The findings support this view and specify it in the context of data-driven B2B prioritization. In the case company, dashboards and customer views improved visibility, but the main gap was connecting this visibility to customer ownership, contact history, next actions, and recorded outcomes. This shows that CRM-type infrastructure matters because it functions as organizational memory. It allows customer signals to become part of repeated customer management practices rather than isolated observations.

Together, these contributions clarify the relationship between analytics and sales capability. The findings support the argument that analytics affects performance indirectly through customer-linking and selling capabilities rather than through data alone (Itani et al., 2024). In this study, data-driven tools created potential value by improving customer visibility and supporting prioritization, but this potential depends on whether the organization can translate signals into coordinated and repeated sales practices.

5.2 Managerial implications

The findings provide practical implications for the case company and for similar firms developing data-driven B2B customer management in data-rich service environments. The central managerial implication is that data-driven prioritization cannot be approached only as a dashboard or reporting project. Customer lists, classifications, and activity views create managerial value only when they are connected to decisions, responsibilities, and follow-up practices. From this perspective, the managerial challenge is not only to produce more customer data, but to create an operating model in which customer signals become actionable.

For the case company, this means that B2B prioritization could be developed around clearer signal-to-action logic. Different customer signals can support different forms of commercial action. New customers may require onboarding, declined customers may require retention-oriented contact, inactive customers may create reactivation opportunities, seasonal customers may benefit from timely pre-season contact, and growing customers may require account-development review. The value of customer classifications therefore depends on whether they help employees understand what kind of attention the customer requires.

The findings also highlight the managerial role of CRM-type infrastructure. In the case company, data-driven views have already made many B2B customers more visible, but follow-up practices could be further supported by shared systems that reduce reliance on manual tracking and individual memory. A CRM-type structure would not only function as a technical database; it would create organizational memory around customer relationships. By connecting customer history, CRM logic could help ensure that customer signals do not remain isolated observations but become part of repeated account-management practice.

Another implication concerns coordination around customer signals. The findings show that metrics do not automatically create shared understanding. Different roles may interpret the same metric or customer view differently, and useful signals may remain underused if there is no shared forum for interpreting them. A regular B2B prioritization rhythm, involving commercial, analytical, and managerial roles, could help connect data interpretation with action. The purpose of such routine would not be to review the entire customer base, but to identify where customer attention is currently most relevant and whether existing action logic is working.

The study also points to the importance of data literacy and practical training. Employees need to understand what customer signals mean, where they come from, when they can be trusted, and what kind of action they support. This is consistent with sales technology research showing that training and support shape whether sales technologies improve performance (Ahearne et al., 2005). For managers, the implication is that dashboard or CRM-type development and employee enablement need to proceed together. Curated views, clear metric definitions, and removal of outdated or confusing reports can make data-driven decisions easier to adopt in daily work.

Automation create further opportunities, but the findings suggest that its value lies mainly in supporting human judgement rather than replacing it. Automation can reduce manual monitoring, generate contact lists, classify customers, and produce follow-up prompts. However, B2B customer work still requires interpretation of potential, reliability, service needs, relationship context, and fit with the company's digital model. A productive managerial direction is therefore a hybrid model in which automation prepares and structures information, while employees focus on judgement, relationship building, exceptions, and account development.

Finally, the findings suggest that B2B prioritization can be understood as customer portfolio management. Not all customers require the same type of attention, and not all customers fit the company's service model equally well. Data-driven prioritization can help managers distinguish between customers that are suitable for automated service, customers that require relationship-oriented attention, and customers with broader account-development potential. In this way, the managerial value of data-driven tools lies in helping the company allocate limited human attention where it creates the most commercial and relational value.

5.3 Limitations

This thesis has limitations that should be considered when interpreting the findings. The first limitation concerns the single case design. The case study approach made it possible to examine data-driven B2B prioritization in detail and in its organizational context. However, the findings cannot be statistically generalized to all B2B firms. The case company operates in a digital mobility and car-sharing service context, where customer behavior, service processes, and sales practices have their own characteristics. Therefore, the findings should be understood as an analytical explanation of how data-driven prioritization is developing in this specific setting.

The second limitation concerns the qualitative and interpretive nature of the study. The thesis explains how data-driven tools reshape customer visibility, interpretation, coordination, and follow-up practices, but it does not quantitatively measure whether these changes directly improve revenue, retention, customer engagement, or account growth. The findings therefore should not be read as evidence that signal-based prioritization automatically leads to stronger business performance. Instead, the study explains the organizational mechanism through which such outcomes may become possible.

The third limitation concerns the stage of development in the case company. The company was studied during a transitional phase in which B2B customer management, CRM-type logic, automation, and AI-related practices were still developing. This means that the study captures an emerging change process rather than a mature and fully institutionalized prioritization system. The findings are therefore especially useful for understanding how data-driven prioritization begins to take shape, but they cannot fully explain how such practices operate once they have become stabilized.

The last limitation concerns researcher familiarity with the case company. Close access made it possible to understand internal tools, routines, and development needs in detail. At the same time, familiarity may influence interpretation. To reduce this risk, the analysis was anchored in interview material and internal contextual data. Nevertheless, the findings should be understood as an interpretive analysis of the case company's current development rather than as a fully detached external evaluation.

5.4 Suggestions for future research

This thesis opens several possibilities for future research. One useful direction would be to examine data-driven lead prioritization in other B2B service companies. Comparative studies across several firms could clarify which findings are specific to the digital mobility context and which are more generally relevant to B2B customer management. Such studies could also examine how different levels of CRM maturity affect the translation of customer signals into sales routines.

Future research could also study data-driven prioritization longitudinally. This study captures the case company at a transitional stage, where useful data-based tools already exist but routines are still developing. A longitudinal study could follow how customer signals become embedded into work over time and how employees accept, adapt to, or resist new CRM, automation, and AI-based tools.

Another important direction would be to connect practice-level changes with measurable customer outcomes. This thesis explains how data-driven tools reshape existing B2B customer sales and relationships, but it does not test whether these changes improve retention, account growth, engagement, or customer lifetime value. Future quantitative or mixed-method studies could examine whether signal-based prioritization produces measurable customer and financial outcomes.

Finally, future research could examine the microfoundations of CRM and AI implementations in B2B sales. The findings suggest that CRM-type infrastructure can help convert data visibility into coordinated action, but the process depends on how actors interpret tools, coordinate responsibilities, and embed new routines into sales work. Studying these processes more closely would help explain how technical systems become part of practical sales capability.

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Appendices

Appendix 1. List of interviewees

Interviewee	Date	Interview length
Interviewee 1	26/3/26	30 min
Interviewee 2	27/3/26	58 min
Interviewee 3	31/3/26	45 min
Interviewee 4	2/4/26	43 min
Interviewee 5	7/4/26	50 min
Interviewee 6	14/4/26	30 min

Appendix 2. Semi-structured interview guide

1. Background

Could you briefly describe your role in the company and your main responsibilities?

How is your work related to the use of data, the development of tools, and the B2B side of the business?

2. Building data-driven tools

What kinds of data-driven tools or solutions have been developed in the company?

What needs have driven the development of these tools?

How is it decided what data is included in the tools?

What are the biggest challenges in building these tools from a data perspective?

How do you ensure that a tool is genuinely useful for the business, and not only technically functional?

3. Bringing tools into practice

How is the information produced by the tools brought into practical work?

How is this information integrated into the everyday work of sales or customer relationship management?

What factors make it easier or more difficult for the tools to be used in practice?

How is user feedback considered in tool development?

4. Developing the B2B side

What role do data-driven tools play in developing the company's B2B side?

How do you see data supporting the development of existing B2B customer relationships?

Where do you currently see the greatest development potential for using data on the B2B side?

5. Customer prioritization

How does customer prioritization currently work in the company?

How does data influence which customer relationships or actions are focused on?

How well do the current tools support customer prioritization?

Where does prioritization currently work well, and where are the biggest challenges?

How do you see the future of customer prioritization in the company?

What should be developed to make prioritization better in the future?

Closing questions

Is there anything important related to data-driven tools, B2B development, or customer prioritization that I did not know to ask about?

Could you give one concrete example of a situation where data or a tool clearly influenced practical action or decision-making?