Monetizing Car Connectivity: Business, Platform, and Ecosystem Strategies to Capture Value from Connected Cars

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Abstract

The automotive industry has shifted from viewing cars as standalone products to an all-encompassing ecosystem built around connected cars facilitating data-driven business models. This evolution has led to a massive influx of data harvested from connected cars, creating a distinctive driving experience while simultaneously allowing automotive firms to foster cost efficiency and revenue growth. Even though we witness several flourishing business models associated with connected cars, the industry's current comprehension falls short in addressing the challenges automotive firms face when monetizing car data. At the same time, the boundaries between automotive and software-oriented industries or the extended smart living sector blur to create a superior customer experience through personalized entertainment features and services. Incumbent automotive companies must forge partnerships with IT giants or start-ups to co-create value within intricate ecosystems, as relying solely on proprietary solutions and internal core competencies is no longer sufficient. Consequently, this thesis aims to enrich the collective understanding of how companies conceptualize and design business models and harness platform ecosystems to capture value from the connected car phenomenon.

To address this research objective, we first review the literature on data-driven business models in the context of connected cars. Drawing upon those results, we search for key characteristics in this nascent domain by additionally conducting case surveys within an iterative taxonomy development process. Subsequently, cluster analysis techniques are employed to empirically derive archetypal patterns that describe essential configurations of the identified key characteristics. Moreover, a design science research approach is used to build an artifact to utilize multi-brand car data effectively. Finally, we conduct two embedded case studies to elaborate on the ecosystem strategies of incumbent firms. All in all, our research encompasses 71 semi-structured interviews with industry experts and senior decision-makers and an analysis of 154 real-world business models.

Within this thesis, we first clarify the conceptualization of data-driven business models in the connected car domain by providing an empirically and theoretically grounded taxonomy and corresponding archetypes. Second, we showcase the value-creation potential of car data from car manufacturers' backends shared by data marketplaces. Thereby, design knowledge is provided in the form of tentative design

principles and instantiated in a prototype artifact that has the potential to contribute to economic and environmental sustainability, as well as maintaining vehicle health. Finally, our case study research results shed light on two paths. One path describes how incumbent firms involve digital platforms by tech players and join existing ecosystems to reallocate uncertainties. Conversely, the other path illustrates how incumbent firms can foster value co-creation to establish their platform ecosystems and operate as orchestrators.

Given the novelty of the phenomenon, our research creates a foundation for investigating car data monetization, analyzing connected car business models, and developing design theories in this emerging field. We further contribute to the body of design knowledge on connected service development, specifically focusing on connected car data and its effective use. The findings from this thesis explain digital business strategies implemented by incumbent firms that transition toward value co-creation within platform ecosystems, thereby contributing to theoretical advances in the field of information systems research.

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List of Abbreviations

AAOS	Android Automotive OS
ACEA	European Automobile Manufacturers' Association
ADAS	advanced driver assistance systems
AI	artificial intelligence
API	application programming interface
B2B	business-to-business
B2C	business-to-consumer
B2G	business-to-government
BEV	battery electric vehicle
CFMS	connected fleet management system
CLEPA	European Association of Automotive Suppliers
DDBM	data-driven business model
DP	design principle
DSR	design science research
eCall	emergency call
FinTech	financial technology
FMS	fleet management systems
FNOS	first notification of service
GAS	Google Automotive Services
HICSS	Hawaii International Conference on System Sciences
HMI	human-machine interface
ICE	internal combustion engine
ICIS	International Conference on Information Systems
IoT	Internet of Things
IS	information systems
KPI	key performance indicator
MR	meta-requirement
MVP	minimal viable product
NDA	non-disclosure agreement
OBD	on-board diagnostics
OEM	original equipment manufacturer
OS	operating system

OTA	over-the-air
PHEV	plug-in hybrid electric vehicle
PII	personally identifiable information
RQ	research question
S-D	service-dominant
SDK	software development kit
SLR	structured literature review
TCO	total cost of ownership
UBI	usage-based insurance
VHAL	vehicle hardware abstraction layer
VUCA	volatile, uncertain, complex, and ambiguous
WI	International Conference on Wirtschaftsinformatik

Part I

Fundamentals

1 Introduction

> *We are just at the very start of a major transformation of what has been a very consistent product for the past 100 years and has looked and felt more or less the same way. Yes, it went a bit faster. Yes, it went a bit more clean over time. But I think now we will see that it will change fundamentally. The reason why that is is mainly because we are seeing the shift from mechanical to software.*
>
> — **Alex Koster (2023a)**
> (Senior Partner, Managing Director, and Global Leader for Automotive Tech & Software at the Boston Consulting Group)

1.1 Motivation

The proliferation of advanced digital technologies, such as cloud computing, artificial intelligence (AI), and the Internet of Things (IoT), has sparked a digital transformation across industries. Despite its global presence and long history of innovation, the automotive industry has been a relative latecomer to the ongoing digital battle. As consumers re-evaluate their driving expectations and increasingly prioritize connected and data-driven experiences in their cars, the automotive industry is at an inflection point, requiring fundamental strategic alignment to capture digital business opportunities. Although digital transformation and the embrace of digital business models rather marginally concerned the automotive industry in the past, the increasing connectivity of cars elevates these areas' significance. As frontrunners in IoT technologies, automotive original equipment manufacturers (OEMs) began equipping cars with telematic control units and multi-layered sensor technology several years ago, which laid the groundwork for collecting highly monetizable in-vehicle data.

Today, a connected car already generates up to 25 GB of data per hour, including a multitude of data signals such as driving behavior, charging profile, or high precision sensor data, whereby big data and analytics have become new sources of value creation (Heid et al., 2018). Data-driven business models (DDBMs) are one notable approach to harness the opportunities of this development. Data from connected cars, for instance, offers valuable insights into drivers' attention, risk-taking behavior, and mobility patterns—all of which hold considerable value for stakeholders within the broader connected car ecosystem, among OEMs, insurers, and regulators (Cichy et al., 2021; Kaiser et al., 2021; Stocker et al., 2021). As of 2030, the annual incremental value from car data monetization is expected to reach \$250 billion to \$400 billion (Martens & Schneiderbauer, 2021). However, the connected car is not only vital for collecting car data as an essential source of future value creation but also as a vital stepping stone toward autonomous driving and advanced infotainment features (Sterk et al., 2023c). Against this backdrop, car connectivity provides a glimpse into a potential future of broader consumer IoT applications (Cichy et al., 2021).

Connected cars already offer a plethora of new features and services, such as predictive maintenance, over-the-air updates, and range improvement of electric vehicles (Dremel et al., 2017; Sterk et al., 2022a). Yet customer expectations change rapidly, necessitating a continuous understanding of preferences and innovation from automotive firms. Alongside traditional values like design, safety, and horsepower, the importance of connectivity and app accessibility is increasingly emphasized (Weiss et al., 2021). Drivers demand smartphone-like entertainment features, with up to 40 % considering changing their favorite car brands for enhanced digital services (Heineke et al., 2020). The concept of connected cars has evolved beyond mere transportation, leading the industry to increasingly refer to them as the "3rd living space," a trend highlighted by the following three examples:

Tesla started integrating powerful onboard computers in their vehicles early, primarily to enable semi-automated driving capabilities. However, they utilize these computer resources to provide in-car entertainment options, including video games typically found on dedicated gaming consoles (Lambert, 2022). Moreover, Huawei pioneers home-to-car connectivity, allowing drivers to activate home functionalities, like heating systems, through an integrated voice assistant (Huawei, 2021). Additionally, the smart home detects the vehicle's arrival, triggering actions like raising shutters and unlocking doors. Another example is Mercedes' cooperation with Visa enabling direct in-car payments of digital services in the company's app store, with plans to expand this payment mode to cover parking fees or fuel costs (Mercedes-Benz, 2023).

The demonstrated examples show the current blurring of boundaries between the automotive industry and other domains, such as smart home, financial technology (FinTech), gaming, or other entertainment areas, meaning that automotive incumbents can no longer rely solely on proprietary solutions and in-house expertise (Kaiser et al., 2019; Riasanow et al., 2017). Similar to other sectors, economic value creation in the automotive industry has shifted in recent years from production in isolated companies to value co-creation in intricate ecosystems (Lusch & Nambisan, 2015; Marheine & Pauli, 2020; Peppard & Rylander, 2006). These ecosystems are centered around digital platforms, serving as intermediaries matching complementors offering products or services and customers (Eisenmann et al., 2006; Rochet & Tirole, 2003). Compared to conventional business structures, platform ecosystems are praised for their capacity to foster generativity, scale rapidly, and adapt flexibly to changing circumstances (Hein et al., 2020; Sterk et al., 2022b). Illustrative examples of this phenomenon can be observed in mobile application platforms such as Google Android with its Google Play Store or Apple's iOS with its App Store, offering an extensive range of applications generated by third-party developers (Eaton et al., 2015; Karhu et al., 2018, 2020). Both platforms have already found their way into the automotive industry, named Android Auto and Apple CarPlay, allowing drivers to mirror their smartphones and associated apps onto the vehicle's head unit (Bohnsack et al., 2021; Bosler et al., 2017).

Following the widespread adoption of digital platforms in the mobile phone market, companies in the automotive industry have begun incorporating platforms business models, beginning with OEMs offering in-vehicle app stores (Bosler et al., 2017; Schreieck et al., 2022). However, due to the remarkable development effort and lack of standardization across multiple car brands, several service providers resisted developing apps for OEM platforms, given the limited user base they could ultimately access (Weiss et al., 2021). Consequently, the app availability was significantly lower than the familiar smartphone ecosystems, which boasted 3.6 million apps on the Google Play Store and 1.6 million apps on the Apple App Store (Statista, 2022). In response, technology companies began to capitalize on their smartphone proficiency to conquer the digital interface between driver and vehicle (Schreieck et al., 2022; Weiss et al., 2020). Whereas the previously mentioned Android Auto or Apple CarPlay were limited to smartphone mirroring, Google introduced Android Automotive OS (AAOS) to OEMs, directly embedded into the car and controlling the entire user interface (Legenvre et al., 2022). It is premature to predict how successful AAOS will be, although early indications are favorable due to several

OEMs[1] declaring its adoption. Industry experts fear a loss of control for OEMs because once they have ceded sovereignty over the user interface to Google, they increasingly risk being commoditized to mere hardware suppliers (Sterk et al., 2023b). They expect AAOS to be a Trojan horse that could demand access to the data in the entire vehicle in the future, handing the potential for profitable data-driven business models to Google.

Access to valuable car data is not only of interest to OEMs and tech firms but also to independent service providers such as suppliers, insurers, and fleet companies (Kaiser et al., 2019; Sterk et al., 2023a). These independent entities are currently forced to seek alternative technical gateways granting similar access options to the data enjoyed exclusively by OEMs (Martens & Mueller-Langer, 2020). Aspiring car data platforms like Caruso Dataplace or Otonomo exploit this business problem. Inspired by successful transaction platforms such as eBay, Uber, or Airbnb, they bring demand and supply sides together to exchange units of value. Thus, they act as neutral intermediaries enabling OEMs to sell standardized data to independent service providers (Martens & Mueller-Langer, 2020; Sterk et al., 2022a). The major advantage lies in the fact that data from multiple OEMs can be accessed through a single point of entry (Stocker et al., 2021). In practice, though, marketplaces encounter difficulties in scaling as they rely on data access conditions determined by OEMs, including data pricing, availability, and willingness to share their data (Sterk et al., 2023a). It is worth noting that the role of such data marketplaces will become increasingly significant in the digital era, where data emerges as a vital asset to facilitate novel business models (Jung et al., 2021).

In sum, information systems (IS) research has established an initial understanding of DDBMs in the connected car domain and associated platform ecosystems (e.g., Bergman et al., 2022; Bohnsack et al., 2021; Kaiser et al., 2021; Ketter et al., 2022). Nevertheless, we observe that the current understanding does not go far enough to address the challenges automotive firms encounter when monetizing car data and moving to a digital platform strategy. On the one hand, we witness several thriving connected car business models (Bohnsack et al., 2021; Dremel et al., 2017; Svahn et al., 2017). On the other hand, it has been shown that automotive firms face drawbacks in establishing connected services (Coppola & Morisio, 2016), in-vehicle app stores (Weiss et al., 2021), or car data marketplaces (Martens & Mueller-Langer, 2020). Therefore, this thesis explores and enhances the general understanding of how companies conceptualize and design business models and leverage platform

[1] OEMs that signed up for AAOS include Volvo, Polestar, Honda, General Motors, Renault-Nissan-Mitsubishi, Ford, Volkswagen Group, BMW Group, and Stellantis

ecosystems to capture value from connected cars. We identified three existing gaps in the status quo of IS research, which we address in this thesis.

First, despite the growing importance of data in the contemporary digital economy, IS research still lacks an understanding of emerging data-driven business models. Initial research focuses on industry-agnostic classifications of data-driven business models (Dehnert et al., 2021; Hartmann et al., 2016; Passlick et al., 2021) or delves into the monetization of data from specific industries, such as logistics (Möller et al., 2020), manufacturing (Müller & Buliga, 2019), or FinTech (Gimpel et al., 2018). Yet, the impact of data-driven business models on various sectors, particularly in traditional industries like the automotive industry, remains poorly researched (Bock & Wiener, 2017). Hence, current research does not navigate firms and scholars through the vastly uncharted territory of monetizing data derived from connected cars (Sterk et al., 2022c).

Second, a significant research gap in design knowledge concerning data-driven business models and services exists. While connected cars generate vast amounts of data, including information regarding vehicle health, driving behavior, and road conditions, there is little experience in using this data effectively to generate value for consumers, businesses, and society. This highlights the need for design science research, which "[...] creates and evaluates IT artifacts intended to solve identified organizational problems" (Hevner et al., 2004, p. 77). Moreover, the lack of research in this area hinders the development of data-driven strategies that can effectively unlock the full potential of car data, fostering opportunities for growth and innovation. In addition, designing car-data-based user interfaces and visualization techniques can aid industry experts and decision-makers in operational and strategic management decisions.

Third, existing literature on digital platform ecosystems primarily concentrates on native platform ecosystems (Hein et al., 2019a), providing limited insights into an incumbent's perspective on how to take advantage of platform economics (Marheine & Petrik, 2021; Pauli et al., 2021; Sandberg et al., 2020). There is a lack of knowledge about how incumbent firms, such as legacy OEMs or Tier-1 suppliers, can establish platform ecosystems to transition from rigid supply chains to value co-creation with autonomous complementors. Furthermore, it must be elucidated how incumbent firms react to tech players like Google entering the automotive industry and the collaboration strategies they can choose to incorporate the tech firms' external platform offerings (e.g., AAOS).

1.2 Research Agenda and Research Questions

The overarching research objective of this dissertation is to explore and enhance the general understanding of how companies conceptualize and design business models and leverage platform ecosystems to capture value from connected cars. Specifically, we focus on incumbent firms that undergo a strategy shift from production within single firms to the co-creation of value within complex ecosystems, a challenge that has been highlighted in recent literature (e.g., Marheine et al., 2021; Sebastian et al., 2017) and has been observed in practical industry contexts (e.g., Horn et al., 2022; Pidun et al., 2022). The connected car is an ideal IoT example for our purposes, as it collects highly monetizable data from multiple sensors and gathers a growing ecosystem around it, composed of stakeholders from various industries (Cichy et al., 2021). Our primary research goal is divided into six research questions (RQs), shedding light on the current state of IS research (RQ1), the conceptualization (RQ2 and RQ3), and the design (RQ4) of business models for connected cars. Furthermore, we address the ecosystem strategies of incumbent firms operating in the connected car area (RQ5 and RQ6). In the following, the individual research questions are introduced.

Due to the novelty of the connected car phenomenon, research investigating corresponding business models is still at an early stage. However, the significance of data-driven business models and associated platform ecosystems has gradually gained momentum within the automotive industry. As scholars in IS research increasingly explore these topics (e.g., Bergman et al., 2022; Cichy et al., 2021; Ketter et al., 2022), our primary objective is to gain a deeper understanding of the extensive discourse in the literature regarding business models with the potential to create and capture value from the data collected by connected cars. To the best of our knowledge, there is no comprehensive overview that provides a concise summary of the existing state of IS research on this specific phenomenon, representing a noteworthy research gap. Against this backdrop, we pose the following research question that forms the basis for the subsequent research questions:

Research Question 1 (RQ1)
What is the state of the art in research covering data-driven business models in the connected car domain?

Despite the increasing importance of car connectivity, there is little theoretical knowledge and a lack of common language in both research and practice of connected car business models (Sterk et al., 2022a). In fact, the specifics of designing empirical business model classifications are generally poorly researched (Groth & Nielsen, 2015; Lambert, 2015). The classification of digital business models in the automotive industry is crucial, as cars themselves cannot be fully digitized (Piccinini et al., 2015), and the impact of digital business models and ecosystems on large, complex products like automobiles needs further exploration for a comprehensive understanding of digital transformation (Hanelt et al., 2021). Thus, our research aims to specify key characteristics of connected car business models addressing recent calls for better understanding data-driven business models in the automotive industry (Ketter et al., 2022) and providing valuable support to practitioners in leveraging vehicle data for their entrepreneurial activities. Since existing classifications of the considered phenomenon neither offer a holistic picture nor cover the essential perspective of car data monetization, we ask the following research question:

Research Question 2 (RQ2)
What are the key characteristics of data-driven business models in the connected car domain?

Current literature also lacks a systematic understanding of how companies operating in the realm of connected cars might configure their business models (Sterk et al., 2022c). In this context, applying stereotypical business model patterns or archetypes (i.e., typical combinations of characteristics) has been repeatedly explored as a promising approach for strategic decision-making (e.g., Gimpel et al., 2018; Hunke et al., 2021; Weking et al., 2020). Indeed, 90 % of all business model innovations can be characterized as re-combinations of pre-existing patterns (Gassmann et al., 2014). As a next step, we want to contribute to systematizing superordinate business model configurations for connected cars by empirically analyzing emerging archetypes. These archetypes highlight established innovation paths executives can follow to digitalize their legacy business models and advance car data monetization. Accordingly, we approach the following research question:

Research Question 3 (RQ3)
What are the archetypal patterns of data-driven business models in the connected car domain?

While the previous two research questions dealt with the overall conceptualization of connected car business models, our intention now is to delve deeper and investigate the design of a particular car-data-based service. For years, all representatives in the extended connected car ecosystem, among OEMs, suppliers, insurers, and tech players, have attempted to design value-adding services for individuals, fleet managers, and administrations (Kaiser et al., 2021). However, scholars have scarcely touched on designing such services based on car data, as most studies are limited to naming, listing, or explaining different related use cases (Sterk et al., 2022a). Thus, we draw on design science, a research paradigm concerned with building and evaluating innovative artifacts to meet identified business needs (Hevner et al., 2004). Our research takes the viewpoint of an independent service provider that, unlike OEMs, lacks exclusive access to car data. Hence, we incorporate the concept of car data marketplaces as an alternative technical gateway offering similar data access options (Martens & Mueller-Langer, 2020). Since car data marketplaces remain in their early stages and currently provide limited data, fleet management is perceived as a solid starting point for connected service development, as it is a high-benefit and low-complexity use case (Arif et al., 2019). Hence, we pose the following research question:

Research Question 4 (RQ4)
How to design a connected fleet management system in order to use car data from data marketplaces effectively?

Besides harnessing in-vehicle data by designing connected services, incumbent firms within the automotive industry must reassess their established business strategies to remain competitive in the digital era dominated by tech players (Hermes et al., 2021; Sebastian et al., 2017). Incumbents encounter difficulties expanding their traditional value-creation logic onto digital platforms to co-create value in complex ecosystems (Marheine et al., 2021; Van Alstyne et al., 2016). However, there is limited research on incumbent firms' transition to the platform economy and the changes required to take advantage of platform economics (Sandberg et al., 2020; Sebastian et al., 2017; Svahn et al., 2017). To date, research tends to assume incumbents face a binary choice between building or joining platforms (Cusumano et al., 2019; Hein et al., 2020), overlooking the potential for collaborating, assembling, configuring, or contributing to platforms that may be open-source, white-label, or provided by tech firms (Hermes et al., 2021). To address this gap and explore non-binary considerations in platform strategy, including varying levels of tech firm involvement, we raise the following research question:

Research Question 5 (RQ5)
How and why do incumbent firms decide on a certain level of tech player involvement in their digital strategy?

Besides joining existing ecosystems by tech firms, industry incumbents aim to preserve or strengthen their competitive position by establishing ecosystems and becoming keystone players to orchestrate a partner network (Metzler & Muntermann, 2020). Well-known pioneers from incumbent industries include General Electric's Predix and Siemens' Mindsphere, where physical products are increasingly connected and expanded into IoT platform ecosystems (Pauli et al., 2021). On the contrary, automotive industry incumbents still struggle when initiating equivalent platforms around the connected car (Sterk et al., 2023b; Weiss et al., 2021). Despite the strategic challenges associated with establishing ecosystems, existing findings primarily focus on a native platform provider's viewpoint (Hein et al., 2019a). Therefore, current research lacks empirical evidence on incumbents' perspectives in establishing and orchestrating IoT platform ecosystems (Marheine & Petrik, 2021; Pauli et al., 2021). It is crucial to address this research gap, as it is essential for understanding incumbent firms' overall business transformation and strategic utilization of platform technologies. Against this backdrop, the following research question is proposed:

Research Question 6 (RQ6)
How can incumbent firms orchestrate their partner network toward value co-creation to establish IoT ecosystems?

In the subsequent section, we introduce the structure employed in this thesis to address the six research questions.

1.3 Structure of Dissertation

The thesis at hand comprises five main parts, encompassing (I) general foundations, (II) studies on the conceptualization of connected car business models, (III) research that sheds light on the potential design of connected car business models, and (IV) investigations offering insights on ecosystem strategies of incumbent firms. Finally, Part V concludes the thesis with implications, limitations, and a research outlook.

Figure 1.1 provides an overview of the dissertation's underlying structure, applied methods, and corresponding research questions. In addition, Table 1.1 below lists the six publications embedded in Part I-IV, assigns them to the RQs and provides an overview of authors, titles, and outlets in which the publications were submitted or published.

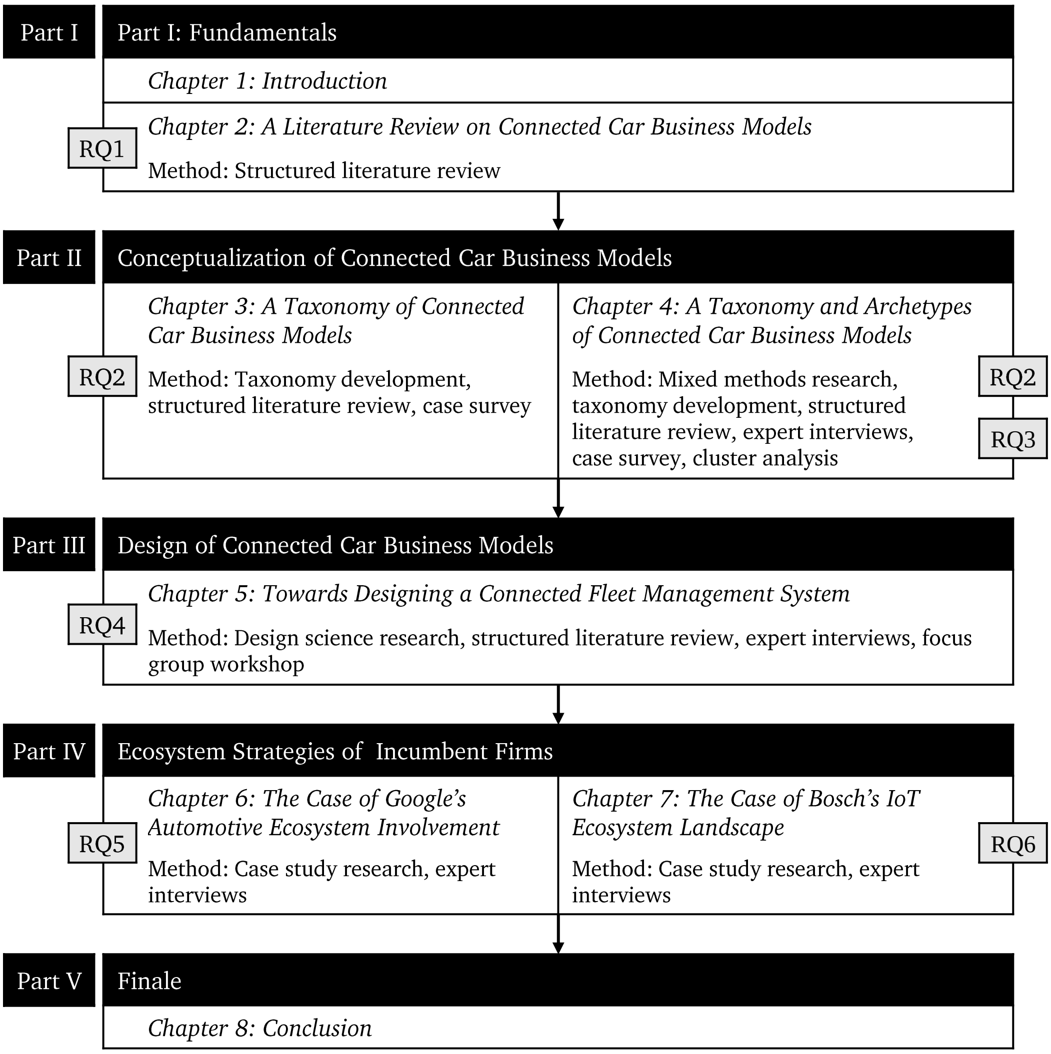


Figure 1.1.: Overview of thesis structure.

In **Part I**, we lay the foundations for the overall research endeavor of the thesis. Thereby, Chapter 1 motivates the research field of connected car business models and corresponding platform ecosystems, highlights the research gap based on six research questions, and outlines the structure of the thesis. We then present the conceptual background of this dissertation in the second chapter.

Chapter 2 sheds light on the current state of IS research on data-driven business models for connected cars. To approach RQ1, we conduct a structured literature review following the guidelines of Vom Brocke et al. (2009) and Webster and Watson (2002) to uncover common approaches, insights, and research foci, allowing us to pinpoint remaining research gaps in that discourse. Therefore, we classify the identified body of literature according to four business model dimensions proposed by Al-Debei and Avison (2010): value proposition, value architecture, value network, and value finance. As our main theoretical contribution, we extend this framework to the context of connected cars, enabling IS scholars to benchmark their work against our categorization, classify it to existing literature, and identify further research gaps. Regarding practical contribution, we summarize key concepts on the design of connected car business models and extract an overview of 38 connected car services from the literature that hold the potential to monetize car data. Ultimately, we derive issues for future research: (1) exploring digital business and platform strategies of incumbent automotive firms beyond traditional OEMs, (2) investigating privacy preservation in car data-enabled services, (3) designing services that build on connected car data, and (4) researching suitable pricing strategies for car data monetization.

In **Part II**, we contribute to a deepened conceptualization of connected car business models, laying the foundations for a more profound comprehension and strategizing attempts in both research and practice. Consequently, RQ2 and RQ3 are addressed.

Chapter 3 focuses on a first step towards developing a conceptual framework describing the key characteristics of data-driven business models for connected cars. In response to RQ2, we develop a business model taxonomy for companies operating in the connected car area. To do so, we follow the iterative taxonomy development process by Nickerson et al. (2013). Thereby, the preceding literature review presented in Chapter 2 (RQ1) is used to conceptualize our taxonomy, and 70 real-life examples of connected car companies are analyzed to revise it empirically. Finally, we demonstrate our taxonomy's applicability by classifying the business models of all 70 selected companies. Next, the overall usefulness of the taxonomy is evaluated with additional raters, who independently apply our taxonomy to a small subset of exemplary companies and measure their inter-coder agreement (Fleiss, 1971; Landis & Koch, 1977). From a research perspective, our study contributes to business model literature and facilitates a common understanding of connected car business models. Moreover, our taxonomy provides a foundation for exploring car data monetization, analyzing connected car business models, and developing design theories in this emerging field. For practice, our taxonomy serves as a strategic management tool, facilitating the design of novel and benchmarking existing connected car business models.

In **Chapter 4**, we expand upon our conceptual framework, initially introduced in Chapter 3, which elucidates the fundamental characteristics of connected car business models. Subsequently, we seek to formalize archetypal patterns that effectively depict and differentiate ideal configurations of connected car business models. Hence, we further develop our business model taxonomy (RQ2) and derive business model archetypes (RQ3) for connected cars. To this end, we follow a sequential mixed methods design (Venkatesh et al., 2013, 2016). In the first iteration, we evaluate and enhance the taxonomy by conducting twelve expert interviews, applying it to 154 connected car business models, and measuring inter-coder agreement from different raters. In the second iteration, we extract seven distinct cluster groups using a cluster analysis technique (Kaufman & Rousseeuw, 1990) and subsequently translate them into business model archetypes: (A1) data platforms, (A2) location-based services, (A3) fleet management, (A4) diagnostics and maintenance, (A5) driving analytics, (A6) cyber-physical protection, and (A7) connected infotainment. Our study theoretically contributes to the comprehension of research concerning the impact of car connectivity on business models and serves as a foundation for future investigations. For practice, we provide guidance on how companies can leverage connected car technology for business model innovation.

In **Part III**, we contribute to the body of design knowledge for developing business models and services based on car data. Thereby, we investigate the design of a particular car-data-based service and delve into answering RQ4.

Chapter 5 addresses the lack of research in IS designing services based on connected car data and investigating their benefits for businesses, consumers, or society. To bridge this gap, we conduct a design science research (DSR) project (Kuechler & Vaishnavi, 2008) focusing on two business model archetypes derived in Chapter 4 (RQ3): fleet management (A3) and data platforms (A1). Thus, we design a connected fleet management system to utilize multi-brand car data traded by data marketplaces effectively (RQ4). In doing so, we draw on findings from our previous literature review (Chapter 2, RQ1), which we extend with a fleet management perspective, and practical insights from interviews with domain experts. Building on those insights and the theory of effective use (Burton-Jones & Grange, 2013) as our theoretical lens, we propose tentative design principles and instantiate them into a prototype artifact. Finally, our artifact is evaluated by means of a focus group workshop and further expert interviews. From a theoretical perspective, we contribute to the body of design knowledge on connected service development, specifically focusing on connected car data and its effective use. Our research informs practitioners on how connected car data can be utilized and how to design an effective connected car service, improving economic performance, environmental sustainability, and vehicle health.

In **Part IV**, we contribute to the research stream focused on ecosystem strategies adopted by incumbent firms. We investigate incumbents' transition to the platform economy and business strategies to remain competitive in the digital age dominated by tech players. Therefore, we deal with RQ5 and RQ6.

Chapter 6 sheds light on incumbent firms whose traditional industries are increasingly disrupted by tech firms providing digital platforms. In response to RQ5, we explore different levels of tech company involvement incumbents can choose in their digital platform strategy beyond binary build or join decisions. To this end, an embedded case study (Yin, 2014) was conducted, focusing on the adoption of Google's automotive platform offering by incumbent OEMs. The platform falls under the connected infotainment archetype (A7) from Chapter 4 (RQ3). Through semi-structured interviews with industry experts and senior decision-makers and the analysis of publicly available information, we find three digital strategies for incumbent OEMs to integrate Google's offerings. Moreover, through grounded-theory-based interpretive data analysis (Gioia et al., 2013), we identify uncertainty reallocation as a core construct of our research. Finally, we derive five aggregate dimensions that represent the building blocks of a grounded model: (1) external digital platform by tech firm, (2) incumbent firm and its goals, (3) uncertainty tradeoffs and affordance of reallocation, (4) strategic actions by incumbent firm, and (5) short- and long-term outcomes. Our findings provide valuable insights into non-binary platform strategy choices and the implications of different levels of tech firm involvement, contributing to theoretical advances in the IS discipline and providing practical guidance for incumbent firms navigating digital transformation.

In **Chapter 7**, we continue to examine the ecosystem strategies of incumbent firms and address the research gap in how incumbent firms can foster value co-creation to become ecosystem orchestrators (RQ6). In response, we present an embedded case study within Robert Bosch GmbH, which draws a comprehensive picture of the departments' challenges in establishing eleven different IoT ecosystems in various industry sectors. Particularly, our study uncovers twelve incumbent-specific challenges within the realm of IoT ecosystems and offers effective design and governance actions taken to overcome these challenges. To organize our findings, we apply the tripartite service innovation framework proposed by (Lusch & Nambisan, 2015) to the IoT context. When discussing the qualitative insights of our study, we tie them in with existing research by elaborating on four prevailing tensions: (1) exploitation versus exploration, (2) commitment versus accessibility, (3) control versus openness, and (4) stability versus flexibility. In addition, actionable design and governance recommendations to resolve them are provided. In practice, our findings support managers of incumbent firms traditionally operating in linear value chains to reshape their business design and governance mechanisms to become ecosystem orchestrators and facilitate value co-creation. For research, our study emphasizes the IS-specific balance between technical and socio-organizational aspects and provides potential solutions to address challenges in ecosystem orchestration.

Finally, **Part V** encompassing **Chapter 8**, concludes the thesis with a concise summary of the insights gained through answering the research questions, a discussion of the limitations encountered during the work, and an outlook on potential future research endeavors.

Table 1.1.: Overview of embedded publications.

RQ	Authors	Title	Outlet
RQ1	Sterk, Dann, Weinhardt	Monetizing Car Data: A Literature Review on Data-Driven Business Models in the Connected Car Domain	HICSS 2022
RQ2	Sterk, Peukert, Weinhardt	Understanding Car Data Monetization: A Taxonomy of Data-Driven Business Models in the Connected Car Domain	WI 2022
RQ2, RQ3	Sterk, Stocker, Heinz, Weinhardt	Unlocking the Value from Car Data: A Taxonomy and Archetypes of Connected Car Business Models	EM 2023 *(under review, second round)*
RQ4	Sterk, Frank, Lauster, Weinhardt	Utilizing Fleet Data: Towards Designing a Connected Fleet Management System for the Effective Use of Multi-Brand Car Data	HICSS 2023
RQ5	Sterk, Heinz, Hengstler, Weinhardt	Reallocating Uncertainty in Incumbent Firms through Digital Platforms: The Case of Google's Automotive Ecosystem Involvement	ICIS 2023 *(under review)*
RQ6	Sterk, Heinz, Peukert, Fleuchaus, Kölbel, Weinhardt	Fostering Value Co-Creation in Incumbent Firms: The Case of Bosch's IoT Ecosystem Landscape	ICIS 2022

Outlet:
EM: Electronic Markets
HICSS: Hawaii International Conference on System Sciences
ICIS: International Conference on Information Systems
WI: International Conference on Wirtschaftsinformatik

2 Monetizing Car Data: A Literature Review on Data-Driven Business Models in the Connected Car Domain

This chapter comprises an article that was published as: Sterk, F., Dann, D., & Weinhardt, C. (2022). Monetizing Car Data: A Literature Review on Data-Driven Business Models in the Connected Car Domain. Proceedings of the 55th Hawaii International Conference on System Sciences (HICSS) (pp. 1975-1984). Note: The abstract has been removed. Tables and figures were reformatted and newly referenced to fit the structure of the thesis. Chapter, section, and research question numbering and respective cross-references were modified. Formatting and reference style was adapted, and references were integrated into the overall references section of this thesis.

2.1 Introduction

Connectivity is a major trend in the global automotive industry, transforming modern vehicles into highly intelligent computers on wheels (Häberle et al., 2015; Kaiser et al., 2018). Equipped with multi-layered sensor technology, they already capture and share a tremendously growing amount of data, including geolocation, fuel consumption, vehicle performance, and driver condition (Hood et al., 2019; Soley et al., 2018; Winkler et al., 2020). Even today, a connected vehicle generates 25 GB of data per hour, whereby big data and analytics become new sources of value creation (Heid et al., 2018). As of 2030, McKinsey & Company expects the annual incremental value from car data monetization to reach $250 billion to $400 billion (Martens & Schneiderbauer, 2021). However, original equipment manufacturers (OEMs) are still struggling with connectivity, so few are realizing the immense potential of connected cars, and even fewer are fully monetizing their car data (Hood et al., 2019; Martens & Schneiderbauer, 2021; Stocker et al., 2017).

Although researchers are investigating big data for years, they have scarcely touched on selling and monetizing data assets directly (Parvinen et al., 2020). However, while the digital transformation and the embrace of data-driven business models (DDBMs) rather marginally concerned the automotive industry in the past, these areas are increasingly gaining relevance, both in research and practice. While OEMs are launching digital services such as BMW ConnectedDrive and Mercedes me connect, they are threatened by major tech companies such as Google, introducing its own car operating system Android Automotive, or Apple, even planning its rumored electric car (Bosler et al., 2017). At the same time, several scholars work on related topics, such as novel connected services (Athanasopoulou et al., 2019; Stocker et al., 2017), required collaboration (Kaiser et al., 2019; Zhao et al., 2020), technological enablers (Coppola & Morisio, 2016; Martens & Mueller-Langer, 2020), or shifting revenue pools (Mikusz et al., 2015, 2017). As our society is strongly driven by mobility, Kaiser et al. state that "[...] it is almost our duty to examine the emergence of digital services based on vehicle usage data more closely" (Kaiser et al., 2020, p. 40).

Against this backdrop, we follow Kaiser et al.'s plea by focusing on better understanding business models with the potential to create and capture value from the data collected by modern vehicles. More specifically, we raise the following research question: *What is the state of the art in research covering data-driven business models in the connected car domain?* We approach this question by conducting a structured review of the literature with the aim to discover common approaches, insights, and research foci and—building on this—identify existing gaps and derive opportunities for future research attention. Therefore, we classify the identified body of literature regarding the business model framework proposed by Al-Debei and Avison (2010) and extend their concept to the context of connected cars. To the best of our knowledge, this work represents the first structured literature review on this topic, closing a research gap in itself.

2.2 Methodology

Selection of Papers: Our literature search and selection process follow the methodological suggestions by Webster and Watson (2002) and Vom Brocke et al. (2009). Following the classification by Paré et al. (2015), the overreaching goal of our research synthesis is explanation building and belongs to the category of theoretical reviews. As the existing literature on DDBMs and connected cars is highly interdisciplinary, we queried several databases (i.e., AIS Electronic Library, Emerald Insight, IEEEXplore Digital Library, ProQuest, ScienceDirect/Scopus, Web of Science) for matching our search query[1] in title, abstract, or keywords. We obtained a total of 787 studies (see Figure 2.1). After removing duplicates, this yielded 547 articles for further review. We then analyzed each article's title and abstract, resulting in 94 articles, and, subsequently, reviewed all full texts. Finally, we excluded articles that do not explicitly fit within the scope of our literature review, applying four inclusion criteria: (1) the study must examine at least one business model dimension, (2) the study must focus on the connected car domain, (3) the paper must be available in English, and (4) only peer-reviewed papers were considered. This resulted in a set of 29 relevant articles. Subsequent forward and backward search with this set of relevant papers yielded 16 additional relevant articles, resulting in a total of 45 papers for in-depth review.

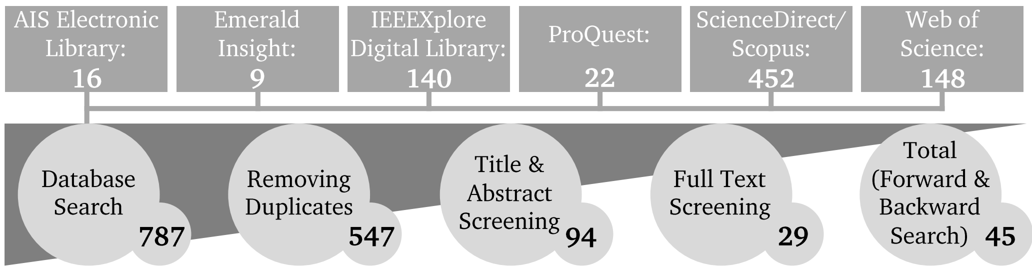


Figure 2.1.: Literature search process.

Classification Procedure: The literature review follows a concept-centric approach (Webster & Watson, 2002). Initially, we examined the identified articles for business model dimensions using the business model framework proposed by Al-Debei and Avison (2010). The framework fits our review endeavor for two reasons. First, it is one of the few business model frameworks developed particularly for digital business models. Second, this framework captures the multidimensionality of business models, including the essential dimensions from previous conceptualizations. The framework contains the four dimensions of value proposition, value architecture, value network, and value finance. The authors outline the four dimensions as follows. Value proposition deals with products and services that are offered to satisfy customer needs. Value architecture includes the organization's technological architecture and organizational infrastructure. Value network describes the coordination and collaboration among parties and multiple companies, and value finance concerns information related to costing, pricing, and revenue breakdown.

[1]"business model*" AND (connected OR data* OR digital*) AND (car* OR vehicle* OR automotive*)

Since the four dimensions according to Al-Debei and Avison (2010) are relatively general, we need a more refined classification, specifically for the connected car context. Consequently, in a second step, we derive key concepts for paper categorization based on their business model framework. Following the suggestions of Vom Brocke et al. (2009), we screened an initial set of papers stemming from recent peer-reviewed conference proceedings and journal papers, as we assumed that these papers well reflect the contemporary state of literature. Next, the author team independently identified a set of concepts for classification. The subsequent discussion of all identified concepts resulted in the following breakdown of the business model dimensions: value proposition (i.e., safety, convenience, cost reduction, traffic efficiency, infotainment), value architecture (i.e., resources, capabilities), value network (i.e., actors & roles, strategic partnerships), and value finance (i.e., revenue streams, cost structure). Note that our categorization is not disjunctive and each publication may be assigned to more than one category. Table 2.1 summarizes the reviewed papers and specifies the assigned concepts. All reviewed articles have been published within the last six years: 2021 (2), 2020 (7), 2019 (5), 2018 (6), 2017 (10), 2016 (8), and 2015 (7).

2.3 Results

With the rise of vehicle connectivity, the amount of data from vehicles will grow exponentially (Soley et al., 2018), receiving a considerable amount of research attention (Stocker et al., 2017). To provide some structure and overview, we use the derived characteristics to discuss, summarize, and synthesize the identified publications. First, we take a look at value propositions for individual drivers and fleet managers, which fall into five broad categories (i.e., *safety*, *convenience*, *cost reduction*, *traffic efficiency*, and *infotainment*). Next, we focus on data and associated infrastructure as enabling *resources* for monetizing car data. In addition, we address the challenge of many incumbents to develop specific *capabilities* either internally or externally. We then examine *actors* in the connected car ecosystem, that will naturally be forced to take on certain *roles* (e.g., service providers or platform providers) and enter into *strategic partnerships* with multiple entities (Grieger & Ludwig, 2019; Svahn et al., 2017; Zhao et al., 2020). Last, we elaborate on financial aspects around connected car business models, including their *revenue streams* and *cost structure*.

Table 2.1.: Classification of literature on DDBMs in the connected car domain.

Source	Value Proposition					Value Architecture		Value Network		Value Finance	
	Safety	Convenience	Cost Reduction	Traffic Efficiency	Infotainment	Resources	Capabilities	Actors & Roles	Strategic Partnerships	Revenue Streams	Cost Structure
Andersson and Mattsson (2015)	×	×	×		×						
Athanasopoulou et al. (2016)	×		×							×	×
Athanasopoulou et al. (2019)	×	×		×	×		×				
Bauer et al. (2020)						×					
Bosler et al. (2017)	×	×		×	×	×		×	×		
Brandt and Ahlemann (2020)	×			×	×	×	×		×		
Bregant et al. (2017)					×						
Chanias and Hess (2016)							×				
Conradi et al. (2016)	×	×	×								
Coppola and Morisio (2016)	×	×	×	×	×	×					
De (2018)	×	×	×	×	×	×		×	×	×	×
Grieger and Ludwig (2019)	×			×			×	×	×		
Hanelt et al. (2015)	×	×			×		×	×		×	
Kaiser et al. (2017b)	×		×		×	×		×			
Kaiser et al. (2017a)	×	×	×	×	×	×		×	×		
Kaiser et al. (2018)	×		×		×	×		×		×	
Kaiser et al. (2019)						×		×			
Kaiser et al. (2020)	×		×					×	×		
Kaiser et al. (2021)	×		×	×		×	×	×	×		
Kukkamalla et al. (2020)	×							×	×	×	×
Llopis-Albert et al. (2021)	×				×						×
Marabelli et al. (2017)	×	×	×			×					
Martens and Mueller-Langer (2020)	×		×		×	×		×	×	×	
Mikusz et al. (2015)	×	×	×	×			×	×		×	
Mikusz and Herter (2016)	×	×	×	×		×		×		×	
Mikusz et al. (2017)	×	×	×	×			×				×
Mocker and Fonstad (2017)		×			×		×				
Nischak and Hanelt (2019)					×			×	×		
Peng et al. (2015)	×		×			×					
Piccinini et al. (2015)					×		×	×	×		
Pütz et al. (2019)	×		×			×			×		
Rahman and Tadayoni (2018)	×				×	×		×	×		
Remane et al. (2016b)								×			
Remane et al. (2016a)			×					×			
Riasanow et al. (2017)		×			×		×	×	×		
Roth et al. (2020)			×			×					
Soley et al. (2018)	×		×		×	×					
Stocker et al. (2017)	×	×	×		×	×		×			
Svahn et al. (2015)		×				×	×				
Svahn et al. (2017)		×			×		×		×	×	
Swan (2015)	×	×	×	×	×	×					
Tian et al. (2016)							×				×
Toglaw et al. (2018)	×	×	×	×							
Uhlemann (2018)			×	×							
Zhao et al. (2020)								×	×		
Σ	29	19	24	14	22	21	14	22	16	9	6

2.3.1 DDBM Dimension 1: Value Proposition

Ongoing digitalization and connectivity virtually force automotive companies to change their business models from a goods-dominant towards a service-dominant logic (Grieger & Ludwig, 2019; Hanelt et al., 2015; Kaiser et al., 2017a, 2019; Riasanow et al., 2017). However, no matter which services car data makes possible, monetizing them is not feasible if customers do not see their benefits (Chanias & Hess, 2016; Piccinini et al., 2015). Accordingly, various scholars highlighted affected services and their primary value propositions to customers. Specifically, we identified in total 38 different connected car services in the literature corpus that may generate added value for private car owners and fleet managers (see Table 2.2) in terms of one or more aspects:

Safety: Connected car data enables a broad range of services to increase vehicle and traffic safety. In this regard, various authors highlight driving style detection as a means to encourage safer and eco-efficient driving behavior (Bosler et al., 2017; De, 2018; Kaiser et al., 2020; Soley et al., 2018). In addition, automated pothole detection could generate cost-efficient maintenance measures of road conditions, which might attract the interest of city planners as further stakeholders (Kaiser et al., 2018; Stocker et al., 2017). Another safety-enhancing service, which was most frequently mentioned is the intelligent emergency call (eCall) (e.g., Athanasopoulou et al., 2019; Martens and Mueller-Langer, 2020; Pütz et al., 2019). In case of an accident, the eCall system automatically contacts an emergency call-center and communicates the vehicle position, including relevant data (e.g., time of the accident, vehicle type).

Convenience: Beyond traffic safety, car data can also improve the overall experience of driving and vehicle usage. BMW, for instance, offers remote services for (un-) locking vehicles, indicating the vehicle's location within an app or activating the vehicle's climate control remotely (Kaiser et al., 2017a). The service tested by Volvo in 2014 goes even one step further, using the remote keyless entry for digital food delivery into the car (Andersson & Mattsson, 2015; Svahn et al., 2015, 2017). This car delivery concept is an example of capitalizing on a continuously changing product, increasing variety, and enabling multi-sided platform solutions to mediate economic transactions (Svahn et al., 2015). Besides remote services, convenience can be enhanced by concierge services, where the driver gets connected to call-center agents to find and book nearby services (e.g., hotel booking), with addresses sent directly to the navigation system (Kaiser et al., 2017a; Mikusz et al., 2015).

Cost Reduction: Another customer value enabled by the increased use of car data are monetary benefits stemming from, for instance, optimized fuel consumption, automated payment schemes on road tolls, or usage-based insurance (UBI) (De, 2018; Stocker et al., 2017). Reviewing existing research shows that the latter, involving data-based pricing models adapted towards users' driving behavior, is the most widespread and intensively studied connected car service hitherto (Conradi et al., 2016; Marabelli et al., 2017; Peng et al., 2015; Pütz et al., 2019; Roth et al., 2020). In this regard, Pütz et al. (2019) show that insurance companies have to adapt their digital service offerings in light of vehicle ownership changing from many individuals to fewer commercial fleet providers. In addition, Roth et al. (2020) investigate privacy issues in UBI models. They observe the necessity for a transparent UBI model that is comprehensible and controllable for users, including thorough data protection.

Traffic Efficiency: Location-based services enable a wide range of smart navigation use cases. Applications such as dynamic routing, real-time traffic information, and parking assistance help reducing users' travel time (Coppola & Morisio, 2016; De, 2018; Mikusz et al., 2017). One example of this is the Google Maps app. Users share personal data via their smartphones while, at the same time, using other users' aggregated real-time traffic information for navigation (Riasanow et al., 2017). Analyzing users' evaluation of smart navigation's value proposition, Mikusz and Herter (2016) distinguish between three service components: (i) customization, including a fully interactive screen, (ii) situational services, enabling reservation of parking spaces or charging stations, and (iii) data co-creation, realizing accurate predictions of traffic congestion. Using conjoint analysis, they show that the customization feature is most valued.

Infotainment: According to Hanelt et al. (2015), preferences are shifting from the pure driving experience or technical performance features to aspects such as information and entertainment (i.e., infotainment), whereby the vehicle itself may change its role from a status symbol to a device for digital experiences. To achieve this, OEMs seek to improve end-user experience with digital technologies (Kaiser et al., 2018; Svahn et al., 2017) such as augmented reality (Tian et al., 2016) and human-machine interface (HMI) enabling seamless infotainment (Piccinini et al., 2015). Infotainment systems in modern vehicles already contain numerous applications, including music and video streaming, internet access via an in-car hot spot, or in-car smartphone integration (Coppola & Morisio, 2016; De, 2018; Soley et al., 2018). Examples for the latter are third-party offerings such as Google Android Auto and Apple CarPlay, enabling the driver to use smartphone apps within the car's head unit (Bosler et al., 2017).

Table 2.2.: Overview of distinct connected car services.

Value Prop.	Connected Car Service	Source	Σ
Safety (29)	Emergency Call (eCall)	Hanelt et al. (2015); Kaiser et al. (2017a); De (2018); Bosler et al. (2017); Mikusz et al. (2015); Mikusz and Herter (2016); Mikusz et al. (2017); Marabelli et al. (2017); Athanasopoulou et al. (2019); Athanasopoulou et al. (2016); Coppola and Morisio (2016); Swan (2015); Martens and Mueller-Langer (2020); Pütz et al. (2019); Kukkamalla et al. (2020)	15
	Breakdown Call (bCall)	De (2018); Bosler et al. (2017); Mikusz et al. (2015); Marabelli et al. (2017); Coppola and Morisio (2016); Rahman and Tadayoni (2018); Stocker et al. (2017)	7
	Remote Diagnostics	Andersson and Mattsson (2015); Rahman and Tadayoni (2018); De (2018); Mikusz et al. (2017); Mikusz et al. (2015); Martens and Mueller-Langer (2020); Athanasopoulou et al. (2016); Grieger and Ludwig (2019); Soley et al. (2018)	9
	Predictive Maintenance	Andersson and Mattsson (2015); Llopis-Albert et al. (2021); Brandt and Ahlemann (2020); Stocker et al. (2017)	4
	Service Reminder	De (2018); Kaiser et al. (2017b); Kaiser et al. (2017a); Stocker et al. (2017)	4
	Stolen Vehicle Recovery	Kaiser et al. (2017a); Swan (2015); De (2018); Coppola and Morisio (2016); Peng et al. (2015); Marabelli et al. (2017); Toglaw et al. (2018)	7
	Road Condition Monitoring	De (2018); Soley et al. (2018); Bosler et al. (2017); Kaiser et al. (2020); Coppola and Morisio (2016)	5
	Driver Fatigue Detection	Athanasopoulou et al. (2019); Swan (2015); Coppola and Morisio (2016)	3
	Driving Style Suggestions	Kaiser et al. (2020); Kaiser et al. (2018); Conradi et al. (2016); Stocker et al. (2017); Mikusz and Herter (2016); Kaiser et al. (2017b); Kaiser et al. (2021)	7
Convenience (19)	Concierge Services	Stocker et al. (2017); Riasanow et al. (2017); Mikusz et al. (2015); Kaiser et al. (2017a)	4
	Over-The-Air (OTA) Updates	Bosler et al. (2017); De (2018); Andersson and Mattsson (2015); Athanasopoulou et al. (2019)	4
	Electronic Driver Logbook	Conradi et al. (2016); Stocker et al. (2017)	2
	In-Car Delivery	Andersson and Mattsson (2015); Mikusz et al. (2017); Svahn et al. (2017); Svahn et al. (2015)	4
	Connected Service Booking	Andersson and Mattsson (2015); De (2018); Swan (2015)	3
	Remote Services (e.g., door (un)lock)	De (2018); Kaiser et al. (2017a); Mikusz et al. (2015); Mikusz and Herter (2016); Mikusz et al. (2017); Bosler et al. (2017); Mocker and Fonstad (2017); Toglaw et al. (2018); Athanasopoulou et al. (2019)	9
	Hands-Free Messaging	Athanasopoulou et al. (2019); Coppola and Morisio (2016); De (2018); Hanelt et al. (2015); Toglaw et al. (2018)	5
	Parked Vehicle Locator	Kaiser et al. (2017a); De (2018); Marabelli et al. (2017); Bosler et al. (2017)	4
Cost Reduction (24)	Usage-Based Insurance (UBI)	Athanasopoulou et al. (2019); Conradi et al. (2016); Coppola and Morisio (2016); Kaiser et al. (2017b); Kaiser et al. (2018); De (2018); Marabelli et al. (2017); Mikusz et al. (2015); Mikusz et al. (2017); Peng et al. (2015); Roth et al. (2020); Toglaw et al. (2018); Pütz et al. (2019); Remane et al. (2016a); Stocker et al. (2017); Martens and Mueller-Langer (2020); Kaiser et al. (2021)	17
	Platooning	Uhlemann (2018)	1
	Fleet Management Solutions	Kaiser et al. (2017b); Stocker et al. (2017); Andersson and Mattsson (2015); Martens and MuellerLanger (2020); Conradi et al. (2016); Athanasopoulou et al. (2019); Kaiser et al. (2020)	7
	Algorithm-Based Vehicle Pricing	Coppola and Morisio (2016)	1
	Automated Payment Schemes	De (2018); Swan (2015); Soley et al. (2018)	3
	In-Vehicle Purchase Payment	De (2018); Athanasopoulou et al. (2019)	2
	Location-Based Advertisement	Coppola and Morisio (2016); De (2018); Athanasopoulou et al. (2016); Remane et al. (2016a)	4
	Eco Driving (e.g., fuel saving)	Coppola and Morisio (2016); Mikusz and Herter (2016); De (2018); Kaiser et al. (2017a); Stocker et al. (2017); Athanasopoulou et al. (2019)	6
Traffic Efficiency (14)	Dynamic Routing	Mikusz et al. (2015); Mikusz and Herter (2016); Mikusz et al. (2017); De (2018); Kaiser et al. (2017a); Kaiser et al. (2021)	6
	Real-Time Traffic Information	Coppola and Morisio (2016); Mikusz and Herter (2016); Mikusz et al. (2017); Kaiser et al. (2017a); Bosler et al. (2017); De (2018); Athanasopoulou et al. (2019)	7
	Real-Time Parking Assistance	Athanasopoulou et al. (2019); Brandt and Ahlemann (2020); Kaiser et al. (2017a); De (2018); Swan (2015); Mikusz and Herter (2016); Toglaw et al. (2018); Uhlemann (2018); Coppola and Morisio (2016); Grieger and Ludwig (2019)	10
	Geofencing	De (2018); Kaiser et al. (2017a)	2
	"Points of Interest"- Search	Mikusz and Herter (2016); De (2018)	2
	Location Air Pollution Data	De (2018)	1
Infotainment (16)	Music Video Streaming	Bosler et al. (2017); Coppola and Morisio (2016); De (2018); Soley et al. (2018); Swan, 2015	5
	Music Video Streaming	Andersson and Mattsson (2015); Athanasopoulou et al. (2019); Bosler et al. (2017); Rahman and Tadayoni (2018); Coppola and Morisio (2016); Martens and Mueller-Langer (2020); Kaiser et al. (2017a)	7
	Social Network Integration	De (2018); Athanasopoulou et al. (2019); Coppola and Morisio (2016)	3
	Wifi-Hotspot	Soley et al. (2018); Athanasopoulou et al. (2019); Coppola and Morisio (2016); De (2018); Mocker and Fonstad (2017)	5
	News, Weather, FM Radio	Bosler et al. (2017); De (2018); Coppola and Morisio (2016); Brandt and Ahlemann (2020)	4
	Vehicle Status (e.g., fuel level)	Hanelt et al. (2015); Kaiser et al. (2017a); Hanelt et al. (2015); Riasanow et al. (2017); Bosler et al. (2017); De (2018)	6
	Gamification	Kaiser et al. (2017a); Kaiser et al. (2017b); Stocker et al. (2017)	3

2.3.2 DDBM Dimension 2: Value Architecture

Besides servitization and digital transformation of their value proposition, businesses face the required evolution of their structural design, including its technological architecture and organizational infrastructure that allows the provision of connected services (Al-Debei & Avison, 2010; Athanasopoulou et al., 2016). We describe this stream of research along the required *resources* and *capabilities* that existing actors want and need to acquire.

Resources: Enabling resources for the monetization of connected car data refers to the data itself as well as infrastructural technologies inside and outside the vehicle, including high-performance computing, in-car HMI, 5G data towers, and data platforms (Kaiser et al., 2019). Regarding these resources, we identified three prevalent themes in the literature:

(1) Data Categories: Soley et al. (2018) provide a general overview of the data categories relevant for connected car services and the monetary value assigned to them by different actors. In line with other scholars (e.g., Bosler et al., 2017; Coppola and Morisio, 2016; Mikusz and Herter, 2016; Peng et al., 2015; Swan, 2015), they distinguish between personally identifiable information data generated outside the vehicle by the drivers (e.g., phone numbers or login data), geolocation data generated either by the vehicles or by peripheral devices (e.g., smartphone), application data generated by smartphones or infotainment systems (e.g., music streaming), and vehicle-specific data generated by and for vehicles themselves (e.g., sensor or performance data). Surprisingly, Soley et al. (2018) reveal that connected car data has a higher monetary value than businesses and individuals assumed, which is why they recommend securing this data and establishing comprehensive rules pertaining to data ownership and management.

(2) Data Access: While OEMs have exclusive access to the data a car generates (Kaiser et al., 2017b, 2019; Martens & Mueller-Langer, 2020), independent service providers have to identify other ways to capture this data. Martens and Mueller-Langer (2020) explored four alternative technical gateways that could offer independent service providers similar data access options. First, the on-board diagnostics (OBD) port establishes a technical standard for data access. Drivers can plug a dongle into the OBD port to allow remote access to the vehicle data (e.g., Coppola and Morisio, 2016; Pütz et al., 2019; Soley et al., 2018). The data is transmitted via USB or mobile network to the driver's smartphone or directly to an external service provider. Second, the central server, controlled by OEMs, collects data directly from the car internal data network. This monopoly for OEMs led to discussions on a neutral server,

where data storage, processing, and customer interaction with service providers are handled by a third-party platform (e.g., Caruso). However, transmitting data from the central server to a third-party server requires driver's consent (Coppola & Morisio, 2016; Martens & Mueller-Langer, 2020). Third, on-board platforms are in-car operating systems on which service providers can install their application software to extract data and run services for the driver, comparable to a smartphone operating system (Martens & Mueller-Langer, 2020). Last, consumer media platforms enable users to seamlessly integrate their favorite smartphone operating systems such as Apple iOS and Google Android into cars (e.g., Bosler et al., 2017; Coppola and Morisio, 2016; Rahman and Tadayoni, 2018). Eventually, all four gateways suffer from shortcomings in data portability, switching costs, and network effects, as well as economies of scale and scope in data analytics (Martens & Mueller-Langer, 2020).

(3) Data Sharing: In addition to the technical requirements necessary for monetizing car data, we examined the articles in terms of incentives and measures encouraging stakeholders to share their car data. Fundamental approaches regarding this issue are monetary incentives (e.g., price discounts on existing services) and non-monetary incentives (e.g., novel services only feasible by data sharing) (Brandt & Ahlemann, 2020). In addition, Brandt and Ahlemann (2020) consider including data collection in the employment contract of professional drivers. Besides that, other studies suggest that privacy concerns have to be mastered to support the emergence of connected services with enough data (Soley et al., 2018; Stocker et al., 2017). Accordingly, it is vital to process data in an anonymized form or increase trust in the other party by being transparent about what kind of data cars generate, process, store, and transmit (Coppola & Morisio, 2016; Roth et al., 2020). Last, several authors point out that customers are willing to share personal and vehicle data if they see a direct benefit from connected services for themselves (Brandt & Ahlemann, 2020; Mikusz & Herter, 2016; Soley et al., 2018; Stocker et al., 2017). Thus, companies need to provide a clear and compelling value proposition to customers to encourage data sharing (e.g., innovative products, driving recommendations, or gamification aspects).

Capabilities: In the face of ongoing digitalization and increasing connectivity, it comes to no surprise that incumbents such as traditional OEMs are struggling to build the specific capabilities they need, either internally or externally (e.g., Athanasopoulou et al., 2016; Chanias and Hess, 2016; Mocker and Fonstad, 2017; Tian et al., 2016). However, we found four approaches to obtain these required competencies. The first is hiring new talents with technological skills such as app programming or big data analytics (Grieger & Ludwig, 2019; Hanelt et al., 2015; Piccinini et al., 2015). Next is the implementation of startup mentality (e.g., be agile, trial and error) (Piccinini et al., 2015) by founding internal startups or labs (Brandt & Ahlemann, 2020) to foster creativity and allow their employees to propose and experiment with new ideas. A prime example of this is Volvo Cars, which set up an innovation hub in 2010. However, in their interview study, Svahn et al. (2015, 2017) observed that Volvo could not realize their connected car vision through an external subsidiary due to the potential risk of turning into a rival organization. Besides these two internal approaches, there are open innovation hackathons (Brandt & Ahlemann, 2020; Mikusz et al., 2015, 2017) and external partnerships (Brandt & Ahlemann, 2020; Riasanow et al., 2017; Svahn et al., 2017) to capture the skills needed.

2.3.3 DDBM Dimension 3: Value Network

Next, we take a closer look at existing *actors* and *roles* in the field of connected car ecosystems, as well as how stakeholders within a value network may achieve win-win situations by forming *strategic partnerships*.

Actors & Roles: Existing literature lists a variety of different stakeholders operating in the connected car ecosystem. Following Al-Debei and Avison (2010), we distinguish between the actors of which a connected car ecosystem is composed and the roles played by these actors. The group of actors capturing the car data monetization opportunity primarily consists of drivers, OEMs, suppliers, startups, tech companies, fleet operators, workshops, infrastructure players, retailers, insurers, roadside assistance, and governments (e.g., Rahman and Tadayoni, 2018; Riasanow et al., 2017; Zhao et al., 2020). One of the first decisions for these actors is what role to play in the connected car ecosystem. Stocker et al. (2017) classification distinguishes between four distinct roles:

(1) Primary End-Users are individual customers (e.g., drivers) who directly benefit from connected services based on their shared car data (Stocker et al., 2017). Hence, the user is not a passive actor but an active integrator of resources and, thereby, value co-creator (Mikusz & Herter, 2016; Riasanow et al., 2017). This co-creation of value is an integral aspect in the realization of a consumer-centric service portfolio (Grieger & Ludwig, 2019). One example of this is sharing personal data via smartphone with Google Maps while using other drivers' aggregated real-time traffic information for navigation (Riasanow et al., 2017). Besides data co-creation, OEMs may involve their customers in the product design processes through digital interaction to rapidly sense and respond to changing customer needs (Hanelt et al., 2015).

(2) Secondary End-Users are organizational customers who indirectly benefit through collected and assessed car data from multiple vehicles by consuming connected services (Stocker et al., 2017). For instance, road traffic departments can make informed decisions based on traffic data to increase road safety and reduce driving emissions (Kaiser et al., 2017b), or city planners may use road condition data for maintenance and repair (Kaiser et al., 2018; Stocker et al., 2017). Besides, organizational customers such as driving schools may be assisted in supervising students based on driving style monitoring, teaching them to drive safer and economically (Kaiser et al., 2017b).

(3) Service Providers are organizations who provide connected services for various end-users, thereby monetizing car data (Stocker et al., 2017). Obviously, OEMs are seeking to exploit their supremacy position with exclusive data access to develop data-based solutions such as mobility services, on-demand services, or infotainment services (Kukkamalla et al., 2020). However, other ecosystem actors also slip into the service provider's role. Bosch, for instance, as a supplier for emergency call management (Mikusz et al., 2015), or various insurers capitalizing on car data by offering usage-based insurance contracts (Conradi et al., 2016; Marabelli et al., 2017; Peng et al., 2015; Roth et al., 2020). Moreover, a large number of startups entered the ecosystem, creating numerous digital services based on car data from the OBD interface or the driver's smartphone. An example is Zendrive.com, providing smartphone-powered and gamified driving analytics (Kaiser et al., 2017a, 2017b; Zhao et al., 2020).

(4) Platform Providers operate the required infrastructure for the connected car ecosystem and allow service providers to establish their data-based services and end-users to consume them in return for their car data (Stocker et al., 2017). Bosler et al. (2017) identified three alternative platform concepts which currently dominate connected car ecosystems. First, OEM platforms offering customers additional services inside and outside vehicles (e.g., BMW ConnectedDrive, Mercedes me connect). Next, platforms for smartphone integration enabling drivers to use their smartphones and related apps via the built-in head unit (e.g., Google Android Auto and Apple CarPlay). Last, "Platform as a Service"-approaches for connected cars offered by third-party providers. These providers operate individual platform concepts to deliver services across the OEM to the end-user and provide an alternative to self-development.

Strategic Partnerships: In the fast-evolving connected car environment, companies cannot succeed independently (Zhao et al., 2020). Thus, the collaboration between multiple actors within the ecosystem is necessary to capture the full value from vehicle data for several reasons. First, strategic partnerships enable companies to maximize their value proposition by operating complex services that they can not realize on their own, such as usage-based insurance models or predictive maintenance approaches (Grieger & Ludwig, 2019; Kukkamalla et al., 2020; Pütz et al., 2019). Furthermore, collaborations facilitate the acquisition of external knowledge and new competencies (Brandt & Ahlemann, 2020; Riasanow et al., 2017; Svahn et al., 2017) and allow access to new revenue sources (De, 2018; Rahman & Tadayoni, 2018; Svahn et al., 2017). While OEMs have incentives to partner with platforms to benefit from the additional data sales (Martens & Mueller-Langer, 2020), platform providers are expecting increasing platform growth through network effects (Bosler et al., 2017). Service providers, in turn, benefit from the data access options offered by these platforms (Martens & Mueller-Langer, 2020). Due to the importance of close strategic partnerships, automotive companies must place the same importance on these ecosystem partners as they do on vehicle owners (De, 2018). In addition to the brand-dependent business approaches that have been most dominant so far, Kaiser et al. (2017a) identified two collaborative approaches to provide connected services. First, there are brand-independent services (e.g., driving behavior analytics) where several organizations use the driving data. Second, strategic alliances being formed between OEMs and technology companies (e.g., BMW, IBM) to establish DDBMs. However, according to Piccinini et al. (2015), on the one hand, cooperation between different actors is necessary to deliver digital products via standardized platforms. On the other hand, however, the same digital players will also become competitors concerning future mobility.

2.3.4 DDBM Dimension 4: Value Finance

Finally, this stream focuses on how players in the connected car ecosystem generate revenue from their DDBMs and what costs are incurred in operating them. More specifically, we refer to the elements *revenue streams* and *cost structures*.

Revenue Streams: Once automotive companies have collected or acquired the connected car data, they seek to monetize them (Martens & Mueller-Langer, 2020). This may be achieved following two different approaches:

(1) Selling Services: Creating novel data-based services leads to new business opportunities and new revenue streams (Andersson & Mattsson, 2015; Athanasopoulou et al., 2016; Kaiser et al., 2018; Svahn et al., 2017). These include the currently emerging subscription-based services that were most frequently mentioned in our

literature corpus (e.g., BMW ConnectedDrive Kukkamalla et al., 2020, Audi connect Mocker and Fonstad, 2017). In line with those, Hanelt et al. (2015) claim that subscription fees are mostly charged for product-related services based on the connection of cars with smartphones. Another way of capturing value is usage-based pricing. So far, this approach was mainly applied in the area of vehicle insurance (Marabelli et al., 2017; Pütz et al., 2019; Roth et al., 2020). However, this type of revenue model is likely to gain relevance once cars are no longer owned as a product but rented, leased, or shared (Athanasopoulou et al., 2016). For services with no or low willingness to pay, the advertising-based revenue model is best suited for indirect monetization, which does not charge users (De, 2018). Three further revenue models are mentioned in the studies on business model patterns for the connected car, namely add-on, freemium, and razor & blade (Mikusz et al., 2015, 2017). They have the composition of different pricing mechanisms (e.g., free basic version, chargeable premium version) in common.

(2) Selling Data: Besides selling services, OEMs can also take the straightforward approach to monetize data by selling it via third-party platforms (e.g., Caruso). These marketplaces, however, are highly dependent on the OEMs' data supply, which leads to the latter having control over the pricing. From OEMs' standpoint, cooperating with marketplaces makes sense in order to profit from additional data sales, but only to the extent that this does not affect their market shares (Martens & Mueller-Langer, 2020).

Cost Structure: In contrast to traditional business models, the main costs in data-driven services shift from R&D, production, sales, and marketing to service design, technology acquisition costs, and knowledge management activities (Kukkamalla et al., 2020). Consequently, automotive companies should carry out a substantial investment in appropriate measures for adaption to the digital transformation to increase their profits, productivity, and competitiveness (Llopis-Albert et al., 2021; Tian et al., 2016). However, Llopis-Albert et al. (2021) observed that companies are somehow reluctant to invest substantial capital in developing new services because there is no immediate payoff, which entails capital risk, and the return on investment is uncertain. Their statement contrasts with the findings of De (2018), who claims that the recurring revenues from connected services will surpass the mainly one-time costs. He adds that the increasing revenue from these services reduces OEMs' costs and leads to positive lifetime value for customers De (2018). Further examples of cost reduction through digitalization include digital co-creation in the design process (Athanasopoulou et al., 2016), or the transformation of existing products and services into digital variants (Mikusz et al., 2017).

2.4 Discussion and Conclusion

2.4.1 Implications and Limitations

Theoretical Implications: In terms of theoretical implications, our work contributes to the body of knowledge on connected cars and related DDBMs, exploring a research area still in its infancy (Kaiser et al., 2018; Marabelli et al., 2017). We argue that studying this topic is a highly worthwhile endeavor, as we expect the number of connected cars, their collected data, and customers' willingness to pay for connected services are proliferating. Thereby, our main contribution is a literature review extending the business model framework by Al-Debei and Avison (2010) and transferring it to the context of DDBMs and connected cars. We propose that scholars publishing novel DDBM research in the connected car domain benchmark their work against our categorization to classify it in the existing body of literature and identify further research gaps. We also provide the following theoretical implications:

(1) Investigate Privacy & Ethics: As the amount of car data collected grows steadily, privacy and ethics are considered vital by scholars, drivers, and businesses. Particularly with behavioral data (e.g., speeding), companies must earn customers' trust by only using driving data to improve the end-user experience and not for other purposes (e.g., tracking speeders for the police) (Kaiser et al., 2018). Accordingly, raising society's awareness of what kind of data vehicles generate and to whom it is potentially transmitted is essential and may be encouraged by research (Stocker et al., 2017). Moreover, the question arises: Who ultimately owns the data and how can it be protected (Athanasopoulou et al., 2016)? Regarding ethical implications, connected car services (e.g., usage-based insurance) may provide significant societal benefits by improving driving styles, thereby reducing congestion, accident risks, and fuel consumption (Kaiser et al., 2017b; Marabelli et al., 2017).

(2) Integrate Empirical Data: As this literature review has exposed, a large share of work on connected car business models builds on empirical data such as white papers, websites, and press releases. For such studies, we observe that the website crunchbase.com is increasingly used as a viable resource, providing data on connected car startups (e.g., founding year, funding rounds, and a description). Likely, this will also be the case for much of the upcoming research. Future work could go beyond the information provided on crunchbase.com and investigate certain startups in-depth regarding customer benefits, data access, or pricing strategies. Consequently, the question remains: How to combine the theoretical knowledge from our literature review with empirical findings from practice?

Practical Implications: Concerning the critical task of monetizing car data, our findings have several practical implications for automotive executives. Specifically, our literature review provides a detailed understanding of leveraging car data to enable innovative services. We propose four implications to unlock the full potential of car data successfully:

(1) Incentivize Data Sharing: For connected car business models, customers' willingness to share data is considered as crucial. We identified several incentives and measures to reduce privacy concerns to overcome end-customers' reservations about allowing their data to be used. First, connected car service providers need to increase transparency about what, how, and why data is used (Coppola & Morisio, 2016; Soley et al., 2018; Stocker et al., 2017) to increase trust in them (Roth et al., 2020). Second, they should offer services based on anonymized data (Roth et al., 2020) to encourage sharing of personalized data. Third, it is crucial to demonstrate benefits from connected services (Brandt & Ahlemann, 2020; Mikusz & Herter, 2016; Soley et al., 2018; Stocker et al., 2017) with a clear value proposition (e.g., positive environmental impact). Last, monetary incentives and savings in connected service use could encourage data sharing (Brandt & Ahlemann, 2020; Roth et al., 2020). Nevertheless, it remains unclear how customers perceive these incentives and whether they are willing to share data without monetary incentives.

(2) Enhance Customer-Centricity: Creating customer-specific services is an arduous task, requiring automotive industry players to understand rapidly changing customer needs comprehensively (Chanias & Hess, 2016; Piccinini et al., 2015). Scholars have noted the importance of two imperatives that may help enhance customer-centricity. First, establishing customer co-creation, where users are treated like active resource integrators and essential value creators. Here, customers should be involved in the product design process in order to satisfy their needs (Hanelt et al., 2015) and, more importantly, be involved for data acquisition purposes (Kaiser et al., 2017b; Mikusz & Herter, 2016; Riasanow et al., 2017) to realize DDBMs. Second, leveraging user experience by combining digital service experience with emotions of physical cars to increase customer satisfaction and incentivize data collection. This might be accomplished through seamless user experience (Piccinini et al., 2015), personalization (Bregant et al., 2017; Coppola & Morisio, 2016), or digital technologies (e.g., augmented reality) (Tian et al., 2016). Both imperatives raise the question: How to establish customer co-creation in a collaborative environment to create service experiences that customers appreciate?

(3) Engage External Collaboration: Several reports have shown that in the rapidly evolving automotive environment with rising competitor pressure (Chanias & Hess,

2016; Mocker & Fonstad, 2017; Piccinini et al., 2015), companies should consider which aspects of data monetization they want to tackle internally and which are best addressed through external collaboration. Hence, companies need to open up to strategic partnerships to operate complex data-based services (Grieger & Ludwig, 2019; Kukkamalla et al., 2020; Pütz et al., 2019) to acquire external knowledge and competencies (e.g., big data analytics) (Brandt & Ahlemann, 2020; Riasanow et al., 2017; Svahn et al., 2017), access new revenue sources (e.g., data sales) (De, 2018; Rahman & Tadayoni, 2018; Svahn et al., 2017), and profit form network effects (Bosler et al., 2017). In particular, the future role of OEMs is changing drastically. By now, they must place the same importance on their ecosystem partners as they do on car owners (De, 2018). The question for legacy OEMs remains: How to execute the required transition from monopolist to orchestrator?

(4) Build Internal Capabilities: To exploit the value of car data fully, companies need to build strong internal capabilities alongside an ecosystem of strategic partners. Our results suggest that incumbent firms could do this by embracing the following implications. First, they need to integrate digital technological competencies by attracting new talents with the right skills and an agile mindset (Grieger & Ludwig, 2019; Hanelt et al., 2015; Piccinini et al., 2015), instead of filling prescribed jobs again. Second, it is crucial to implement startup mentality (Piccinini et al., 2015) by structuring the connected car business as a separate entity. Thereby, the question of which approach (e.g., innovation hubs Svahn et al., 2017 or internal startups Brandt and Ahlemann, 2020) is most appropriate is left open. However, practice has witnessed that agile teams should be located outside the current line organization to create an innovation culture and enable DDBMs at tech company speed (Piccinini et al., 2015).

Limitations: As any study, ours is subject to limitations. While a systematic review should ensure a relatively complete count of the relevant literature (Webster & Watson, 2002), it is unlikely that we have identified every article that is potentially relevant to our objective. Moreover, DDBMs and connected cars are two fast-evolving research disciplines. Therefore, this review must be considered as a quick blink in time. Furthermore, our work focuses on connectivity as a megatrend disrupting the mobility industry and excludes all research that specifically addresses other technological drivers such as electric, autonomous, and shared mobility.

2.4.2 Agenda for Future Research

There are several research opportunities for future investigations. First, there is no denying that incumbents are still struggling when it comes to monetizing car data. It is surprising that research to date has predominantly focused on OEMs and other traditional players in the supply chain have been largely overlooked. For example, there are several studies that focus on specific car manufacturers, namely Volvo (Andersson & Mattsson, 2015; Rahman & Tadayoni, 2018; Svahn et al., 2017), Audi (Mocker & Fonstad, 2017), and BMW (Kukkamalla et al., 2020; Tian et al., 2016), while the digital transformation of automotive suppliers has not yet been analyzed. It is particularly important to address supplier challenges and explore alternative distribution channels, new data platforms, and novel DDBM. In fact, suppliers currently have no or only limited access to end-customers and their vehicle data (Martens & Mueller-Langer, 2020). However, this will change with the growth of online channels and data marketplaces. Second, since no theoretical evaluation of car data privacy has been done in the existing literature, theory building is essential. From a theoretical building perspective, an appropriate starting point would be the privacy calculus model (Dinev & Hart, 2006), which proposes an individual's intention to disclose information based on a risk-benefit analysis. Accordingly, one could apply the model to investigate how people preserve their privacy in car data-enabled business models and test, adapt and extend corresponding theories. Third, connected cars' digital services have hardly been investigated in terms of their benefits for businesses, consumers, or society. In addition, most studies are limited to merely naming, listing, or explaining various services. Accordingly, studies designing services and associated DDBMs for connected cars are needed. These could be carried out, considering actual vehicle data (e.g., Caruso). Last, revenue models and pricing strategies are rather unexplored outside the traditional automotive business models and are at best mentioned or explained. Investigating how customers would like to pay for connected services is vital to shaping pricing and sales models according to customer preferences. Experimental studies may represent a suitable means to investigate these. Another unresearched topic is the direct sale of vehicle data by the OEM. In this context, it is crucial to consider suitable pricing strategies for monetizing vehicle data that are attractive to OEMs, independent service providers, and end-users.

In conclusion, the tremendously growing amount of car data has considerable potential for the provision of DDBMs shaping future mobility. Researchers and practitioners may find this review helpful for better understanding and developing innovative DDBMs for the connected car and use it as a reference for further research endeavors. To conclude, although the monetization potential of car data is immense, it is still at an early stage, leaving the question of how to monetize car data unanswered. We encourage scholars to join us in our search for answers.

Part II

Conceptualization of Connected Car Business Models

3 Understanding Car Data Monetization: A Taxonomy of Data-Driven Business Models in the Connected Car Domain

This chapter comprises an article that was published as: Sterk, F., Peukert, C., & Weinhardt, C. (2022). Understanding Car Data Monetization: A Taxonomy of Data-Driven Business Models in the Connected Car Domain. Proceedings of the 17th International Conference on Wirtschaftsinformatik (WI) (pp. 1-16). Note: The abstract has been removed. Tables and figures were reformatted and newly referenced to fit the structure of the thesis. Chapter, section, and research question numbering and respective cross-references were modified. Formatting and reference style was adapted, and references were integrated into the overall references section of this thesis.

3.1 Introduction

The connected car has become the next big thing for the automotive industry (Kilian et al., 2017). There is no doubt that this megatrend will shape future mobility shifting to high-value services for drivers and fleet owners (Bertoncello et al., 2016). As of 2025, Accenture (Gissler et al., 2015) expects all newly sold passenger cars to be connected, capturing and sharing a tremendously growing amount of data (e.g., fuel consumption, vehicle health, and driver condition) with their embedded sensors. This valuable car data eventually paves the way for novel types of data-driven business models (DDBMs), forcing original equipment manufacturers (OEMs) to wade more deeply into connectivity (Kaiser et al., 2021; Pütz et al., 2019). However, although the opportunity is vast, most legacy companies still struggle to harness connected cars' potential and fully monetize the captured data (Hood et al., 2019; Martens & Schneiderbauer, 2021; Stocker et al., 2017). Ultimately, the transition to DDBMs will be crucial to achieving connected car profitability and making software-driven services the primary revenue driver in the long term.

Despite the increasing importance of vehicle connectivity, there is little theoretical knowledge of connected cars and their associated business models. Broadly speaking, the issue of directly selling and monetizing data assets has been little discussed in the literature so far (Parvinen et al., 2020). As a result, we do not know in detail how to use the valuable data generated by these "computers on wheels" (Häberle et al., 2015, p. 11) to create a data-driven service ecosystem (Kaiser et al., 2018, 2019; Stocker et al., 2017). Alongside drivers and OEMs, new players outside the automotive sector are also entering this traditionally closed ecosystem, increasingly launching data-driven services such as remote diagnostics or road condition monitoring (Kaiser et al., 2021). While OEMs are seeking to exploit their supremacy position with exclusive data access, independent service providers explore alternative gateways to get access to vehicle data, for instance, through emerging data marketplaces (Kaiser et al., 2017b, 2019; Martens & Mueller-Langer, 2020). Accordingly, the current research addresses both the digital transformation of incumbents (Dremel et al., 2017; Mocker & Fonstad, 2017; Svahn et al., 2017) and the penetration of emerging startups (Kaiser et al., 2017a, 2017b; Stocker et al., 2017) competing or collaborating in the connected car market.

Since existing classifications for companies operating in the connected car ecosystem neither provide a holistic picture nor cover the essential perspective of car data monetization, we pose the following research question: *What are the key characteristics of data-driven business models in the connected car domain?* We address this question by developing a taxonomy to help classify connected car companies and their respective DDBMs. In general, taxonomies have proven to enable researchers and practitioners to understand and analyze subject areas by structuring and organizing knowledge, grouping similar objects from a domain based on common characteristics, and explaining the relationships between those characteristics (Cook et al., 1999; Nickerson et al., 2013). As the connected car remains in its infancy, there is little knowledge and guidance for analyzing existing and developing new DDBMs in this emerging research field, which we aim to extend this knowledge with our taxonomy development. To do so, we follow the iterative development process by Nickerson et al. (2013). Thereby, we build on a preceding literature review to conceptualize our taxonomy and analyze 70 real-life examples of connected car companies to revise it empirically. Structured along the four business model perspectives by Al-Debei and Avison (2010) (i.e., value proposition, value architecture, value network, and value finance), we derive ten dimensions and 36 corresponding characteristics. We demonstrate the applicability and feasibility of our taxonomy by classifying the 70 selected companies and having three additional raters classify a small subset of exemplary companies for evaluation. The results of our article contribute to business model literature and facilitate a common understanding of connected cars' DDBMs. For researchers, our taxonomy forms the basis to investigate car data monetization, analyze DDBMs of connected cars, and develop design theories in this area. For practitioners, our taxonomy serves as a strategic management tool for designing novel and benchmarking existing connected car companies and their DDBMs. In general, the taxonomy provides a solid foundation for analyzing the connected car market, identifying novel DDBMs, and paving the way for future research endeavors on related topics.

The remainder of this paper is structured as follows: In Section 2, we lay the conceptual foundations about connected cars and introduce existing DDBM taxonomies. Following, Section 3 describes our methodological approach to develop the taxonomy. In Section 4, we introduce our comprehensive taxonomy and evaluate it against real-life examples. Section 5 discusses implications, limitations, and future research opportunities. Finally, Section 6 concludes the work.

3.2 Conceptual Foundations

3.2.1 Connected Cars and Their Emerging Service Ecosystem

Within this work, we refer to the *connected car* as a vehicle capable of accessing the internet, communicating with its ecosystem, and generating and transmitting real-time data, which is in line with prior definitions (Bosler et al., 2017; Coppola & Morisio, 2016). Equipped with multi-layered sensor technology, connected cars already capture an enormously growing amount of data and send it to OEMs' servers, enabling, for instance, usage-based insurance schemes or predictive maintenance (De, 2018; Soley et al., 2018; Stocker et al., 2017). Hence, an ecosystem for such data-based services emerges, composed of incumbents (e.g., traditional OEMs) and new players (e.g., startups) (Kaiser et al., 2021; Nischak & Hanelt, 2019).

In general, OEMs launch digital services such as BMW ConnectedDrive, Mercedes me connect, and VW Car-Net, including remote services, vehicle monitoring, and on-street parking information, among other benefits (Bosler et al., 2017; Kaiser et al., 2017a). Consequently, incumbent automakers look for additional data-based profit pools as they face increased competition from young arrivals such as NIO or Tesla. The latter offers on demand services to consumers through its Autopilot, including features such as performance- and battery-boosting software (Heineke et al., 2020). However, while OEMs have exclusive access to the generated car data, independent service providers have to identify other approaches to capture this valuable data (Kaiser et al., 2017b, 2019; Martens & Mueller-Langer, 2020). The majority of startups, including Mojio, Vinli, and Zubie, utilize a telematics-equipped dongle connected to the on-board diagnostics (OBD) interface to allow remote access to the vehicle data (Coppola & Morisio, 2016; Kaiser et al., 2017a; Pütz et al., 2019; Soley et al., 2018)). Whereas other startups such as Zendrive and Vialytics use the sensors built into modern smartphones to capture data while driving (Kaiser et al., 2017a, 2017b). Furthermore, emerging data marketplaces such as Caruso Dataplace or Otonomo offer another alternative for getting access to vehicle data (Martens & Mueller-Langer, 2020; Naab et al., 2018; Pillmann et al., 2017). Those marketplaces are third-party platforms acting as neutral intermediaries and allowing others to sell standardized data products (Spiekermann, 2019). The objective of car data marketplaces is to make data collected from different car brands available to independent service providers through a single point of access. From the OEMs' perspective, cooperation with marketplaces is worthwhile in order to profit from additional data sales (Martens & Mueller-Langer, 2020).

3.2.2 Taxonomies for DDBMs

The term *taxonomy* is often used synonymously with other classification concepts such as *framework* or *typology* in the existing literature (Gimpel et al., 2018; Paukstadt et al., 2019). Taxonomies help researchers and practitioners understand, analyze, and structure knowledge in emerging research areas by identifying common characteristics within an unambiguous conceptual framework (Nickerson et al., 2013).

Although DDBMs are still at an early stage (Möller et al., 2020), several taxonomies already exist in the literature, which may be divided into generally applicable and industry-specific taxonomies (Dehnert et al., 2021). One of the first and renowned articles on industry-agnostic taxonomies proposed by Hartmann et al. (2016) is based on a conceptual approach with dimensions deductively obtained from a systematic literature review. In contrast, Engelbrecht et al. (2016) provide an empirically developed, generally applicable DDBM taxonomy based on experts' perceptions. Further publications adopt a combined conceptual-empirical approach to characterizing DDBMs (e.g., Dehnert et al., 2021; Passlick et al., 2021; Schüritz et al., 2017). In addition to general taxonomies, various taxonomies exist in the literature that focus on DDBMs in specific industries, for instance, logistics data (Möller et al., 2020), manufacturing data (Müller & Buliga, 2019), and urban data (McLoughlin et al., 2019). To the best of our knowledge, there is currently no taxonomy dealing with DDBMs that spotlights connected car data, allowing this work to represent the first industry-specific taxonomy on this subject, providing a sound basis for researchers as well as practitioners.

3.3 Methodological Approach to Taxonomy Development

Our taxonomy building process follows the methodological approach suggested by Nickerson et al. (2013), which is based on the three-level indicator model of Bailey (1984) and the design science research guidelines of Hevner et al. (2004). In essence, the method seems appropriate for our research endeavor as it facilitates the combination of theoretical knowledge from literature and empirical findings from practice. Moreover, numerous IS scholars successfully adopted this research approach to different contexts (e.g., taxonomy for carsharing business models (Remane et al., 2016b), taxonomy for FinTech startups (Gimpel et al., 2018), taxonomy for analytics-based services (Hunke et al., 2019)). Finally, to assess the applicability of our taxonomy, we adopt central elements from previous studies (e.g., Gimpel et al., 2018; Hunke et al., 2019; Passlick et al., 2021) and classify a selection of use cases with our taxonomy and subsequently conduct an evaluation with three individual raters.

3.3.1 Procedure

The proposed method by Nickerson et al. (2013) represents an iterative approach that allows taxonomies to be created both conceptually grounded on the existing body of literature and empirically based on real-world cases. Initially, the researcher identifies meta-characteristics reflecting the purpose and basis of the taxonomy. Next, ending conditions need to be determined that define when the development process is terminated. Overall, eight objective (e.g., no new dimension added) and five subjective (e.g., explanatory) ending conditions[1] are proposed by Nickerson et al. (2013), which we adopted for our research design. Subsequently, the actual

[1]A detailed list of all ending conditions can be found in the paper by Nickerson et al. (2013).

taxonomy building process begins with one of two possible paths applied sequentially in multiple iterations. First, the conceptual-to-empirical approach follows a deductive procedure to derive dimensions and characteristics from theory. Second, in the empirical-to-conceptual approach, the researcher develops dimensions and characteristics inductively from a given sample of objects. Eventually, the procedure is iterated until the ending conditions are met.

3.3.2 Iterations

Meta-characteristic. Initially, we defined the meta-characteristics as the components of DDBMs for connected cars. As we consider the V^4 business model framework developed by Al-Debei and Avison (2010) to be compelling for guiding this process, we derive our meta-characteristics from it. Hence, each dimension of the taxonomy must relate to one of the V^4 framework's dimensions—value proposition, value architecture, value network, and value finance. The selected framework fits our research endeavor for two reasons. First, it is one of the few business model frameworks that particularly addresses digital business models. Second, the framework covers the multi-dimensionality of business models, including the crucial dimensions from prior conceptualizations.

1st Iteration. For the first iteration, we chose the conceptual-to-empirical approach, allowing us to build upon the already existing body of literature. For this purpose, we rely on a previously conducted structured literature review (SLR) (Sterk et al., 2022a) focusing on DDBMs in the connected car domain, in which a total of 45 papers were analyzed in depth. Whereas the SLR provided a general overview of this research area, we examined the identified articles to further use in developing the taxonomy. Based on the concept-centric approach (Webster & Watson, 2002) of the SLR, we identified twelve articles relevant to our research endeavor that address four key topics related to DDBMs of the connected car. Adopting these topics, we derived 16 characteristics and four initial taxonomy dimensions, namely value for customer (Coppola & Morisio, 2016; De, 2018), data access, (Bosler et al., 2017; Coppola & Morisio, 2016; Kaiser et al., 2017b; Martens & Mueller-Langer, 2020), role in ecosystem (Kaiser et al., 2017b, 2021; Rahman & Tadayoni, 2018; Riasanow et al., 2017; Stocker et al., 2017), and revenue model (De, 2018; Kukkamalla et al., 2020; Mikusz et al., 2015, 2017) (references cited in this sentence stem from the SLR).

2nd Iteration. For the second and all further iterations, we opted for the empirical-to-conceptual approach and examined sample connected car companies from various sources. In order to efficiently build a large dataset and obtain a reasonably complete picture of global connected car companies, we decided to query different sources with each iteration. In Iteration 2, our source was the 45 articles from the previous SLR (Sterk et al., 2022a), which we filtered for relevant articles analyzing connected car companies. Here, we excluded duplicates and companies that are no longer active[2]. Finally, we extracted 18 real-life examples (i.e., companies), from six articles (i.e., (Bosler et al., 2017; Kaiser et al., 2017a, 2017b, 2021; Rahman & Tadayoni, 2018; Stocker et al., 2017)). By analyzing the company websites of real-life examples, we added 13 characteristics and three further dimensions to our taxonomy, namely customer segment, vehicle ownership, and data monetization.

3rd Iteration. For the third iteration, we extended our sample with two practice reports from leading consulting firms: the "Connected Vehicle Trend Radar" by Arif et al. (2019) that includes 27 emerging connected car startups and the "Digital Auto Report 2020" by PwC (2020), that contains 27 leading connected car companies. After removing duplicates, this yielded 42 company websites for further review. Finally, we excluded companies that do not explicitly focus on connected cars and are no longer active[2]. This yielded 32 companies, from whose analysis we derived seven characteristics and three further dimensions, namely data personalization, influence of car data, and influence of autonomy.

4th Iteration. For the fourth iteration, we queried Crunchbase, the world's largest startup database, to gain a deeper understanding of connected car startups. Using the search term "connected car" we obtained 147 companies, of which 144 remained after duplicates were removed. Then, we skipped companies that are no longer active[2] (28), do not provide an English website (7), or do not explicitly focus on connected cars (29; e.g., the music streaming service Deezer). Subsequently, we screened the remaining 80 cases until we found a subset of 20 connected car companies with sufficient website information (this number seemed adequate to cover the startup view in the further taxonomy development). After having analyzed these 20 companies, we felt to experience saturation (no further dimensions or characteristics were identified) and decided to end the screening process at this point, mainly because we do not want to over-represent the startup share across all iterations. Since the additional sample confirmed our taxonomy's existing dimensions and characteristics, this iteration caused no changes. Finally, all objective and subjective ending conditions were met after this iteration, leading us to agree on the final set of dimensions and characteristics. Based on the aforementioned sources yielding 70 connected car companies (see Table 3.1), we are confident that we cover a fairly complete picture of the global connected car domain.

[2]Companies with any inactivity information (e.g., on crunchbase.com) or no active web presence.

Table 3.1.: Connected car company sample for the 2nd to the 4th iteration of taxonomy development.

No.	Company Name	I	No.	Company Name	I	No.	Company Name	I
1	Aeye	3	25	GM OnStar	3	49	Parkopedia	3
2	Affectiva	3	26	GoFar	4	50	Passport Parking	3
3	Airbiquity	3	27	Google Android Auto	2	51	Phantom Auto	3
4	Anagog	3	28	High Mobility	2	52	Pony AI	3
5	Aplicom	4	29	**Hum**	4	53	Porsche Car Connect	2
6	Apple CarPlay	2	30	IMS (Insurance & Mobility Solutions)	4	54	Reviver	3
7	Audi Connect	2	31	Innoviz Technologies	3	55	RideCell	3
8	Automile	2	32	Innovusion	3	56	Sensetime	3
9	Autotalks	3	33	KOBA Insurance	4	57	SiriusXM	3
10	Autox	3	34	Koola	4	58	Smartcar	4
11	Bliq	3	35	**Mercedes me connect**	2	59	Smartdrive	3
12	**BMW ConnectedDrive**	2	36	MetaWave	3	60	Teralytics	3
13	CARFIT	4	37	Metromile	2	61	**Vimcar**	3
14	CarIQ	4	38	Mojio	2	62	Vinli	2
15	Carmera	3	39	Momenta	3	63	Visual Threat	4
16	**Caruso Dataplace**	2	40	MotorQ	4	64	Volvo Sensus Connect	2
17	CarX	4	41	Nauto	2	65	Voyomotive	4
18	Continual	4	42	Nexar	3	66	VW Car-Net	2
19	Cortica	3	43	Nonda	4	67	Wayray	3
20	Dashroad	4	44	**Otonomo**	2	68	Wejo	3
21	Drivemode	4	45	Ottoo	4	69	Zendrive	2
22	Evopark	3	46	**OwlCam**	3	70	**Zubie**	2
23	Fensens	4	47	Pace Car				
24	Geotab	3	48	PARK NOW				

I=Iteration in which the company was examined. Companies ranked by the three independent raters are **bold**

3.4 Results

3.4.1 Taxonomy of Connected Car DDBMs

This section presents our taxonomy of DDBMs for connected car companies. Table 3.2 provides an overview of the ten key dimensions with their 36 corresponding characteristics. Following the recommendations of Nickerson et al. (2013), we employed three dimensions with characteristics that are mutually exclusive. However, for the remaining seven dimensions, it was more reasonable to model the characteristics as non-exclusive (Gimpel et al., 2018; Hunke et al., 2019; Möller et al., 2020). This decision is due to the wide variety of services, data sources, and stakeholders related to business models for connected cars, resulting in enormous complexity. Accordingly, the right-hand column of Table 3.2 indicates whether a dimension is exclusive (E) or non-exclusive (N). For exclusive dimensions, exactly one characteristic is observable at a time. In contrast, for non-exclusive dimensions, potentially multiple characteristics are observable at a time. In addition, the superscript numbers in Table 3.2 indicate the iteration in which dimensions or characteristics were added or revised. In the following, we introduce the dimensions and characteristics in detail.

Table 3.2.: Taxonomy of data-driven business models in the connected car domain.

	Dimension	Characteristic						E/N*
Value Proposition	Value for customers[1]	Safety & security[1]	Convenience[1]	Cost reduction[1]	Traffic efficiency[1]	Infotainment[1]	Data accessibility[2]	N
Value Proposition	Influence of car data[3]	Car data core business model[3]			Car data-enabled business model[3]			E
Value Proposition	Influence of autonomy[3]	Enhanced value by autonomy[3]		Reduced value by autonomy[3]		Autonomy not relevant[3]		E
Value Architecture	Data personalization[3]	Anonymized data[3]			Personal data[3]			E
Value Architecture	Data access[1]	Exclusive access[1]	OBD2-dongle[1]	Central server[1]	Retrofit[1]	Smartphone[2]		N
Value Network	Role in ecosystem[1]	Service provider[1]		Platform provider[1]		Technology provider[2]		N
Value Network	Customer segment[2]	B2C[2]		B2B[2]		B2G[2]		N
Value Network	Vehicle ownership[2]	Private ownership[2]		Fleet ownership[2]		Mobility on demand[2]		N
Value Finance	Data monetization[2]	Selling data[2]		Selling analysis[2]		Selling services[2]		N
Value Finance	Revenue model[1]	Direct sale[1]	Subscription fee[1]	Licensing fee[1]	Transaction fee[1]	Usage fee[1]	On demand[2]	N

*E = Exclusive dimension (one characteristic observable); N = Non-exclusive dimension (more than one characteristic observable)
Dimensions and characteristics were added or revised in the following iteration: [1] first, [2] second, or [3] third iteration

Value Proposition. The first perspective deals with the compelling value propositions delivered by connected car companies by operating complex services to satisfy various customer needs. This perspective comprises three dimensions, namely value for customers, influence of car data, and influence of autonomy.

1. *Value for customers* deals with the benefits to the distinct customers delivered by the value proposition. Regardless of what services car data enables, monetizing them is only viable if the customer experiences its value and the cost is worth the benefit (Chanias & Hess, 2016; Piccinini et al., 2015). Consequently, customers are only willing to share the required personal and vehicle data if they see direct benefits from connected services (Brandt & Ahlemann, 2020; Mikusz & Herter, 2016; Soley et al., 2018; Stocker et al., 2017). Overall, connected car services typically fall into six broad categories, namely safety & security (e.g., emergency call services), convenience (e.g., concierge services (Riasanow et al., 2017)), cost reduction (e.g., usage-based insurance (Roth et al., 2020)), traffic efficiency (e.g., dynamic route planning (Coppola &

Morisio, 2016)), infotainment (e.g., smartphone integration (Bosler et al., 2017)), and data accessibility (e.g., data access via marketplaces (Martens & Mueller-Langer, 2020)).

2. *Influence of car data* captures the importance of car data to realize certain business models. Finally, with the current rise of connected vehicles, their generated data, including geolocation, fuel consumption, and driver condition, can be exploited (Kaiser et al., 2021; Stocker et al., 2017). Nevertheless, vehicle data is more important for some connected services than for others. First, there are services (e.g., predictive maintenance) that are only implementable through access to particular vehicle data (Bertoncello et al., 2016). Second, there are services (e.g., workshop booking) that also operate without vehicle data; however, the full potential is only unleashed by its use.
3. *Influence of autonomy* describes the impact of the vehicle's autonomy on the business model's main or aggregate value proposition. Accordingly, the business model changes considerably, as the driver no longer needs to fully concentrate on the critical task of driving (Athanasopoulou et al., 2016, 2019; Hanelt et al., 2015). Consequently, preferences are shifting from driving experience or technical performance to aspects such as information and entertainment. For example, today's infotainment systems, which deliver audio and primary interactive content, may offer virtual reality movies or video games once the driver takes on a passenger role (Bertoncello et al., 2016). Hence, full vehicle autonomy may increase the value created through certain data-driven services (e.g., networked parking services) while also decreasing the value of others (e.g., driving style suggestions).

Value Architecture. The second perspective characterizes an organization's architecture, including its technological architecture and organizational infrastructure, which allows the provision of connected services. It comprises two dimensions, namely data personalization and data access.

4. *Data personalization* refers to the collected vehicle data, which can be divided into two main types. First, anonymized data, also commonly abbreviated as aggregated data, does not contain personally identifiable information (PII) that allows a specific car to be identified from the crowd (Martens & Mueller-Langer, 2020; Soley et al., 2018). For instance, when providing data to a smart city to improve road conditions through automatic pothole detection, anonymized data is sufficient (Kaiser et al., 2018; Stöckel et al., 2021; Stocker et al., 2017). Second, personal data contains PII generated either by vehicles or by peripheral devices (e.g., smartphones) (Soley et al., 2018). For example, it is necessary to identify the specific car for usage-based insurance systems, as

the data-based pricing model adapts to the user's driving behavior (Conradi et al., 2016; Marabelli et al., 2017; Peng et al., 2015; Roth et al., 2020).

5. *Data access* distinguishes different technical gateways that enable connected car actors to access the required data a car generates. While OEMs have exclusive access, independent service providers must find alternative avenues to capture this data (Kaiser et al., 2017b, 2019; Martens & Mueller-Langer, 2020). One option is the OBD port, into which the driver can plug a telematics-equipped dongle to allow remote access to the vehicle data (e.g., Coppola and Morisio, 2016; Pütz et al., 2019; Soley et al., 2018). Data access is also possible through a central server, where data storage, processing, and customer interaction is managed by a data marketplace (e.g., Caruso Dataplace, Otonomo) providing standardized vehicle data by multiple OEMs (Coppola & Morisio, 2016; Martens & Mueller-Langer, 2020). In addition to accessing in-vehicle data, some startups are leveraging the potential of self-developed retrofitted sensors (e.g., dash cams) or traditional smartphone sensors (e.g., GPS, accelerometer, or luminance) to collect driving data (Kaiser et al., 2017a, 2017b).

Value Network. The third perspective refers to the various stakeholders entering the connected car ecosystem. Here, we also consider the customer, who under the realm of connected car business models is often not a passive actor but co-creator of value (e.g., data collection) (Mikusz & Herter, 2016; Riasanow et al., 2017). The perspective comprises three dimensions, namely role in ecosystem, customer segment, and vehicle ownership.

6. *Role in ecosystem* describes certain roles that actors must assume in the connected ecosystem or value chain. For example, as service providers, they offer end-customer solutions for specific use cases (e.g., usage-based insurance), thereby monetizing car data (Kaiser et al., 2017a, 2017b; Stocker et al., 2017). Other actors provide a cloud-based data exchange platform for sharing and accessing data about connected cars across multi-sided marketplaces (Kaiser et al., 2019, 2021; Martens & Mueller-Langer, 2020). In addition, technology providers offer devices (e.g., dash cams) that make vehicles smart and connected while monetizing the data they collect.
7. *Customer segment* defines the distinctive groups of people or organizations to which a company aims to provide its offerings (Osterwalder & Pigneur, 2010). The most generic classification distinguishes between business-to-business (B2B) and business-to-consumer (B2C) (Hartmann et al., 2016; Lim et al., 2018). We extend this dimension to include business-to-government (B2G) (Dehnert et al., 2021; Passlick et al., 2021), as, for instance, city planners can

use road condition data for maintenance and repair works (Kaiser et al., 2018; Stocker et al., 2017).

8. *Vehicle ownership* is about who owns the vehicles for data collection to realize the desired DDBM (Remane et al., 2016b). Consequently, the connected cars are owned either by private drivers for personal use, fleet operators for commercial use, or mobility service providers for rental or shared mobility. For instance, private drives directly benefit from driving recommendations, gamification aspects, or remote diagnostics based on assessing their shared vehicle data (Grieger & Ludwig, 2019; Rahman & Tadayoni, 2018; Stocker et al., 2017). Moreover, fleet operators and mobility service providers can increase uptime by avoiding breakdowns or unplanned repairs by using predictive maintenance to prevent accidents (Andersson & Mattsson, 2015; Brandt & Ahlemann, 2020; Llopis-Albert et al., 2021).

Value Finance. The fourth perspective represents how stakeholders in the connected car ecosystem generate revenue from their DDBMs. It comprises two dimensions, namely data monetization and revenue model.

9. *Data monetization* refers to capturing the monetary value from data (Parvinen et al., 2020; Teece & Linden, 2017). Here, a distinction can be made between three approaches (Parvinen et al., 2020): First, the most straightforward approach involves selling car data directly to another party, as OEMs do to data marketplaces (e.g., Caruso Dataplace) (Thomas & Leiponen, 2016). In particular, data marketplaces go one step further by selling harmonized multi-brand data from different OEMs to independent service providers, giving them a data access option. The second approach involves selling data-based analyses but constraining access to the original data (Thomas & Leiponen, 2016). Third, several companies develop and sell data-driven services such as driving style suggestions or fleet management solutions.
10. *Revenue model* represents the structure of how a company generates revenue or income from each customer segment (Osterwalder & Pigneur, 2010). Most widely known is the direct sale, where the ownership of an asset (e.g., data) is transferred in return for money (Hartmann et al., 2016; Osterwalder & Pigneur, 2010; Schüritz et al., 2017). Another way to capture value is through usage fees, which can be charged per kilometer (e.g., usage-based insurance) (Marabelli et al., 2017; Pütz et al., 2019; Roth et al., 2020). Moreover, subscription fees can generate revenue for continuous service access (Hanelt et al., 2015; Kukkamalla et al., 2020; Mocker & Fonstad, 2017). Transaction fees are charged for an intermediate service such as trading vehicle data through marketplaces (Martens & Mueller-Langer, 2020). Licensing fees are

generated by giving customers permission to use protected intellectual property in exchange (Hartmann et al., 2016; Osterwalder & Pigneur, 2010; Schüritz et al., 2017). Last, we have on demand pricing tailored to a customer's individual request (e.g., for additional data access).

3.4.2 Application and Evaluation of the Taxonomy

To get an impression of the applicability of our taxonomy, we classified the DDBMs of all 70 connected car companies that we used to develop the taxonomy. Here, the aforementioned definitions of characteristics and dimensions served as a guiding codebook. Based on this common understanding, a single author classified the 70 companies. In summary, Table 3.3 shows the distribution of each dimension. Concerning the relative frequencies presented in Table 3.3, we had to deal with publicly unavailable information that resulted in missing values for seven companies in the data access dimension and 22 companies in the revenue model dimension. Due to this missing data, the proportions of the characteristics in the affected dimensions may be even higher than obtained.

Table 3.3.: Distribution of characteristics based on the classification of the author.

	Dimension	Characteristic					
Value Proposition	Value for customers	Safety & security (57%)	Convenience (43%)	Cost reduction (47%)	Traffic efficiency (47%)	Infotainment (14%)	Data accessibility (17%)
	Influence of car data	Car data core business model (81%)	Car data-enabled business model (19%)				
	Influence of autonomy	Enhanced value by autonomy (30%)	Reduced value by autonomy (21%)	Autonomy not relevant (49%)			
Value Architecture	Data personalization	Anonymized data (19%)	Personal data (81%)				
	Data access	Exclusive access (10%)	OBD2-dongle (26%)	Central server (11%)	Retrofit (37%)	Smartphone (26%)	
Value Network	Role in ecosystem	Service provider (80%)	Platform provider (19%)	Technology provider (39%)			
	Customer segment	B2C (50%)	B2B (67%)	B2G (7%)			
	Vehicle ownership	Private ownership (77%)	Fleet ownership (59%)	Mobility on demand (39%)			
Value Finance	Data monetization	Selling data (13%)	Selling analysis (23%)	Selling services (83%)			
	Revenue model	Direct sale (26%)	Subscription fee (36%)	Licensing fee (3%)	Transaction fee (10%)	Usage fee (6%)	On demand (9%)

Cumulated relative frequencies can be different from 100% if a dimension is non-exclusive or in case of missing data.

By analyzing the statistics from Table 3.3, we made some noteworthy observations: Looking at the value proposition to the customer, it is noticeable that the percentages of infotainment and data access are relatively low compared to the other characteristics. This might change with the proliferation of self-driving cars, as vehicle occupants focus on media and infotainment services rather than on the road (Hanelt et al., 2015). In addition, the prevalence of intermediaries providing data access will increase as connected vehicles become more widespread. Despite the difficulty accessing car data, they form the core of 81% of the business models studied, which would not be feasible without it. Further, half of the companies investigated designed their business model to remain independent of increasing autonomy; around a third would even be strengthened by autonomous driving. In the data personalization dimension, only one-fifth of all companies build their business model on anonymized data. The underlying reason could be that there are few ideas on how to use anonymized data to establish profitable services (Stocker et al., 2017). For the data access dimension, the different characteristics are relatively evenly distributed, with the exception of exclusive access and central server. This observation may be related to the fact that most connected car companies are independent startups that want to avoid the tedious process of purchasing in-vehicle data from OEMs or intermediaries and therefore rely on retrofitted dashcams, dongles, or smartphones (Kaiser et al., 2017b). Most companies using retrofit solutions or dongles for data acquisition also develop them, thus slipping into the role of technology providers. However, the vast majority of companies participate in the ecosystem as service providers. Concerning the customer segment, primarily consumers (B2C) and businesses (B2B) are addressed. One reason for the low number of B2G business models could be the insufficient coverage of connected vehicles (Caruso Dataplace, 2021) to realize services such as intelligent road condition monitoring or traffic management systems based on aggregated data. In terms of vehicle ownership, we found that a clear majority of private vehicles are used to collect the required data. Nevertheless, the mobility landscape will change in the future as shared mobility becomes more prevalent and new corporate fleet customers enter the market (Heid et al., 2018). Finally, more than one-third of the examined companies rely on generating revenue through subscription-based revenue models. Therefore, they might hope that recurring revenues from subscription fees will exceed the predominantly one-time costs incurred by connected services (De, 2018).

Further, to prove the feasibility of our taxonomy, a subset comprising eight of the 70 companies (see Table 3.1) was classified by independent raters. Here, we received complete responses from three raters, on which our analysis is based. In selecting the eight evaluation cases, we ensured that most of the required information was available on the companies' websites. The classification results were compared using Fleiss' kappa (Fleiss, 1971) to measure the level of agreement. Therefore, we calculated the average agreement of the raters for all 36 dimensions and the eight selected cases. This yielded a value of 61% for Fleiss' kappa (Fleiss, 1971), which according to Landis and Koch (1977) corresponds to "substantial agreement". Additionally, the responses from the three individual raters were compared to the initial classification by one of the paper's authors. The results revealed a value of 62% for Fleiss' kappa, which also indicates "substantial agreement". Thus, it can be assumed that our taxonomy is suitable for a consistent classification and concise description of connected car companies' DDBMs.

3.5 Discussion, Limitations and Future Research

As for theoretical implications, our research ties in and contributes to the descriptive knowledge on connected cars and associated DDBMs, exploring a domain that is still in its early stages (Kaiser et al., 2018; Marabelli et al., 2017). Thereby, our main contribution is a theoretically grounded and empirically validated taxonomy that summarizes the key characteristics describing DDBMs of distinct connected car companies in ten dimensions. The domain-specific view of our taxonomy complements existing general, industry-agnostic DDBM classifications. Although generally applicable taxonomies pose a good reference point and may help distinguish connected car companies based on aforementioned dimensions such as value proposition, customer segment, or revenue model, they are insufficient to fully understand the connected car phenomenon and the configuration of underlying DDBMs. Accordingly, our taxonomy is the first to focus on the connected car domain, proposing novel dimensions such as influence of autonomy, data access, or vehicle ownership. From a theoretical perspective, our taxonomy serves as a basis for analyzing, designing, and configuring DDBMs for connected cars, investigating connected car startups, and strategically classifying incumbents' offerings. Furthermore, our taxonomy provides a common language and structure for the investigated research field, helping scholars position their work therein. We also follow Parvinen et al. (2020) call for a better understanding of data monetization by examining different roles in the ecosystem and their approaches to create and capture value from data. Summing up, our work offers deeper insights into the structure of data-driven business models and will help classify research in this area.

In terms of managerial implications, the taxonomy allows practitioners to navigate the still largely unexplored field of DDBMs more effectively. Based on empirical development using 70 real cases, our taxonomy provides a comprehensive market overview and status quo analysis of the connected car ecosystem. Practitioners, such as traditional OEMs, will gain a detailed understanding of how startups leverage vehicle data to enable innovative services and learn about different ways to monetize their valuable data assets. Moreover, our taxonomy represents a strategic management tool for developing novel and documenting existing business models in the automotive industry. Therefore, current startups or incumbents can use the taxonomy to systematically analyze competitors or identify combinations of characteristics that have not been employed so far. Thus, in systematically generating new ideas, practitioners may benefit from our work using our taxonomy as a basis for applying a morphological analysis (Geum et al., 2016; Hunke et al., 2019).

As any study, ours is not without limitations. First, with the field of connected mobility and resulting business models constantly evolving, the taxonomy needs to be constantly updated to remain useful in the future. Second, our sample of analyzed connected car companies does not raise the claim to be exhaustive. Particularly in the fourth iteration, we only analyzed 20 startups. Therefore, our work is limited by the fact that since not all remaining startups have been analyzed in the last iteration, there might be the chance that further dimensions may have been derived from the companies that have not been analyzed. Nevertheless, in future research, we plan to further evaluate the taxonomy by means of expert interviews with representatives from research and practice for another confirmation or revision. Third, our results stem only from publicly available information. However, the websites provided by the connected car companies often contain limited information on their business model, especially concerning revenue models. Hence, in future investigations, it can be valuable to contact certain companies with missing data to obtain a complete data set. Fourth, our reported results rely on the classification of one author (70 companies) and three individual raters (eight companies). To improve the validity of the results, we believe that our taxonomy should be tested quantitatively for completeness and applicability. Therefore, we intend to let further individuals rate the whole set of companies. Finally, building on our research, a cluster analysis could identify archetypes of DDBMs in the connected car domain, i.e., typical combinations of characteristics across all ten dimensions included. These archetypes could help provide a theoretically sound basis for developing connected car DDBMs.

3.6 Conclusion

Against the backdrop of the increasing importance of car connectivity and data monetization, we examined ten dimensions and 36 corresponding characteristics that describe DDBMs for connected cars. In sum, we executed four iterations, one being conceptually based on a SLR and three iterations being empirically grounded on a data set of 70 connected car companies. By applying our taxonomy to the dataset, we demonstrated the feasibility of the taxonomy to analyze and understand the DDBMs of various connected car companies. Overall, our conceptually grounded and empirically validated taxonomy contributes to the existing literature by extending the descriptive body of knowledge on DDBMs and connected cars.

4 Unlocking the Value from Car Data: A Taxonomy and Archetypes of Connected Car Business Models

This chapter comprises a working paper that was submitted as: Sterk, F., Stocker, A., Heinz, D., & Weinhardt, C. (2023). Unlocking the Value from Car Data: A Taxonomy and Archetypes of Connected Car Business Models. Note: By this thesis's submission date, this study was in the second review round at the Electronic Markets Journal. The abstract has been removed. Tables and figures were reformatted and newly referenced to fit the structure of the thesis. Chapter, section, and research question numbering and respective cross-references were modified. Formatting and reference style was adapted, and references were integrated into the overall references section of this thesis.

4.1 Introduction

The transition toward increased vehicle connectivity, autonomous driving, powertrain electrification, and shared mobility mutually reinforces advances in the automotive landscape (Burkacky et al., 2023). Taken together, they not only reshape the automotive value chain by attracting newcomers from various industries but also critically drive business innovation in the mobility space (Kaiser et al., 2021; Stocker et al., 2017). As pioneers of Internet of Things (IoT) technologies, automotive original equipment manufacturers (OEMs) have invested heavily in equipping vehicles with telematic control units and related capabilities to ensure connectivity and facilitate additional service offerings (Cichy et al., 2021; Svahn et al., 2017). Leading consultancies (i.e., Bertoncello et al., 2016; Gruendinger and Seiberth, 2018) argue that despite the long-term decline in car sales, monetizing car data will compensate for this and even increase OEM's revenues by leveraging data-based services. However, many players in the connected car space struggle to capitalize on the potential of data monetization and connected services (Hood et al., 2019; Martens & Schneiderbauer, 2021), leading to numerous companies ceasing operations (e.g., Automatic Labs or Dash Labs). Nonetheless, the industry is currently at an inflection point that could create $250 billion to $400 billion in annual incremental value, enabled using vehicle data by 2030 (Martens & Schneiderbauer, 2021).

The automotive sector is a technological frontrunner for IoT applications and connected products (Cichy et al., 2021), as OEMs began equipping vehicles with connectivity many years ago to establish vehicle-to-vehicle and vehicle-to-infrastructure communications and to enable cooperative intelligent transportation systems (Kerber & Gill, 2019; Sterk et al., 2022c)). Vehicle data is personal, high-volume, high-velocity, and highly diverse data often combined with contextual data such as weather or location data to develop new services (Kaiser et al., 2021; Soley et al., 2018). Integrating digital technologies into physical products gradually changes the dynamics of the automotive sector (Bohnsack et al., 2021) and drives the formation of organizational and technological ecosystems aimed at sharing and leveraging data (Heinz et al., 2022). Google, for example, enables smartphone-like in-vehicle applications with its open-source "Android Automotive"[1] operating system, to which numerous OEMs have signed up, including Volvo, Renault, GM, and Ford (Legenvre et al., 2022).

Connected cars offer a unique setting to examine and expand existing theories and evidence on business models (Cichy et al., 2021). Equipped with telematic control units and connected to OEMs' data centers, they generate continuous streams of data through multiple powerful sensors, making them a central component of innovative data-driven business models (DDBMs) (Cichy et al., 2021; Kaiser et al., 2021; Koester et al., 2022). Independent form makes and models, they already generate massive amounts of valuable data, not only about the cars themselves, but also about their surroundings via various sensors (e.g., to measure temperature, humidity, or position), also of interest for multiple ecosystem representatives (e.g., suppliers, workshops, or insurers) (Sterk et al., 2023a). Although the research directions linked to car data-sharing mechanisms and associated privacy concerns have received attention lately (e.g., Cichy et al., 2021; Kaiser et al., 2021; Koester et al., 2022), the information systems (IS) literature has not adequately explored the topic of connected cars comprehensively. Particularly, the current literature lacks a structural analysis that explicitly examines the anatomy, such as stereotypical patterns (i.e., archetypes) of business models for connected car companies (Sterk et al., 2022c). Indeed, the specifics of designing empirical business model classifications require further research (Groth & Nielsen, 2015; Lambert, 2015). Classifying digital

[1]https://developers.google.com/cars/design

business models in the automotive industry is pivotal as the car itself cannot be fully digitized (Piccinini et al., 2015), and the emergence and impact of digital business models and ecosystems in the non-digital context of large, complex products (e.g., automobiles) remain to be elucidated to fully understand digital transformation (Hanelt et al., 2015). As a step towards operationalizing this issue, our research responds to recent calls to better understand data-driven business models (DDBM) in the mobility domain (Ketter et al., 2022) and specifies their key features better to ultimately support decision-makers in their entrepreneurial activities to leverage connected vehicle data. Therefore, we pose the following research questions:

> **Research Question 2:** *What are the key characteristics of data-driven business models in the connected car domain?*

> **Research Question 3:** *What are the archetypal patterns of data-driven business models in the connected car domain?*

To address both questions, we follow a sequential mixed methods design (Venkatesh et al., 2013, 2016) comprising two iterations, each dedicated to addressing one research question. In the first iteration, we follow the taxonomy development process of Nickerson et al. (2013) by conducting a structured literature review (SLR) on connected car business models and analyzing 70 real-world examples of connected car companies to empirically verify and revise our findings, ensuring both theoretical rigor and practical relevance. We evaluate the taxonomy by conducting twelve expert interviews, applying it to 154 connected car business models, and having four raters classify a subset of these cases to compare their ratings. Our final taxonomy is structured along Al-Debei and Avison (2010) four business model perspectives (i.e., value proposition, value architecture, value network, and value finance) and includes a total of ten dimensions and 48 corresponding characteristics. In the second iteration, we use the taxonomy to re-classify the set of 154 real-world business models and perform a cluster analysis (Kaufman & Rousseeuw, 1990) to derive seven cluster groups of business models that share similar characteristics across the taxonomy dimensions. By comparing the respective cases within each cluster, we derive archetypes as qualitative interpretations that describe and distinguish ideal configurations of connected car business models. Finally, we evaluate the structural strength and quality of each cluster using silhouette width as a measure of cluster validity (Rousseeuw, 1987).

The contribution of our work is threefold. First, we provide a systematically analyzed dataset of connected car business models that overviews how companies use digital technologies in the connected car domain. Second, our taxonomy and archetypes complement the existing business model literature by providing a common language for analyzing, classifying, and configuring connected car business models, enabling a better understanding of higher-level business model configurations. Taxonomies structure a body of knowledge that constitutes a new field, such as DDBMs around connected cars in IS research, and allow a systematic description of the domain of interest (Glass & Vessey, 1995). Our initial literature review revealed a lack of industry-specific taxonomies in the connected car domain (and the automotive domain in general), which we see as a research gap to be addressed in our paper. Finally, practitioners can use our taxonomy and archetypes as strategic management tools for developing new connected car business models and benchmarking existing ones. Both artifacts pave the way for future research, such as upcoming research in this highly relevant domain.

This article is structured as follows: In the next section, we review related work on business models, associated taxonomies and archetypes, and their application in the connected car field. Subsequently, we describe our mixed methods approach. Section 4 presents a business model taxonomy and corresponding archetypes for the connected car domain. Section 5 discusses implications, limitations, and future research opportunities. Finally, Section 6 provides a summary and conclusion of our work.

4.2 Related Work

4.2.1 Taxonomies and Archetypes of Data-Driven Business Models

In the prevailing literature, the term *taxonomy* is often used as a synonym for other classification concepts, such as typology (Gimpel et al., 2018; Paukstadt et al., 2019). However, while typologies are conceptually derived through a top-down approach with predefined dimensions, taxonomies are obtained through an empirical bottom-up approach by observing real-world objects, with categories being designed retrospectively (Baden-Fuller & Morgan, 2010; Fiedler et al., 1996). The taxonomies at the core of our research are intended to guide researchers and practitioners in understanding, analyzing, and structuring knowledge in emerging research areas (Nickerson et al., 2013).

Although data monetization is still a largely unexplored area in current research (Parvinen et al., 2020), various taxonomies of data-driven business models exist in the literature, which can be divided into generally applicable and industry-specific taxonomies (Dehnert et al., 2021). In total, we identified 28 DDBM-related taxonomies, which we categorized in Table 4.1. For example, Hartmann et al. (2016), provided one of the first generally applicable DDBM taxonomies deductively derived from a structured literature review. Conversely, Engelbrecht et al. (2016) designed an industry-agnostic DDBM taxonomy based on questioning experts. Several publications combine both conceptual and empirical approaches in a conceptual-empirical procedure to classify DDBMs (Passlick et al., 2021; Schüritz et al., 2017). In addition to generally applicable DDBM taxonomies, the body of existing literature also contains several DDBM taxonomies that focus on specific industries and address the monetization of more specific types of data, such as logistics data (Möller et al., 2020), manufacturing data (Müller & Buliga, 2019), or FinTech data (Gimpel et al., 2018).

Several articles (e.g., Gimpel et al., 2018; Müller and Buliga, 2019; Passlick et al., 2021) go beyond merely designing taxonomies and develop so-called business model *archetypes* by performing a cluster analysis and interpreting the findings to identify typical combinations of characteristics across all included dimensions. These archetypes serve as stereotypical patterns for business development and empirical work in their respective research areas.

Despite the substantial progress in DDBM taxonomy development and archetype generation, there exists a notable gap in the context of connected car business models. Current taxonomies and archetypes, whether general or industry-specific, do not adequately provide a clear analytical frame for understanding and developing business models in the connected car domain, given its unique data characteristics and specific industry dynamics. Recognizing this research gap, our article extends the existing corpus by creating a taxonomy and corresponding archetypes specifically designed for DDBMs in the connected car domain. In the next subsection, we elaborate on the specifics of data-driven business models in the connected car domain and link our research to related work in this area.

4.2.2 Data-Driven Business Models in the Connected Car Domain

The term *connected car*, as used in this article, refers to a vehicle with the ability to access the internet, communicate with its ecosystem, and generate and transmit real-time data, which aligns with previous definitions (Bosler et al., 2017; Coppola & Morisio, 2016). The combination of built-in cameras, radars, ultrasonic sensors, and actuators of a connected car is causing the amount of data generated by modern cars

Table 4.1.: Overview and categorization of existing DDBM-related taxonomies.

Industry	Focus of the Developed Artifacts	Authors	Methodol. Approach	Archetype Development
Industry-agnostic	IIoT platforms' architectural features	Arnold et al. (2022)	C&E	Yes
	Digital business models	Bock and Wiener (2017)	C&E	No
	Data-based value creation in companies	Baecker et al. (2021)	C&E	No
	Smart product-service systems and value proposition types in B2C	Dehnert and Bürkle (2020)	C&E	No
	Data-driven business models	Dehnert et al. (2021)	C&E	No
	Data-driven business models	Engelbrecht et al. (2016)	E	No
	Data-driven business models used by start-up firms	Hartmann et al. (2016)	C	Yes
	Analytics-based services	Hunke et al. (2021)	C&E	Yes
	Data-based value creation in information-intensive services	Lim et al. (2018)	C&E	No
	Analytics as a Service	Naous et al. (2017)	C&E	Yes
	Predictive maintenance as an IoT enabled business model	Passlick et al. (2021)	C&E	Yes
	Smart services	Paukstadt et al. (2019)	C&E	No
	Proactive services	Rau et al. (2020)	C&E	No
	Data-driven services	Rizk et al. (2018)	C&E	Yes
	Big data business models	Schroeder (2016)	C&E	No
	Data-infused business model innovation	Schüritz and Satzger (2016)	C&E	Yes
	Revenue models for data-driven services	Schüritz et al. (2017)	C&E	No
	Smart interactive services	Wünderlich et al. (2013)	E	No
Manu-facturing	Data-driven services in manufacturing industries	Azkan et al. (2020)	C&E	No
	Industrial service systems enabled by digital product innovation	Herterich et al. (2016)	C&E	No
	Data-driven business models for manufacturing companies in Industry 4.0	Müller and Buliga (2019)	C&E	Yes
	Data-driven industrial services	Schuh and Kloz (2017)	C&E	No
	Smart machines in the mechanical engineering industry	Scharfe and Wiener (2020)	C&E	No
FinTech	Service offerings of consumer-oriented FinTech startups	Gimpel et al. (2018)	C&E	Yes
Smart living	Smart services for smart living	Fischer et al. (2020)	C&E	Yes
Logistics	Data-driven business models in logistics	Möller et al. (2020)	C&E	No
Smart city	Urban data business models	McLoughlin et al. (2019)	C&E	No
Car data market-places	Data marketplaces in the automotive industry	Bergman et al. (2022)	C&E	Yes
Methodological approach: C = conceptual, E = empirical, C&E = conceptual & empirical				

to increase exponentially (Karmanska, 2021). As a result, industry incumbents (e.g., legacy OEMs) and new entrants (e.g., startups) in the evolving automotive ecosystem are seeking to transform the data generated by cars into valuable information and, ultimately, to innovate products, services, and business models that leverage this information (Kaiser et al., 2021; Nischak & Hanelt, 2019).

Accessing vehicle data is critical for implementing data-driven business models, and researchers from different disciplines have recently begun to identify early approaches to monetizing these valuable data assets. For example, Kaiser et al. (2017b), investigate OEMs' digital service strategies and the novel business models established by connected car startups. OEMs offer services such as remote car (un-)locking, real-time traffic information, and intelligent emergency calls, which are integrated into digital service platforms such as BMW ConnectedDrive, Mercedes me connect, and VW Car-Net. Since OEMs typically retain exclusive access to car data, third-party service providers (e.g., startups, insurers, suppliers) are forced to find alternative technical gateways that offer equal access options. To address this issue, Martens and Mueller-Langer (2020) identified four alternative data access options for independent service providers. A number of startups, including Mojio, Vinli, and Zubie, have chosen to use telematics-equipped "dongles" that plug into the on-board diagnostics (OBD) interface for remote data access (Coppola & Morisio, 2016; Pütz et al., 2019; Soley et al., 2018). However, because such OBD dongles entail time-consuming installations, expensive hardware purchases, and limited data quality, another option for third-party data access has recently emerged that does not require additional hardware and is directly supported by OEMs (Sterk et al., 2023a). Emerging data marketplaces, such as Caruso Dataplace or Otonomo, serve as neutral intermediaries that enable OEMs to sell multi-brand vehicle data to independent service providers (Kaiser et al., 2021; Martens & Mueller-Langer, 2020). Bergman et al. (2022) explore business model archetypes of such data marketplaces, ranging from private to independent ownership and from a hierarchical to a market orientation.

Even though several aspects of the automotive data value chain have been investigated, we have observed through an initial literature review that a synthesis of existing knowledge on DDBM in the connected car domain is lacking in existing research. We aim to address this gap by developing a taxonomy and archetypes to consolidate this knowledge and guide future research in this field. In this way, we are responding to the recent calls for IS research to take a more active role in the discussions on leveraging the emergence of connected, autonomous, shared, electric (CASE) vehicles to design a smart, sustainable mobility ecosystem beneficial to users, mobility providers, and the environment (Ketter et al., 2022). Our research contributes to the initial steps in IS research to develop and evaluate digitally enabled business models for smarter, more sustainable mobility, balancing profitability, customer value, and sustainability (Ketter et al., 2022).

Lastly, the connected car is a key facilitator of DDBMs in general due to several reasons: (1) the established data sharing mechanisms and data marketplaces facilitate the rapid deployment of DDBMs, (2) the expected mass market entry of connected cars points to significant scalability potential for new DDBMs, (3) connected cars have a broader range of sensors and actuators compared to other mass-connected products like smartphones or smart meters; and (4) within the mobility and transportation sectors, connected cars are the focal point of most DDBMs. Therefore, a better understanding of connected car business models could also serve as a leading indicator of future DDBMs in other domains.

4.3 Research Design

Our research follows a sequential mixed methods design (Venkatesh et al., 2013, 2016) to provide a taxonomy and archetypes of business models in the connected car domain. This procedure allows us to generate rich insights by combining qualitative and quantitative methods in the same inquiry. Mixed methods research is particularly well-suited to "provide a holistic understanding of a phenomenon for which extant research is fragmented, inconclusive, and/or equivocal" (Venkatesh et al., 2016, p. 36), which holds for the relatively unexplored area of classifying connected car business models. Our research design comprises two major sequential iterations (see Figure 4.1), each with three phases, adopting the structure of previous studies (e.g., Weking et al., 2020). In the first iteration, we design and evaluate the taxonomy by adapting Nickerson et al.'s (2013) taxonomy development method and supplementary evaluation guidelines (Kundisch et al., 2022; Szopinski et al., 2020). In the second iteration, we build on the results of the first iteration to develop and evaluate archetypes by conducting a cluster analysis (Kaufman & Rousseeuw, 1990) and interpreting the results.

4.3.1 Iteration 1: Taxonomy Development

The first iteration of our research design focuses on developing a taxonomy that adopts the methodological approach Nickerson et al. (2013) suggested to guide our design process. At the outset, we defined the meta-characteristics that reflect the

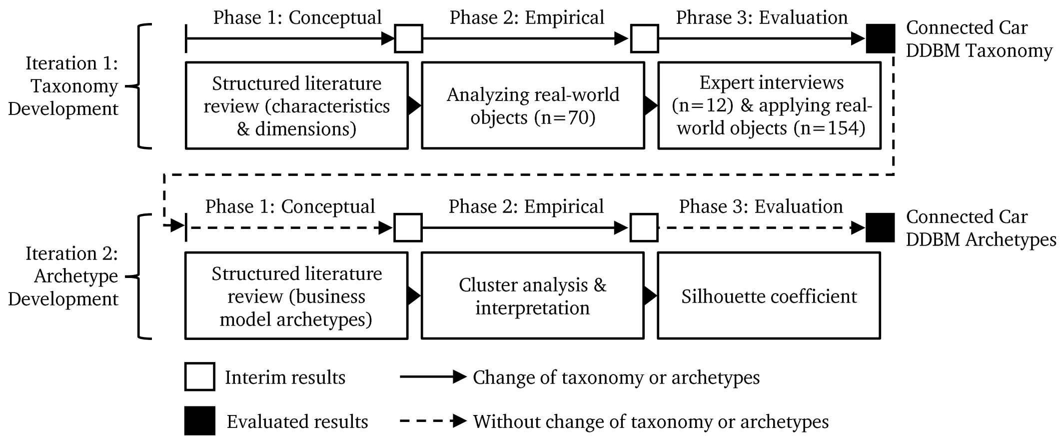


Figure 4.1.: Research design of the mixed methods approach in two consecutive iterations consisting of three phases.

taxonomy's purpose and foundation as the components of connected car business models. All dimensions must be a consequence of this meta-characteristic and help to describe the structural differences observed in connected car business models. As we found the "V^4 business model framework" by Al-Debei and Avison (2010) compelling or guiding this process, we embraced their framework and integrated our meta-characteristic into it. Consequently, we choose the V^4 concepts (i.e., value proposition, value architecture, value network, and value finance) as meta-dimensions, ensuring that each dimension in the taxonomy corresponds to one of these concepts. We also established ending conditions to define when the iterative taxonomy development process is terminated, following Nickerson et al.'s (2013) proposed conditions. With these foundations in place, we proceeded with the taxonomy development and evaluation process in three phases.

Phase 1: Structured Literature Review (Conceptual)

In our initial phase, we adopt the conceptual-to-empirical approach of Nickerson et al.'s (2013) taxonomy development method. Thereby, we build on the existing literature by conducting a structured literature review, following the methodological suggestions of Vom Brocke et al. (2009) and Webster and Watson (2002). The literature base is established by querying various interdisciplinary research databases[2] to identify articles that match our search term[3] in title, abstract, or keywords. Our initial search yielded a total of 787 studies, of which 547 remained after removing

[2]AIS Electronic Library, Emerald Insight, IEEEXplore Digital Library, ProQuest, ScienceDirect/Scopus, Web of Science
[3]"business model*" AND (connected OR data* OR digital*) AND (car* OR vehicle* OR automotive*)

duplicates (see Figure 4.2). To assess their relevance to our study, we analyzed the title and abstract of each article and chose 133 of them. Afterward, we reviewed the article's full text, applying four inclusion criteria: the study must (1) examine at least one of the four business model dimensions represented by the taxonomy's meta-characteristics, (2) focus on the connected car domain, (3) be available in English, and (4) be peer-reviewed. This process yielded 29 relevant articles, and 16 additional articles were included through forward and backward searching, resulting in a total set of 45 articles.

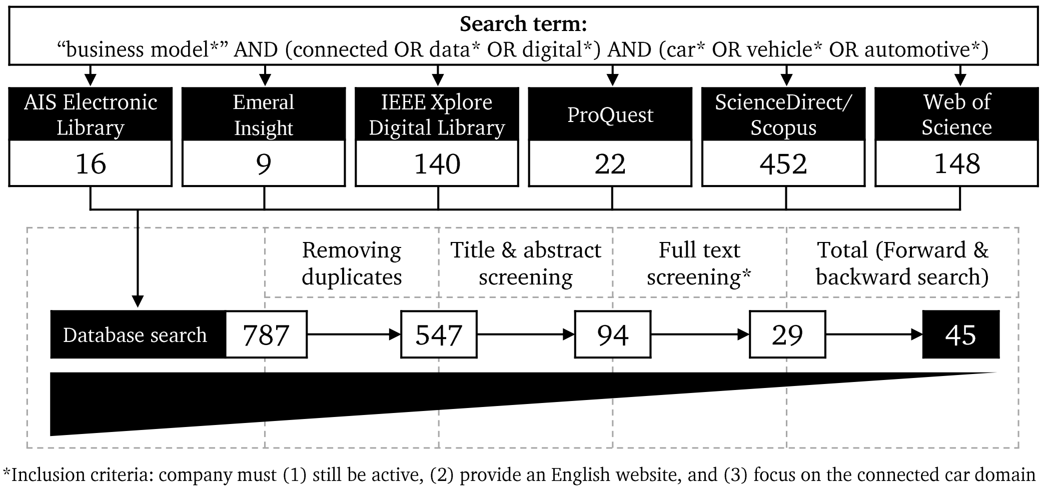


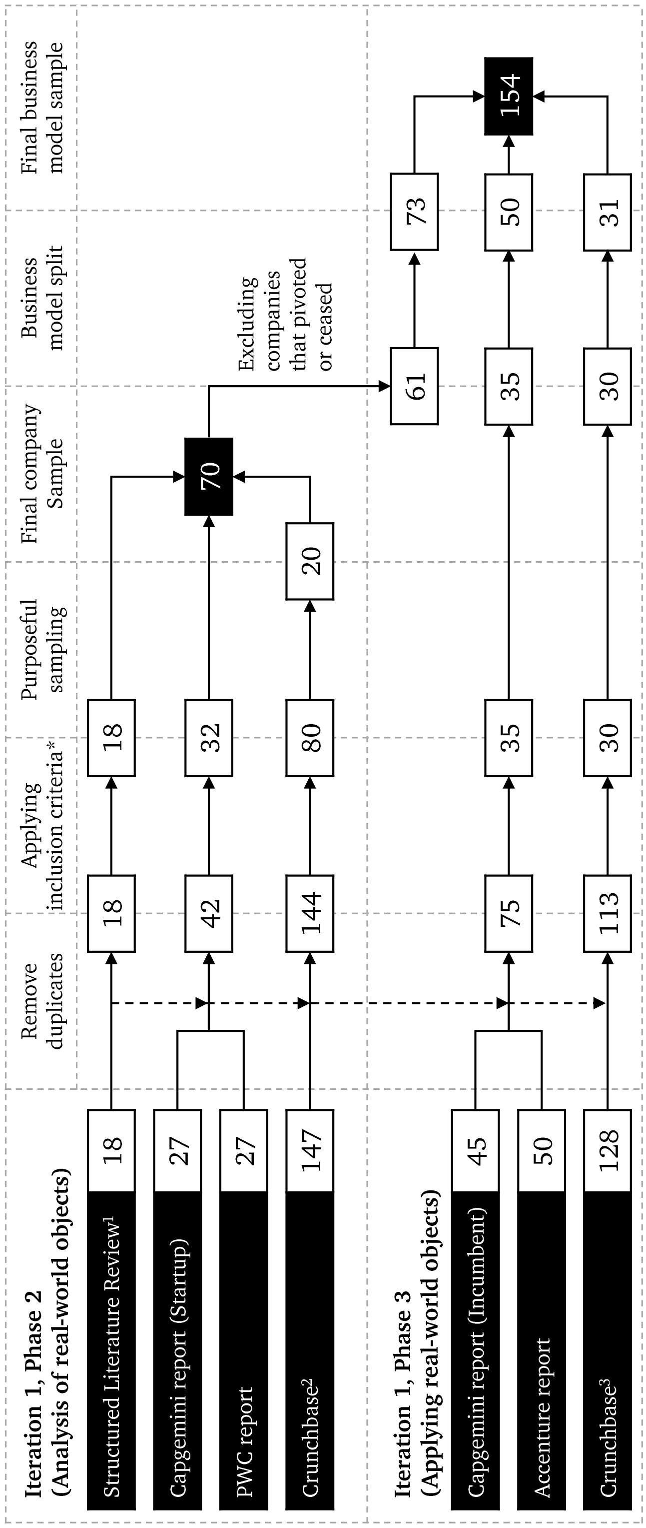
Figure 4.2.: Literature search process.

Next, we used the 45 articles identified to derive an initial set of taxonomy dimensions and characteristics. The selected articles were analyzed for recurring themes, frameworks, or models to categorize the subject matter. This led us to twelve articles that were most suitable to guide concrete concepts for our taxonomy, such as dimensions, their definitions, and the associated characteristics. The remaining articles helped throughout the work to contextualize the research field concerning connected car business models and to situate our findings in the existing literature. We uniformly summarized and named the identified taxonomy dimensions and characteristics and mapped them to the superordinate dimensions of Al-Debei and Avison (2010). Overall, we discovered a total of four primary taxonomy dimensions during our analysis: value for customer (Coppola & Morisio, 2016; De, 2018), *data access* (Bosler et al., 2017; Coppola & Morisio, 2016; Kaiser et al., 2017b; Martens & Mueller-Langer, 2020), *role in ecosystem* (Kaiser et al., 2017b, 2021; Rahman & Tadayoni, 2018; Riasanow et al., 2017; Stocker et al., 2017), and *revenue model* (De, 2018; Kukkamalla et al., 2020; Mikusz & Herter, 2016; Mikusz et al., 2015). These dimensions were supported by 16 corresponding characteristics representing different manifestations within these dimensions for connected car business models.

Phase 2: Analysis of Real-World Objects (Empirical)

In the next phase, we used an empirical-to-conceptual approach to examine real business models in the connected car domain and aimed to link our conceptual findings to real-world phenomena. To build a comprehensive and representative dataset of connected car business models, we decided to query different sources and examine the sample in a sequential analytical procedure. First, we extracted 18 real-world examples (i.e., companies) from six out of the 45 articles from the previously conducted SLR (i.e., Bosler et al., 2017; Kaiser et al., 2017b, 2021; Rahman and Tadayoni, 2018; Stocker et al., 2017). Next, we expanded our sample using two practitioner-oriented business reports published by leading consulting firms: Capgemini's report (Arif et al., 2019) helped us identify 27 emerging startups, and PwC's report (PwC, 2020) added 27 leading companies. Finally, we also queried Crunchbase, the world's largest startup database, and obtained 147 companies using the search term "connected car". After removing duplicates, we were left with 204 companies for further review. Third, we reviewed the companies' websites and applied three inclusion criteria—the company must (1) still be active, (2) provide an English website, and (3) focus on the connected car domain—resulting in a set of 130 potentially relevant companies. However, we only included 70 of the 130 identified companies in the further taxonomy development process to avoid overrepresenting the startup share within the sample. Thus, we excluded 60 of the companies stemming from the Crunchbase source in a purposive sampling approach (Bryman, 2016). Figure 4.3 gives a detailed overview of our company selection approach, and Table A.1 in the Appendix shows the sample with the name and references of each company.

We subsequently scanned the company websites for dimensions and characteristics to add to the preliminary taxonomy artifact. By analyzing the companies that emerged from the SLR, we identified three additional dimensions (i.e., *customer segment, vehicle ownership,* and *data monetization*) and added 13 characteristics to our taxonomy. We also examined the websites of the consulting sub-sample, which revealed seven characteristics and three further dimensions, namely *data personalization, influence of car data,* and *influence of autonomy*. Finally, we analyzed the Crunchbase sub-sample but did not identify any further dimensions or characteristics, confirming the existing dimensions and characteristics of the taxonomy and



[1] Databases: AIS Electronic Library, Emerald Insight, IEEEXplore Digital Library, ProQuest, ScienceDirect/Scopus, Web of Science
Search term: "business model*" AND (connected OR data* OR digital*) AND (car* OR vehicle* OR automotive*)
[2] Search term: "connected car"
[3] Search term: "connected car" AND "connected vehicle" AND "connected mobility" AND "car data" AND "vehicle data"
* Inclusion criteria: company must (1) still be active, (2) provide an English website, and (3) focus on the connected car domain

Figure 4.3.: Company and business model selection process in Phase 2 and 3 of the first iteration.

suggesting theoretical saturation. According to Nickerson et al. (2013), the ending conditions were met, and the taxonomy development process was terminated.

Phase 3: Expert Interviews and Applying Real-World Objects (Evaluation)

We extended Nickerson et al.'s (2013) original taxonomy development process considering recent suggestions (Kundisch et al., 2022; Szopinski et al., 2019). Therefore, as the final phase of the first iteration, we evaluated the taxonomy by applying Szopinski et al.'s (2019) taxonomy evaluation framework. We performed two successive episodes using both qualitative and quantitative methods. In the first episode, we conducted twelve expert interviews, six with practitioners and six with academic researchers with extensive experience in data-driven business models, connected cars, and/or taxonomy building (see Table 4.2). We used a semi-structured approach based on the suggestions of (Myers & Newman, 2007) and asked questions about the taxonomy's adequacy, completeness, and relevance, encouraging an open discussion. We also solicited suggestions to modify the taxonomy, such as adding, renaming, or removing dimensions or characteristics based on Kundisch et al.'s (2022) basic taxonomy operations on taxonomy elements. All interviews were conducted by two authors using video-conferencing software, lasted on average 38 minutes, and were recorded, transcribed, and then analyzed using MAXQDA software. With this process, we qualitatively evaluated the taxonomy on the criteria of comprehensibility, completeness, perceived usefulness, and the level of abstraction of characteristics and dimensions.

Table 4.2.: Overview of interviewees with background, role, institution, and expertise.

Background	Role of Interviewee	Institution	Expertise
Corporate	Managing Director	Consulting Firm	DDBMs, Connected Cars
	Managing Director	Consulting Firm	DDBMs, Connected Cars
	Lead Software Developer	Tier 1 Supplier	DDBMs, Connected Cars
	Business Developer	Tech Company	DDBMs, Connected Cars
	Head of Sales	Data Marketplace	DDBMs, Connected Cars
	Product Owner	Car Manufacturer	DDBMs, Connected Cars
Academia	Postdoctoral Researcher	University	DDBMs, Connected Cars
	Postdoctoral Researcher	Research Center	DDBMs, Connected Cars
	PhD Candidate	University	DDBMs, Taxonomies
	PhD Candidate	University	DDBMs, Taxonomies
	PhD Candidate	University	DDBMs, Taxonomies
	PhD Candidate	University	DDBMs, Taxonomies

In the next step, we used Mayring's (2000) qualitative content analysis as a flexible research technique to analyze and interpret the qualitative interview data (Krippendorff, 2019). In doing so, we conducted a deductive coding approach, employing the previously defined meta-characteristics and tentative taxonomy dimensions and characteristics as our coding scheme to analyze the interview data in a structured manner. Based on the resulting codes, we applied taxonomy operations such as adding, renaming, swapping, splitting, or deleting dimensions or characteristics (Kundisch et al., 2022). To ensure the validity and robustness of the coding process, we independently analyzed the data with two authors and critically reviewed and discussed it with a third author. Finally, we compared the identified codes with the initial version of the taxonomy, incorporated them, and produced the final version of the taxonomy artifact (see Table 4.3). More details on the taxonomy operations on specific elements and the taxonomy's changes after the evaluation can be found in Table A.2 in the Appendix.

After redesigning the taxonomy, we conducted a second evaluation episode to assess its practical applicability and usefulness in classifying, differentiating, and comparing real-world objects, using the evaluation criteria robustness, utility, efficacy, stability, and completeness. As we did not want to base the evaluation only on objects already used in the previous taxonomy development process in Phase 2, we expanded our sample (n = 70) to include more connected car companies that had not previously been involved. However, nine companies were excluded from our initial sample for changing their business focus or exiting the market. To find more established companies in the connected car domain, we referred to practitioner-oriented reports from consulting firms such as the Capgemini report (Arif et al., 2019), which listed 45 incumbent firms, and an Accenture report (Gruendinger & Seiberth, 2018), which identified 50 additional incumbent firms. We also queried Crunchbase with an extended search term[4] and obtained 351 startups, of which we excluded 223 that had not received funding. After removing duplicates and comparing the remaining companies to those included in Phase 2, we were left with 188 companies. When reviewing the companies' websites, we applied the three inclusion criteria from the previous phase, resulting in a set of 65 relevant companies. During this analysis, we noticed that many of the selected companies offered multiple connected car business models, which we separated into distinct objects of analysis (e.g., Google split into Android Auto, Android Automotive OS, Google Automotive Services, and Google Maps). We also returned to the 61 companies from Phase 1 to identify any additional underlying business models that had not been adequately considered. In total, we found 28 additional business models, leading to a final set of 154 objects. Figure 4.3 depicts the overall selection process, and the final business model sample is presented in Table A.1 in the Appendix.

[4]"connected car*" OR "connected vehicle*" OR "connected mobility" OR "car data" OR "vehicle data"

The identified set of objects was then classified based on the dimensions and characteristics of the taxonomy. Here, a single author classified the 154 business models according to the definitions provided in Table 4.4, which served as a codebook for provisional coding (Hunke et al., 2021; Saldaña, 2009). To verify the quality of the classification, a random sample of 10 % of all business models (n = 15) was coded individually by three independent raters. Fleiss's (1971) Kappa was used to measure the degree of agreement, which resulted in a value of 63 %, indicating "substantial agreement" according to Landis and Koch (1977). Furthermore, the responses of the three individual raters were compared to the original classification by one of the authors, which yielded a Fleiss' Kappa value of 64 %, also indicating "substantial agreement." Based on these results, it can be assumed that our taxonomy meets our evaluation criteria and is suitable for a coherent classification and concise description of connected car business models.

4.3.2 Iteration 2: Archetype Development

In the second iteration of our work, we developed a set of business model archetypes, salient configurations of our taxonomy. To ensure rigor and relevance, we incorporated input from the existing literature and real-world objects throughout the process. We performed two primary design activities: a quantitative cluster analysis (Kaufman & Rousseeuw, 1990) to identify groups of similar real-world objects and a qualitative cross-table analysis of the clustering solution (Hambrick, 1984) to interpret the clusters and derive meaningful archetype descriptions. Finally, we evaluated the results by determining the silhouette width (Kaufman & Rousseeuw, 1990), which provides a reference value for the structural strength of the clusters.

Phase 1: Structured Literature Review (Conceptual)

The initial stage of our second iteration builds upon the previous literature review, using the set of 45 formerly identified academic articles. We systematically reviewed the articles to obtain an initial set of 15 potential business model archetypes, primarily based on four articles that focused on different application domains: *in-vehicle infotainment* (n = 3) (Bosler et al., 2017), *data trading* (n = 4) (Bergman et al., 2022), *data access* (n = 4) (Möller et al., 2020), and *connected cars in general* (n = 4) (Bohnsack et al., 2021). In the subsequent phases of this iteration, we incorporate the findings of this step to interpret the quantitative results of the cluster analysis. This allows us to develop appropriate labels, definitions, and descriptions for the identified archetypes.

Phase 2: Cluster Analysis and Interpretation (Empirical)

In the next phase, we conducted an initial agglomerative cluster analysis using the R statistical analysis package to identify groups of similar objects in the sample of 154 real-world business models (see Table A.1 in the Appendix). We created a dataset of these objects using dichotomous variables representing the characteristics within each dimension of the business model taxonomy. Each row in the dataset represents an object (i.e., a connected car business model), and each column is a taxonomy characteristic assigned a value of 1 if identified in the corresponding real-world object and 0 if not. Due to publicly unavailable information for some objects regarding the revenue model dimension, we excluded the related characteristics to avoid skewing the results, leaving nine dimensions and 41 characteristics for the cluster analysis. We measured the distance between all pairs of observations using Gower's (1971) distance measure and computed a dissimilarity matrix as a mathematical expression of how different the observations in the dataset are. This allowed us to group the closest observations or separate the most distant ones as a basis to derive clusters.

We calculated the agglomerative coefficient (Rousseeuw, 1986) to measure the quality of the clustering structure and compare the five most common hierarchical clustering algorithms, single, complete, average, McQuitte, and Ward. This value ranges from 0 to 1, with values closer to 1 indicating a more balanced and robust clustering structure with a better dendrogram. Of the five algorithms used, Ward.D2, also known as the minimum variance method, produced the most balanced clustering structure and was clearly superior to the others. In addition, Ward's (1963) method is prevalent among researchers and is a commonly used method for determining archetypes that are also used by many other researchers (Gimpel et al., 2018; Hunke et al., 2021; Remane et al., 2016a; Weking et al., 2020).

Agglomerative hierarchical clustering merges clusters to generate a solution for all possible numbers of clusters (Backhaus et al., 2011; Gimpel et al., 2018). The partitioning into clusters within the dendrogram can be visually identified by moving a horizontal cut-off line. However, determining the most appropriate number of clusters is a known problem without clear recommendations (Wu, 2012). To address this, we used a common set of 13 measures (Gimpel et al., 2018; Passlick et al., 2021) to derive an appropriate number of clusters for our business model archetypes, as listed in Table A.3 of the Appendix. However, each algorithm applied resulted in a different number of suggested clusters, ranging from 1 to 14. Thus, we used an interpretative approach to derive an appropriate number of cluster groups, following recent suggestions (e.g., Nahr and Heikkilä, 2022). We ran several iterations, selecting different numbers of cluster groups, visually evaluating the dendrogram, and comparing the interpretability and informative power of the results. In the end, we chose a clustering output with seven cluster groups, which were the most meaningful results given our previous research insights. The selected cluster groups represented a compromise between the manageability of the overall cluster solution and homogeneity within each cluster (Backhaus et al., 2011; Milligan & Cooper, 1985; Sneath & Sokal, 1973), resulting in easily distinguishable and explainable archetypes. Figure 4.4 illustrates the dendrogram, highlighting the final set of seven cluster groups.

Finally, we undertook two qualitative interpretive steps to label and describe the business model archetypes based on the cluster analysis results. First, we performed a within-cluster analysis by re-reading all the collected data on the business models assigned to each cluster. Second, we conducted a cross-table analysis (see Table 4.5), inspecting the frequency distributions of each cluster's characteristics to identify the most pronounced ones (Hambrick, 1984). Based on this bipartite analysis, we derived archetype labels for the seven clusters: (A1) data platforms, (A2) location-based services, (A3) fleet management, (A4) diagnostics and maintenance, (A5) driving analytics, (A6) cyber-physical protection, and (A7) connected infotainment.

Phase 3: Silhouette Coefficient (Evaluation)

In the final phase of the second iteration, we evaluated each cluster's structural strength using the average silhouette width as a measure of cluster validity, which ranges from 1.00 (proper clustering) to -1.00 (incorrect clustering) (Rousseeuw, 1987). We applied a threshold of 0.25 as a minimum for the silhouette coefficient to indicate a substantial structure in the data, as recommended by Kaufman and Rousseeuw (1990). All seven clusters had an average silhouette width of 0.34 or greater, indicating sufficiently strong cluster structures. Clusters A1 ($s = 0.70$), A2 ($s = 0.66$), A3 ($s = 0.57$), A4 ($s = 0.51$), A6 ($s = 0.64$), and A7 ($s = 0.56$) had highly positive average silhouette widths, which we interpret as reliable indicators of valid clusters. Although cluster A5 ("Driving Analytics") had a lower value of $s = 0.34$, it still met the threshold ($s \geq 0.25$) and was considered valid. Consequently, our quantitative evaluation suggested that all seven clusters and archetypes constitute a meaningful representation of the data sample and the phenomenon under study. Figure A.1 in the Appendix shows the corresponding silhouette plot, with an average width of 0.56 for the sample of $n = 154$.

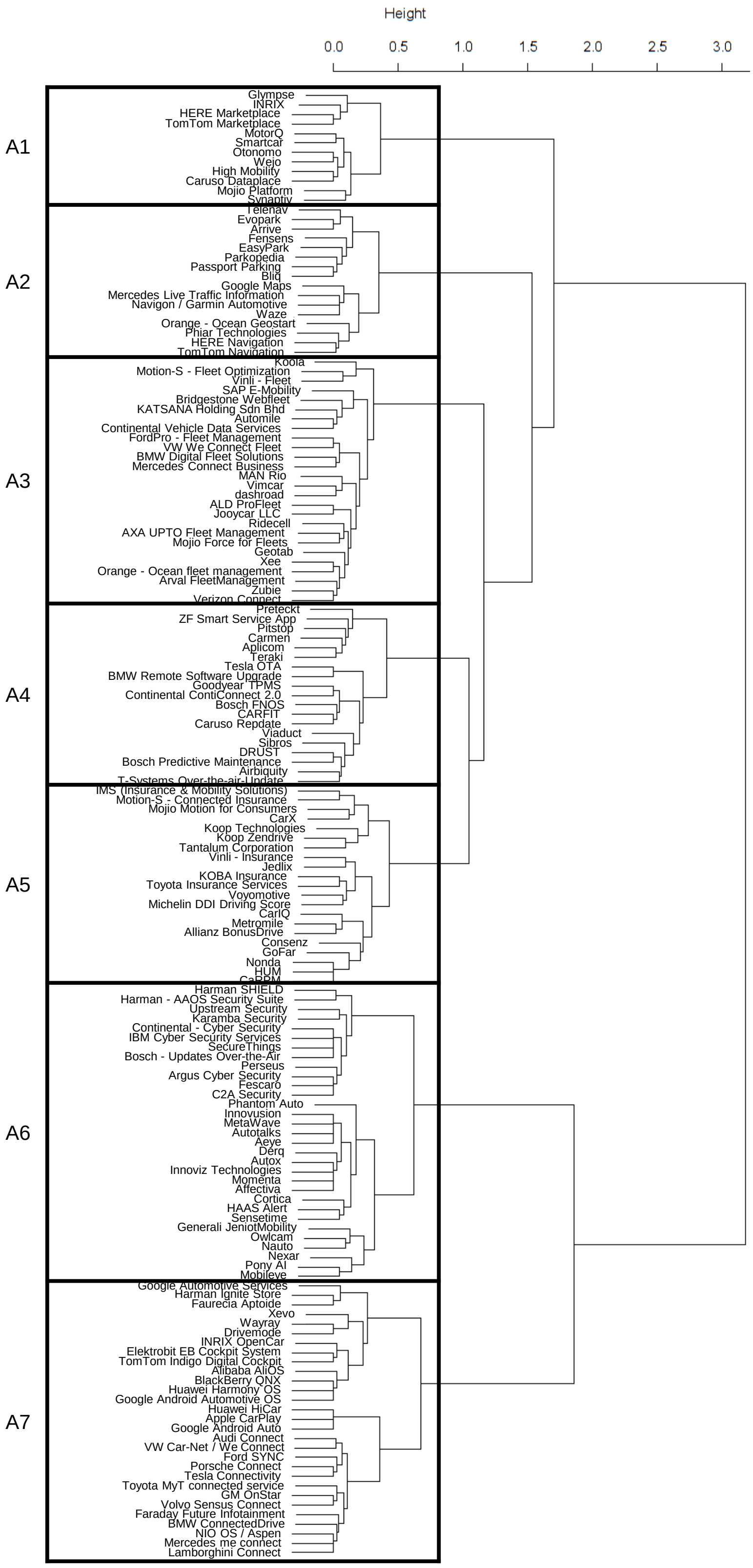


Figure 4.4.: Results of Ward.D2 clustering visualized by a dendrogram with seven cluster groups.

4.4 Results

We now present the results of our research, an empirically and theoretically grounded taxonomy of data-driven business models in the connected car domain, and seven corresponding business model archetypes. Since we have already communicated an intermediate state of the taxonomy in detail in a conference article (Sterk et al., 2022c), our results section focuses on the second artifact, the business model archetypes.

4.4.1 A Taxonomy of Connected Car Business Models

Our research's first interim result is a taxonomy of connected car business models comprising ten dimensions with 48 corresponding characteristics. Table 4.3 provides an overview of the complete taxonomy in the form of a morphological box, and Table 4.4 provides the respective definitions for each dimension and characteristic. We employed two mutually exclusive dimensions and eight non-exclusive dimensions. The right-hand column of Table 4.3 indicates whether a dimension is exclusive (E), such as *car autonomy impact on value*, or non-exclusive (N), such as *role in ecosystem*. Additionally, the superscript numbers in Table 4.3 indicate the phase in which dimensions or characteristics were added or last revised.

Table 4.3.: Taxonomy of data-driven business models in the connected car domain.

	Dimension	Characteristic							E/N*
Value Proposition	Value for car owner or driver[3]	Safety & security[1]	Cost reduction[1]	Traffic efficiency[1]	Infotainment[1]	Environmental sustainability[3]	Convenience[1]	Indirect value[3]	N
Value Proposition	Car data impact on value[3]	Car data core business model[2]	Car data-enabled business model[2]						E
Value Proposition	Car autonomy impact on value[3]	Enhanced value by autonomy[2]	Reduced value by autonomy[2]	Autonomy not relevant[2]					E
Value Architecture	Data category[3]	PII[3]	Contextual data[3]	Diagnostic data[3]	Usage data[3]	ADAS data[3]	Application data[3]		N
Value Architecture	Data access[1]	OEM proprietary access[3]	OEM specific cloud or neutral server[3]	OBD2-dongle[1]	Other retrofit devices[3]	Smartphone or other non-in-vehicle sources[3]			N
Value Architecture	Enabler technology[3]	Blockchain[3]	Augmented reality[3]	Over-the-air architectures[3]	ADAS Technology[3]	Artificial intelligence[3]	Cellular networks[3]		N
Value Network	Role in ecosystem[1]	End-customer solution provider[1]	Platform provider[1]	Technology provider[2]					N
Value Network	Customer segment[2]	Private individuals (B2C)[3]	Fleet providers (B2B)[3]	OEMs (B2B)[3]	Third-party providers (B2B)[3]	Governments (B2G)[3]			N
Value Finance	Data monetization strategy[3]	Data source & data provision[3]	Data aggregation & data exchange[3]	Data analysis & data insights[3]	Data application & data service[3]				N
Value Finance	Revenue model[1]	One-time payment[3]	Pay-per-use[3]	Subscription fee[1]	Licensing fee[1]	Commission fee[3]	On-demand[2]	Open source[3]	N

*E = Exclusive dimension (one characteristic observable); N = Non-exclusive dimension (more than one characteristic observable)
Dimensions and characteristics were added or revised in the following development phase: [1] phase 1, [2] phase 2, or [3] phase 3

Table 4.4.: Definitions of taxonomy dimensions and characteristics.

Value for car owner or driver	What are the direct benefits for the car owner or car driver?
Safety & security	Created value increases safety or security
Cost reduction	Created value reduces costs
Traffic efficiency	Created value increases traffic efficiency
Infotainment	Created value improves infotainment (i.e., information or entertainment)
Environmental sustainability	Created value increases environmental sustainability
Convenience	Created value increases convenience
Indirect value	Car owner or driver indirectly benefits from the solution
Car data impact on value	What is the impact of car data on the main value proposition?
Car data core business model	Solutions are only implemented through access to vehicle data
Car data-enabled business model	Solutions where vehicle data is not the core of the application (i.e., infotainment system)
Car autonomy impact on value	What is the impact of the car's autonomy on the main value proposition?
Enhanced value by autonomy	Value proposition is enhanced in case of car autonomy
Reduced value by autonomy	Value proposition is enhanced in case of car autonomy
Autonomy not relevant	Value proposition is enhanced in case of car autonomy
Data category	What are the required types of data to enable the business model?
PII	Personally identifiable information (e.g., phone number, biometric data)
Contextual data	External road and environmental conditions (e.g., ice warning)
Diagnostic data	Technical status of the vehicle (e.g., diagnostic trouble codes)
Usage data	Vehicle usage data of the vehicle (e.g., speed, location)
ADAS data	Data generated by advanced driver assistance-systems (e.g., radar data)
Application data	Data stored by applications running on the infotainment system or driver's smartphone connected to the vehicle
Data access	Which technical gateways enable acceding the required data for the company?
OEM proprietary access	Exclusive data access of the OEM
OEM-specific cloud or neutral server	Data access directly from the OEM's cloud or via data marketplaces acting as neutral server
OBD2-dongle	A dongle is plugged into the on-board diagnostic port to access in-vehicle data
Other retrofit devices	Data is collected using retrofitted vehicle sensors (e.g., dash cams)
Smartphone or other non-in-vehicle sources	Data is collected using smartphone sensors (e.g., GPS, accelerometer, luminance) or other non-in-vehicle sensors
Enabler technology	What are the key technologies to enable the business model?
Blockchain	Business model is enabled by blockchain (e.g., smart contracts)
Augmented reality	Business model is enabled by augmented reality (e.g., augmented reality head-up displays)
Over-the-air architectures	Business model is enabled by OTA architectures (e.g., software or feature over-the air updates)
ADAS technology	Business model is enabled by advanced driver assistance-systems (e.g., lidar, camera, radar)
Artificial intelligence	Business model is enabled by artificial intelligence (e.g., predictive maintenance)

Table 4.4.: Definitions of taxonomy dimensions and characteristics (continued).

Role in ecosystem	Which role does the company play for the other network actors?
End-customer solution provider	Company offers end-customer solutions for specific use cases (e.g., usage-based insurance)
Platform provider	Company offers multi-sided platform business models (e.g., data marketplaces)
Technology provider	Company offers technological hardware and software solutions (e.g., sensor technology enabling car data collection)
Customer segment	To whom does the company provide its offerings?
Private individuals (B2C)	Offering is provided to private drivers (i.e., business-to-consumer)
Fleet providers (B2B)	Offering is provided to fleet providers, mobility service providers, or logistic service providers (i.e., business-to-business)
OEMs (B2B)	Offering is provided to original equipment manufacturers (i.e., business-to-business)
Third-party providers (B2B)	Offering is provided to third-party providers (i.e., business-to-business)
Governments (B2G)	Offering is provided to public authorities (i.e., business-to-government)
Data monetization strategy	How does the company capture monetary value from the data?
Data source & data provision	Company operates as car data source and provider
Data aggregation & data exchange	Company operates as car data aggregator for data exchange
Data analysis & data insights	Company provides car data-based analysis and insights
Data analysis & data insights	Company provides car data-driven applications and services
Revenue model	How does the company generate revenue or income from each customer segment?
One-time payment	Revenue is generated by direct one time-sale of data or hardware
Pay-per-use	Fees can be charged based on usage, such as pay per kilometer
Subscription fee	Fees are generated by subscriptions
Licensing fee	Fees are generated by permitting customers to use protected intellectual property in exchange
Commission fee	Fees charged for an intermediate service such as trading vehicle data through marketplaces
On-demand	Pricing is tailored to the individual request of a specific customer
Open source	Source code made freely available for modification and redistribution

4.4.2 Archetypes of Connected Car Business Models

As a second research outcome, we present seven connected car business model archetypes that are distinctive configurations of real-world business models. Each archetype is associated with a cluster of twelve to 31 cases and has different centers along the characteristics of the taxonomy. The cross-table results from the cluster analysis provide an overview of the frequency distribution of the taxonomy characteristics for each archetype (see Table 4.5). By analyzing the companies in the seven different cluster groups and the corresponding cross-table results, we developed the following interpretive labels for the archetypes: (A1) data platforms, (A2) location-based services, (A3) fleet management, (A4) diagnostics and maintenance, (A5) driving analytics, (A6) cyber-physical protection, and (A7) connected infotainment. Table 4.6 summarizes the seven archetypes, highlights their distinguishing characteristics, and provides examples of typical applications. The subsequent section provides a more comprehensive explanation of the archetypes and illustrates them using business models (BM) extracted from our sample (see Table A.1 in the Appendix).

Archetype 1: Data Platforms

The first cluster comprises *data platforms* that operate marketplaces for trading vehicle data between companies. These data marketplaces act as neutral intermediaries that allow data owners, such as OEMs or fleet operators, to monetize collected vehicle data by selling it to independent service providers, who use it to develop data-driven services (Möller et al., 2020). The primary value proposition of this business model archetype is to provide a single point of access for vehicle data (Kaiser et al., 2021), along with necessary enabling functionalities such as consent management and secure data exchange between parties.

Prominent examples of this archetype include Otonomo (BM22), Caruso Dataplace (BM7), and High Mobility (BM13). Besides these traditional marketplaces for vehicle data, navigation service providers like HERE (BM89) and TomTom (BM104) distribute contextual data, including geospatial, weather, traffic, or map data, that can be used for location-based services. Data platforms harmonize the received vehicle data in a standardized format, so independent service providers only need to integrate their technology stack with one application programming interface (API) instead of dealing with multiple relationships with different data owners and individual data formats (Stocker et al., 2021). Accordingly, standardized data access provides indirect value for vehicle owners or drivers by incentivizing the development of third-party services. At the same time, OEMs retain control over what data is available and which services can access it.

Archetype 2: Location-Based Services

The second archetype involves *location-based services* that use GPS location data enriched with traffic, weather, and parking data to enhance transportation efficiency and minimize travel time, for instance, through route optimization or real-time parking assistance. For example, navigation services like Google Maps (BM12), HERE (BM90), and TomTom (BM105) collect granular map data from mobile

Table 4.5.: Characteristics' frequency distribution for each archetype.

Dimension	Characteristic	Archetype						
		A1: Data platforms	A2: Location-based services	A3: Fleet management	A4: Diagnostics and maintenance	A5: Driving analytics	A6: Cyber-physical protection	A7: Connected infotainment
Number of cases per cluster		12	16	26	19	21	31	29
Value for car owner or driver	Safety & security	8 %	0 %	81 %	100 %	48 %	100 %	17 %
	Cost reduction	8 %	44 %	100 %	95 %	100 %	6 %	0 %
	Traffic efficiency	33 %	100 %	77 %	0 %	5 %	29 %	66 %
	Infotainment	0 %	0 %	0 %	0 %	0 %	3 %	100 %
	Environmental sustainability	0 %	6 %	38 %	5 %	5 %	0 %	0 %
	Convenience	0 %	50 %	19 %	63 %	24 %	0 %	100 %
	Indirect value	100 %	0 %	0 %	0 %	0 %	0 %	0 %
Car data impact on value	Car data core business model	100 %	100 %	100 %	100 %	100 %	0 %	0 %
	Car data-enabled business model	0 %	0 %	0 %	0 %	0 %	100 %	100 %
Car autonomy impact on value	Enhanced value by autonomy	0 %	100 %	0 %	68 %	0 %	90 %	100 %
	Reduced value by autonomy	0 %	0 %	0 %	0 %	24 %	6 %	0 %
	Autonomy not relevant	100 %	0 %	100 %	32 %	76 %	3 %	0 %
Data category	PII	0 %	0 %	0 %	0 %	0 %	0 %	69 %
	Contextual data	42 %	100 %	23 %	0 %	0 %	61 %	21 %
	Diagnostic data	67 %	0 %	92 %	100 %	5 %	0 %	0 %
	Usage data	67 %	0 %	100 %	0 %	100 %	97 %	100 %
	ADAS data	0 %	0 %	4 %	0 %	5 %	100 %	10 %
	Application data	0 %	38 %	12 %	0 %	43 %	19 %	86 %
Data access	OEM proprietary access	0 %	0 %	15 %	21 %	10 %	10 %	79 %
	OEM-specific cloud or neutral server	83 %	0 %	15 %	53 %	24 %	42 %	3 %
	OBD2-dongle	17 %	0 %	65 %	16 %	62 %	0 %	0 %
	Other retrofit devices	8 %	25 %	12 %	16 %	24 %	55 %	7 %
	Smartphone or another non-in-vehicle sources	17 %	100 %	12 %	0 %	29 %	3 %	14 %
Enabler technology	Blockchain	58 %	0 %	0 %	0 %	0 %	39 %	0 %
	Augmented reality	0 %	0 %	0 %	0 %	0 %	0 %	100 %
	Over-the-air architectures	0 %	50 %	4 %	100 %	0 %	100 %	76 %
	ADAS technology	0 %	100 %	0 %	0 %	5 %	100 %	0 %
	Artificial intelligence	0 %	6 %	100 %	100 %	19 %	3 %	0 %
	Cellular networks	100 %	0 %	23 %	100 %	100 %	3 %	0 %
Role in ecosystem	End-customer solution provider	25 %	100 %	100 %	100 %	100 %	23 %	66 %
	Platform provider	100 %	0 %	4 %	0 %	5 %	3 %	24 %
	Technology provider	0 %	0 %	0 %	0 %	0 %	100 %	55 %
Customer segment	Private individuals (B2C)	0 %	44 %	0 %	16 %	57 %	16 %	100 %
	Fleet providers (B2B)	0 %	6 %	100 %	5 %	10 %	6 %	0 %
	OEMs (B2B)	100 %	44 %	0 %	53 %	33 %	74 %	45 %
	Third-party providers (B2B)	100 %	13 %	0 %	26 %	10 %	10 %	0 %
	Governments (B2G)	17 %	0 %	4 %	5 %	0 %	6 %	0 %
Data monetization strategy	Data source & data provision	100 %	0 %	0 %	0 %	0 %	100 %	59 %
	Data aggregation & data exchange	100 %	0 %	0 %	0 %	0 %	0 %	0 %
	Data analysis & data insights	0 %	38 %	12 %	84 %	100 %	6 %	0 %
	Data application & data service	0 %	100 %	100 %	47 %	67 %	0 %	66 %

Legend: 0 % - 20 % · 21 % - 50 % · 51 % - 80 % · 81 % - 100 %

Table 4.6.: Summary of the identified archetypes.

ID	Archetypes	Distinguishing characteristics	Typical applications
A1	Data platforms	• Operating as a data platform provider in the automotive ecosystem • Making car data available for third-party service providers at scale • Accessing data directly from the OEM and acting as a neutral server	Car data marketplaces, contextual data providers
A2	Location-based services	• Delivering end-customer value through navigation or parking services enhancing overall transportation efficiency • Collecting data by mobile mapping vehicles equipped with remote sensing systems • Exploiting contextual data such as external road and environmental conditions to create real-time maps	Navigation systems, parking applications
A3	Fleet management	• Addressing fleet providers, logistics service providers and mobility service providers as customer segment • Delivering end-customer value primarily in the areas of driving safety, cost reduction, and traffic efficiency • Accessing data commonly by means of retrofitted OBD2-dongles	Fleet management systems, digital driver logbooks
A4	Diagnostic and maintenance	• Analyzing diagnostic data such as trouble codes to offer proactive and predictive maintenance • Providing value not only to end-customers but also to aftermarket players such as car dealers or workshops • Utilizing over-the-air architectures to do incremental remote updates and repairs in future scenarios	Remote diagnostics services, predictive maintenance services
A5	Driving analytics	• Analyzing car usage data for monitoring driving patters and behavior • Reducing cost through pay-as-you-drive tariffs or recommendations for fuel-efficient driving • Providing driving assistance and driver tutoring to increase road safety	Usage-based insurance tariffs, applications for driving style suggestions
A6	Cyber-physical protection	• Delivering end-customer value by ensuring occupant safety and cybersecurity • Enabling data-driven business models by providing crucial and secure connected car technologies • Harboring huge future potentials, for instance trough over-the-air driver-assistance system updates	Cybersecurity solutions, driver-assistance systems
A7	Connected infotainment	• Delivering end-customer value via in-car infotainment applications • Providing a standardized platform that enables in-car third-party applications on the head unit • Increasing value through car autonomy, e.g., by watching virtual reality films or playing video games	Digital cockpit solutions, infotainment operating systems

mapping vehicles equipped with remote sensing systems and leverage dynamic, real-time geospatial information gathered by connected vehicles or devices. This rich data and location technologies enable other location-based services such as geo-fencing, hazard zone alerts, or traffic alerts. Beyond direct monetization of vehicle data through third-party services, access to granular map data is a crucial enabler for autonomous driving.

Smart parking applications are another group of location-based services that locate and navigate to available parking spaces, facilitate payment transactions, and enable parking space management. Smartphone applications, such as EasyPark (BM34) or Passport Parking (BM38), allow drivers to conveniently find available parking spaces and manage parking processes. In addition, charging station advisors make it easy to plan trips with electric vehicles. For example, Telenav (BM149) provides range estimation and route planning tools based on artificial intelligence and machine learning to ensure drivers are always close to the nearest charging station when needed.

Archetype 3: Fleet Management

The third archetype comprises companies providing *fleet management* solutions to corporate fleets, logistics and mobility service providers. Live data insights are essential for successfully managing a company's transportation activities related to a vehicle fleet (Sterk et al., 2023a). The primary value proposition in this cluster is to assist fleet managers in monitoring and reducing the total cost of ownership of the fleet. However, some services also directly or indirectly improve vehicle safety, transportation efficiency, and environmental sustainability.

Several of the business models in this cluster originate from the banking sector, such as Arval (BM48) (owned by the BNP Paribas Group) and ALD Automotive (BM45) (owned by Société Générale). These bank-backed companies offer a wide range of data-driven services, such as comprehensive reporting tools, efficient workflow management, invoice verification, and real-time insight into cost trends. Many OEMs also provide similar services to manage homogeneous fleets of their own brands, such as Ford Fleet Management (BM84) and BMW Digital Fleet (BM5). Geotab (BM32) goes a step further by offering a holistic marketplace with hundreds of in-house and third-party developed solutions in various categories, including fuel management, routing and dispatching, or maintenance and diagnostics. Some companies specialize in specific fleet software solutions for small and medium-sized businesses, such as Vimcar (BM79), the market leader in providing a digital logbook that uses an OBD2-device to collect driving data and store it in the cloud.

Archetype 4: Diagnostics and Maintenance

The fourth archetype comprises business models that use vehicle data to provide *diagnostics and maintenance* by monitoring and improving vehicle health and managing vehicle-related maintenance activities between vehicle owners and related businesses such as repair shops. The value proposition for customers is increased vehicle uptime, convenience, and cost reduction through remote services and proactive maintenance enabled by continuous vehicle monitoring. This is done by leveraging vehicle usage and diagnostic data from multiple sources, such as neutral servers, OBD2-dongles, or other retrofitted devices.

Proactive maintenance services include data-based alerts to repair shops, fleet managers, or drivers. One example is a pilot project by Bosch and BMW to automatically transmit data as part of a first notification of service (FNOS) (BM53). Based on live vehicle data, drivers receive a notification that a service or repair is due. If they agree, FNOS automatically transmits all relevant data to the preferred workshop, sends an appointment with a proposed quote, and prepares for service or repair. More advanced maintenance services go beyond reporting service needs, including remote onboard diagnostics or predictive maintenance. For example, Preteckt (BM143) offers cloud-based vehicle diagnostics to identify technical issues early before they progress to expensive repairs. Similarly, Pitstop (BM142) provides fleet managers with predictive insights to increase and balance fleet uptime and minimize maintenance costs by anticipating vehicle issues in advance and recommending appropriate actions. Other business models reduce the need for on-site vehicle service through incremental updates using over-the-air (OTA) technology. For example, T-Systems (BM100) offers network-based, OEM-independent solutions for OTA updates to improve recall rates, which can be implemented virtually without disturbing the driver.

Archetype 5: Driving Analytics

The fifth archetype covers *driving analytics* aiming to reduce usage costs incurred by the end-customers by monitoring and profiling actual driving patterns. Insurance companies have been early adopters of this archetype, offering usage-based insurance (UBI) programs that utilize dynamic behavioral data collected via OBD2-dongles, other retrofit devices (e.g., black boxes), or modern smartphones to calculate premiums (Coppola & Morisio, 2016). For example, KOBA Insurance (BM133) and Metromile (BM17) offer pay-as-you-drive insurance plans in which the vehicle owner pays a monthly rate plus a set amount for each mile driven. Other companies, including Allianz with its BonusDrive app (BM47), expand this approach to pay-how-you-drive models by monitoring and analyzing not only mileage but also risk-related data (such as braking, acceleration, or speeding) to assess driving behavior. These driving scores can be calculated for individual drivers, specific vehicles, or entire fleets.

Insurance companies also use telematics data to obtain accident reports for better claims processing. For example, IMS (BM129) provides “connected claims” that enable early detection of theft or accidents and reduce claims processing costs through data-driven decision-making. In the future, with the possibility of autonomous driving, even more comprehensive data-driven insurance tariffs can be offered. For example, Koop (BM135) sells next-generation insurance products that focus on the risks of autonomous vehicles, robotics, and automation. In addition to insurance use cases, some companies are developing applications that monitor driver behavior to provide driving assistance, such as Michelin’s Ideal Driver Pro app (BM69), which allows drivers to access a continuous analysis of their driving behavior. The results are reflected in an overall score and sub-scores (i.e., pace, adaptability, anticipation), serving as a connected driving coach.

Archetype 6: Cyber-Physical Protection

The sixth archetype refers to *cyber-physical protection* aiming to improve the physical safety of drivers and passengers, as well as the cybersecurity of the vehicle using hardware and software solutions. These business models are mainly targeted at OEMs, such as Innoviz Technologies (BM66), which provides them with hardware technologies like advanced driver assistance systems (ADAS). In addition, some startups like Nauto (BM21) offer retrofit solutions like dashcams directly to drivers or fleet managers, while others like Owlcam (BM73) use existing smartphone sensors (e.g., GPS, accelerometer, or luminance) to collect and analyze safety-related driving data.

However, both retrofitted and built-in sensor technologies raise security concerns, as decisions based on available driving data can become vulnerable targets for hackers. For this reason, newly developed or upgraded software components undergo rigorous testing procedures to ensure a high level of cybersecurity. For example, Fescaro (BM125) offers cybersecurity testing to OEMs to detect and handle vulnerabilities. Despite this, there is still a possibility that vulnerabilities could be exploited by attackers. Therefore, the component vendor’s software must be integrated into the vehicle’s central cybersecurity management system to be informed and able to be fixed through OTA updates. Bosch (BM52), for example, provides regular software and firmware OTA updates to ensure that connected vehicles are always up to date, protected from hacker attacks, and vulnerabilities are resolved.

Archetype 7: Connected Infotainment

The seventh archetype, *connected infotainment*, represents business models that contribute to a personalized in-car experience through touchscreens or display-equipped head units. These infotainment systems seamlessly integrate automotive features, interfaces, and applications, and can go beyond displaying relevant vehicle information to providing interactive content for increased safety, traffic efficiency and convenience. Overall, infotainment systems consist of several layers (Sivakumar et al., 2020) that should not be considered as isolated systems, but rather have supporting, alternating, or substituting relationships.

The first two layers comprise the operating system (OS) and middleware, which enable rapid development and deployment of data-based applications for the car. For example, BlackBerry's QNX (BM82) provides a comprehensive white-label service package that can be customized by OEMs. However, the traditional proprietary approach to development and functionality is increasingly being replaced by open source models, such as Google's Android Automotive OS (AAOS) (BM10). Second, the human-machine interface and application layers encompass everything the driver sees. To this end, automotive suppliers provide frameworks for OEMs to develop digital cockpits, such as the TomTom Digital Cockpit (BM103), which supports the development of highly integrated applications based on AAOS. These applications can come from third-party vendors or directly from the OEM, although OEMs have historically encapsulated infotainment features (e.g., remote vehicle access, real-time traffic information) under their own sub-brands, such as BMW ConnectedDrive (BM4). As vehicles become autonomous, passengers are likely to demand more infotainment services that are currently more typical of smartphones, such as media streaming and video games. As a result, the world of smartphones is already making its way into the cockpit with mirroring capabilities that allow seamless projection of smartphone interfaces into the digital cockpit. The most prominent example is Apple CarPlay (BM1), where the operating system (i.e., iOS) and applications (e.g., the voice assistant) still run through the smartphone.

4.5 Discussion

Our study examines the generativity of connected cars for business model innovation, leveraging vehicle data by providing two artifacts: a taxonomy and seven archetypes for connected car business models. To the best of our knowledge, this work represents the first industry-specific taxonomy on the subject and complements existing industry-agnostic classifications (e.g., Passlick et al., 2021; Schüritz et al., 2017). While generally applicable taxonomies help distinguish connected car companies based on industry-agnostic dimensions such as *role in ecosystem, data monetization strategy,* or *revenue model*, they are insufficient to fully comprehend the connected car landscape and the configuration of underlying business models. Instead, our proposed taxonomy captures the peculiarities of the connected car, which is highly complex and not fully digitizable, by introducing novel dimensions such as value *for car owner or driver* (e.g., infotainment), *car autonomy impact on value* (e.g., enhanced value by autonomy), or *data access* (e.g., OBD2-dongle).

In the second part of our study, we developed a systematic understanding of business model configurations and derived seven archetypes from real use cases, summarized in Figure 4.5. Fundamentally, our archetypes can be divided into three overarching categories. Category 1 consists of context-related business models (A2-A5) providing direct value to drivers or vehicle owners through *data-driven applications*. In contrast, categories 2 and 3 represent cross-contextual business models that enable further business models through either *in-vehicle* (Category 2, A6-A7) or *off-vehicle* (Category 3, A1) *infrastructure solutions*. Category 2 archetypes (A6-A7) rely on in-vehicle software architecture (e.g., infotainment systems or ADAS) assembled by OEMs from various software vendor components, creating enabler technologies and valuable data sources for implementing the data-driven applications summarized in Category 1 (A2-A5). Category 3 encompasses a single archetype (A1), which operates entirely outside the vehicle and acts as a marketplace for data exchange between car manufacturers and third parties, facilitating independent service providers to implement business models in the first category (A2-A5).

4.5.1 Theoretical Implications

Our research ties into the descriptive knowledge of connected cars and associated business models, an emerging and still-developing domain (Kaiser et al., 2018). Although vehicle connectivity is a major trend, the connected car is a relatively new topic in IS research, with most of the available work focused on exploring privacy concerns rather than business potentials (Cichy et al., 2021; Koester et al., 2022; Lechte et al., 2023). The outcome of our study resulted in a theoretically sound and empirically validated taxonomy summarizing the critical characteristics of connected car business models, along with seven archetypes representing recurring patterns across all characteristics. We contribute to comprehend this domain and enrich future research with theoretical, empirical, and methodological implications.

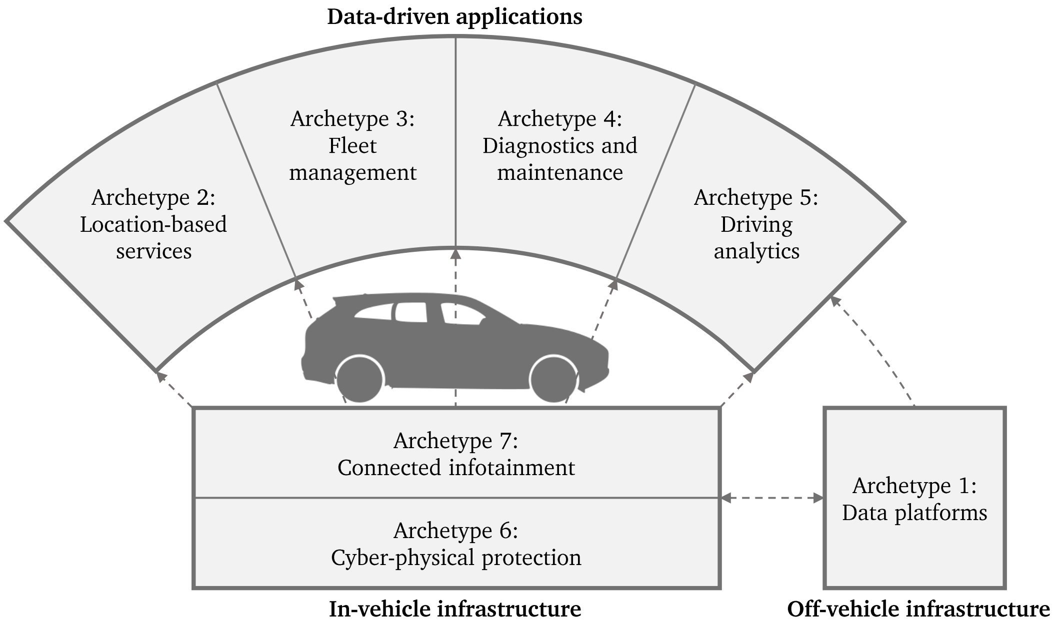


Figure 4.5.: Visualization of archetypes and their relationships.

Connected cars provide a unique setting to examine and expand existing theory and evidence on business models for connected device data (Cichy et al., 2021).

First, our taxonomy provides theoretical insights in the form of a common language and structure for analyzing, classifying, and configuring connected car business models, paving the way for further research and helping scholars position their work therein. The corresponding archetypes can serve as a starting point for understanding superordinate business model configurations in the connected car domain. Moreover, our study's empirical findings enhance the knowledge of data monetization by presenting seven established configuration options for business models in the connected car space. These archetypal patterns and the underlying taxonomy reveal the technical prerequisites (i.e., *value architecture*) required by ecosystem actors, their potential roles (i.e., *value network*), and the data-driven services they can offer (i.e., *value proposition*) to successfully monetize vehicle data (i.e., *value finance*). Hence, our research responds to recent calls for a better understanding of "the role that data aggregators and refiners play in data monetization, how they create value, and how different parties can capture it" (Parvinen et al., 2020, p. 44).

Second, empirically we provide a systematically analyzed dataset of connected car business models that demonstrates how companies leverage digital technologies in the mobility sector. Our data collection process primarily relied on publicly available sources such as company websites and industry-specific business reports, making the dataset easily reproducible and extendable to reflect future developments in the automotive industry. Therefore, this dataset serves as a valuable resource for guiding further studies on digital innovation in the connected car domain.

Third, our research methodology illustrates how a technology-specific business model taxonomy and business model archetypes can be derived by following a mixed methods design (Venkatesh et al., 2013, 2016), ensuring both theoretical rigor and practical relevance by using inputs from the existing literature corpus and industry-specific real-world objects (i.e., 154 connected car business models). Our taxonomy, evaluated quantitatively and qualitatively, represents an analytic theory that classifies, according to (Gregor, 2006), the specific dimensions or characteristics of individuals, groups, situations, or events by summarizing commonalities in discrete observations. Thus, our research contributes to structuring a body of knowledge that constitutes a new field in IS research (Glass & Vessey, 1995) and enables a more systematic description.

Finally, the success of connected car business models, as represented by our developed taxonomy and archetypes, is increasingly tied to ensuring data privacy and security (Wiener et al., 2020). Unlike other connected products, connected cars have already become a mass IoT case, and data from connected cars is already being shared with third parties through APIs. Of course, exchanging connected car data raises a series of privacy-related concerns (Cichy et al., 2021) as both the car users' informational and physical spaces may be intruded (Koester et al., 2022), which may result in an increased privacy risk. Sensitive information about actual driving behavior or daily routines might be inferred from connected car data (Lechte et al., 2023). To mitigate this privacy risk, in Europe, for example, the data shared by connected products such as connected cars is being regulated by the European Commission, forcing automakers to build data collection and sharing systems that do not compromise individual privacy but also do not prohibit data sharing. Applying a privacy-by-design approach (Schaar, 2010) and implementing user consent procedures are two possible ways to address the privacy challenge.

4.5.2 Managerial Implications

Our research offers significant managerial implications by providing valuable tools for navigating the vastly uncharted territory of data-driven business models in the automotive industry. Thereby, our taxonomy goes beyond technical or economic considerations, offering a differentiated view of business model design in the connected car space. This enables automotive incumbents, startups, and non-industry players to gain a detailed understanding of the interactions among car data-driven business models and learn about different ways to monetize connected car data. In addition, our research provides a comprehensive market overview and analysis of the connected car ecosystem and presents seven representative archetypes that specify the relevant dimensions for business model innovation. Managers can use these archetypes to identify business opportunities and potential market entry points in the automotive ecosystem and assess their implementation in their company's specific context, as discussed by Kaiser et al. (2021). By employing archetypes, practitioners can gain insights into potential configurations that have been widely applied, serving as a reference point for further exploration and customization, thus helping to develop unique business models tailored to their specific goals and target markets. In doing so, our cross-table (see Table 4.5) is a valuable tool that facilitates assessing how market participants typically structure their business models concerning specific archetypes. While our work does not provide a one-size-fits-all prescription, it does offer a prescriptive component in providing actionable insights and guiding principles.

Practitioners can use the taxonomy and archetypes as strategic management tools to explain their current business model to stakeholders, focus on improving specific operational aspects, or develop new business models aligned with their corporate strategy (Spieth et al., 2014). They may further use them to systematically analyze competitors and identify unique combinations of features that have not yet been used in the market. By conducting a morphological analysis, our work can help practitioners systematically develop innovative ideas (Geum et al., 2016). The archetypes and associated real-world business models highlight established innovation paths that executives can follow to digitalize their legacy business models and advance car data monetization. Overall, the taxonomy and archetypes provide industry-specific support for business model innovation, enabling practitioners to expand their market offerings and create value throughout the vehicle life cycle.

In addition, several policy initiatives are underway, such as the European Data Act (European Commission, 2022b), to protect the privacy of individuals in the case of connected products that will impact the implementation of DDBM. The European Data Act regulates data generated by connected products and grants stakeholders more control over their data through a strengthened right to data portability. The directive is also expected to give users of connected vehicles more control over their data and allow third parties fair and non-discriminatory access to and use of the data in services. Due to the complexity of the connected car context and the reactions of European automotive organizations, represented by the European Automobile Manufacturers' Association (ACEA) and the European Association of Automotive Suppliers (CLEPA), we expect sector-specific legislation to be published shortly that will provide more detail on OEMs' obligations regarding what connected car data can be shared for use in DDBMs and how.

4.5.3 Limitations and Future Research

Like any study, ours is subject to limitations that also suggest potential avenues for further research. Taxonomy-based research is never complete as it reflects a snapshot in time (Nickerson et al., 2013), which is also true for our taxonomy and archetypes that represent the current state of connected car business models. As the field is still developing, future research could revisit and extend our findings to keep them relevant and applicable. For example, legislation (e.g., European Commission, 2022a) mandating safety-related systems in cars (e.g., to monitor driver attention, distraction, drowsiness, and even health) will likely drive future innovation and potentially lead to further archetypes. However, our findings cannot represent such future trends because they are empirically informed only by existing real-world business models.

Because our research aimed to develop a taxonomy and associated archetypes for the manifold connected car domain, our findings are still broad in scope. For instance, our study covers business models with very different foci, including end-user applications for navigation or driver assistance, technology provision in the area of safety and security, or platform-based business models as enablers for novel services. Future studies should explore specific archetypes in more depth by developing more specific taxonomies and sub-archetypes for these business models, similar to the study on vehicle data marketplaces by Bergman et al. (2022).

We built the taxonomy and performed the coding process based on publicly available information, triangulating data from company websites, Crunchbase, and reports to maximize the validity of our dataset. However, information on companies' revenue models was often limited, so we excluded this dimension from the cluster analysis. Future research should fill these data gaps by contacting companies directly to complete data sets and verify or extend our cluster analysis with new insights. Furthermore, there was a notable lack of comprehensive information regarding the techniques employed for data analysis or the sensors and additional systems utilized to access in-vehicle data. We evaluated the taxonomy both quantitatively and qualitatively but primarily evaluated the archetypes from a quantitative perspective by calculating silhouette width as a measure of cluster validity (Rousseeuw, 1987). Future research endeavors could complement our work by qualitatively evaluating the archetypes through expert interviews. This could reveal dependencies between different business model archetypes and important strategic decision factors for how companies consider the different archetypes in their business model innovation processes.

4.6 Conclusion

Driven by the growing importance of connected cars, OEMs as technical pioneers in the IoT and established technology players as experienced orchestrators of digital ecosystems are competing to deliver a "smartphone on wheels." Existing research on business models in the connected car domain has mainly focused on topics such as privacy concerns (Cichy et al., 2021), ecosystem conceptualization (Kaiser et al., 2021), or path dependence (Bohnsack et al., 2021). While there have been efforts to create taxonomies for data-driven business models and data monetization in general (Bock & Wiener, 2017; Hartmann et al., 2016; Passlick et al., 2021), there is little conceptual or empirical evidence on the specifics of the connected car phenomenon (Sterk et al., 2022c). Consequently, research so far does not explain the potential impact of vehicle data on automotive business models and lacks in-depth empirical investigations. Moreover, in practice, there is a gap between the potential business value of car data monetization and the actual value delivered.

The objective of this study is to bridge this gap trough two successive iterations. First, following Nickerson et al.'s (2013) methodological guidance, we developed a business model taxonomy based on a structured literature review and an analysis of 154 connected car business models, which was evaluated both qualitatively and quantitatively. In the second iteration, a cluster analysis (Kaufman & Rousseeuw, 1990) was performed to identify seven connected car business model archetypes by interpreting and evaluating the corresponding clusters. This research extends the existing body of knowledge on data-driven business models and connected cars by providing a comprehensive examination of connected car business models. These artifacts can serve as a common language for scholars to analyze, classify, and configure connected car business models and as a basis for understanding higher-level business model configurations. Decision-makers in the automotive industry can use the findings as strategic management tools for developing new business models and benchmarking existing ones. Ultimately, this work provides a foundation for future research using the extensible taxonomy and archetypes as constructs to shed more light on the proliferation of connected cars and related business models.

Part III

Design of Connected Car Business Models

5 Utilizing Fleet Data: Towards Designing a Connected Fleet Management System for the Effective Use of Multi-Brand Car Data

This chapter comprises an article that was published as: Sterk, F., Frank, S., Lauster, I., & Weinhardt, C. (2023). Utilizing Fleet Data: Towards Designing a Connected Fleet Management System for the Effective Use of Multi-Brand Car Data. Proceedings of the 56th Hawaii International Conference on System Sciences (HICSS) (pp. 1489-1498). Note: The abstract has been removed. Tables and figures were reformatted and newly referenced to fit the structure of the thesis. Chapter, section, and research question numbering and respective cross-references were modified. Formatting and reference style was adapted, and references were integrated into the overall references section of this thesis.

5.1 Introduction

With the ongoing proliferation of connected cars, in-vehicle data has become a key theme on the automotive industry agenda and, thus, an essential source of value creation (Carter et al., 2018; Kaiser et al., 2021). To harness the game-changing opportunities of this tremendously growing amount of data, not only original equipment manufacturers (OEMs) but also insurers, rental companies, and repair shops, among other players in the connected car ecosystem, seek to offer data-driven services (Sterk et al., 2022a). In exploring car data monetizing, leading consultancies identified data-based fleet management as one of the industry's most impactful use cases (Arif et al., 2019; Carter et al., 2018). In fact, the share of private vehicles is declining, leading to a greater demand for professionally managed fleets (Pütz et al., 2019). Consequently, it is not surprising that McKinsey & Company forecasts the global connected fleet solutions market to grow at around 23% annually, becoming a $75.79 billion industry by 2025 (Carter et al., 2018).

While numerous data-driven fleet management use cases, such as predictive maintenance (Killeen et al., 2019) or driver monitoring (Walnum & Simonsen, 2015), are being discussed in research and practice, effective implementation is hindered by the problem of data access (Kaiser et al., 2019; Martens & Mueller-Langer, 2020). More precisely, while OEMs exclusively access car data, independent service providers must identify alternative access options, for instance, installing retrofit solutions (e.g., dongles) (Kaiser et al., 2019). However, this is fraught with severe drawbacks, such as expensive hardware, time-consuming installation, and limited data quality (Martens & Mueller-Langer, 2020). Nonetheless, the emergence of data marketplaces (e.g., Caruso Dataplace) offers another approach to accessing car data without hardware and installation, directly from OEMs (Kaiser et al., 2021; Martens & Mueller-Langer, 2020). Since car data marketplaces remain in their infancy and currently provide limited data, fleet management is a solid starting point for connected service design due to its high utility and manageable data requirements (Arif et al., 2019). However, scholars have scarcely touched on designing connected car or fleet services incorporating the concept of data marketplaces (Sterk et al., 2022a). Hence, we pose the following research question: *How to design a connected fleet management system in order to use car data from data marketplaces effectively?*

We address this question by conducting a design science research (DSR) project (Kuechler & Vaishnavi, 2008), using knowledge from a preceding literature review as well as practical insights from interviews with domain experts. Thereby, we derive theory-grounded meta-requirements and tentative design principles justified by the theory of effective use (Burton-Jones & Grange, 2013). We then instantiate them in a connected fleet management system based on in-vehicle data collected in a field test initiated by Caruso Dataplace (Mokeev et al., 2021). Finally, we evaluate our artifact by means of a focus group workshop and further expert interviews. Overall, we contribute to the body of design knowledge on connected service development, specifically focusing on fleet management data and its effective use. Practically, our research informs fleet managers on how connected car data can be utilized and how to design an effective fleet management system.

5.2 Related Work and Foundations

Connected Cars harbor the potential to deliver a unique customer experience while bringing cost and revenue benefits to mobility enterprises (Coppola & Morisio, 2016). To date, OEMs have sought to monetize valuable car data by offering digital services such as BMW ConnectedDrive or Mercedes me connect, enabling concierge services, remote diagnostics, and on-street parking information, among others (Kaiser et al., 2021). However, such data is not only of interest to OEMs but also to independent service providers (e.g., suppliers, workshops, insurers) who are forced to explore alternative technical gateways granting similar access options (Kaiser et al., 2019). The most common solution is retrofitting a telematics-equipped dongle into the on-board diagnostics (OBD) port to allow remote car data access (Coppola & Morisio, 2016; Pütz et al., 2019). According to Martens and Mueller-Langer (2020), despite initial optimistic forecasts for OBD dongle adoption, the market remains fragmented, and scaling up is challenging for several reasons. First of all, OBD dongles are characterized by time-consuming installations and expensive hardware purchases. Moreover, they are limited in terms of car park coverage, data point availability, as well as quality of the data collected. To counteract these drawbacks, another opportunity for third-party data access has emerged—without hardware or installation, directly from the OEMs. In fact, aspiring car data marketplaces such as Caruso Dataplace or Otonomo act as neutral intermediaries allowing OEMs to sell standardized data to independent service providers (Kaiser et al., 2021; Martens & Mueller-Langer, 2020). The significant benefit is that data from multiple OEMs can be made available via a single point of access (Martens & Mueller-Langer, 2020). In practice, though, marketplaces remain dependent on data access conditions (e.g., pricing or data coverage) set by OEMs.

Fleet Management is an essential instrument in the successful administration of a company's transportation activities (Redmer, 2022). Especially when operating diversified car fleets, managers can benefit from the multi-brand data accessed by retrofit-dongles or third-party marketplaces (Martens & Mueller-Langer, 2020). In general, fleet management systems (FMS) improve the efficiency and productivity of cars and drivers by mitigating the risks associated with their fleet investments (Salhieh et al., 2021), such as purchasing, placement, and maintenance of the fleet (Arulraj et al., 2019). Accordingly, an FMS allows enterprises to keep track of their fleet conveniently and cost-effectively (Karmanska, 2021). With the rapid proliferation of connected cars, the global FMS market witnesses tremendous growth (Carter et al., 2018; Kerber & Gill, 2019), which also entails a higher academic relevance in this area. Current research, for instance, addresses predictive maintenance by developing machine learning algorithms (Killeen et al., 2019) or dashboards (Arulraj et al., 2019) for an existing FMS. Moreover, the driving behavior of fleets is analyzed to reduce risky behavior through app notifications (Levi-Bliech et al., 2018). Similarly, lowering fuel consumption is also studied by identifying environmentally and economically beneficial driving modes (Walnum & Simonsen, 2015). In parallel, as companies become more environmentally conscious, the issues of reducing air pollutant emissions (Longo et al., 2016) and providing strategic decision support for fleet electrification come to the forefront (Schmidt et al., 2021). However, the research has not considered developing an FMS utilizing data from third-party marketplaces to date.

Theory of Effective Use. Effective use is vital to achieving the benefits of an information system. To this end, Burton-Jones and Grange (2013, p. 633) established the effective use theory, in which they define "effective use as using a system in a way that helps attain the goals for using the system." Their conceptualization describes effective use based on three dimensions forming a hierarchy, as every lower-level dimension is necessary but not sufficient for the next higher-level dimension. Initially, (1) user access to the system's representations must be unimpeded by the surface and physical structures (transparent interaction). Thereby, (2) the ability to obtain representations that faithfully reflect the domain represented by the system is improved (representational fidelity). Eventually, (3) the latter increases the users' ability to act on faithful representations they obtain from the system to improve their state in the domain (informed action). In our case, for instance, fleet managers need to access accurate vehicle information via comprehensive dashboards (transparent interaction), providing a representative overview of the current fleet condition and driving behavior (representational fidelity) that enables decision-making to optimize fleet processes such as vehicle ordering, maintenance, or invoicing (informed action).

5.3 Design Science Research Methodology

To provide a connected fleet management system (CFMS) based on vehicle data, we conduct a DSR project as described by Kuechler and Vaishnavi (2008) as it strongly emphasizes an iterative procedure in rapid iterating cycles, enabling flexible artifact development. Overall, our DSR project comprises two consecutive design cycles consisting of five phases each (see Figure 5.1). This paper reports the results achieved during the first cycle, starting with the awareness of the problem perceived in practice. We ensure both rigor and relevance by using inputs from the existing body of knowledge (rigor) and the practical problem domain (relevance) (Hevner, 2007).

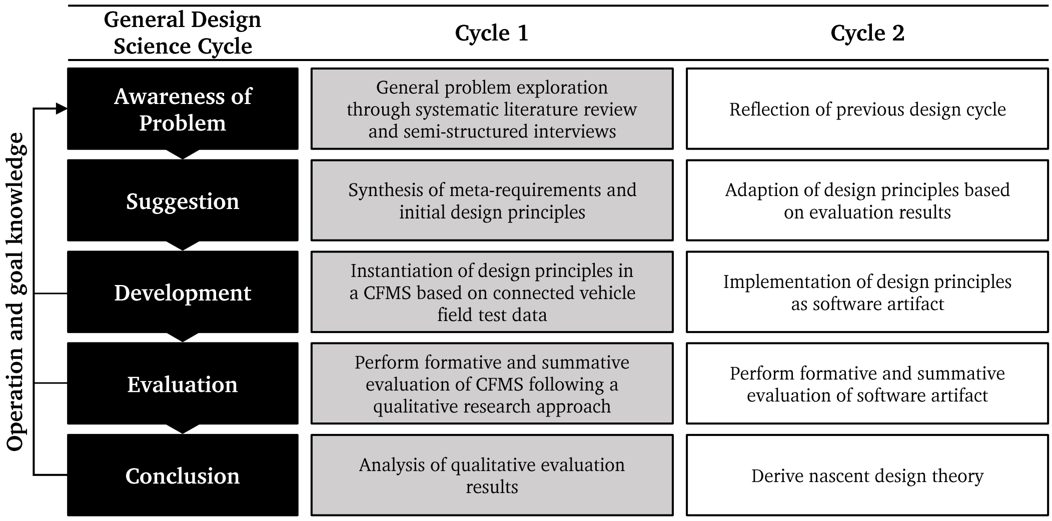


Figure 5.1.: Design science research methodology based on Kuechler and Vaishnavi (2008).

Awareness of Problem. We rely on a previously conducted systematic literature review (Sterk et al., 2022a) focusing on data-driven business models in the connected car domain. To include recently published articles, we repeated the literature review following the methodological suggestions by Webster and Watson (2002). Thereby, we extended the search term[1] by Sterk et al. (2022a) for the keyword *fleet** to shift focus to the fleet perspective and queried several databases[2] in title, abstract, or keywords. Our renewed search obtained 1121 studies, of which 779 remained after duplicates were removed. We then analyzed each article's title and abstract, yielding 133 articles. Afterward, we reviewed all full texts applying three inclusion criteria—the study must (1) address the fleet domain, (2) be available in English, and (3) be peer-reviewed—resulting in 34 relevant articles. Subsequent forward and backward search yielded 20 additional articles, resulting in a total of 54 papers.

To further refine and validate the awareness of the problem, we performed an explorative study using qualitative interviews with 21 fleet domain experts operating in five different areas: corporate fleet (n = 11), car subscription (n = 4), car sharing (n = 2), ride pooling (n = 1), and fleet service provider (n = 3). An interview overview including unique labels is provided in Table 5.1. The interviews were conducted through open questions along predefined discussion points to gain a

[1]"business model*" AND (connected OR data* OR digital*) AND (fleet* OR car* OR vehicle* OR automotive*)

[2]AIS Electronic Library, Emerald Insight, IEEEXplore Digital Library, ProQuest, ScienceDirect/Scopus, Web of Science

deeper understanding of the real-world phenomenon. Thereby, we adopted a semi-structured approach to ensure similarity in the general structure of each interview. All interviews were recorded and transcribed before being coded and analyzed by two researchers using MAXQDA and Excel. When analyzing the transcribed interviews, we opted for qualitative content analysis according to Mayring (2000), as it is a flexible research technique that facilitates the analysis and interpretation of qualitative data (Krippendorff, 2019). Finally, our data analysis enabled us to justify the research gap regarding its practical relevance before artifact development (Sonnenberg & Vom Brocke, 2012).

Table 5.1.: Overview of interviewees and focus group.

DSR Phase	Method	Domain	NI (NE)*	Label
Awareness of Problem	Interview	Corporate Fleet	11 (11)	Alpha 1-11
Awareness of Problem	Interview	Car Subscription	4 (4)	Beta 1-4
Awareness of Problem	Interview	Car Sharing	2 (2)	Gamma 1-2
Awareness of Problem	Interview	Ride Pooling	1 (1)	Delta 1
Awareness of Problem	Interview	Service Provider	3 (3)	Epsilon 1-3
Evaluation	Focus Group	Service Provider	1 (5)	Zeta 1
Evaluation	Interview	Corporate Fleet	4 (6)	Eta 1-4
Evaluation	Interview	Service Provider	3 (6)	Theta 1-3
*NI = Number of interviews or focus group workshops; NE = Number of experts involved				

Suggestion & Development. Next, we reviewed the theory of effective use (Burton-Jones & Grange, 2013) that should guide the design of the CFMS to improve overall fleet management effectiveness. Based on the issues identified in the interviews and literature and the adopted kernel theory, we then derived meta-requirements (MRs). Drawing on the MRs, we formulated design principles (DPs) for artifact development following the suggestions of Gregor et al. (2020). In the development phase, we instantiated the proposed DPs based on in-vehicle data of 89 cars collected in a field test initiated by Caruso Dataplace (Mokeev et al., 2021). Thereby, we developed a prototypical CFMS in Microsoft Power BI, enabling fleet managers to utilize car data effectively.

Evaluation & Conclusion. Finally, the CFMS was evaluated according to the human risk and effectiveness strategy by Venable et al. (2016). We opted for this strategy as the design risk (i.e., potential problems the design may face) of the proposed artifact is user-oriented. First, we conducted a formative ex-ante evaluation using an exploratory focus group workshop (Tremblay et al., 2010) with five decision-makers from a leading connected car company (see Table 5.1). This allowed us to gather feedback for further improvements by demonstrating our tentative DPs and artifact and discussing completeness, consistency, and applicability. After implementing the changes, we applied a summative ex-post evaluation through seven semi-structured interviews with twelve fleet experts (see Table 5.1). In this step, we demonstrated the instantiated artifact to the participants by a click-through. Afterward, they gave feedback on effectiveness, efficiency, and consistency with the real-world context leading to inputs for the second cycle to deliver the final DPs and artifact.

5.4 The Design Science Research Project

5.4.1 Awareness of Problem

By analyzing the literature corpus and the interviews conducted, we identified eight critical issues encountered by fleet experts that vehicle data could potentially address. In doing so, we divide the identified issues into three dimensions—economic sustainability (I1, I2), environmental sustainability (I3, I4, I5), and vehicle health (I6, I7, I8)—and define them as follows. While the economic dimension covers the fleet's long-term financial viability, the environmental facet involves resilience to climate change. Finally, vehicle health refers to keeping the fleet in optimal use during its economic life by maintaining its condition.

Economic Sustainability. From a fleet manager's perspective, the total cost of ownership (TCO) is vital for identifying cost-saving opportunities and reducing operating costs stemming from fuel, maintenance, tires, or repairs (Fatin Amirah et al., 2013; López-Ibarra et al., 2020). Nevertheless, due to a lack of information on current mileage and energy consumption (**I1**), the potential for transparently managing and effectively optimizing costs is still little (Fatin Amirah et al., 2013). In this regard, one of the experts interviewed (Beta 4) emphasized that *"the topic of cost transparency is still in its infancy. Even the big fleet management companies still work with Excel."* Analyzing current fleet data would thereby help address the poor predictability of TCO (**I2**) and provide a basis for future resource planning and strategic decision-making (Redmer, 2022). Ultimately, monitoring fuel consumption could help decide what portion of the fuel costs the company and the driver should bear (Bätz et al., 2020).

Environmental Sustainability. With ongoing climate change, environmental sustainability has become a crucial strategic pillar for fleet managers globally (Karmanska, 2021). Consequently, ambitious greenhouse gas reduction targets dominate current discussions about fleet management. Thus, as electric mobility has proven to be a powerful technology for decarbonizing the transportation sector (Longo et al., 2016; Schmidt et al., 2021), multiple fleets are changing their car policies from internal combustion engines (ICEs) toward battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) (Karmanska, 2021). However, without effectively accessing information (**I3**) about vehicle usage, sufficient calculation of a fleet's carbon footprint is limited (Bätz et al., 2020; Walnum & Simonsen, 2015). Moreover, in setting up their strategy toward a low carbon economy, companies are expected to establish reporting tools (Salhieh et al., 2021) faithfully reflecting the fleet's carbon footprint (Gonder & Simpson, 2007). Nevertheless, they still struggle to implement such a CO_2 reporting (**I4**). Ultimately, a sustainability strategy should also include appropriate measures to raise drivers' partially limited awareness of sustainable driving (**I5**). To this end, one interviewee (Alpha 7) explicated that *"employees opted for PHEVs primarily because of the tax advantage, never drove electric, and left the charging cable in its original packaging."*

Vehicle Health. Another prominent concern fleet managers face is maintaining vehicle conditions to ensure long-lasting vehicle health and driver safety (Coppola & Morisio, 2016). In some cases, however, fleet managers lack detailed information about the current health of the fleet (**I6**). In particular, they cannot remotely check vehicle conditions due to lacking access to relevant data such as error messages, missing supplies, or illuminated indicator lights (Killeen et al., 2019). Hence, preventive actions cannot be initiated to reduce maintenance calls and associated vehicle downtime (**I7**) (Fatin Amirah et al., 2013). Regarding this, one interviewed expert (Epsilon 3) mentioned that they *"usually only find out too late when maintenance intervals are not adhered to, or vehicles run without oil for weeks, causing enormous costs."* This aspect is closely related to drivers' decreasing responsibility for vehicle care (**I8**), occurring primarily in shared fleets.

5.4.2 Suggestions

In general, adequate fleet management is essential for successfully governing an enterprise's transportation activities (Redmer, 2022). This requires effective use of a fleet management system enabling the enterprise to improve vehicle and driver efficiency (Karmanska, 2021; Salhieh et al., 2021). For this purpose, we structured our MRs along the three dimensions of the effective use theory (Burton-Jones & Grange, 2013)—transparent interaction (MR1, MR2), representational fidelity (MR3, MR4), and informed action (MR5, MR6)—as it perfectly fits our research endeavor. Finally, based on the six MRs, we continued our research by identifying DPs for the CFMS following established guidelines (Gregor et al., 2020). We thereby divide our

DPs into the two areas of fleet management—strategic (DP1-DP3) and operational (DP4-DP6). The translation process from MRs to corresponding DPs is depicted in Figure 5.2.

Strategic Fleet Management. To increase *transparent interaction* of strategic activities, fleet managers require to access detailed information regarding the overall fleet operating cost (**I1**), usage (**I3**), and condition (**I6**). This means providing unimpeded access to the vehicle data, as well as their transparent representation in the CFMS (**MR1**). Thereby, the system should contain a comprehensive set of key performance indicator (KPI) that keep management informed and track fleet progress (Schmidt et al., 2021). However, to capture overall fleet sustainability, the KPIs need to cover not only economic but also environmental performance and vehicle health. Furthermore, to visually display the most important information on a single screen, the CFMS requires graphical dashboards providing relevant information at a glance (Few, 2006). Therefore, we propose the following design principle.

> **DP1:** *Provide the CFMS with essential KPIs and their visualization via comprehensive dashboards in order to access the current fleet status.*

Intending to achieve *representational fidelity*, the CFMS is required to provide consolidated information regarding fleet status for reporting at an enterprise level (**MR3**). Correspondingly, a single report template must support meaningful KPIs and visualizations. Especially companies shifting toward a low-carbon economy are expected to implement reporting tools faithfully reflecting the fleet's CO_2 emission (**I4**) (Karmanska, 2021). Another example is the reporting of PHEVs' engine utilization—the share of kilometers driven electrically—to determine the extent to which the car's potential is utilized (Gonder & Simpson, 2007). However, beyond reporting environmental KPIs, cost-related data (e.g., fuel cost) is crucial (**I1**) for leveraging strategic action (López-Ibarra et al., 2020). Therefore, we propose the following design principle.

> **DP2:** *Provide the CFMS with a reporting tool including essential KPIs and visualizations within a single template in order to reflect the current fleet status.*

Finally, to increase fleet managers' ability to take *informed action*, the CFMS should help identify ways to improve fleet performance, for example, by estimating operational fleet cost (**I2**). Accordingly, as a sound basis for static strategic decision-making, the system should permit calculating future costs, energy consumption, or emissions (**MR5**). The aim is to compare the current KPIs from the faithful representation of the reporting tool with target KPIs defined by a calculation tool, thereby estimating potential savings. This could help fleet managers improve future

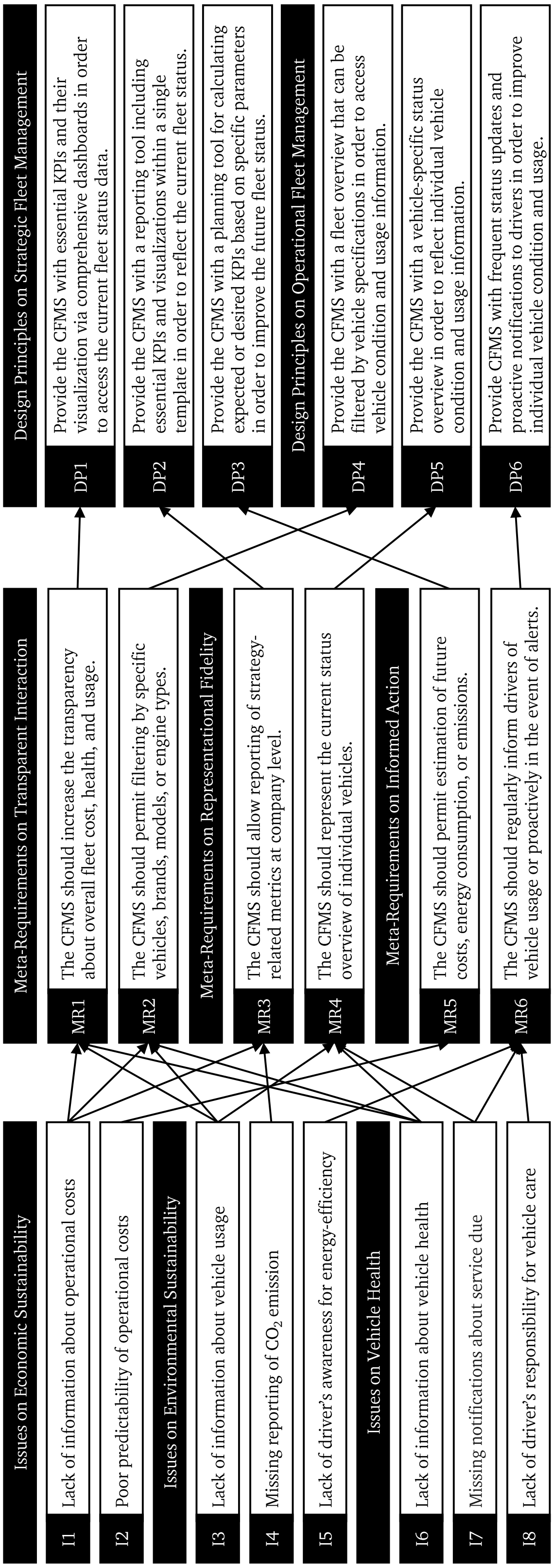


Figure 5.2.: Mapping of issues, meta-requirements, and design principles for the CFMS.

fleet status by, for example, capping fuel costs and thus having the company pay only a portion of the expenses to optimize fuel consumption and utility factor (Bätz et al., 2020). Therefore, we propose the following design principle.

DP3: *Provide the CFMS with a planning tool for calculating expected or desired KPIs based on specific parameters in order to improve the future fleet status.*

Operational Fleet Management. To increase *transparent interaction* of operational activities, fleet managers require vehicle-specific information on operating cost (**I1**), usage (**I3**), and condition (**I6**). Accordingly, the CFMS must provide a tabular overview of all vehicles, including meaningful KPIs, which must be filterable by specific cars, brands, models, or engine types (**MR2**). Hence, transparent and unhindered interaction is enabled by only displaying data items that match the defined criteria. For instance, comparing vehicles of the same models or powertrains helps identify those with conspicuous driving behavior. Therefore, we propose the following design principle.

DP4: *Provide the CFMS with a fleet overview that can be filtered by vehicle specifications in order to access vehicle condition and usage information.*

Next, to obtain *representational fidelity*, the CFMS should ensure a detailed status overview of each vehicle (**MR4**) including representations that faithfully reflect driving behavior (**I3**), vehicle condition (**I6**), or warnings such as overdue services (**I7**). Thereby, fleet managers can remotely check relevant data such as fuel consumption, missing supplies, or illuminated indicator lights (Killeen et al., 2019). Accordingly, the CFMS provides a detailed look at vehicles that became conspicuous (informed action) to initiate maintenance measures if necessary and thus avoid vehicle downtime (Levi-Bliech et al., 2018). Therefore, we propose the following design principle.

DP5: *Provide the CFMS with a vehicle-specific status overview in order to reflect individual vehicle condition and usage information.*

Finally, to improve fleet managers' ability to take *informed action* at the operational level, the CFMS should allow communication of the faithful representations of individual vehicles to respective drivers. The latter should raise their awareness of environmentally and cost-saving driving and ensure adequate vehicle care (**I5, I8**). This means regular updates informing drivers (**MR6**) about their driving behavior and proactive notifications with appropriate actions in case of warnings (**I7**). For instance, the CFMS could alert drivers to their above-average fuel consumption or unfriendly driving habits through monthly updates that compare their driving behavior to the average driving behavior of similar vehicles in the fleet (Walnum &

Simonsen, 2015). Furthermore, if the maintenance intervals are not adhered to, the drivers of the affected cars should be informed that a service appointment must be made. Therefore, we propose the following design principle.

DP6: *Provide CFMS with frequent status updates and proactive notifications to drivers in order to improve individual vehicle condition and usage.*

5.4.3 Development

To instantiate our DPs into a prototypical CFMS, we used car data from a field test initiated by Caruso Dataplace (Mokeev et al., 2021). The field test data set included pseudonymized data in JSON format collected from 213 vehicles over five months in 2020. Initially, we transformed the JSON files into a tabular form and excluded files that were either empty or had an error message. In our data preprocessing, we set minimum data requirements for each vehicle due to the different data availability among the five participating OEMs. Accordingly, we specified *mileage* as a mandatory data point for all cars and energy resources depending on the powertrain: *fuel level* for ICEs, *state of charge* for BEVs, and both for PHEVs. Ultimately, a total of 89 vehicles remained for artifact development consisting of 80 ICEs, eight PHEVs, and one BEV. Following our data processing, we mapped our DPs to concrete features and implemented them using Microsoft Power BI. Figure 5.3 depicts the DPs addressed by the prototype, whereby a detailed representation of the artifact is shown in the Appendix in Figure A.2.

Strategic Feature Implementation. Initially, we instantiated **DP1** by defining a comprehensive set of KPIs based on the available field test data (see Table 5.2). For example, we determined fuel consumption by calculating the differences in fuel level values from two consecutive data transmissions. Then, depending on the sign, we knew whether the car consumed fuel (-) or was refueled (+), allowing us to calculate fuel consumption in a given time. The procedure for electric vehicles was analogous. To determine energy costs, CO_2 emissions, and utility factors, we needed additional information that did not come directly from the vehicle; we obtained it from the sources listed in Table 5.2. Next, we implemented graphical **dashboards** visualizing the previously calculated KPIs. Building on this, we integrated the **reporting tool** described in **DP2** by listing the KPIs in tabular form and displaying essential charts on a single page. Next, we instantiated **DP3** by implementing the **calculation tool**. Here, we defined what-if parameters allowing users to simulate the impact of changing individual KPIs (e.g., fuel consumption) on the remaining KPIs (e.g., fuel cost) using sliders. Additionally, we adopted the KPI visualization from the reporting tool with the *actual* values and added columns with the *calculated* values and corresponding *savings*.

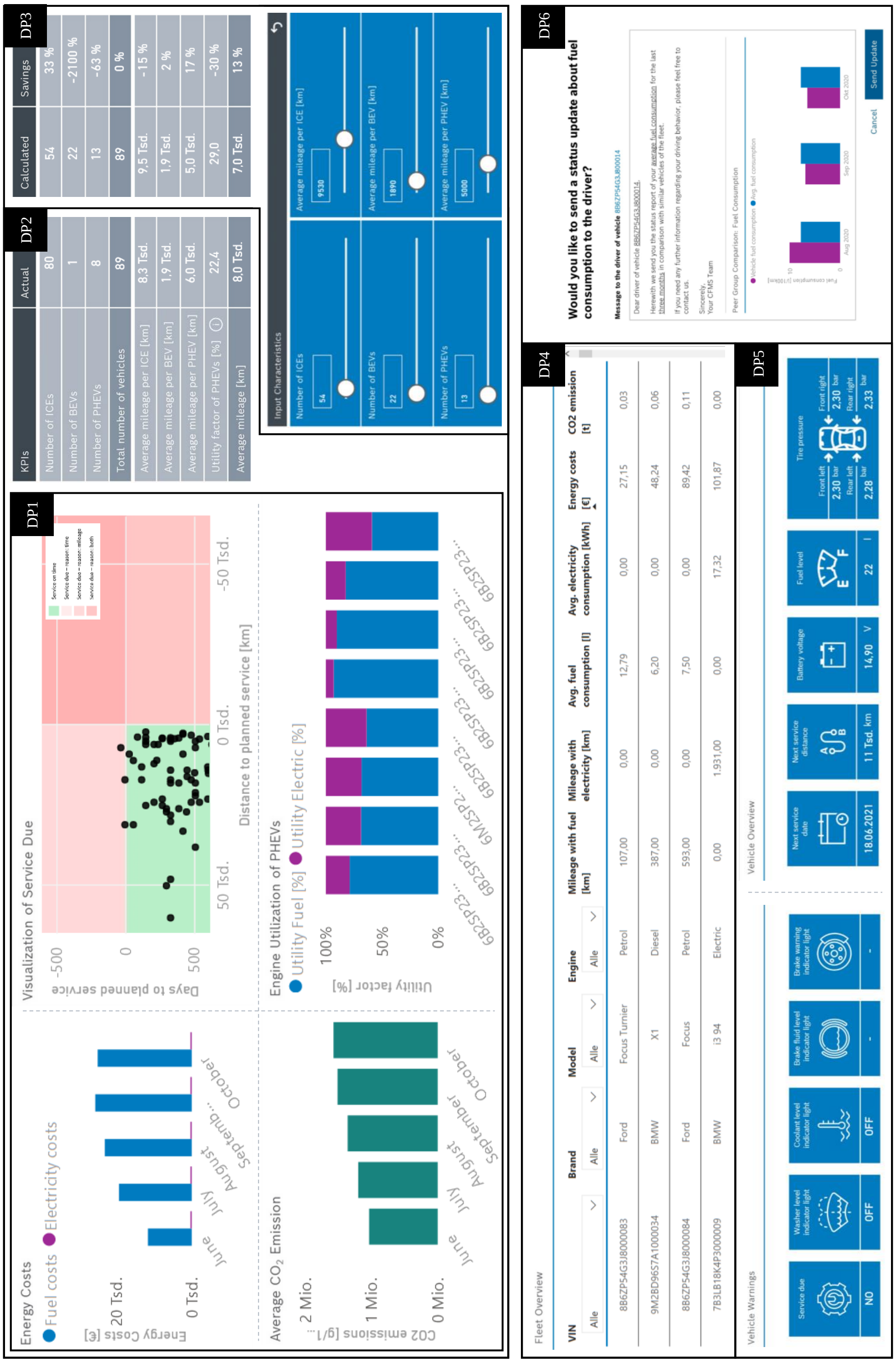


Figure 5.3.: Instantiation of design principles within the CFMS prototype.

Table 5.2.: Overview of KPIs and field test data points.

No.	Key Performance Indicator	Field Test Data Point
1	Mileage	Mileage, timestamp
2	Total fuel consumption [l]	fuel level, timestamp
3	Total electricity consumption [kWh]	state of charge, timestamp
4	Average fuel consumption [l/100km]	mileage, fuel level, timestamp
5	Average electricity consumption [kWh/100km]	mileage, state of charge, timestamp
6	Fuel cost [€][1]	fuel level, timestamp
7	Electricity cost [€][2]	state of charge, timestamp
8	Total CO_2 emission [g/km][3]	fuel level, timestamp
9	Average CO_2 emission [g/km][3]	mileage, fuel level, timestamp
10	Engine utilization of PHEVs [%][4]	mileage, fuel level, state of charge, timestamp
11	Service due based on days and distance [km]	next service distance, next service date, timestamp

[1] Constant fuel prices were assumed based on local German fuel prices in April 2022
[2] Constant electricity prices were assumed based on an analysis of the BDEW e.V. (2022)
[3] Constant CO_2 emissions were assumed based on a report from Deutscher Bundestag (2019)
[4] Necessary data on PHEV models were taken from test reports of the automobile club ADAC (2022)

Operational Feature Implementation. To instantiate **DP4**, we created a tabular **fleet overview** of all vehicles containing information regarding vehicle identification number, brand, model, and engine type. Moreover, we added additional columns containing the previously defined KPIs for each vehicle. We then implemented a filter function allowing users to find or compare specific vehicles by filtering either by vehicle identification number, brand, model, or engine type. Next, we deployed **DP5** by allowing users to click on a specific vehicle in the fleet overview to view a car's detailed **vehicle status**. The overview contains further information regarding missing supplies, illuminated indicator lights, or service information obtained from the field test data. Ultimately, **DP6** was realized by extending the vehicle status overview and adding graphs displaying upcoming service needs and fuel consumption compared to other fleet vehicles. Thereby, we added click-dummy buttons to send drivers **proactive notifications** in case of an overdue service and **status updates** comparing the driver's fuel consumption with its peer group.

5.4.4 Evaluation and Conclusion

The first evaluation of our CFMS served as a formative ex-ante assessment to ensure the artifact's completeness, consistency, and applicability (Venable et al., 2016). For this purpose, we conducted an explanatory **focus group workshop** with five decision-makers from a leading connected car company operating as a service provider (see Table 5.1). One author guided the focus group through our tentative DPs and the prototype artifact and asked the participants to comment on the initial version. For instance, we collected feedback regarding the design, order, or arrangement of individual features, buttons, and graphs. Afterward, we incorporated their recommendations leading us to the DPs and artifact presented previously.

We then performed a summative ex-post evaluation by conducting seven **semi-structured interviews** with twelve fleet experts operating in two areas: corporate fleet ($n = 6$) and service provider ($n = 6$) (see Table 5.1). In this course, we demonstrated the improved artifact to the participants by having them assess each DP and feature regarding effectiveness, efficiency, and consistency. Firstly, concerning **DP1**, the experts praised the clear and transparent presentation of the graphical **dashboards**. In particular, the visualizations of environmental KPIs, such as engine utilization for PHEVs, were perceived as beneficial. In addition, it was suggested by one expert (Eta 4) to use KPIs (i.e., mileage) for the plausibility check of fuel invoices. When discussing **DP2**, the experts (Eta 1, Theta 3) indicated the respective **reporting tool** as highly useful. Since the corporate controlling currently has to report CO_2 emissions to the management once a year, the CFMS could automate this task. However, one participant (Theta 2) emphasized the need for holistic TCO reporting (e.g., lease, tire, and maintenance costs) for different management levels: Aggregated costs at strategic and detailed costs at operational levels. Notably, **DP3** and the respective **calculation tool** was evaluated as the most exciting and innovative. The participants (Eta 1, Eta 3, Theta 3) liked the parameters variable by sliders that could replace the current less comfortable calculations via Microsoft Excel. Thus, the tool would be helpful improve transparency and justification of decisions and strategies. However, the experts desired to consider the investment in the in-house charging infrastructure depending on the number of BEVs. Concerning **DP4**, one expert (Eta 2) noted that the **fleet overview** is a vital feature, but it is already the status quo for common fleet management systems. Nevertheless, the participants (Eta 4, Theta 1) highlighted the need for an additional driving behavior analysis per vehicle that would provide added value, for instance, to ensure optimal and route-related vehicle deployment. Regarding **DP5**, the experts (Eta 2, Eta 3) argued that the **vehicle status** overview is particularly suitable for cars with no permanently assigned driver due to lacking responsibility for occurring issues. Thus, pool vehicles needing maintenance could be predictively taken out of service until the required repair is made. They further recommended introducing color differentiation in the visualization of vehicle supplies and indicator lights (e.g., *green=good*, *red=bad*). Finally, concerning **DP6**, one expert (Eta 1) noted that **proactive notifications** and **status updates** should be directed either to drivers (e.g., for leasing) or fleet managers (e.g., for sharing), depending on the periods of vehicle use. Overall, the feature was perceived as saving time and resources and would add significant value, mainly through automated service reminders.

5.5 Discussion and Conclusion

Building on the completion of cycle 1, our work reports on identifying issues, MRs, and tentative DPs, as well as developing and evaluating a prototypical CFMS. Initially, we identified issues in three dimensions (i.e., economic sustainability, environmental sustainability, and vehicle health) confirmed by both methodological approaches, a literature review and expert interviews. However, while the existing body of knowledge provided us with relatively high-level insights (e.g., transparency on TCO, CO_2 emission, or vehicle condition), the practical problem domain yielded in-depth insights that could be addressed explicitly through vehicle data usage (e.g., cost prediction, engine utilization, or service reminders). Building on that and drawing on the effective use theory (Burton-Jones & Grange, 2013), we developed MRs and DPs and instantiated them in a prototype artifact. Finally, we evaluated the artifact using a focus group workshop and expert interviews, highlighting additional functions we plan to incorporate in the second cycle.

From a theoretical perspective, our work contributes to the body of design knowledge for data-driven car service development in general and fleet management systems in particular. We thereby implemented an artifact in the form of a prototypical fleet management system (level 1 contribution (Gregor & Hevner, 2013)) and evaluated it using a human risk and effectiveness strategy (Venable et al., 2016). In this regard, we took the first steps toward developing a nascent design theory by formulating tentative DPs. Building on this, we aim to contribute to the prescriptive knowledge base (potential level 2 contribution (Gregor & Hevner, 2013)) in the second cycle. Generally, we consider our work as an "improvement" in the DSR knowledge contribution framework (Gregor & Hevner, 2013), as it represents an efficient and effective solution for a known problem. More specifically, our evaluation results indicate that fleet management systems' effective use can be increased by offering a calculation tool (DP3) for planning expected or desired KPIs, leading to improved transparency and justification of strategic decision-making. Furthermore, the system creates awareness among drivers regarding vehicle health and usage through proactive notifications and status updates (DP6), increasing environmentally friendly and cost-efficient driving, as well as process efficiency.

In terms of practical contribution, our proposed artifact provides a user-centric solution to help enterprises effectively manage their carpools, thereby improving economic performance, environmental sustainability, and vehicle health. From a strategic perspective, the CFMS provides users with the required fleet information via comprehensive dashboards and KPIs (DP1) that can be displayed in aggregate form for internal reporting (DP2). In addition, strategic decisions can be prepared transparently by simulating different scenarios (DP3). Next, from an operational standpoint, the CFMS provides an overview of all vehicles and essential metrics (DP4). It also enables a detailed display of specific vehicles that stand out (DP5). Based on this, status updates regarding energy consumption and service notifications help improve drivers' environmental awareness and maintenance responsibility (DP6). Finally, our DPs provide practical guidance for automotive companies to develop novel data-driven services beyond fleet management.

As with any study, ours is subject to limitations. First, it is unlikely to have identified all potentially relevant articles in our literature review. Second, our sample of participating experts does not claim to be exhaustive, as we only spoke to representatives of corporate mobility, car subscription, car sharing, ride pooling, and fleet service providers. Unfortunately, experts active in logistics or leasing companies have not been taken into account yet. Nevertheless, due to our approach consisting of both literature and expert interviews, we are confident that we have ensured both rigor and relevance, thus creating a solid foundation for problem awareness. In addition, we plan to involve a broader range of experts in the second design cycle. Third, while we believe that focusing on the theory of effective use (Burton-Jones & Grange, 2013) and evaluating human risk and effectiveness (Venable et al., 2016) is most appropriate for developing design knowledge for a CFMS, the consideration of another theoretical lens may have led to a different set of DPs. Within the second cycle, we will therefore refine our tentative DPs based on our evaluation results before implementing them into a software artifact.

Part IV

Ecosystem Strategies of Incumbent Firms

6 Reallocating Uncertainty in Incumbent Firms through Digital Platforms: The Case of Google's Automotive Ecosystem Involvement

This chapter comprises a working paper that was submitted as: Sterk, F., Heinz, D., Hengstler, P. & Weinhardt, C. (2023). Reallocating Uncertainty in Incumbent Firms through Digital Platforms: The Case of Google's Automotive Ecosystem Involvement. Note: By this thesis's submission date, this study was under review at the 44th International Conference on Information Systems (ICIS). The abstract has been removed. Tables and figures were reformatted, and newly referenced to fit the structure of the thesis. Chapter, section, and research question numbering and respective cross-references were modified. Formatting and reference style was adapted and references were integrated into the overall references section of this thesis.

6.1 Introduction

The automotive industry has a long history of innovation, and the emergence of sophisticated digital technologies presents disruptive opportunities for original equipment manufacturers (OEMs) (Bohnsack et al., 2021; Svahn et al., 2017). Today's OEMs must reinvent themselves to meet the goal of generating up to 50 % of their profits from recurring digital revenue streams by 2030 (Römer et al., 2022). However, to date, established OEMs have struggled to adopt a digital mindset and strategic management techniques to realize the vision of software-defined vehicles (Dremel et al., 2017; Svahn et al., 2017). As cars evolve from status symbols to "smartphones on wheels" (Hanelt et al., 2015; Kaiser et al., 2018), infotainment systems play an increasingly important role (Weiss et al., 2021). Drivers demand integrated navigation and entertainment features, with up to 40 % considering switching vehicle brands for superior digital services (Heineke et al., 2020). This shift favors tech players that can capitalize on their smartphone proficiency by using the infotainment system as a gateway to occupy the digital interface between driver and vehicle (Schreieck et al., 2022; Weiss et al., 2021). Google, for instance, lures with its navigation solution Google Maps—but also offers an operating system (OS) for the entire infotainment system (Legenvre et al., 2022). The growing automotive competence of tech players could lead to a significant shift in the value chain, threatening legacy OEMs with commoditization into mere hardware suppliers.

Incumbent firms in various industries must rethink their business strategies to remain competitive in the digital age dominated by tech players (Hermes et al., 2021; Sebastian et al., 2017). With decades of experience in incrementally improving their pipeline business models, incumbents can now extend traditional value-creation logic through digital platforms (Marheine et al., 2021; Van Alstyne et al., 2016). However, pursuing digital innovation presents unique challenges, including a lack of expertise, surging costs, and changing customer expectations (Gao et al., 2022; Oberländer et al., 2021; Sterk et al., 2022b). There is limited research on incumbent firms' transition to the platform economy and the changes required to take advantage of platform economics (Sandberg et al., 2020; Sebastian et al., 2017; Svahn et al., 2017). However, existing research typically assumes incumbents face a binary build or join decision regarding platform strategies (Cusumano et al., 2019; Hein et al., 2020), neglecting the possibility of collaborating, assembling, configuring, or contributing to platforms that may be open-source, white-label, or provided by tech firms (Hermes et al., 2021). To explore non-binary considerations in platform strategy and the outcomes of varying levels of tech firm involvement, we pose the research question: How and why do incumbent firms decide on a certain level of tech player involvement in their digital strategy?

We conduct an embedded case study (Yin, 2014) focusing on Google's Android Automotive OS (AAOS) and its underlying Google Automotive Services (GAS) as the sole locus of our research. Our research is based on semi-structured interviews with industry experts and senior decision-makers knowledgeable about Google's digital platforms and their adoption by incumbent OEMs, as well as publicly available information published from the AAOS inception in May 2017 through April 2023. In the process, we find three distinct digital strategies that incumbent OEMs can adopt to integrate Google's offerings. Through grounded-theory-based interpretive data analysis (Gioia et al., 2013), we identified uncertainty reallocation as a core construct and derived five aggregate dimensions that represent the building blocks of a grounded model—(1) external digital platform by tech firm, (2) incumbent firm and its goals, (3) uncertainty tradeoffs and affordance of reallocation, (4) strategic actions by incumbent firm, and (5) short- and long-term outcomes.

The remainder of this paper is organized as follows: First, we review the theoretical foundations of uncertainty in digital innovation processes and boundary resources in digital platforms. Next, we outline the research method of our case study, followed by our analytical results. Finally, we discuss our findings by presenting a grounded model of uncertainty reallocation through digital platforms, the implications of our research, and a brief conclusion on its limitations and further research opportunities.

6.2 Theoretical Foundations

6.2.1 Uncertainty in Digital Innovation Processes

The digital era introduces numerous uncertainties for incumbent firms (Salmela et al., 2022; Svahn et al., 2017) as they navigate a volatile, uncertain, complex, and ambiguous (VUCA) environment while redefining their organizational identity and purpose (Wessel et al., 2021). Uncertainty, defined as "a potential deficiency in any phase or activity of the process, which can be characterized as not definite, not known, or not reliable" (Kreye et al., 2012, p. 683), or simply, a "lack of understanding" (Kreye et al., 2012; Ramirez Hernandez & Kreye, 2021), leads decision makers to have low confidence in predicting future outcomes resulting from their decisions (Erkoyuncu et al., 2013; Ramirez Hernandez & Kreye, 2021). Unlike risk, which is defined as a measurable unknown, uncertainty cannot be assigned a probability (Jalonen, 2012).

Uncertainty management throughout the innovation process has been studied in service management and new product development (Ramirez Hernandez & Kreye, 2021). However, recent research emphasizes its importance also in digital innovation processes in the context of Information Systems (IS) (Poeppelbuss et al., 2022). These processes involve decisions under highly variable and uncertain future states, influencing perceptions of strategic options for structuring, developing, using, and deploying IT artifacts (Kohli & Melville, 2019; Nambisan, 2017; Nylén & Holmström, 2015). Factors contributing to increased uncertainty include rapid technological developments, evolving customer demands, internal challenges in understanding the affordances of digital technologies, determining the level of collaboration with suppliers and partners, and assessing whether investments in digital innovation will yield the required returns for all actors involved in the ecosystem (Nambisan, 2017; Poeppelbuss et al., 2022; Svahn et al., 2017).

We adopt a multidimensional conceptualization of uncertainty (Poeppelbuss et al., 2022; Ramirez Hernandez & Kreye, 2021), while recognizing the interrelated nature of these dimensions (O'Connor & Rice, 2013). Ramirez Hernandez and Kreye (2021) distinguish between the unpredictability of the external environment (environmental uncertainty), the lack of experience with the technologies the organization intends to adopt and employ (technical uncertainty), the organizational dynamics throughout the change process (organizational uncertainty), the adequacy of financial, technical, and human resources (resource uncertainty), and the inability to predict and explain the actions of external related actors (relational uncertainty). This distinction allows us to delineate the different sources of uncertainty in our study.

Existing research suggests strategies for managing uncertainty by reducing it at its source or coping with it by minimizing its impact (Poeppelbuss et al., 2022; Simangunsong et al., 2012). Organizations may also engage in uncertainty reallocation by shifting criticality between uncertainty types (Poeppelbuss et al., 2022; Ramirez Hernandez & Kreye, 2021). For instance, Poeppelbuss et al. (2022) empirically show how participation in multi-actor innovation settings can reduce technical and resource uncertainty while increasing relational uncertainty. In this context, our study explores how external digital platforms, such as Google's automotive platforms AAOS and GAS, enable incumbents to reallocate uncertainties and how they determine strategic actions to actualize and exploit these affordances.

6.2.2 Affordances of Boundary Resources in Digital Platforms

We define a digital platform as "a set of digital resources—including services and content—that enable value-creating interactions between external producers and consumers" (Constantinides et al., 2018, p. 381). Digital platforms can provide technological affordances, which refer to "what one individual or organization with particular capabilities and purposes can or cannot do with a technology" (Majchrzak & Markus, 2013, p. 381). To provide new affordances, digital platforms must possess inherent flexibility, enabling them to be reconfigured as needed (Hein et al., 2019b; Yoo et al., 2010). In addition, the architecture of digital platforms is characterized by a high degree of modularity, facilitating the integration of new modules without jeopardizing the entire system (Tiwana et al., 2010).

To design for such affordances, platform owners use boundary resources that enable complementors to develop products or services on the digital platform (Eaton et al., 2015; Ghazawneh & Henfridsson, 2013; Hein et al., 2019b). Boundary resources can be software tools or rules that "serve as the interface for the arm's-length relationship between the platform owner and the application developer" (Ghazawneh & Henfridsson, 2013, p. 174). The concept of boundary resources can be understood as a theoretical device (Ghazawneh & Henfridsson, 2013) for digital platform owners to balance the tension between retaining platform control and stimulating the generativity of third-party developers (Tilson et al., 2010). These resources include technical and social elements, such as application programming interfaces (APIs), and regulations, incentives, and guidelines, respectively (Aanestad et al., 2019).

Prior research has mainly focused on boundary resources in digital smartphone platforms (Eaton et al., 2015; Karhu et al., 2018, 2020). For instance, Eaton et al. (2015) studied how boundary resources in Apple's iOS platform undergo change through distributed tuning, a process that leads to a cascade of adaptations and rejections in a network of heterogeneous actors and artifacts. Karhu et al. (2018) study Google's Android mobile platform and assign boundary resources to four functions: defining openness, facilitating, loosening couplings, and capturing value. Besides research on purely digital ecosystems, research has addressed boundary resources in digital platforms under the Internet of Things (IoT) paradigm (Hein et al., 2019c; Petrik & Herzwurm, 2020; Petrik et al., 2021). Our study integrates these research directions through a case study on Google's automotive platforms, AAOS and GAS, focusing on software-defined vehicles as complex IoT devices. Specifically, we examine the affordances of boundary resources within AAOS and GAS to understand how platform owners facilitate generativity for OEMs and third-party developers while retaining control.

6.3 Research Method

We use an embedded single-case study approach (Yin, 2014) to examine how incumbent firms adapt their digital strategies in terms of engaging with technology firms in response to them introducing digital platforms to the market. In this section, we describe our case selection, data collection, and data analysis.

Case Selection. We employ a revelatory single case strategy (Yin, 2014) to examine previously inaccessible dynamics of a phenomenon. Our embedded case study includes multiple subunits of analysis and allows for variation across these subunits (Yin, 2014). We chose the automotive industry and Google's AAOS and underlying GAS (i.e., Google Maps, Google Assistant, and Google Play Store) for several reasons. First, the automotive industry is currently facing significant IT-driven innovation efforts from incumbents and external tech firms. Second, Google has achieved a central market position with its deeply integrated AAOS. Third, unlike other automotive solutions, such as Android Auto or Apple CarPlay, AAOS is purpose-built for direct in-vehicle integration, offering greater ability to interact with the car's internal systems to deliver innovative features. Finally, with the recent increase in OEM collaboration with Google, the question has shifted from whether Google will be in the car to the extent of Google's access to individual vehicle functions and data (e.g., AAOS with/without GAS). As embedded subunits within Google's involvement in the automotive ecosystem, we examine the strategic positioning of different incumbent firms with respect to Google's AAOS and GAS offerings over time. Following a sampling logic that emphasizes subunit diversity (Yin, 2014), we identified three distinct OEM actualization strategies by comparing their strategic actions from 2017 to 2023. We used the diversified strategic directions of traditional OEMs as a basis for abstracting knowledge across multiple embedded units of analysis. In Figure 6.1, we present a timeline of the evolution of Google's AAOS and GAS offerings and the strategic positioning of different OEMs.

Data Collection. We used interviews and archival documents as primary data sources, allowing us to combine different perspectives on our case (Yin, 2014). From June 2021 to April 2023, we conducted 17 semi-structured interviews with industry experts and senior decision-makers familiar with Google's automotive offerings (i.e., AAOS and GAS) and their adoption by automotive OEMs (see Table 6.1). We applied a mix of convenience and theoretical sampling, first relying on our personal network within the automotive industry and then acquiring additional interviewees after initial data analysis to deepen specific emergent aspects (Bryman, 2016). We encouraged informants to share their specific insights by asking open-ended questions along predefined discussion points (e.g., value-capturing strategy, data sovereignty, or scalability). All interviews were conducted by two authors via video-conferencing software, averaging 53 minutes in length, and were recorded, transcribed, and then analyzed using MAXQDA software. Our second data source consisted of publicly available archival documents, such as website and news articles, strategy update reports, and press releases published from May 2017 to April 2023. We focused on OEM's strategic activities related to Google's AAOS and GAS, resulting in 67 relevant documents, and identified 19 strategic activities by Google or OEMs (see Figure 6.1). OEMs that planned to incorporate AAOS or GAS in any way include Volvo, Polestar, Honda, General Motors, Renault-Nissan-Mitsubishi, Ford, Mercedes-Benz, Volkswagen Group, BMW Group, and Stellantis.

Data Analysis. We used established procedures to analyze our data inductively (Gioia et al., 2013; Gioia, 2021). In a first-order analysis, two authors individually reviewed interview transcripts and documents and assigned descriptive open and in-vivo codes to relevant passages. Supported by initial memoing (e.g., through preliminary diagrams), we collaboratively identified similarities and differences among the codes, reached a consensual understanding, and reduced the codes to 46 informant-centered first-order concepts. In the second-order analysis, we further condensed related first-order concepts into 17 researcher-centered second-order themes. Finally, we distilled the second-order themes into five aggregated dimensions and developed a grounded model. In the latter analytical steps, we the applied affordance-actualization theory (Strong et al., 2014) as a theoretical lens to explain the conceptual relationships among constructs.

Table 6.1.: Overview of interviewees.

Industry Sector	Company	Role of Interviewee	Duration
Car Manufacturer	OEMCorp1	Product Owner App Store	72 min
		Android Automotive Developer	46 min
	OEMCorp2	Lead Android Automotive Developer	45 min
	OEMCorp3	Senior Project Manager Vehicle Platform	67 min
		Project Manager Automotive Software	68 min
	OEMCorp4	Product Manager Digital Services	59 min
	OEMCorp5	Company Builder Automotive	61 min
	OEMCorp6	CEO/CTO Digital Innovation Unit	66 min
Tier-1 Supplier	SupplierCorp1	Senior Android Automotive Developer	51 min
		Senior Vice President Engineering	41 min
		Product Lead Software-Defined Vehicle	27 min
		Product Manager Infotainment	42 min
		Business Owner Android Automotive	46 min
	SupplierCorp2	Director Navigation Software	58 min
Consulting	ConsultingCorp1	Strategy Consultant Automotive	44 min
	ConsultingCorp2	Strategy Consultant Automotive	44 min
Applied Research	ResearchCorp	Senior Automotive Software Architect	62 min

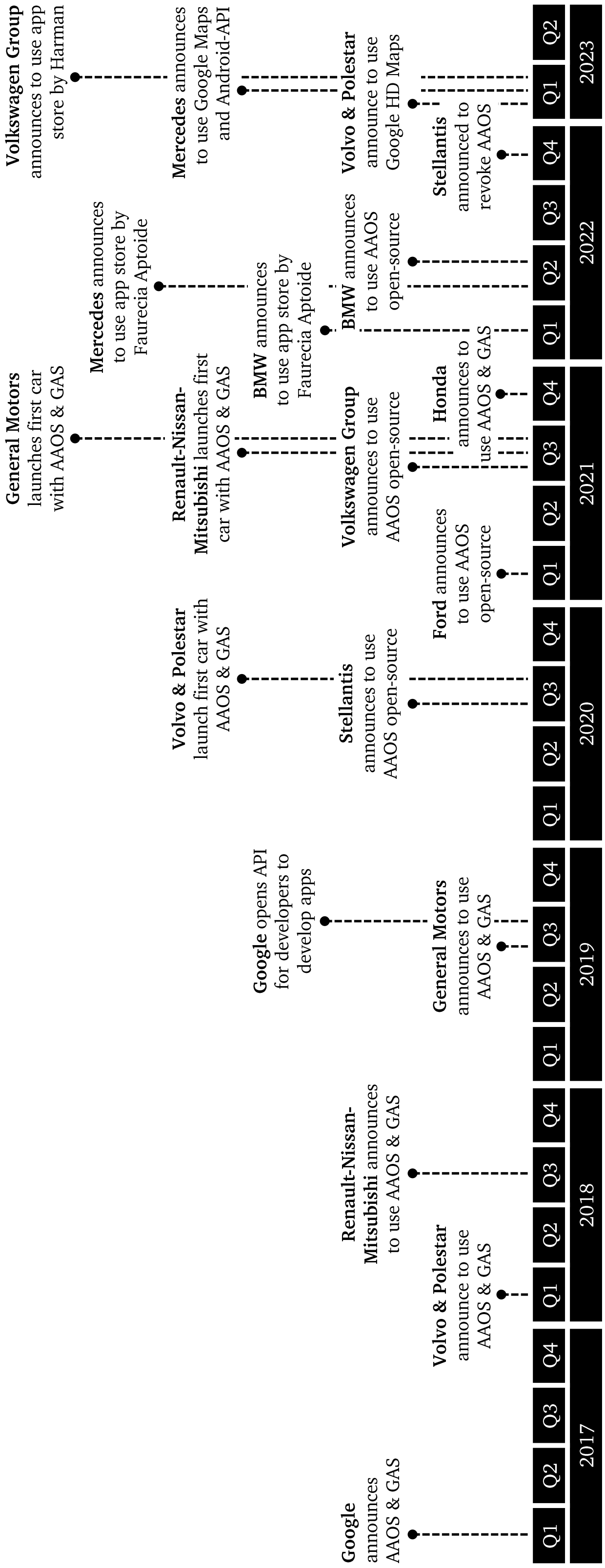


Figure 6.1.: Case timeline of AAOS and GAS development and adoption by OEMs.

6.4 Insights from Google's Automotive Ecosystem Involvement

In this section, we present analytical insights into how and why incumbent firms reallocate uncertainty by deciding on the level of tech player involvement in their digital strategy. The focus of our embedded case is Google's automotive platform offering (i.e., AAOS and GAS), as Google currently holds the predominant position in infotainment and operating systems, forcing traditional OEMs to reconsider their digital strategy. We first describe the affordances of uncertainty reallocation by incumbent firms (i.e., carmakers) via the utilization of a tech firm's (i.e., Google) external platform and then present findings regarding the actualization strategies taken by incumbent firms.

6.4.1 Affordance of Uncertainty Reallocation

External Digital Platform by Tech Firm

The influx of tech players into the automotive industry has resulted in a more fragmented competitive landscape. They provide external digital platforms to penetrate the market for certain areas of the technology stack, as observed with Google's operating system (AAOS) and the accompanying service offerings (GAS). Boundary resources play a crucial role and are an indispensable tool for platform owners to implement digital platform strategies. In the context of Google's digital in-vehicle platform, we identified boundary resources used to pursue four strategies—scale, capture value, standardize, and facilitate. In the following, we elaborate on the boundary resources associated with Google's AAOS or GAS (see Figure 6.2).

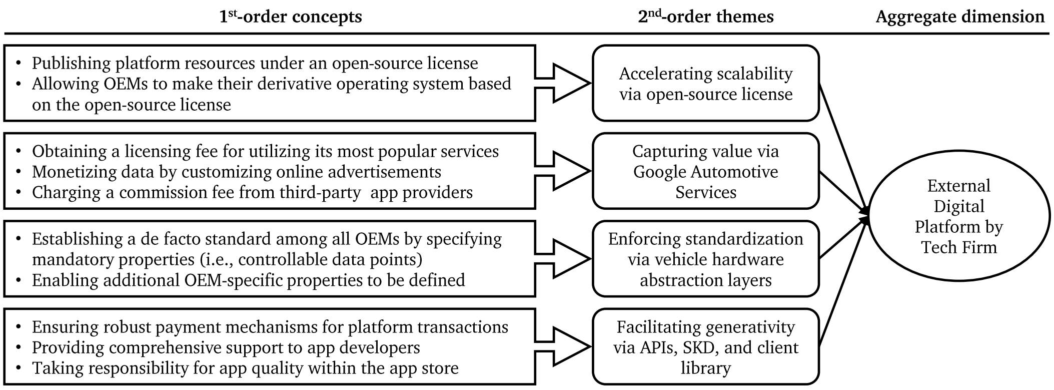


Figure 6.2.: Data structure for "external digital platform by tech firm."

Accelerating scalability via open-source license. Analogous to its smartphone OS, Google has released AAOS under an open-source license so that OEMs can install AAOS in their cars without involving Google and without entering into a contractual relationship with Google to make their derivatives of the OS. The Product Lead of SupplierCorp2's software-defined vehicle program pointed out the distinction between a *"true"* open-source approach like Linux and having *"a commercially interested firm like Google as the shepherd of the open-source project."* In the end, AAOS itself is always *"just an enabler for Google, but it does not generate any monetary gains,"* as ResearchCorp's Senior Software Architect added. From a strategic perspective, the open-source license encourages as many OEMs as possible to integrate AAOS to scale the ecosystem quickly. ConsultingCorp1's Strategy Consultant summarized this aspect as follows:

> "*Android Automotive open-source is Google's brilliant idea to make carmakers dependent without directly charging licensing fees. [...] Some OEMs are afraid to work directly with Google due to the licensing costs and dependency. However, some of them are being convinced because it is possible to use AAOS open-source, which seems like Linux. This is the Trojan horse that OEMs fall for because they don't have to pay licensing fees.*" (Strategy Consultant, ConsultingCorp1).

Capturing value via Google Automotive Services. While AAOS itself is open-source, Google has developed value-adding software artifacts called Google Automotive Services (GAS) that interact with the OS, including Google Maps, Google Assistant, and the Google Play Store. To use GAS, implementing OEMs must enter into a licensing agreement and share proprietary data with Google. According to Research-Corp's Software Architect, *"Google's focus is not on acquiring in-vehicle data. From a marketing standpoint, the user is a more appealing target than the vehicle itself."* Thus, Google's primary scaling mechanism depends on gaining access to user data in order to extract patterns to develop customized online advertising, and improve the quality of applications such as Google Maps. Google's third monetization mechanism is its Play Store, which is mandatory for OEMs using GAS and charges a commission fee for third-party applications hosted there. The Product Owner of OEMCorp1's app store stressed the analogy to the smartphone world:

> "*The most exciting thing, from my point of view, is the business model. Who will earn money with digital products in the vehicle in the future? If you look at how things have worked in the mobile phone world, third-party app developers are the only ones earning money directly from digital products. But who is the only one who gets a revenue share? It's the two big stores, Apple and Google. The Play Store is one of three apps that come with GAS. And that means that the likelihood*

that you as an automotive OEM can still earn money with digital products in the car afterwards will be diminished."(Product Owner App Store, OEMCorp1).

Enforcing standardization via vehicle hardware abstraction layer. Regardless of whether an OEM chooses the open-source option or licenses AAOS, the most important requirement for integrating Android into their cars is the implementation of the vehicle hardware abstraction layer (VHAL). The VHAL extends the original Android framework for the automotive context and defines properties, such as powertrain-related data, that must be supported by all OEMs implementing AAOS. Google enables OEMs to extend the VHAL and integrate custom, manufacturer-specific properties, giving them control and data sovereignty over the vehicle data sent to Google. However, according to analysis by ConsultingCorp1's Strategy Consultant, the authority ultimately remains with Google, as market demand for advanced applications will force OEMs to share specific vehicle data items with Google and third-party developers:

"*The belief that the OEM has full control over the VHAL and data is a widespread misconception. In reality, the OEM can only define supported data, and this poses a challenge as developers are hesitant to build applications for a platform that is not based on a common foundation of supported data and functionality. The platform business operates within a merciless economy of scale, and without external developer support, the OEM's capacity to build customer relationships is severely limited. [. . .] This lack of scale and content will cause the standard to fail, as it will not be able to secure a customer base.*"(Strategy Consultant, ConsultingCorp1).

Facilitating generativity via APIs, SKD, and client library. The success of Google's expansive digital ecosystem can be attributed to its robust third-party developer community, which delivers a diverse set of third-party apps available to end users. Implementing GAS comes with APIs and a software development kit (SDK) that facilitates app development while guaranteeing a robust payment infrastructure for all platform transactions through the Google Play Store. GAS provides extensive support for app developers, including various resources such as tools, test suits, documentation, and collaborative events (e.g., developer conferences). In addition, AAOS provides a client library called Google Play Services, which facilitates frequent updates to developer APIs independently of OEMs. Finally, with its established control mechanisms, Google takes responsibility for excluding undesirable or malicious apps, relieving the OEM of the burden of ensuring the app quality in the store. SupplierCorp1's AAOS Business Owner summarized the similarities and differences to a Linux-based OS for developers as follows:

"The bottom part of Android and the Linux system is similar because it's a Linux kernel with certain similarities, but the architecture of Android is different, for example, because of the virtual machine and the high-level APIs, which are mainly for third-party developers to develop apps in their ecosystem. They just promote it as an app development environment. The documentation for Android Automotive is not extensive for OEMs; it's mostly for app development. So, from that perspective, the whole architecture and the setup for Android is just to promote third-party apps."(Business Owner Android Automotive, SupplierCorp1).

Incumbent Firm and Its Goals

The ongoing digital transformation is turning cars from status symbols into rolling computing platforms. This paradigm shift has pushed OEM to re-evaluate their strategic goals, forcing them to make crucial decisions about their future service offering and digital business models to remain their competitive edge in the market. By implementing an appropriate digital strategy, OEMs can retain control of their businesses, avoid commoditization by tech players, continue providing high-quality services to end customers, and tap into recurring digital revenue streams. We found that OEMs have formulated four overarching goals concerning their infotainment offering, which we discuss below (see Figure 6.3).

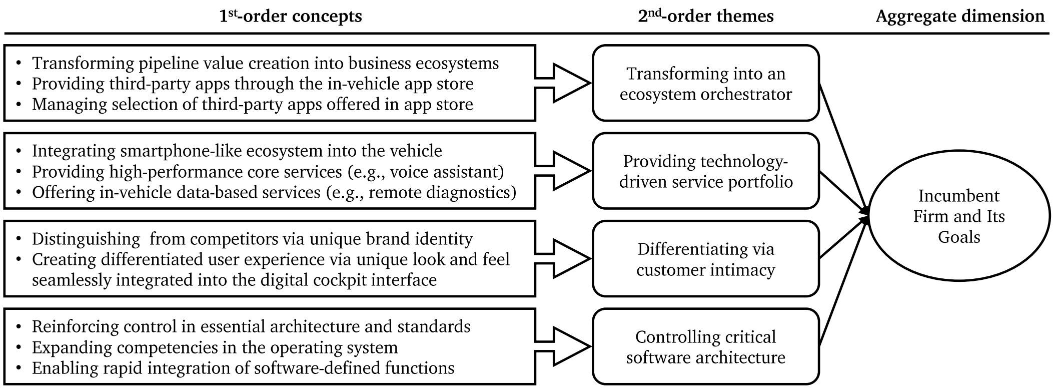


Figure 6.3.: Data structure for "incumbent firm and its goals."

Transforming into an ecosystem orchestrator. OEMs want to move from selling physical cars within a linear value chain to orchestrating service-oriented business ecosystems. Due to the complex nature of software-defined vehicles, they rely on third-party developers to expand their application offerings while maintaining quality standards and managing costs efficiently. Implementing in-vehicle app stores not only enhances the driving experience but also provides an opportunity to earn a significant revenue share from third-party apps. The ecosystem orchestrator takes on the role of a gatekeeper, controlling the selection of third-party apps and determining which are ultimately offered in the app store. The Product Owner of OEMCorp1's app store emphasized the difference between the OEMs' existing business models and the coveted role of an ecosystem orchestrator:

> "*Today, we don't have a platform business model, which means we don't build a two-sided marketplace but sell products in the pipeline value creation, where we end up enriching the product more and more through suppliers and sell it once to the customers. In the future, we want to build a platform ecosystem where third-party developers develop apps for us. As a store provider, we can set certain rules, such as what is allowed and what is prohibited. We can also ensure that these rules are adhered to, and we can earn money with [the app store]. But as of today, no one makes money with apps in cars.*"(Product Owner App Store, OEMCorp1).

Providing technology-driven service portfolio. An additional goal of incumbent firms is to provide a value-adding digital app portfolio to meet increasing end user expectations. This includes the integration of the user's other digital ecosystems, such as music streaming, into the vehicle, which has become standard practice. Moreover, OEMs try to improve the performance of other in-vehicle services and reduce the dependencies on smartphone mirroring, with navigation systems and voice assistants being the most prominent. For instance, map application providers have the power to influence the driver with targeted and prominently placed points of interest. With the vast amounts of in-vehicle data generated by sensors and software, OEMs are looking to create analytical insights about the vehicle, the driver, and their environment, enabling data-driven business models in areas such as insurance, after-sales, and fleet management. Appropriately, the Product Owner of OEMCorp1's app store drew an analogy to the smartphone and confirmed the significant potential underlying digital in-vehicle services:

> "*Is there even a market for digital products in cars or not? Nobody can say, but I believe there is. [...] But in 2005, very few people would have said that many billions of Euros would be turned over in a quarter via an app store that runs on a mobile phone. And if you look at the possibilities, a smartphone offers only a fraction of the interfaces and sensors or data that a car theoretically has. If you take that as a measure of the potential for innovation, the business potential for digital automotive products is enormous.*"(Product Owner App Store, OEMCorp1).

Differentiating via customer intimacy. As a third goal, OEMs seek to differentiate themselves through unique brand identity and direct interaction with the end user via the digital cockpit. Control of the digital interface, and therefore customer interaction, allows for a differentiated user experience and improved customer value. In particular, premium carmakers strive to deliver rich digital experiences seamlessly integrated with their overall brand identity and familiar aesthetics, such as intuitive touchscreens. However, OEMs must retain control over the user touchpoint and central data to generate and capitalize on increased satisfaction via brand-exclusive onboard experience. SupplierCorp2's Director Navigation Software affirmed:

> "*Today, it's all about software and the experience you create for your customers, but also the relationship you build with them. If the big screen in your car belongs to a third party [...] and they own the direct relationship with the consumer, what is left for the OEM? How can they differentiate themselves? How are they going to create and monetize value-added services on that platform in the future? [. . .] This is not about the operating system, but what they build on top of it, like their own applications or ecosystem to keep that direct relationship with the consumer and collect and use data to improve and monetize their products.*"(Director Navigation Software, SupplierCorp2)

Controlling critical software architecture. Finally, OEMs aim to strengthen their control over key architectures and standards by expanding capabilities in OS and middleware. Both serve as critical vehicle components that enable carmakers to integrate essential software-defined features into the vehicles rapidly. These functionalities include remotely integrating additional battery power or activating seat heating features through over-the-air updates. However, while OEMs are eager to expand their in-house software stack development to avoid external dependencies, lack of expertise, escalating costs, and lack of economies of scale are putting pressure on them to partner with large tech companies. ResearchCorp's Automotive Software Architect added specific reasons for the strong emphasis on in-house development by OEMs:

> "*It can be more efficient and cost-effective for the OEM to develop a custom proprietary operating system. For example, AAOS requires a lot of heavy hardware. [...] Additionally, allowing external tech players to take responsibility for the further development of the operating system poses significant risks for the OEM. [...] Utilizing a third-party operating system entails a potential loss of control over data, as the vendor may try to get as deep into the vehicle as possible.*"(Senior Automotive Software Architect, ResearchCorp)

Uncertainty Tradeoffs and Affordance of Reallocation

The rise of digital platforms such as AAOS and GAS presents a significant potential to reduce uncertainty for legacy carmakers. However, these also increase uncertainty compared to established pre-digital strategies. In sum, external platforms may not necessarily reduce uncertainties but offer the potential to reallocate them, requiring incumbents to balance multiple tradeoffs, as illustrated below (see Figure 6.4).

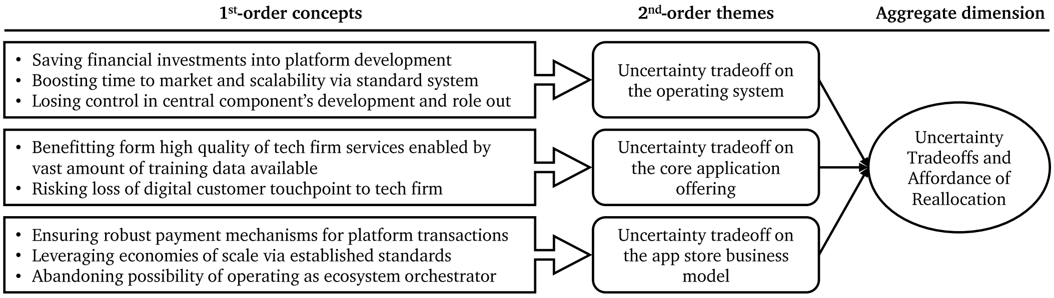


Figure 6.4.: Data structure for "uncertainty tradeoffs and affordance of reallocation."

Uncertainty tradeoff on the operating system. Whether to implement AAOS or build a proprietary OS is a key consideration for OEMs. Using an external platform such as AAOS provides significant financial benefits by reducing the need for continuous system updates with each new generation of hardware. Developing and maintaining in-house technology stacks requires a large financial investment, including the cost of hiring software developers with the necessary skills. Also, integrating mature off-the-shelf solutions such as AAOS can improve time-to-market and scalability, especially in the low-volume luxury segment. On the other hand, Google's control over the AAOS system raises uncertainties, even without the use of GAS. Since AAOS is likely to become a standard feature in many cars, Google's role as the provider of AAOS would give them considerable power. They could cease releasing open-source versions of AAOS and offer new versions under license agreements that require GAS or let the VHAL specifications force OEMs to share critical vehicle data. A Company Builder from OEMCorp5 commented on this tradeoff as follows:

> "*Implementing AAOS entails considerable uncertainty to OEMs, as it may result in a loss of control over user data, user behavior, and system usage information. On the other hand, it must be acknowledged that the automotive industry has yet failed to develop a stable operating system. In this regard, I believe it is necessary to strike a balance. While this approach may present challenges, I believe that the benefits of integrating a trusted and well-established operating system outweigh*

> *the potential drawbacks associated with data business, information loss, and usage profiling.*"(Company Builder Automotive, OEMCorp5).

Uncertainty tradeoff on the core application offering. The next critical strategic decision for OEMs is whether to use GAS or develop and integrate comparable solutions. Google's advantage lies in its vast training data from widespread smartphone use, which makes it difficult to develop navigation services with comparable real-time geo-information as Google Maps or similar voice recognition capabilities as Google Assistant. Moreover, many drivers currently use Google Maps via their smartphone's projection mode and may demand a built-in version, exposing OEMs with alternative solutions to the threat of losing customers. Despite the potential benefits, there are downsides to implementing GAS for OEMs, including losing their digital customer touchpoints and user interactions to Google or limited visibility into data exchange. Finally, GAS offers limited customization of the infotainment system's user interface, resulting in a reduced impact on brand identity and customer experience. The impact of this uncertainty factor varies depending on the OEM's target audience, as explained by OEMCorp1's Product Owner App Store:

> "*An important aspect that OEMs must weigh up is the issue of user experience, user interface, and differentiation. When using GAS, they have limited control over the user interface and experience compared to building on plain Android open-source. However, this is not a general argument for or against GAS; not all OEMs see differentiation in user experience and interface design as a competitive differentiator, especially volume OEMs with lower-priced vehicles who place less emphasis on these aspects.*"(Product Owner App Store, OEMCorp1).

Uncertainty tradeoff on the app store business model. When deciding on GAS, carmakers must consider that it includes the integration of the Google Play Store as the in-car app store. Using GAS reduces OEMs' technical uncertainty by ensuring robust payment mechanisms for all transactions and quality control for third-party apps. Also, adherence to established standards can reduce the OEM's potential threat of limited app developer engagement and failure to achieve economies of scale. As a result, experts suggest that the Google Play Store could outpace proprietary alternatives in terms of app quantity, as it facilitates third-party app development through specific boundary resources (i.e., SDK, APIs, and client library). However, embedding the Play Store increases OEMs' uncertainty about its business model, as it prevents them from pursuing the goal of becoming an ecosystem orchestrator by delegating control over third-party app selection, user engagement, app sales tracking, and revenue sharing to Google. SupplierCorp1's Business Owner AAOS stressed the strategic options OEMs have regarding in-car app stores:

“There was a time when every major manufacturer was trying to develop their own app store. [...] And how many apps did they have in there? Negligible. That approach has failed. In the second wave, a few manufacturers started using the Google Play Store instead. However, what are the others doing? They are looking for third-party app stores, ideally working with other OEMs to hopefully reach a critical mass of customers and ensure the marketplace’s sustainability and profitability.”(Business Owner Android Automotive, SupplierCorp1).

6.4.2 Strategic Actualization Process

Strategic Actions by Incumbent Firm

When integrating Google into an OEM’s in-vehicle offering, three actualization strategies have emerged that involve the uncertainty tradeoffs discussed (see Figure 6.5). To illustrate the actions taken for each strategy, we supplement the description of each type with a corresponding real-world example in the form of a case vignette, also visualizing which architecture components come from Google (grey) and which come from the OEM (white) (see Figures 6.6 to 6.8).

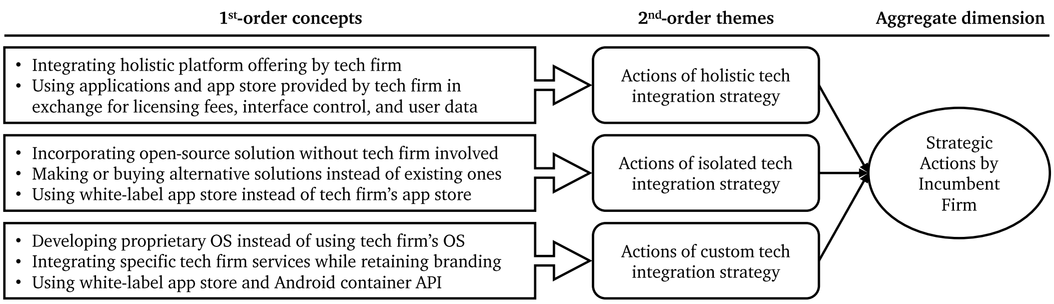
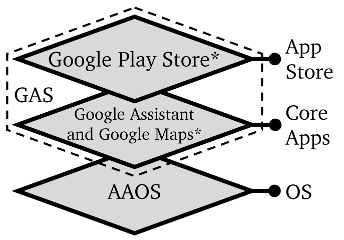


Figure 6.5.: Data structure for “strategic actions by incumbent firm.”

Actions of holistic tech integration strategy. This strategy involves the comprehensive integration of the tech firm’s digital platform offerings, in our case both the AAOS and GAS platforms (see Figure 6.6). OEMs that adopt this strategy benefit from a rapid go-to-market, allowing them to focus on their existing core competencies. Regular over-the-air updates of the AAOS base architecture provided by Google ensure a continuous update of the OS and the pre-installed GAS provide the OEM with an attractive service offering in exchange for licensing fees and dedicated vehicle data, reducing the OEM’s software development effort to a minimum. With this strategy, OEMs offer their end-users a seamless experience that they are familiar with from their smartphones, including Google ID login, the established Android look and feel, and popular Google applications. Google takes care of the app store, security, and support for app developers, while the OEM takes the role of a complementor, allowing the tech firm to orchestrate the digital ecosystem, including shaping ecosystem policies and receiving revenue shares from third-party apps.

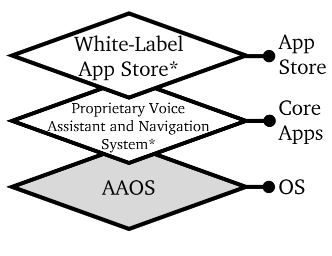


*Design and user data controlled by Google

Swedish carmaker Volvo Cars and its subsidiary Polestar, both owned by Chinese carmaker Geely, have been offering cars with built-in AAOS since 2020. Volvo is fully committed to the partnership resulting in all new cars featuring the whole infotainment system supplied by Google, including the pre-installed GAS. Thereby, Volvo or Polestar car drivers are prompted to link their Google accounts. Furthermore, Google and Volvo are taking their partnership to the next level with the integration of "HD Maps," where Google Maps will use additional car sensor data in real-time to provide highly detailed and up-to-date road information.

Figure 6.6.: Illustrating "holistic tech integration" via Volvo's Google built-in approach.

Actions of isolated tech integration strategy. The second strategy adopted by OEMs is to integrate the open-source versions of a digital platform (e.g., AAOS), but not to use proprietary platforms and services (e.g., GAS) in order to avoid becoming too dependent on the external platform providers (e.g., through contractual agreements or payment obligations with Google) (see Figure 6.7). In pursuing this strategy, OEMs need to find alternatives to proprietary services. For example, for in-car navigation systems and voice assistants, OEMs can either rely on their existing service offerings or choose between the traditional make or buy binary. For the app store, most OEMs adopting this strategy procure an Android-based white-label app store from a software vendor to retain the benefits for app developers while outsourcing the app store development effort and retaining platform control. Compared to the first strategy, the OEM replaces Google as the orchestrator, gaining the authority to set app store rules and earn revenue share from third-party applications. The look and feel of the infotainment system and data sovereignty remain with the OEM using open-source and white-label solutions.

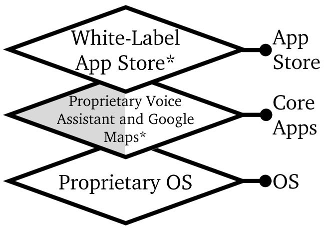


*Design and user data controlled by OEM

Starting in 2023, the BMW Group will be the first German carmaker to launch an infotainment system based on the open-source variant of AAOS, called BMW OS 9. This approach excludes permanently installed GAS applications (e.g., Google Maps), as BMW wants to retain independence in these areas. BMW also does not use the Google Play Store and instead tries to build up its own Android-based commercial ecosystem supported by selected suppliers. Here, BMW integrates Faurecia Aptoide's white-label app store, with BMW developing the user interface to preserve its brand-specific design and experience.

Figure 6.7.: Illustrating "isolate tech integration" via BMW's open-source approach.

Actions of custom tech integration strategy. Apart from the two strategies of using open-source platforms such as AAOS with or without proprietary platforms and services (here: GAS), Mercedes-Benz has exemplified in our case a so far unique third strategy (see Figure 6.8), which relies on a proprietary OS without the tech firm's involvement to retain full control over the base-layer of software architecture and overall integration. Although GAS is not involved, this strategy includes the integration of certain Google services in exchange for licensing fees. For example, the OEM integrates Google Maps, which includes rich location details and real-time and predictive traffic information. Under this strategy, the OEM integrates specific Google services while maintaining its own brand and design, and retaining sovereignty over user data. For the app store, the OEM also takes on the role of the platform owner and uses a white-label solution for the app store. In the case of Mercedes, in order to provide a functional app store despite the absence of AAOS, a container API is integrated to run Android apps.



*Design and user data controlled by OEM

Mercedes-Benz took a distinctive approach to its software strategy starting in 2023, opting against an off-the-shelf operating system like AAOS. Instead, Mercedes developed a proprietary infotainment system called MB.OS to retain control over customer relationships and data privacy, and to integrate unique car functions. Mercedes is using Faurecia Aptoide's white-label app store, but has also established a strategic, long-term partnership with Google to be the first OEM to build its own branded navigation system based on in-car data and Google Maps navigation capabilities.

Figure 6.8.: Illustrating "custom tech integration" via Mercedes' exclusive approach.

Short- and Long-Term Outcomes

The commitment of incumbent OEMs to an actualization strategy, characterized by their degree of tech firm integration, ultimately leads to different short- and long-term outcomes. In this subsection, we analyze the (anticipated) outcomes for each of the specified strategies (see Figure 6.9 6).

Anticipated outcomes of holistic strategy. The holistic tech integration strategy offers early adopters in the short term a state-of-the-art infotainment system with high recognition value (e.g., due to the popularity of Android in the smartphone sector) and a time advantage over other OEMs, since white-label app store providers have to follow Google's Android development. This time advantage is reinforced by close collaboration with the tech partner, allowing the OEM to be the first to release new services, such as in our case the next-level navigation feature "HD Maps".

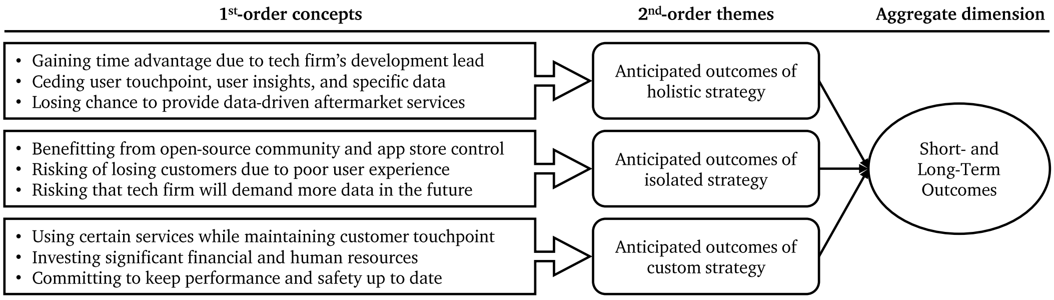


Figure 6.9.: Data structure for "short- and long-term outcomes."

However, OEMs cede the direct touchpoint with the end user, along with valuable insights into user engagement with the infotainment system and specific vehicle data, to Google. In the long run, this approach results in the OEM losing critical infotainment capabilities and the ability to provide data-driven aftermarket services to various end users (consumer, business, and government), including the domains of fleet management, driving analytics, and location-based services. OEMCorp3's Automotive Software Project Manager highlighted this aspect as follows:

> "*Google's data capabilities enable it to offer unique vehicle data-based services that OEMs currently lack the competence to provide. As a result, OEMs may transform into pure chassis suppliers, leaving Google to derive services and business models from the data. In the past, car ownership was a simple process with limited customer interaction. Now, customers can pay for additional vehicle functions and personalize their vehicles. Aftersales, for example, is the absolute cash cow of the automotive industry and involves continuous customer support and the exploration of new sales channels. By handling this over to tech players, OEMs will lose vital monetization channels.*"(Project Manager Automotive Software, OEMCorp3).

Anticipated outcomes of isolated strategy. The OEM's short-term outcome of pursuing the isolated tech integration strategy is to initiate a stable and scalable OS based on the established open-source standards (here: AAOS), which, due to its open-source nature, is constantly being supplemented by a vast developer community. In addition, this approach allows for the creation of a proprietary ecosystem that is mostly independent of the tech firm and gives OEMs control over key differentiators and business model elements, including data ownership, user interface, and app store orchestration. However, OEMs must find competitive alternative solutions with equivalent performance to the tech firm's service suite (here: GAS) to avoid customer churn due to a potentially inferior user experience compared to the tech firm's mature digital offerings. Moreover, the long-term viability of working with white-label app store providers as a genuine alternative to the Google Play Store remains unclear.

This approach can only succeed if the adaptation effort for third-party developers to place their apps in multiple Android-based app stores remains manageable, and the tech firm continues to provide the necessary boundary resources (e.g., Google's APIs). Finally, a Company Builder Automotive from OEMCorp5 stressed that a possible long-term outcome could be Google using its position of power to gain more access to vehicle data in the future:

> "*In the future, Google may try to get access to as much car sensor data as possible. For years I've been discussing using all powers of persuasion that we as an OEM can tap into insanely cool data, whether it's from the camera, temperature, or light sensors. Conversely, Google has seen through this potential of moving sensor stations [i.e., cars] for years because they collect everything that isn't nailed down with their smartphones. Google may exploit this lock-in effect to get access to more vehicle sensor data. I have no idea how the OEMs are going to fight this.*"(Company Builder Automotive, OEMCorp5).

Anticipated outcomes of custom strategy. OEMs that negotiate individual deals with a tech firm reap the immediate benefits of both strategies discussed so far: leveraging powerful services like Google Maps, while retaining customer touchpoints, including brand, design, and data sovereignty. The app store-related outcomes are similar to the second strategy because of the same white-label approach. However, the peculiarity of this strategy of not using open-source standards such as AAOS and instead developing a proprietary system result in a high short-term financial expenditure, but also has two critical long-term consequences. On the one hand, this approach is primarily characterized by the fact that a significant part of the base system is programmed in-house, thus retaining important software competencies and central control (e.g., over vehicle data) over the OS. On the other hand, the OEM is responsible for maintaining and evolving the system, including performance and security updates, over multiple generations of vehicles. Because of the latter, industry experts, including the Senior Project Manager Vehicle Platform from OEMCorp3, are skeptical about the long-term viability of a proprietary OS:

> "*No [OEM] can avoid Android in the long run. Simply for one reason: it has proven itself! There are two big options when it comes to touchscreen devices, user interface frameworks, operating systems, and development environments: iOS and Android. Show me another framework, another SDK that I can use today, where I can get a good look and feel and user experience. [...] It's not an option anymore to develop it in-house.*"(Senior Project Manager Vehicle Platform, OEMCorp3).

6.5 Discussion and Conclusion

6.5.1 A Grounded Model of Uncertainty Reallocation in Incumbent Firms

We set out to explore how and why incumbent firms decide on a certain level of tech player involvement in their digital strategy. We apply affordance-actualization theory as a theoretical lens to develop a grounded model of uncertainty reallocation in incumbent firms (see Figure 6.10). In doing so, we combine the insights gained so far using the five inductively derived aggregate dimensions as building blocks of the model—(1) external digital platform by tech firm, (2) incumbent firm and its goals, (3) uncertainty tradeoffs and affordance of reallocation, (4) strategic actions by incumbent firm, and (5) short- and long-term outcomes.

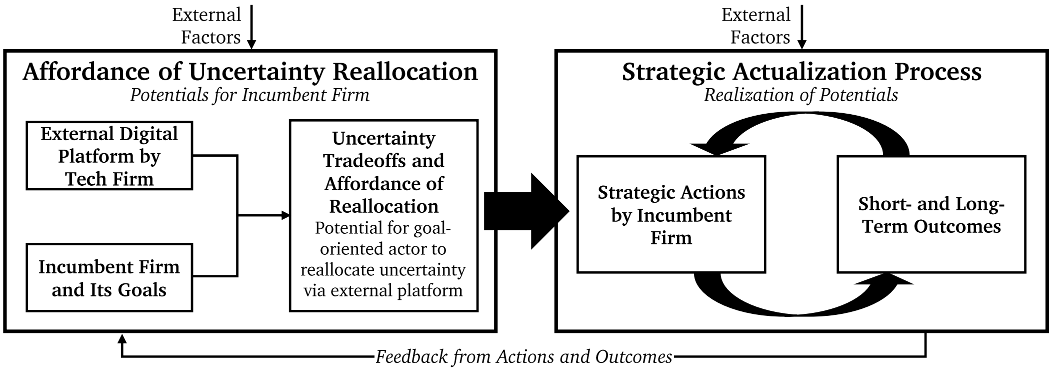


Figure 6.10.: Grounded model of uncertainty reallocation in incumbent rirms.

By offering a digital platform, tech firms aim to dominate and control specific technology areas in traditional markets, creating an attractive platform offering for incumbent manufacturers and third-party service providers while maintaining platform control through boundary resources (Ghazawneh & Henfridsson, 2013). At the same time, incumbent firms are reevaluating their strategic goals in the face of ongoing digital transformation, forcing them to make critical decisions about investments in technology development and their intended digital portfolio in the future. The combination of these two aspects, leads to uncertainty tradeoffs between different dimensions (e.g., technical, resource, and relational uncertainty), but the means offered by the external platform also provide the affordance to reallocate uncertainty between these dimensions. Given these different sources of uncertainty, incumbent firms must critically weigh their strategic goals, capabilities, and constraints to decide whether to engage with a tech firm's digital platforms. With the construct of "uncertainty reallocation" at the center of our model, we emphasize that external digital platforms do not necessarily reduce uncertainty but provide the potential to reallocate it, requiring incumbents to make a variety of tradeoffs.

On the right side, we illustrate how incumbent firms choose specific strategic actions after perceiving the affordance of uncertainty reallocation. Their chosen strategy influences their role in the ecosystem and their future business model. For example, incumbents that opt for holistic integration of the external digital platform typically adopt rather a contributor role, giving up customer touchpoints and access to user data. Conversely, the openness of a digital platform may allow incumbents to create platform derivatives and act as orchestrators. Depending on the strategy, short- and long-term outcomes will result, allowing incumbent firms to immediately and iteratively evaluate and adjust their actions and, in the long run, also adjust their strategic goals based on the fit between intended goals and the feedback from actions and outcomes. Finally, although outside the scope of our empirical study, the entire process is also subject to external factors such as political, economic, or technological changes in the incumbent's environment.

6.5.2 Implications, Limitations, and Future Research

Our analytical findings contribute empirical insights into the growing involvement of tech firms in established industries, such as the automotive sector. Further, our grounded model provides theoretical insights into how and why incumbent firms decide on a certain level of tech player involvement in their digital strategy. In doing so, our findings offer several **theoretical implications**. First, our research complements existing knowledge on digital platform affordances (e.g., Beverungen et al., 2020; Hein et al., 2019b, 2020) by presenting the affordance of uncertainty reallocation as a core construct in the context of incumbent firms responding to external digital platform offerings. We empirically show that incumbent automotive firms share certain goals and contextual factors, but resource availability, targeted customer segments, and organizational structures shape the way external platform providers enable goal-directed uncertainty reallocation. This also has implications for recent adaptations of the uncertainty construct in multi-actor digital innovation settings (e.g., Poeppelbuss et al., 2022), as applying the affordance lens highlights the socio-technical nature of uncertainty reallocation processes in a digital innovation context and the heterogeneity of affordances for uncertainty reallocation when firms face similar external offers. Finally, the case of the automotive industry pinpoints that the high level of uncertainty in dealing with digital transformation in incumbent firms acts as a negative socio-technical antecedent that serves as a constraint for organizations to realize shared and collective affordances of leveraging the material properties of increasingly smart products in multi-actor settings (Herterich et al., 2023).

Our study also has **managerial implications**. Our findings provide a benchmarking opportunity to evaluate strategies relative to the embedded subunits in our case study, illustrating the variety of strategic options automotive OEMs can pursue with Google's digital offerings. We show that incumbents must compromise on their ambitious goals to remain competitive, and that there is no one-size-fits-all strategy for engaging tech players. Instead, incumbents should carefully consider which technology and business control points in the ecosystem they need to own, based on their internal capabilities and goals. Decision-makers in other industries can also learn from the advanced car industry about the larger phenomenon of industrial IoT frameworks, clarify their role in the ecosystem, and assess the capabilities they need. Being a contributor to a business ecosystem can be just as appealing as being an orchestrator, which requires careful consideration of which aspects of the business and technology should be developed in-house, through collaboration with traditional suppliers, or by partnering with dominant tech companies.

Our research design comes with **limitations** that provide avenues for **future research**. First, the study is limited by the lack of information on this novel phenomenon and the methodological constraints of expert interviews. Despite our extensive exchange with industry experts within and beyond OEMs, we faced constraints in finding interview participants due to incumbent OEMs' ongoing strategic discovery phase. Future investigations could use in-depth case studies of a small set of organizations with multiple informants to unveil more granular organizational dynamics influencing the sensemaking process touched upon with our theoretical model. Such a setting could also allow to observe organizations over a more extended period, which was unfeasible as some OEMs only recently disclosed their Google involvement strategy. Nevertheless, we remain confident that studying the phenomenon of our case in its early stages of development provides preliminary but unique insights. Second, our single case study focusing on one firm's digital platforms, Google's AAOS and GAS, limiting the generalizability and external validity of our findings (Yin, 2014). Consequently, our findings do not claim to be exhaustive or applicable to every incumbent firm striving to involve digital platforms in every study context. Looking ahead, we see great potential in transferring our theoretical model to through in-depth studies that specifically emphasize other industry contexts beyond automotive (e.g., manufacturing, agriculture, or smart home platforms) to complement this research to improve the results' applicability. Finally, the inherent emphasis of our study on the Western market, due to the investigation of Google's service system, may not be directly applicable to markets with restricted access to Google services. Future case studies could address collaboration models with for example Chinese tech players, as established Western OEMs recently forfeited market shares due to the country's high technology affinity and demand for a holistic software experience.

7 Fostering Value Co-Creation in Incumbent Firms: The Case of Bosch's IoT Ecosystem Landscape

This chapter comprises an article that was published as: Sterk, F., Heinz, D., Peukert, C., Fleuchaus, F., Kölbel, T., & Weinhardt, C. (2022). Fostering Value Co-Creation in Incumbent Firms: The Case of Bosch's IoT Ecosystem Landscape. Proceedings of the 43rd International Conference on Information Systems (ICIS) (pp. 1-17). Note: The abstract has been removed. Tables and figures were reformatted and newly referenced to fit the structure of the thesis. Chapter, section, and research question numbering and respective cross-references were modified. Formatting and reference style was adapted, and references were integrated into the overall references section of this thesis.

7.1 Introduction

The proliferation of the Internet of Things (IoT) paradigm, interconnecting the physical and digital world, is moving organizations' value creation from selling physical products to exchanging connected products with integrated digital services (Marheine et al., 2021). To harness the transformative opportunities of the IoT, leading enterprises worldwide are increasingly driving the evolution of their partner networks from product-oriented supply chains to service-oriented business ecosystems (Marheine & Pauli, 2020). Compared with more conventionally organized business structures, such ecosystems are praised for fostering generativity, scaling rapidly, and adapting flexibly to changing circumstances (Hein et al., 2020). Consequently, the emergence of IoT platforms and ecosystems surrounding the platform and keystone players is widespread. This phenomenon creates a highly competitive environment in multiple industries, such as mobility, manufacturing, and agriculture (Lingens et al., 2021). Besides many startups and established tech companies (e.g., Microsoft Azure, Amazon Web Services), industry incumbents also aim to preserve or strengthen their competitive position by becoming keystone players in emerging IoT ecosystems and fostering value co-creation among partners (Metzler & Muntermann, 2020). Prominent pioneers from traditional industries include General Electric's Predix and Siemens' Mindsphere, where physical products are increasingly connected and extended into IoT platform ecosystems (Pauli et al., 2021).

Even though incumbent firms re-evaluate existing organizational and IT strategies, most of their established platform ecosystems have not been successful in the long run (Pauli et al., 2020). Indeed, a recent study by the BCG Henderson Institute found that approximately 85 per cent of observed failures are related to weaknesses in ecosystem design, including wrong ecosystem configuration or governance choices (Pidun et al., 2020). Furthermore, despite numerous strategic challenges associated with ecosystem establishment, such as solving the "chicken-and-egg" problem (Stummer et al., 2018), existing findings often stem from a native platform provider's perspective, which solely deals with offering the digital platform (Hein et al., 2019c). Hence, current literature lacks empirical insights into incumbents' perspectives on establishing and orchestrating IoT platform ecosystems (Marheine & Petrik, 2021; Pauli et al., 2021). However, such research has a pivotal role in the academic discourse of platform ecosystems as it scrutinizes both incumbent firms' overall business transformation and strategic use of platform technologies. Against this backdrop, we pose the following research question: *How can incumbent firms orchestrate their partner network toward value co-creation to establish IoT ecosystems?* By exploring this question, we take a holistic view of ecosystem orchestration that considers different phases (i.e., initiation, scaling, and control) and levels of orchestration (i.e., technological, economic, institutional, and behavioral) (Autio, 2022).

We contribute to this question by conducting a single case study (Yin, 2014) within the conglomerate of Robert Bosch GmbH (hereafter abbreviated as "Bosch"), a leading IoT company offering innovative solutions for smart homes, smart cities, connected mobility, and connected manufacturing. Our analysis draws a comprehensive picture of Bosch's departments' challenges in establishing eleven different IoT ecosystems in various industry sectors. Particularly, our study reveals twelve incumbentspecific challenges related to IoT ecosystems and offers successful design and governance actions taken to approach these challenges. We structure our findings by applying the tripartite service innovation framework proposed by Lusch and Nambisan (2015) to the IoT context, deriving the dimensions of *IoT ecosystem*, *IoT platform*, and *value co-creation*. After presenting the results of our single case study, we discuss these qualitative insights and tie them in with existing research by elaborating on four prevailing tensions—*exploitation versus exploration, commitment* *versus accessibility, control versus openness,* and *stability versus flexibility*. Further, we provide actionable recommendations on how Bosch's IoT ecosystems reconciled the tensions to guide other incumbents towards fostering value co-creation and establishing IoT ecosystems.

The remainder of this article is structured as follows: The following section elaborates on the theoretical foundations of IoT ecosystems. Subsequently, we describe the methodological approach of our case study. In the fourth section, we present key challenges Bosch's departments encountered in ecosystem design and governance and their actions to overcome them before discussing our findings and linking them to existing research. Finally, we draw a brief conclusion on the article's limitations and further research opportunities.

7.2 Theoretical Foundations

Incumbent firms that have been successful with product manufacturing recently began to adopt IoT-related technologies to expand their value creation capabilities and to bring forth many new smart products and services (Marheine et al., 2021). The IoT combines the potential of recent technological advancements to remotely access physical products and interact and create value during product usage (Wünderlich et al., 2015). However, adopting IoT-related technologies increases the complexity of technical and organizational requirements, forcing firms to build service-oriented ecosystems (Marheine & Pauli, 2020). This trend is closely related to a changing perspective on value creation processes from a goods-dominant logic, which focuses on the material goods created in an organization toward a service-dominant (S-D) logic emphasizing the importance of collaborative resource integration, value co-creation, and service-for-service exchange (Vargo & Lusch, 2017). This change in perspective is also closely related to technological advancements that change our discipline's perception of information systems: for example, unlike the pre-IoT era, where information systems were designed and built for a specific purpose at a given time, purposefully designing IoT platforms and governing IoT ecosystems needs to reflect that data analysis and data output are ex-ante unknown (Ikävalko et al., 2018).

Compared to startups and digitally native tech companies, incumbent firms face unique challenges when adopting this perspective. While embarking on their digitalization journey, they need to maintain the profitability of their legacy-based business activities while reaping the full potential in radically new business fields

(Frankenberger et al., 2021). However, not only these internal specifics of an incumbent impact their success but also the overall service ecosystem in which it orchestrates the co-creation of value (Hein et al., 2019c; Marheine et al., 2021). This actor-to-actor perspective is required as large-sized incumbent firms often act as facilitators and major drivers of value-creating processes, thus becoming platform providers (Hein et al., 2019c) and keystone actors that can "significantly influence ecosystem well-being" (Frow et al., 2019, p. 2666). To structure our research, we adapt the tripartite S-D framework of Lusch and Nambisan (2015) for the context of IoT, similar to previous research (Hein et al., 2019c; Marheine et al., 2021). The framework particularity suits our research endeavor, as each dimension elaborates issues and concepts related to value co-creation via platform ecosystems, which closely aligns with our research question.

IoT ecosystem. A service ecosystem refers to an emergent actor-to-actor network created and recreated by actors through their effectual actions and offers an organizing logic to exchange service and co-create value (Lusch & Nambisan, 2015). Lusch and Nambisan (2015) consider three underlying critical aspects: First, the service ecosystem needs to enhance both structural flexibility and integrity. Second, it must develop and maintain a shared worldview among a set of cognitively distant actors. Third, it needs to devise and implement an architecture of participation to coordinate actors and their service exchanges. Considering the proliferation of IoT and its underlying organizational and technological complexity (Pauli et al., 2021), industrial companies need to shift their perspective toward collaborating in IoT ecosystems by opening new avenues of co-creating value for a wide range of participants (Jacobides et al., 2018). Unlike purely digital ecosystems, keystone actors in the IoT cannot rely solely on third-party application providers but must also encourage sensor, software, and application providers (Hein et al., 2019c). While incumbents are well-experienced in managing contractually defined supply chains to create incrementally improved products, they now must learn to form less-hierarchical networks to connect and orchestrate their actors for mutual value creation (Marheine & Pauli, 2020). Ecosystem orchestration also poses unique strategic challenges to the scalability of a business model, such as solving the chicken-and-egg problem of whether to start building the demand side or the supply side to reach a critical user mass (Stummer et al., 2018).

IoT platform. A service platform provides a modular structure consisting of tangible and intangible components, facilitating the interaction of actors and resources (Lusch & Nambisan, 2015). The main purpose of service platforms is leveraging resource liquefaction and increasing resource density. Resource liquefaction refers to decoupling information from its related physical form or device (Normann, 2001), whereas resource density describes whether resources can be quickly mobilized for an actor (Lusch et al., 2010; Normann, 2001). Overall, two platform concepts are predominant: innovation platforms as a technological foundation of innovation mechanisms and transaction platforms as market intermediaries (Cusumano et al., 2019; Pauli et al., 2021). Both concepts need to define and implement rules for the exchange of service (Lusch & Nambisan, 2015). Innovation platforms enable the creation of complementary solutions by providing boundary resources such as application programming interfaces (APIs) or software development kits (SDKs) to third-party developers (Ghazawneh & Henfridsson, 2013). In contrast, transaction platforms facilitate the interaction between the supply and demand side by offering marketplaces for specific resources (Parker et al., 2016). IoT platforms represent an instantiation of innovation platforms or hybrid forms combining both transaction and innovation platforms (Marheine & Petrik, 2021). The overall complexity of operating IoT platforms is determined by device management, compatibility with sensors and machines, and communication protocols. (Hein et al., 2019c).

Value co-creation. Value co-creation is defined as the processes and activities that underlie resource integration and incorporate different actors in the ecosystem (Lusch & Nambisan, 2015). The adopted framework distinguishes three key roles to analyze value co-creation mechanisms: the ideator, designer, and intermediary. First, the ideator disseminates knowledge about specific customer needs in a unique context. Second, the designer combines and adapts existing resources or knowledge to develop new services. Third, the intermediary distributes and shares knowledge across multiple ecosystems. Ultimately, diverse actor roles must create a supportive resource integration environment. This requires promoting generativity through consistent processes and boundary resources while ensuring sufficient transparency of resource integration activities (Lusch & Nambisan, 2015). The complexity, especially in an IoT context, arises from the need to bring the various stakeholders (e.g., sensor, software, and application providers) together with the customer in order to co-create value (Marheine et al., 2021). Accounting for these three dimensions, we further incorporate a sociotechnical perspective elaborating on the areas of design and governance as primary factors affecting the establishment of IoT ecosystems. Within this work, we refer to the **design** of IoT ecosystems as a conceptual blueprint describing how the ecosystem is divided into a stable platform, highly variable yet easily exchangeable components, and the design rules binding on both (Tiwana et al., 2010). Further, we refer to **governance** of IoT ecosystems as the establishment of effective ecosystem-wide mechanisms that uniformly regulate how and under what conditions complementors gain access to the platform owner's resources and assets, therefore serving as guiding principles for value co-creation (Tiwana et al., 2010; Wareham et al., 2014). However, although scholars have been investigating IoT and platform ecosystems for years, they have scarcely touched on designing and governing IoT ecosystems from the viewpoint of incumbents.

7.3 Case Study Methodology

Our case study provides early but unique insights into the journey of Bosch's IoT initiatives across several departments, transforming their structure and roles from directional value chains to IoT ecosystem orchestrators. Therefore, the case deals with the fundamental challenges of strategic use, governance, and technology implementation and how they were overcome in three dimensions (i.e., IoT ecosystem, IoT platform, and value co-creation). Thus, our study is well suited to shed light on what design and governance choices bear in incumbent IoT ecosystems.

Case description. Our exploratory research follows a revelatory single case strategy as this is particularly suitable to analyze a phenomenon previously inaccessible to scientific investigation (Yin, 2014). Even though our case study focuses on a single organization, Bosch's IoT ecosystem landscape, our analysis includes outcomes of the different IoT ecosystem initiatives within Bosch with varying maturity levels (i.e., planned, development, live, failed). In total, we cover eleven IoT ecosystem initiatives representing the embedded units of our single case by interviewing in total 14 informants (see Table 7.1). The embedded units are sampled from different application contexts to incorporate the perspectives of five different industries: connected mobility (Alpha, Beta, Gamma, Delta), connected manufacturing (Epsilon, Zeta, Eta), smart building and home (Theta, Iota), smart agriculture (Kappa) and renewable energy (Lambda). In doing so, we leverage the company's diversified corporate structure to analyze existing approaches to ecosystem establishment within the company. The applied sampling approach seems to provide a reasonable basis for our purpose of abstracting knowledge across multiple embedded units of analysis.

Data collection. We collected data between May 2021 and June 2021 by conducting 14 interviews with experts and senior decision-makers with broad experience building and orchestrating IoT-enabled ecosystems (see Table 7.1). We employed a generic purposive sampling approach to identify suitable interviewees for each ecosystem initiative (Bryman, 2016). In this process, we applied our previously developed understanding of IoT ecosystems as pre-defined criteria to evaluate sufficient exposure to our research problem. While carrying out the interviews, we

Table 7.1.: Overview of IoT ecosystem initiatives and interviewees.

Industry Sector	Initiative	Status	Role of Interviewee	Duration
Connected Mobility	Alpha	Planning	Business Developer	58 min
	Beta	Development	Product Owner	62 min
			Senior Manager	59 min
	Gamma	Development	Technical Consultant	71 min
			Product Owner	66 min
	Delta	Live	Business Consultant	52 min
Connected Manufacturing	Epsilon	Development	Business Developer	46 min
	Zeta	Live	Business Model Manager	90 min
	Eta	Live	Managing Director	58 min
Smart Building and Home	Theta	Live	Managing Director	69 min
	Iota	Live	Vice President	45 min
Smart Agriculture	Kappa	Live	Business Model Manager	60 min
			Senior Manager	51 min
Renewable Energy	Lambda	Failed	Managing Director	58 min

followed a semi-structured interview guideline that ensured a similar overall structure of the interviews so that we could compare individual findings across the entire data set. Throughout the interview, we encouraged the informants to share their specific insights by asking open questions along pre-defined discussion points (e.g., ecosystem control, scaling, or monetization) about the challenges they encountered in establishing IoT ecosystems and how they overcame them. In doing so, we probed for clarification and further insights where appropriate. Using video-conference software, a single author performed all interviews ranging between 45 and 90 minutes. All interviews were recorded and transcribed before being coded and analyzed using MAXQDA software. In addition to conducting interviews, publicly available information such as websites or articles and internal documents related to the ecosystem initiatives served as secondary data sources.

Data analysis. Throughout the data analysis, we applied a qualitative content analysis approach (Hsieh & Shannon, 2005; Mayring, 2000), performing two iterations. In the first iteration (conventional content analysis), we performed an inductive open coding approach to grasp organizational success factors and challenges for building and orchestrating an ecosystem, focusing on the unique characteristics of the examined company and case. Thereby, the resulting codes related to different aspects of Bosch's challenges and actions taken to address them (e.g., "standardization," "monetarization," or "incentivization"). However, to ensure a consistent level of abstraction, we focused on findings transferable to a broader range of application scenarios and used the coding to abstract individual perceptions towards a rather holistic perspective. Furthermore, we ensured the validity and robustness of our analysis conducted by a single researcher by critically examining and discussing the progress of coding and the conclusions drawn from the analysis with a second researcher. In the second iteration (directed content analysis), we performed a deductive approach and defined a coding scheme based on the previously obtained theoretical knowledge and preliminary insights obtained from the first iteration. Finally, we arranged the identified codes with the theoretical coding scheme to synthesize our results into twelve separable yet related challenges. In this process, we linked and structured the identified challenges and managing actions with the three dimensions—IoT ecosystem, IoT platform, and value co-creation (Lusch & Nambisan, 2015) and the areas of design and governance (Tiwana et al., 2010).

7.4 Insights from Bosch's IoT Ecosystem Landscape

To harness the disruptive opportunities of the IoT, Bosch's Corporate Strategy Development defined an overreaching corporate IoT strategy. In this regard, IoT ecosystems represented a crucial strategic pillar while obsoleting the design of directional value chains to some extent, forcing Bosch to reshape its stakeholder relationships and value creation. Nonetheless, this audacious vision starkly contrasted existing innovation practices and presented complex strategic design and governance challenges. In response, we present the key challenges Bosch's departments encountered in establishing and orchestrating IoT ecosystems and the actions taken to overcome them in three dimensions—IoT ecosystem, IoT platform, and value co-creation.

7.4.1 Dimension 1: IoT Ecosystem

Pursuing the corporate IoT ecosystem strategy, Bosch's departments had to shake up their pipeline business model to attract stakeholders for joint value creation. Consequently, they had to rethink their deep hierarchies and slow but well-established internal processes to establish themselves as a flexible and trustworthy orchestrator. This change raised different challenges in configuring and maintaining inter-organizational relationships and governance mechanisms (see Table 7.2).

Table 7.2.: IoT Ecosystem-related challenges and actions to address them.

Area	Challenges	Actions Taken
Ecosystem Design	Overcoming traditional legal and risk-management processes to enable fast and simple onboarding of all partners	Providing standardized and transparent onboarding processes and standardized non-disclosure agreements (NDAs) to achieve the desired ecosystem design speed
	Convincing and incentivizing all required partners through a supportive environment to join the ecosystem	Setting up low entry barriers by short notice periods and financial support and implementing traceable processes
Ecosystem Governance	Deciding on the right level of openness to encourage growth and diversity while also ensuring quality and control	Providing explicit partnership guidelines that define which participants are allowed to offer services in which categories
	Establishing strategic flexibility to adapt to changing circumstances and emerging obstacles	Introducing a flexible one-year strategy to create space for experimentation and driving agility to realize minimum viable products (MVPs) quickly

Ecosystem Design: Challenges and Actions Taken

Standardized onboarding processes. The first challenge Bosch's ecosystem initiatives faced was *overcoming traditional legal and risk management processes* to enable fast and simple onboarding of all partners. Hence, Eta, Epsilon, and Kappa focused on standardizing their onboarding process to accelerate collaboration and avoid serious setbacks. For instance, Eta designed a streamlined ten-step onboarding process revealing exactly how far ahead the partner is and what steps are yet to be fulfilled to move forward. *"It creates trust when partners realize they are not dependent on any goodwill,"* Eta's Managing Director concluded. In the Kappa initiative, partners first signed general terms and conditions of collaboration in a memorandum of understanding to ensure at least a minimum of contractual assurance. As a result, however, *"the risk of partners jumping off increases, requiring the orchestrator to fill the different ecosystem roles multiple times."*, Kappa's Business Model Manager emphasized. Another challenge the ecosystem initiative Epsilon encountered was the establishment of non-disclosure agreements (NDAs) between the ecosystem participants. For that reason, the collaboration was massively slowed, although there was no initial need to exchange critical information. Finally, the collaborating research campus solved this issue by standardizing NDAs, as a Business Developer of Epsilon concluded:

> *"It is very challenging to cooperate with new partners because you also need an NDA. That is extremely difficult, especially if you are totally motivated and want to start immediately, and then you hit the brakes completely with the NDA. [...]*

So thanks to [the research campus], all the partners involved have a standard NDA with each other, which is enormously practical. [...] Especially, in the beginning, it is not yet about complex issues, and there is not so much that needs to be protected. ” (Business Developer, Epsilon)

Supportive ecosystem environment. Another critical challenge in initiating an ecosystem was *convincing and incentivizing all required partners* through a supportive environment to join the ecosystem. One example is Theta, which addressed this concern by having no participation restrictions on the supply side, thus keeping the entrance barriers low. Accordingly, Theta charged no access fees or required specific co-investments from partners to enter the ecosystem. Instead, Theta invested in the partners' compatibility, reducing the financial risk of participating. To further ease partners' fears of being tied down for an extended period, Theta has set a notice period of only six months. Besides contractual fairness, Theta's Managing Director emphasized the trust placed in incumbents like Bosch as an essential success factor in encouraging companies to participate in their ecosystem. Trust was also highlighted as a vital incentive mechanism in the ecosystem initiative Delta. The required level of trust was achieved by transparent and traceable processes that ensured all partners felt they were treated appropriately and equally. In this way, an atmosphere of trust and reliability was created, as noted by a Business Consultant of Delta:

"*Trust, transparency and clear rules are the success factors of an ecosystem. However, this does not necessarily mean that [the orchestrator] has to deal with everyone in the same way, and everyone has the same conditions. [. . .] Nevertheless, everyone must theoretically have the chance and the offer to switch to the other status, and it must be clear under what conditions this happens. This atmosphere of transparency and comprehensibility, which ensures that everyone feels treated fairly in some way, is essential.*" (Business Consultant, Delta)

Ecosystem Governance: Challenges and Actions Taken

Adequate ecosystem openness. In designing the governance model, Bosch's ecosystem initiatives encountered the challenge of *deciding on the right level of openness* to encourage growth and diversity while ensuring quality and control. In the initiative of Eta, this balance was achieved through explicit partnership guidelines that prescribe who is allowed to offer services in which areas. Accordingly, there are areas in the ecosystem where only Bosch offers its services, areas reserved exclusively for partners, and areas open to both. In the latter case, Bosch services compete with partner services, leaving it up to customers to choose which one they like best. In this regard, Eta's Managing Director stated, *"In some cases, it makes sense to deliberately allow things to be left to partners to demonstrate openness."* Unlike Eta, Theta's ecosystem initiative has no exclusivity for offering services, allowing partners to provide any service themselves. However, despite its open approach, the ecosystem is governed by contracts, rules, and precise distribution of roles. Accordingly, when a partner tried to bypass Theta's control points (e.g., the user interface), Theta intervened and threatened to dismiss them from the alliance to defend the ecosystem. However, the Managing Director of Theta illustrated their approach to non-exclusivity as follows:

> "*It is vital that we do not do this exclusively. If the partner wants to offer the same service under its flag, we see which service sells better. Thus, it is allowed to compete with us. The data belongs to the end-user, who must first agree to its use and then pay for the service. Therefore, the best service should simply prevail. It is all fair game within the ecosystem. We do not care because our margin on partner service is often higher than if we have to offer it ourselves. Accordingly, we win in both cases.*" (Managing Director, Theta)

Flexible ecosystem strategy. Another challenge Bosch's ecosystem initiatives faced was *establishing strategic flexibility* to adapt to changing circumstances and emerging obstacles. To permit rapid innovation detached from traditional corporate structures, Bosch chose the path of spinning off several ecosystems into separate subsidiaries. One example is Iota, which was spun off from Bosch as a wholly owned startup aiming to attract more investors and accelerate the expansion of its global ecosystem through external partners. In the beginning, however, Iota struggled to hire employees with the desired technical skills and startup mentality. The latter was reflected in applicants from Bosch, who demanded to keep their existing contracts and a guarantee to return to their parent company in the event of failure. As a result, Iota hired many external employees bringing in the required agile mindset. Ultimately, flexibility and risk tolerance were incorporated into the strategy by not anticipating everything in detail and creating room for adjustments through only one year of planning. This emergent strategy gave room for experimentation and fostered agility to realize rapid minimal viable products (MVPs), as Iota's Vice President Strategy emphasized:

> "*The success factors here are the strategy of continuous adaptation and the firm focus on MVPs. In other words, no overengineering, but always customer-oriented and tested. That also applies to the strategy. We do not have a 10-year strategy*

but an emergent strategy. That means we plan for one year.” (Vice President Strategy, Iota)

7.4.2 Dimension 2: IoT Platform

From a technical perspective, Bosch’s departments each had to create an interconnected and coherent solution from various products or services provided by a group of largely independent economic players. Hence, they faced the challenge of designing and managing an IoT platform that attracts developers for joint service creation through a modular design, highly variable components, and a scalable architecture (see Table 7.3).

Table 7.3.: IoT platform-related challenges and actions to address them.

Area	Challenges	Actions Taken
Platform Design	Enabling standalone solutions that complement each other and operate on the same database	Basing interfaces on existing technical standards and providing stable APIs and a cross-manufacturer compatible control unit
	Convincing app developers to join the platform and unleash their generativity to deliver complementary applications	Offering easy-to-use and flexible SDK, setting no access fee for the platform, and hosting an app development competition
Platform Governance	Controlling the platform’s accessibility while mitigating partners’ concerns about overly dominant platforms	Requiring partner status before granting access to APIs and SDKs and allowing individual look and feel of partner apps
	Quickly realizing the first working version of the ecosystem to prevent partners from bailing out due to trust issues	Filling each role at least once to realize an initial MVP right from kick-off and communicate joint success stories

Platform Design: Challenges and Actions Taken

Modular platform architecture. Unlike hierarchical supply chains, the service enabling resources of IoT ecosystems are developed independently but function as an integrated whole. Hence, Bosch’s ecosystem initiatives faced the challenge of *enabling standalone solutions that complement each other and operate on the same database* in order to leverage holistic use cases. An example is Kappa, which *“[...] did not discard everything, but continued to use existing norms and established standards,”* as its Senior Manager stressed. Thus, Kappa relied on reusing existing interfaces whenever possible to significantly save time and resources in designing their data architecture. They also provided APIs and secure end-to-end infrastructure to orchestrate the flow of data from data generation to import into application providers’ cloud systems. As a result, the entire system is comparable to the operating system of mobile devices. On the hardware side, the applications run on a standardized control unit that ensures cross-manufacturer compatibility. In addition, an authorized partner can quickly and easily retrofit the control unit or pre-install it on future machines. In conclusion, Kappa's Business Model Manager resumed their approach as follows:

> "*The idea of [Kappa] is to create a first-level support hotline where all partners work and communicate to provide the [customer] with a holistic solution. In practice, an operating system for agriculture runs on a control unit, onto which a wide variety of manufacturers can upload their applications. Moreover, everything takes place on standardized interfaces so that the end-user no longer has all these compatibility problems.*" (Business Model Manager, Kappa)

Attractive platform environment. Another challenge was *convincing app developers to join the platform and unleash their generativity* to deliver complementary applications. Commonly, most ecosystems provide SDKs that contain development tools and standard code, allowing third-party developers to create plug-and-play solutions for the platform. One example is Kappa, which offers an easy-to-use and flexible SDK, allowing developers to freely choose between common programming languages. Besides offering a free SDK, Iota launched a developer challenge to attract software developers to join the platform. Further, to avoid stifling the growth of their ecosystem, Iota does not charge an access fee for developers but a transaction fee for purchasing applications. To conclude, Iota's Vice President described the status of partner acquisition:

> "*More and more integrators are joining in themselves, which applies to all stakeholder groups. It is a mixture of joining in because you believe in it and out of fear that you will somehow miss out on something. This effect is created because we do a lot of marketing and have formed our own brand. We are present at trade shows and ecosystem conferences. We organize app challenges and give out innovation awards. We have a lot of activities in the classic partner management.*" (Vice President, Iota)

Platform Governance: Challenges and Actions Taken

Neutral platform governance. In ramping up their platform-based ecosystem, some of the investigated ecosystems faced the challenge of *controlling the platform's accessibility while mitigating partners' concerns about overly dominant platforms.* Although some of the examined ecosystems show parallels to Android for mobile devices, there are significant differences in control and openness. For example, while almost anyone can start programming an Android app, developers at Kappa must first achieve partner status before accessing the APIs and SDKs. Moreover, to guarantee the functionality and compatibility of the applications, a precisely documented certification process first takes place before applications are launched on the marketplace. Furthermore, unlike Android, Kappa retains control over the business relationship between the application provider and the end-user to preserve complete neutrality. In parallel, Kappa allowed individual branding of partner applications. Thus, the end-user only saw Kappa's branding when opening the primary user interface and had the look and feel of the respective app providers within the individual applications. The objective was to emphasize neutrality even more, as Kappa's Business Model Manager of Kappa explained:

> "*We have allowed individual branding. That means our [partners] could brand their solution, screen, or interface with their company. In this way, we made it possible in the platform for the competitors to distinguish themselves externally and still access each other's customer base to a certain extent.*" (Business Model Manager, Kappa)

Rapid platform realization. Several investigated ecosystem initiatives highlighted the challenge *of quickly realizing the first working version of the ecosystem* to prevent partners from bailing out due to trust issues. In this context, Lambda and Kappa addressed this challenge by launching a basic but demonstrably successful version of the ecosystem, despite building an ambitious long-term vision. According to Kappa's Business Model Manager, intensive partner management was undertaken to fill each role in the ecosystem at least once in order to realize an initial MVP right from kick-off. Lambda's formerly appointed Managing Director noted that ecosystems *"[...] need an initial set of partners and must not think too big because otherwise high coordination costs occur, and the ecosystem becomes sluggish."* Consequently, Lambda took a similar approach to Kappa and joined forces with a limited number of partners to present a simplified version of their joint value proposition at a trade fair. Thereby, they showcased an initial low-complexity prototype consisting of a solar-powered washing machine and a simple representation of demand-side management to demonstrate the technical feasibility of the ecosystem. Not surprisingly, the first joint success and subsequent communication strengthened the existing partnerships and helped convince skeptical companies to join. Once the investigated ecosystems proved their commercial viability, they extended their initial value proposition to scale by quickly reaching a critical mass of additional players. Although Lambda's ecosystem failed due to internal conflicts, the Managing Director at the time aptly summarized:

"You can certainly develop a shared vision in your ecosystem [...], but then you need a concrete implementation step, which should not be too complex—a showcase project. That is actually what we did. We developed prototypes for the trade fairs. [...] The first joint successes then brought us closer together. My conclusion is that you should start small, achieve initial successes, and then communicate them. These shared success stories also help to get critics on board. [...] And then you go step by step into the future." (Managing Director, Lambda)

7.4.3 Dimension 3: Value Co-Creation

Bosch's departments had to move forward from contributing as a supplier to orchestrating value co-creation by incorporating and governing different actor roles in the IoT ecosystem. To further keep the system running, it was crucial implementing both mechanisms, increasing the overall co-created value while at the same time ensuring each stakeholder is appropriately rewarded for their continued co-creation of value. In the following, we describe these value co-creation-related challenges Bosch's departments faced in designing and governing for value co-creation (see Table 7.4).

Table 7.4.: Value co-creation-related challenges and actions to address them.

Area	Challenges	Actions Taken
Design for Value Co-Creation	Finding an appropriate monetization strategy that avoids stifling ecosystem growth	Awaiting sufficient ecosystem growth before monetization and charging the right side of the market (e.g., supply side)
	Allocating the generated revenue fairly, enabling all essential ecosystem participants to earn a decent profit	Breaking down and sharing revenue from value creation to the end of the value chain among all participating actors
Governance for Value Co-Creation	Establishing rules and processes that define how partnerships with competitors or much smaller firms are managed	Evaluation of rivals in competitive analysis to clarify collaboration potential and granting space for smaller firms
	Solving the chicken-and-egg problem to secure enough participation from both market sides	Partnering with highly scaled and established app providers to access end customers and secure the ecosystem

Design for Value Co-Creation: Challenges and Actions Taken

Scalable monetization strategy. With most traditional businesses selling welldefined, incrementally improved products directly to an existing customer base, Bosch's ecosystem initiatives struggled to *find an appropriate monetization strategy* that avoids stifling ecosystem growth. According to Beta's Product Owner, resistance to the initiative was exceptionally high among mid-level managers, who saw the risk of already changing their position by the time the ecosystem's return on investment materialized. Consequently, they were reluctant to invest substantial capital in the ecosystem initiative and pushed for immediate and direct monetization. This reservation clashed with Beta's monetization strategy, which sought indirect monetization through end-users in addition to the previous direct sale of hardware products to OEMs. Due to the risk of jeopardizing ecosystem growth, Beta initially tried to foster network effects to scale the ecosystem quickly. Therefore, they decided not to charge its platform users, as they were the primary scaling lever of their ecosystem. As the number of users increases, the number of connected sensors and, ultimately, the value of the service increases. Beta's Product Owner further stressed building up the required level of trust and awaiting user lock-in before considering asking for money:

> "*[We] make the mistake of selling something and wanting money for it immediately. [...] The point at which you can monetize an ecosystem is exactly when the pain of switching is high enough. You have quite a few foundational elements that you need to build beforehand to make that happen, and trust is the key, not hard binding. [...] It is better to earn nothing than to lose trust. That is why it is also important not to put your monetization points where you want to scale. If you want more users, forget about asking the user to pay.*" (Product Owner, Beta)

Sustainable win-win situations. Another challenge was *allocating the generated revenue fairly,* enabling all essential ecosystem participants to earn a decent profit. Kappa focused on establishing multiple win-win situations among partner roles to achieve this objective. For example, while digital service providers benefited from extending and locking in their customer base through standardized interfaces, manufacturers could more easily develop functionalities for their machines through an SDK, thus decreasing development effort. Naturally, the most substantial driver for participation was tapping into additional revenue streams. Here, Kappa faced the challenge of defining a fair revenue-sharing mechanism. According to the Business Model Manager, the fundamental approach was to break down revenue from value creation to the end of the value chain. Hence, the service providers are paid directly by the end customers, and Bosch as the platform provider, receives a commission for each sale in return for market access. Following the value chain, the manufacturers received a commission share for providing their machines. Eventually, Kappa communicated its revenue-sharing approach transparently to strengthen the partners' trust. Finally, a Senior Manager of Kappa stressed the importance of fairness in their actions:

> "*The success factor is creating multiple win-win situations so that everyone plays along because they feel they are treated fairly and can make money from it, which is simply the strongest driver for any business. Only if that is given and they see business opportunities for themselves will they invest something. [. . .] The basic approach was to consider where added value is created and then try to charge money there. [...] Coming from the customer, you break it down further and further until you get to the end of the value chain.*" (Senior Manager, Kappa)

Governance for Value Co-Creation: Challenges and Actions Taken

Unbiased collaboration model. Connecting stakeholders for value co-creation often results in various constellations of collaboration when small and medium-sized or even competing companies work together with incumbent firms. Accordingly, Bosch's ecosystems were challenged to *establish rules and processes* that define how partnerships with competitors or much smaller firms are managed. For example, direct competitors participated in Zeta's ecosystem. In this respect, Zeta's Business Model Manager pointed out that *"[...] the old enemy image of the competitor no longer exists."* Nevertheless, the rival companies were clustered and evaluated in competitive analysis. Ultimately, the analysis indicates which competitors have the potential for partnering. In the case of cooperation, extensive contracts ensure that business is conducted under fair conditions and that competition still takes place without monopolies. In contrast, Beta collaborated with newly established startups, facing the challenge of not exploiting its role as an incumbent firm and giving the partners enough room to flourish. A critical success factor of such an asymmetrical partnership is not to hinder the collaborating startups in their strategic alignment. A Senior Manager of Beta further explained:

> "*It is not always about the orchestrator dictating what to do [...] but about listening and being open. Thereby, we can learn from successful startups [...]. It is vital not to hinder their strategic orientation and what they are doing successfully today. As Bosch, we also must be very sensitive to this. When dealing with partners, it is essential to give them as much space as they need and offer them as much collaboration as possible. They should not be restricted and legitimized but listened to and understood.*" (Senior Manager, Beta)

Timely supply-side scaling. Another challenge Bosch's ecosystem initiatives faced during the launch was *solving the chicken-and-egg problem* to secure enough participation from both market sides. Notably, most ecosystem initiatives we observed focused first on partner acquisition to provide a compelling value proposition for the demand side of the market from the outset. For example, Eta launched its innovation platform and built a dense network of twelve partners. These partners ranged from startups to larger companies, but according to Eta's Managing Director, bringing in one or two household names was vital to gaining traction. Finally, the app store went live with a comprehensive range of partner apps. Another example is Beta, which also focused on building supply first by partnering with app providers. Instead of acquiring nascent startups, Beta targeted highly scaled and established app providers to access their existing customer base. According to Beta's Senior Manager, this strategic decision was justified as follows:

> "*We partner with skilled, highly scaled, and successful app providers because we can also deliver added value to them with data, and the partner sort of takes over the interface to the end customer for us. [...] You can start with the app partners with very few users, but it takes a correspondingly long time for the ecosystem to become lucrative, or you can go directly to the big players. And we chose the latter because we also want to secure our ecosystem.*" (Senior Manager, Beta)

7.5 Discussion

Our single case study derives empirical insights into the challenges of designing and governing platform-based IoT ecosystems. We provide actionable design and governance recommendations based on how Bosch's IoT ecosystem initiatives managed and overcame these challenges. After all, other incumbents running traditional pipeline businesses and seeking to become IoT ecosystem orchestrators face similar challenges even though they might operate in different industries. Hence, the recommendations derived from our analysis of Bosch's IoT ecosystem landscape can therefore also apply to other industry incumbents. Adding to these empirical findings, we synthesize four overreaching tensions that emerged across all three dimensions analyzed—*exploitation versus exploration, commitment versus accessibility, control versus openness,* and *stability versus flexibility* (see Figure 7.1). While these tensions are generally seen as incompatible and mutually exclusive, we present how they can be reconciled using our recommendations in the following section.

		Dimension			Tension	Resolution
		IoT Ecosystem	IoT Platform	Value Co-Creation		
Area	Design	Standardized Onboarding Process	Modular Platform Architecture	Scalable Monetization Strategy	Exploitation versus Exploration	Organizational Ambidexterity
		Supportive Ecosystem Environment	Attractive Platform Environment	Sustainable Win-Win Situations	Commitment versus Accessibility	Architecture of Participation
	Governance	Adequate Ecosystem Openness	Neutral Platform Governance	Unbiased Collaboration Model	Control versus Openness	Trustworthy Governance
		Flexible Ecosystem Strategy	Rapid Platform Realization	Timely Supply-Side Scaling	Stability versus Flexibility	Minimum Viable Ecosystem

Figure 7.1.: Summary of case study findings.

7.5.1 Organizational Ambidexterity: Exploitation versus Exploration

When shifting from conventional business processes to IoT ecosystems, incumbents must achieve organizational ambidexterity to foster both *exploitation and exploration* (O'Reilly & Tushman, 2013). Especially when designing processes seeking to connect partners for value co-creation, regulatory requirements collide with the desired speed of ecosystem establishment. On the one hand, time delays due to lengthy contracts and coordination between legal departments should be prevented. On the other hand, no compromises should be made in legal and risk management. Accordingly, it is vital to reshape existing practices by standardizing processes and contracts. A high degree of standardization leads to efficiency (Farjoun, 2010) and reduces the need for coordination due to the low diversity of activities, ultimately cutting onboarding time and costs.

Furthermore, when designing IoT platforms, stability is required to leverage joint investments in standard components and variability to meet changing market demand (Wareham et al., 2014). Consequently, a modular setup with a stable core and interchangeable components has become the dominant platform design (Tiwana, 2014). An alternative approach to developing everything from scratch is to exploit existing or proprietary standards such as standardized communication systems or APIs. This results in significant time and resource savings in platform design. Apart from this, the stability of platforms and boundary resources such as APIs ensures that complementary modules are developed and integrated, while the modular architecture enables the scalability of new modules (Hein et al., 2020; Tiwana et al., 2010). However, due to the hardware component and user heterogeneity, scaling and network effects tend to be weaker for IoT platforms than purely digital ones (Jung et al., 2021)

Since it is not enough for companies to build and run an ecosystem, they also need to monetize it sustainably. Therefore, it is critical to design monetization mechanisms so that revenue grows with the ecosystem without burdening it with high fixed costs when it is still in its infancy (Williamson & De Meyer, 2019). Therefore, incumbents must defer monetization and finally charge the right side of the market to avoid stifling ecosystem growth. Apart from that, in IoT ecosystems, compatibility is often made possible by selling physical connection units in the first place. Hence, a duality of traditional one-time revenue and scalable platform monetization emerges. In summary, a well-designed IoT ecosystem is a prime example of an ambidextrous organization resolving the tension between exploitation and exploration.

7.5.2 Architecture of Participation: Commitment versus Accessibility

Building IoT ecosystems is mainly about creating an architecture of participation (Lusch & Nambisan, 2015) that balances *commitment and accessibility* by encouraging potential partners to join and specifying the level of engagement they must bring in. Transparent partner management processes and clear rules of exchange must be established to create an atmosphere of trust between partners and prevent abuse of the orchestrator's power (Moore, 2006). However, this does not necessarily mean that the orchestrator grants access to all aspirants and collaborates with every partner on the same terms. Nevertheless, everyone must theoretically have the chance to participate and improve their conditions. Especially in IoT ecosystems, access control can be helpful since the enormous complexity places a significant demand on the collaborating technology providers (Hein et al., 2019c). However, we also found IoT ecosystems without participation restrictions, incentivizing participation via contractual fairness and covering partners' ecosystem-specific costs (Perscheid et al., 2020).

In addition, an accessible platform design encourages stakeholders in their intent to participate and service contribution, ultimately increasing their level of engagement (Storbacka et al., 2016). To reinforce this effect, platform owners provide boundary resources stimulating the partners' generativity (Ghazawneh & Henfridsson, 2013). While technical boundary resources such as APIs and SDKs govern access to core modules of the platform, social boundary resources such as developer communities and hackathons promote creativity and community building (Marheine et al., 2021; Pauli et al., 2020).

Last, the architecture of participation also defines how participants benefit from the exchange and are rewarded for their engagement (Lusch & Nambisan, 2015). While value co-creation is one of the main drivers of forming an ecosystem, a profitable overall business model is crucial to its sustainability and resilience (Beverungen et al., 2020). Especially in the IoT context, the ecosystem design must reflect win-win situations among all roles, including sensor, software, application, and platform providers (Heinz et al., 2022). Therefore, fair revenue allocation among all value-adding parties is essential for a healthy ecosystem (Pauli et al., 2021). In summary, the architecture of participation is built on the pillars of fairness, transparency, and incentivization that balance commitment and accessibility.

7.5.3 Trustworthy Governance: Control versus Openness

As incumbent firms establish IoT ecosystems, they must face the central question of managing the tension between *control and openness* (Tilson et al., 2010; Wareham et al., 2014). A decisive issue involves input control—the extent to which orchestrators define rules and guidelines to judge whether a partner's offering should be allowed to be placed on the platform (Cardinal et al., 2004; Tilson et al., 2010). Hence, explicit and transparent partnership guidelines must enable third-party developers to fully understand how to create and distribute their solutions on the platform (Benlian et al., 2015). In this context, it is promising to either have no exclusivity in approving partner solutions or grant full transparency on the areas in which partners can offer solutions.

Further, to balance this tension, the orchestrator must control critical points such as boundary resources to ensure the complementors' generativity (e.g., designing apps). Fundamentally, boundary resources (e.g., API, SDK, or marketplace) provide practical governance means by which digital platforms are exploited and defended (Karhu et al., 2018). Interestingly, fundamental differences in the governance of business-to-consumer (B2C) and business-to-business (B2B) platforms are noted. For example, B2B platforms are used only by legal organizations for mainly business-critical processes and are characterized by significantly higher complexity (Hein et al., 2019c). In the case of industrial IoT platforms, partners must enter contractual commitments, and platform owners must provide quality-assuring certification processes for apps before they are listed on the marketplace. In addition, partners should be able to differentiate themselves from competitor solutions and the platform interface through custom branding and unique application design.

Finally, the orchestrating incumbent must also determine the degree of openness to value co-creation with competitors or startups. Fostering the ecosystem's transparency could lead to dynamic co-opetition (Bengtsson et al., 2010), increasing the capacity to innovate and thus exploit generative potential (Pauli et al., 2020). In the case of asymmetric partnerships (Schleef et al., 2020), the incumbent's adoption of a restrained position of the incumbent could have a similarly positive effect, as the startups are given sufficient space to develop and rapidly build on their strengths. In summary, a coexistence of openness and control is best achieved with transparent governance regulated by boundary resources.

7.5.4 Minimum Viable Ecosystem: Stability versus Flexibility

IoT ecosystems require incumbents to balance stability and flexibility demands through configuring digital infrastructure and governance mechanisms (Tilson et al., 2010). Due to well-established internal processes, a vast customer set, and incrementally improved core products, ensuring long-term stability is not the central issue for incumbents. Instead, they have to overcome slow decision-making processes and deep hierarchies, as partner companies are aware of their interdependencies and are likely to lose trust in the orchestrator if things develop too slowly (Lingens, 2021). Ultimately, incumbents can achieve the required flexibility, for example, by outsourcing the department responsible for orchestrating the ecosystem, thereby replicating startup-like structures and cultures (Lange et al., 2021; Svahn et al., 2017).

In addition, it is critical to start with a minimal viable ecosystem and offer basic but unique value to increase the chances of a quick time to market. (Adner, 2012). Furthermore, the associated governance model should be as less complex as possible and thus easy for partners to understand. In order to respond to changing circumstances, the platform governance strategy must be regularly monitored and adjusted (Jain & Ramesh, 2015). Finally, the platform's scalability and flexibility leverage extraordinary growth in scale and scope (Tilson et al., 2010). However, the chicken-and-egg problem must be solved in advance to reach a critical user mass that generates network effects.

Building an appropriate IoT ecosystem network goes beyond including third-party developers as fully digital ecosystems since sensor, software, and application providers, such as consumers, must also be involved (Hein et al., 2019c). Nevertheless, we found that a stable supply side must first be established in order to be able to offer industrial customers a compelling range of services. Finally, an initial set of partners ("minimum viable ecosystem") is required, with each role filled at least once, to enable a stable platform core and agile value co-creation.

7.6 Conclusion

In this article, we investigated the business departments of Robert Bosch GmbH, an IoT incumbent, on their transformative journey from acting in hierarchical supply chains to orchestrating IoT ecosystems. Our work contributes to the existing literature on IoT ecosystems by describing twelve interrelated challenges and corresponding design and governance decisions to bridge them. We demonstrate that the tripartite S-D framework (Lusch & Nambisan, 2015) and the areas of ecosystem design and governance (Tiwana et al., 2010) complement each other in describing value co-creation practices. Finally, based on our findings, we synthesize four overarching tensions that have emerged in all three dimensions and provide actionable empirically based recommendations on how to reconcile them. We argue that decision-makers operating in business ecosystems must deliberately address these challenges cohesively to foster value co-creation.

Theoretical implications. As a first theoretical implication of our research, we introduce the perspective of incumbents to the discussion of IoT ecosystems by deriving a general framework of service innovation consisting of three dimensions and two areas that can be applied by further research on the topic. Our framework adopts a holistic, long-term view that crosses and connects the boundaries of the different phases of ecosystem orchestration (Autio, 2022)—initiation, scaling, and control. For instance, governance aspects such as a neutral platform environment, flexible strategic alignment, or appropriate openness are essential throughout the lifecycle of an ecosystem.

Second, we elaborate on the IoT incumbent's perspective and emphasize the IS-specific balance between technical and socio-organizational aspects. More specifically, our results include possible solutions to address challenges regarding both aspects arising in ecosystem orchestration. For example, in terms of scalability, the framework we propose helps to combine both perspectives by considering a solution to the chicken-and-egg problem and the realization of modular platform architecture. Eventually, this study supports the idea that an IoT ecosystem is an inseparable socio-technical system whose technical and socio-organizational challenges underlie strong interactions (Alter, 2013). On the one hand, the socio-organizational requirements for managing platform access determine the technological requirements. On the other hand, the technological possibilities determine the solution space for managing the platform.

Third, we identify four tensions across the three dimensions: *exploitation versus exploration, commitment versus accessibility, control versus openness*, and *stability versus flexibility* (see Figure 1). These tensions can serve as a starting point for further research to assist incumbents' managers in leading their company's transition to become an IoT ecosystem orchestrator. Such research could be of different nature: further empirical research could, for example, focus on one of the identified tensions and provide more in-depth insights on resolving the tensions in the context of IoT-ecosystem design and governance. Another approach could be to derive design-oriented knowledge on management assistant tools or define well-suited key performance indicators to assist the managers' decision process.

Practical implications. Up to this point, current research lacks empirical findings with practical applicability for establishing IoT ecosystems from the perspective of incumbent companies. Therefore, our findings may help business leaders previously operating in linear value chains to reshape enterprise design and governance mechanisms to facilitate value co-creation. To this end, we present the empirical results of a single case study covering eleven IoT ecosystems from various industries and provide insights into strategic decision-making to coordinate monetization, scalability, or incentivization. In this regard, we provide twelve design and governance-related challenges and corresponding actions to overcome them.

Although we selected an IoT incumbent and its embedded ecosystem initiatives as our unit of analysis, our focus was also to draw a comprehensive picture of the challenges and actions taken. Accordingly, our research also contains insights into the overarching topic of establishing and orchestrating ecosystems that are not only inherent to incumbents or IoT (e.g., modular architecture, strategic flexibility). Nevertheless, we have drawn specific insights for IoT incumbents from these general themes. For example, all types of platform ecosystems are usually characterized by a modular architecture, but in the field of IoT, additional hardware components need to be standardized, ensuring cross-manufacturer compatibility. Moreover, IoT ecosystems are usually long-term initiatives that require a resilient governance model that can adapt to changing circumstances. In the case of incumbents, this challenge is even more difficult to overcome, as they usually pursue an overarching long-term strategy. Consequently, they must maintain profitability in their legacy-based business while at the same time exploiting the full potential of disruptive ecosystem businesses.

Finally, the explorative findings can help managers of incumbent firms address the identified tensions. Thereby, we recommend focusing on four concepts for IoT ecosystem establishment—*organizational ambidexterity, architecture of participation, trustworthy governance,* and *minimum viable ecosystem*—to reach the audacious vision of becoming an incumbent orchestrator.

Limitations and future research. Like any study, ours is subject to limitations which are, at the same time, potential avenues for future research. First, within a single case study, we investigated challenges and recommendations for action among eleven Bosch ecosystems with various focuses and degrees of maturity. Therefore, we took on a rather exploratory high-level perspective trying to capture as many different facets as possible to form an initial big picture. Instead, we could have zoomed in on one of these specific ecosystem initiatives for in-depth investigation within a longitudinal case study or zoomed out to examine Bosch's IoT journey from a holistic company perspective.

Second, despite the successful provision of our case study overview with its corresponding challenges and tensions, we cannot yet make a statement about the interdependence of the individual challenges and tensions. In addition, our analysis did not include the classification regarding suitability and significance of the individual challenges and tensions among all eleven initiatives studied or compare the investigated initiatives and associated industries. Instead, our research provides a comprehensive overview of challenges in establishing IoT ecosystems across initiatives and industries. In future research, we might re-engage with the interviewees and other informants familiar with our case to validate our findings and gain further industry-specific and industry-agnostic insights into the design and governance of IoT ecosystems (e.g., through a Delphi study, workshops, further interviews, or focus groups).

Finally, despite carefully selecting multiple units of analysis, specifying a general roadmap for the incumbent's IoT ecosystem establishment is challenging to assess. Therefore, the generalizability and, thus, the external validity (Yin, 2014) of our results are subject to certain limitations and must be further verified. For instance, our findings do not claim to be exhaustive or applicable to every incumbent operating in the IoT. Looking ahead, we see great potential in using the case of Bosch's IoT ecosystem landscape to explore one of the four theoretical concepts we elaborated on in the previous section in more depth to gain further insights into the phenomenon of IoT ecosystems. However, in-depth studies with a stronger focus on other incumbent forms in the IoT sector beyond Bosch should complement this research to improve the results in terms of applicability to other companies.

Part V

Finale

8 Conclusion

The motivation for this work emerges from the increasing proliferation of connected cars and the rapidly growing amount of car data enabling enterprises to exploit novel business opportunities. Additionally, with new players entering the automotive industry and evolving customer expectations, economic value creation shifts away from product-oriented supply chains to service-oriented ecosystems. In this regard, the connected car perfectly illustrates the Internet of Things, as it acquires valuable data from numerous sensors and cultivates an expanding ecosystem involving stakeholders from diverse industries (Cichy et al., 2021). Furthermore, platform ecosystems are increasingly emerging around the connected car, such as infotainment platforms offered by tech players leveraging their smartphone expertise in the automotive sector (Schreieck et al., 2022) or car data marketplaces that act as neutral intermediaries facilitating OEMs to sell data to independent service providers (Stocker et al., 2021). Despite research and practice recognizing the potential of data-driven business models around the connected car, most incumbent firms still struggle with connectivity and seizing the immense business opportunities of car data monetization (Kaiser et al., 2021).

In pursuit of our overarching research objective to explore and enhance the general understanding of how companies conceptualize and design business models and leverage platform ecosystems to capture value from connected cars, we contribute to various thematic areas. First, we shed light on the key characteristics and archetypal patterns observed in business models related to connected cars. Subsequently, design knowledge is generated and instantiated into a prototype artifact that deals with the realization of a concrete car-data-based service, showcasing the value-creation potential of car data marketplaces. Lastly, our case study research contributes to the current body of knowledge regarding digital business strategies employed by incumbent firms that transition toward value co-creation within platform ecosystems.

The remainder of this chapter concludes the research presented in this thesis. First, we summarize the findings of our work and point out its contributions to the research field. Afterward, we delve into managerial implications and then point out limitations regarding our work's generalizability. Finally, possible avenues for future research are outlined.

8.1 Summary and Theoretical Contributions

This section summarizes the different research studies conducted as part of this thesis based on four research questions. RQ1 explores the existing state of research on business models for connected cars, whereas RQ2 and RQ3 specifically emphasize their conceptualization. Subsequently, RQ4 deals with developing a specific business model based on connected car data. Finally, RQ5 and RQ6 address the ecosystem strategies of incumbent firms operating in the connected car domain. To organize our findings, we revisit the research questions and highlight the theoretical contributions of each study.

> **Research Question 1 (RQ1)**
> What is the state of the art in research covering data-driven business models in the connected car domain?

As discussed in Chapter 2, there have been some initial research efforts exploring connected cars and their associated business models (Kaiser et al., 2018; Marabelli et al., 2017). However, the significance of data-driven business models and associated platform ecosystems has gained momentum both in the automotive industry and in academic discourse (e.g., Bergman et al., 2022; Cichy et al., 2021; Ketter et al., 2022). Moreover, we argue that studying connected cars is a highly worthwhile endeavor, as technologies such as high-performance computing, in-car HMI, car OS, 5G, data storage, and data platforms disrupt the automotive industry and increasingly impact how people live. Addressing RQ1, our primary objective is to enhance our understanding of the literature corpus on business models capable of creating and capturing value from data collected by connected cars.

We conduct a structured literature review to uncover common approaches, insights, and research foci, allowing us to pinpoint remaining research gaps in that particular domain. In this process, our findings are organized along the four dimensions of the V^4 business model framework by Al-Debei and Avison (2010): value proposition, value architecture, value network, and value finance. As our primary theoretical contribution, we extend this framework to the context of connected cars and discuss, summarize, and synthesize the identified publications, aligning them with the V^4 dimensions. We propose that scholars publishing novel business model research in the connected car context utilize our framework to benchmark their work against the existing body of literature and identify additional research gaps. Ultimately, the results of our literature review reveal a research agenda comprising four opportunities that have been hardly addressed: (1) examining the digital business and platform strategies of established automotive companies, (2) investigating methods for preserving privacy in car data-enabled services, (3) designing services that leverage connected car data effectively, and (4) researching suitable pricing strategies for the monetization of car data. Our dissertation thoroughly addresses the first research gap by comprehensively exploring RQ5 and RQ6, while RQ4 explicitly targets the third research gap.

> **Research Question 2 (RQ2)**
> What are the key characteristics of data-driven business models in the connected car domain?

By addressing this question in Chapters 3 and 4, our research contributes to the descriptive understanding of connected cars and their corresponding business models, representing an emerging and continuously evolving field (Kaiser et al., 2018). Connected cars provide a unique setting to review and extend established theories and evidence on business models for connected device data (Cichy et al., 2021). To this end, the outcome of our study resulted in a theoretically sound and empirically validated taxonomy summarizing the critical dimensions and characteristics of connected car business models. Through an iterative process (Nickerson et al., 2013), we develop our taxonomy by incorporating insights from the existing body of knowledge and empirical analysis of 70 real-life examples of connected car companies. The taxonomy design is finalized by a quantitative and qualitative evaluation, including twelve expert interviews and its application to 154 connected car business models. We identify ten key dimensions with 48 corresponding characteristics to describe connected car business models holistically.

Our taxonomy offers theoretical insights by introducing a shared language and framework to analyze, categorize, and arrange connected car business models, paving the way for future research and assisting scholars in situating their work within this domain. Following Gregor (2006), our taxonomy represents a Type I theory contribution (“theory for analyzing”). As the most basic type of theory, “they describe or classify specific dimensions or characteristics of individuals, groups, situations, or events by summarizing commonalities in discrete observations” (Gregor, 2006, p. 623). Hence, our research contributes to structuring a body of knowledge that constitutes a novel field in IS research (Glass & Vessey, 1995) and facilitates a more systematic description.

Research Question 3 (RQ3)
What are the archetypal patterns of data-driven business models in the connected car domain?

Chapter 4 explores RQ3 using the previously developed taxonomy to identify archetypes that serve as qualitative interpretations to describe and distinguish the optimal configurations of connected car business models. We apply the set of 154 real-world business models to our taxonomy and perform a cluster analysis (Kaufman & Rousseeuw, 1990) to reveal seven distinct groups of business models that exhibit similar characteristics across the taxonomy dimensions. By comparing the respective cases within each cluster, we derive seven generic archetypes of connected car business models: (A1) data platforms, (A2) location-based services, (A3) fleet management, (A4) diagnostics and maintenance, (A5) driving analytics, (A6) cyber-physical protection, and (A7) connected infotainment. Finally, we assess each cluster's structural strength and quality using silhouette width to measure cluster validity (Rousseeuw, 1986).

In contrast to the purely descriptive nature of taxonomy research, our archetypes offer insights into wildly applied configurations, acting as a reference point for further research and adaptation. They aid the development of unique business models tailored to specific goals and target markets. Although our work does not offer a universally applicable solution, it contains a prescriptive component that provides actionable insights and guiding principles. Our archetypes contribute to a conceptual understanding of how and why different types of car data might be monetized within data-driven business models, representing a Type II mid-range theory ("theory for explaining") according to Gregor (2006). By offering insights into the complex dynamics and potential directions of the emerging field of connected car business models (Cichy et al., 2021; Kaiser et al., 2021; Koester et al., 2022), our research meets the requirement of being "new and interesting, or [explaining] something that was poorly or imperfectly understood beforehand" (Gregor, 2006, p. 625).

Research Question 4 (RQ4)
How to design a connected fleet management system in order to use car data from data marketplaces effectively?

This next question, discussed in Chapter 5, tackles the IS research gap in designing services based on data from connected cars and examining their benefits for businesses, consumers, and society. To accomplish this, we conduct a design science research project (Kuechler & Vaishnavi, 2008), centered around developing a connected fleet management system that incorporates the concept of car data marketplaces. We integrate inputs from the existing body of literature and interviews with domain experts to ensure both theoretical rigor and practical relevance (Hevner, 2007). Building on that and drawing on the theory of effective use (Burton-Jones & Grange, 2013) as our kernel theory, we derive theory-grounded meta-requirements and tentative design principles. After instantiating them into a prototypical fleet management system using Microsoft Power BI, we demonstrate the artifact's effectiveness through a risk and effectiveness strategy (Venable et al., 2016) employing a focus group workshop and further expert interviews.

The primary contribution of this work is the situated implementation of our artifact, which can be considered a level 1 contribution, as stated by Gregor and Hevner (2013). Moreover, by formulating six tentative design principles, we take initial steps towards developing a nascent design theory that aims to contribute to the prescriptive knowledge base. We thereby provide a potential level 2 contribution according to Gregor and Hevner's categorization. Broadly speaking, we perceive our work as an "improvement" in the DSR knowledge contribution framework (Gregor & Hevner, 2013), representing a new but more efficient and effective solution for a known problem. Overall, our research adds to the existing body of design knowledge for data-driven car services in general, specifically within the realm of fleet management.

Research Question 5 (RQ5)
How and why do incumbent firms decide on a certain level of tech player involvement in their digital strategy?

By answering this question raised in Chapter 6, we explore the necessity for incumbent OEMs to rethink their business strategies to remain competitive in the digital age, which tech players primarily control. In an embedded case study (Yin, 2014), we explore what options automotive OEMs have to collaborate with Google and integrate its comprehensive digital platform offering consisting of Android Automotive OS (AAOS) and the underlying Google Automotive Services (GAS) in their digital strategy. Our main contribution is a grounded model of uncertainty reallocation in incumbent firms, which we developed based on semi-structured interviews and publicly available data, guided by the affordance-actualization theory (Strong et al., 2014) as a theoretical lens. In doing so, we combine the insights gained so far using the five inductively derived aggregate dimensions that represent the building blocks of a grounded model: (1) external digital platform by tech firm, (2) incumbent firm and its goals, (3) uncertainty tradeoffs and affordance of reallocation, (4) strategic actions by incumbent firm, and (5) short- and long-term outcomes. Through our grounded model, we offer theoretical insights into the decision-making process of incumbent firms regarding their level of involvement with tech players in their digital strategies. Furthermore, we offer evidence on how external digital platforms by tech firms have the potential to redistribute incumbent firms' uncertainty, which requires them to make several trade-offs. Finally, our analytical findings offer empirical insights into the growing involvement of tech firms in established industries, such as the automotive sector.

The associated study carries additionally various theoretical implications. First, our research enhances the existing understanding of digital platform affordances (e.g., Beverungen et al., 2020; Hein et al., 2019b, 2020). We achieve this by introducing the concept of uncertainty reallocation in the context of incumbent firms responding to external digital platforms offered by tech firms. Our study empirically shows that incumbent OEMs in the automotive industry share common goals in their digital strategy. However, we also demonstrate that incumbent OEMs are forced to partner with technology players to benefit from their external digital platforms (e.g., Android Automotive OS), leading to an uncertainty trade-off and reallocation of uncertainty. For instance, incumbent OEMs must weigh whether integrating a tech firm's trusted and well-established operating system outweighs the associated loss of control over user data, user behavior, and system usage information. This also has implications for understanding uncertainty in multi-actor digital innovation settings (e.g., Poeppelbuss et al., 2022). By applying the affordance lens, we highlight the socio-technical nature of reallocating uncertainty in a digital innovation context, particularly when firms face similar external platform offers.

Research Question 6 (RQ6)
How can incumbent firms orchestrate their partner network toward value co-creation to establish IoT ecosystems?

In order to address RQ6 posed in Chapter 7, we delve into the ecosystem strategies employed by incumbent firms. By presenting an embedded case study (Yin, 2014) within Robert Bosch GmbH, we draw a comprehensive picture of the challenges, departments face in designing and governing platform-based IoT ecosystems. Our single case study provides actionable recommendations based on the strategies employed by Bosch's IoT ecosystem initiatives. To structure our findings, we apply the tripartite service innovation framework by Lusch and Nambisan (2015) to the

IoT context. Particularly, our study uncovers twelve incumbent-specific challenges within the realm of IoT ecosystems and offers effective design and governance actions taken to overcome these challenges. Despite operating in different industries, other incumbents aiming to transition from traditional pipeline businesses to IoT ecosystems encounter similar challenges. The recommendations derived from our analysis of Bosch's IoT ecosystem landscape also apply to these industry incumbents to some extent. In addition to these empirical findings, we consolidate four overarching tensions that have surfaced across all three dimensions of the service innovation framework: (1) exploitation versus exploration, (2) commitment versus accessibility, (3) control versus openness, and (4) stability versus flexibility. Although these tensions are commonly perceived as incompatible and mutually exclusive, our study presents how they can be reconciled using four concepts for IoT ecosystem establishment: (1) organizational ambidexterity, (2) architecture of participation, (3) trustworthy governance, and (4) minimum viable ecosystem.

In terms of theoretical implications, we contribute to the discourse on IoT ecosystems by incorporating the perspective of incumbents by introducing a general framework that can be applied by further research on the topic. Our framework takes on a holistic, long-term view that crosses and connects the boundaries of the different stages of ecosystem orchestration, such as initiation, scaling, and control (Autio, 2022). For example, throughout the entire lifecycle of an ecosystem, governance aspects such as a neutral platform environment, flexible strategic alignment, or appropriate openness are crucial. Moreover, the study emphasizes the IS-specific balance between technical and socio-organizational aspects and delivers potential solutions to address challenges in ecosystem orchestration. Our findings support the idea that an IoT ecosystem is an inseparable socio-technical system where technical and socio-organizational challenges underlie strong interdependencies (Alter, 2013). Finally, the tensions identified can serve as a starting point for further research to assist managers of incumbents in guiding their company's transition towards becoming an orchestrator of an IoT ecosystem. Further empirical research could focus on one of the four identified tensions and provide more in-depth insights on resolving the tensions in the context of IoT ecosystem design and governance. Alternatively, a design-oriented approach could be adopted to develop a management assistant tool or define suitable key performance indicators to assist the decision process of managers.

8.2 Managerial Implications

Apart from the theoretical contributions outlined earlier, this dissertation also holds direct implications for practice. The automotive industry witnesses a growing trend of connected cars, requiring proactive measures to capitalize on this emerging opportunity. As previously mentioned in Chapter 1, McKinsey & Company projected that the annual added value generated from monetizing car data could range from $250 billion to $400 billion by the year 2030 (Martens & Schneiderbauer, 2021). Our findings contribute to a better understanding of conceptualizing and designing data-driven design business models and leveraging platform ecosystems to capture value from connected cars.

First, our structured literature review in Part I sheds light on the crucial task of monetizing car connectivity. To offer actionable guidance for automotive executives, we propose four key implications derived from our in-depth analysis of the current body of knowledge to assist practitioners in leveraging car data: (1) Foster drivers' willingness to share car data and facilitate data sharing between OEMs and independent service providers to counteract the monopolization of data by OEMs. (2) Enhance customer-centricity to design connected services that meet customers' increasing demand for digital experiences. (3) Engage collaboration between vehicle-specific players (e.g., OEMs, suppliers) and the wider ecosystem (e.g., tech players, insurance firms). (4) Build strong internal capabilities, including software development, cybersecurity, and data analytics. Beyond these implications, our literature review yields further managerial contributions. On the one hand, it consolidates essential concepts for developing connected car business models. On the other hand, it provides an overview of 38 connected car services documented in the literature, highlighting their potential to generate revenue by monetizing vehicle data.

Second, our taxonomy and archetype-building activities highlighted in Part II carry noteworthy managerial implications by providing valuable tools to navigate the unexplored realm of connected car business models. They provide a differentiated perspective on business model design in the connected car space, enabling industry players to comprehend the interplay between car data-driven business models and explore various options for monetizing connected car data. Our taxonomy and archetypes can serve as strategic management tools for managers across various purposes. They can identify business opportunities and potential market entry points in the automotive ecosystem and evaluate our archetypes' applicability within their company's specific context. Furthermore, the provided artifacts can help explain their current business model to stakeholders, focus on improving specific operational aspects, or develop new business models aligned with their corporate strategy (Spieth et al., 2014). By conducting a morphological analysis (Geum et al., 2016), our work can finally assist in systematically developing innovative ideas. The archetypes and underpinning real-world business models highlight proven innovation paths for executives to digitalize their existing business models. In general, the taxonomy and archetypes deliver industry-specific support for innovating business models, empowering practitioners to broaden their market offerings and create value across the vehicle life cycle.

Third, the DSR project presented in Part III provides insights to practitioners regarding the utilization of connected car data and the design of efficient connected car services. We offer design recommendations to promote improved economic and environmental performance, and vehicle health, positively impacting consumers, businesses, and society. Moreover, by adopting the design science research paradigm, we systematically tackle the desirability and feasibility aspects of potential connected car business models, providing insights into the observed areas of fleet management and data marketplaces. On the one hand, the in-depth analysis of our interview study involving fleet stakeholders reveals a holistic understanding of the present obstacles and prospects that can be tackled by utilizing vehicle data. On the other hand, instantiating the design principles based on in-vehicle data collected in a field test initiated by a car data marketplace shows which fleet management use cases are already feasible via this approach and, therefore, for companies in the automotive industry without exclusive data access. Furthermore, we illuminate the highly complex fleet domain by offering design principles for an information system that takes into account both strategic (DP1-DP3) and operational (DP4-DP6) fleet management activities.

Finally, the case studies introduced in Part IV carry strategic implications for managers in incumbent firms who aim to transition their organizational structures toward platform ecosystems. We investigate two aspects in one embedded case study each: incumbent firms seeking to collaborate with tech players and become part of an existing platform ecosystem and incumbent firms aiming to establish and orchestrate a new platform ecosystem. Regarding the latter, we demonstrate that incumbents can adopt various strategies concerning the involvement of technology companies. These strategies include utilizing solely the open-source version of the technology company's platform offering, integrating it comprehensively, or opting for a customized approach. Moreover, our findings indicate that there is no one-size-fits-all strategy for engaging tech players. Instead, incumbents must carefully consider which technology and business control points in the ecosystem they need to possess based on their internal capabilities and goals. However, even though being a contributor to an ecosystem can be equally appealing as being a platform provider, our second case study contains managerial insights into establishing and orchestrating platform ecosystems. Our findings may help business leaders traditionally operating in linear value chains to reshape their enterprise design and governance mechanisms to foster value co-creation. In this regard, we offer twelve design and governance-related challenges and corresponding actions to overcome them effectively.

8.3 Limitations

The studies embedded in this work bear several limitations. While each publication covers a detailed discussion of its limitations, we will now reflect on the major shortcomings of the research endeavors that should be considered regarding the findings' generalizability.

First, the primary constraint of literature reviews (RQ1-RQ4) lies in their dependency on the search process (e.g., selected databases or search terms) and the papers identified through it. Even when employing forward and backward search techniques (Webster & Watson, 2002), it is unlikely that the search process captures every single article relevant to the objective. Additionally, the investigation of connected cars and associated business models is a rapidly evolving field of research. Therefore, our work reflects only a brief glimpse of the literature in this area, and future investigations may yield different outcomes.

Second, the iterative taxonomy development process that we employ to address RQ2 also entails certain limitations. While it is essential to acknowledge that taxonomies may not be flawless, their value lies in their usefulness rather than in achieving perfection and full comprehensiveness (Nickerson et al., 2013). Taxonomy-based research is never complete as it only reflects a snapshot in time and needs to be constantly updated to remain helpful in the future (Nickerson et al., 2013). Nonetheless, the taxonomy presented in this thesis has been designed to be extendable with further dimensions or characteristics, serving as a robust framework for identifying forthcoming business model patterns. Moreover, classifying real-world objects and applying them to taxonomies (RQ2 and RQ3) is prone to coding biases. Coding, for example, depends on the authors' interpretations of the taxonomy dimensions and features. To counteract this, we employed multiple coders and assessed intercoder reliability. In addition, the coding process was only based on publicly available information. We triangulate data from company websites, press releases, startup databases, and company reports to maximize the validity of our dataset.

Third, another limitation emerges from following the design science research paradigm when investigating RQ4. The DSR approach is characterized by its iterative nature, aiming to achieve "learning through the act of building" (Kuechler & Vaishnavi, 2008, p. 489) rather than following a linear research path. The kernel theory we draw on during our DSR study to underpin the design of artifacts represents just one possible approach to achieving our objectives. While we consider the effective use theory (Burton-Jones & Grange, 2013) the most suitable for developing design knowledge to address RQ4, alternative kernel theories could have resulted in a distinct set of design principles. The same applies to the sample of interviewed experts, which does not claim to be exhaustive. Nevertheless, through our comprehensive approach that integrates both literature review and expert interviews, we ensured both rigor and relevance, establishing a robust foundation for problem awareness.

Last, despite the extensive and detailed information that case studies offer, they also have certain limitations that we acknowledge when examining RQ5 and RQ6. The generalizability and, thus, the external validity (Yin, 2014) of case studies are subject to limitations and require further verification. Hence, our findings do not claim to be exhaustive or universally applicable to every incumbent firm in developing their platform ecosystem strategy across all industries. Furthermore, the primary data source of both case studies consists of interviews, which may include biases. On the one hand, researchers are mainly responsible for data collection during interviews, relying on their skills and instincts. On the other hand, interviewees themselves may introduce biases in the information provided. To mitigate this limitation, a diverse group of experts and senior decision-makers were interviewed (Eisenhardt & Graebner, 2007). Additionally, we complement the interviews with secondary data sources, including websites, news articles, press releases, and internal documents.

8.4 Opportunities for Future Research

By 2030, approximately 95 % of newly sold vehicles worldwide will be connected (Martens & Schneiderbauer, 2021). This indicates that automotive companies continuously seek opportunities to leverage car data in innovative business models while developing associated platform ecosystems. Hence, we see encouraging future research opportunities to occupy this field.

First, investigating privacy and ethical considerations within data-driven connected car business models and ecosystems presents a promising avenue for future research. Unlike other connected products, connected cars have already emerged as a prominent example of IoT implementation on a large scale, and the generated data is already being shared with third parties through APIs. Sharing connected car data raises a series of privacy-related concerns (Cichy et al., 2021) as the car users' informational and physical spaces may be intruded (Koester et al., 2022), which can elevate privacy risks. Particularly sensitive information about actual driving behavior or daily routines may be inferred from connected car data (Lechte et al., 2023). To advance research in this area, it is important to address the issue of data ownership and the measures required to safeguard it. Moreover, the current literature lacks a theoretical evaluation of car data privacy, emphasizing the need for theory building (Sterk et al., 2022a). From a theoretical standpoint, a suitable initial reference would be the privacy calculus model (Dinev & Hart, 2006), which proposes that individuals assess their willingness to share information through a risk-benefit analysis. In light of this, further research could apply the model to investigate how drivers preserve their privacy in car-data-based business models and test, adapt, and extend corresponding theories.

Second, to keep our taxonomy and archetypes in the developing field of connected car business models relevant and applicable future research could revisit and extend our findings. Moreover, as our research aimed to construct a taxonomy and associated archetypes encompassing the diverse connected car domain, our findings are still broad in scope, covering diverse foci, including data marketplaces, fleet management systems, and infotainment systems. To gain a deeper understanding of the seven archetypes we derived in our work, future studies could delve into them more comprehensively by crafting more specific taxonomies and sub-archetypes for these business models within the connected car domain. Our proposed approach is similar to the study conducted by Bergman et al. (2022), wherein a taxonomy and associated archetypes for data marketplaces were developed. In this context, further taxonomy research is needed, particularly in the domain of two specific archetypes we identified: At first, the domain of fleet management (A3) needs more consideration due to the growing proportion of professionally managed fleet vehicles (Pütz et al., 2019) and its significant heterogeneity, encompassing diverse fleet types (e.g., logistics service providers or mobility service providers) and vehicle categories (e.g., cars, light commercial vehicles, or trucks). The second business model archetype that lends itself to in-depth investigation is connected infotainment (A7) due to the ongoing smartphonization of connected cars and the complex layer architecture of infotainment systems provided by multiple ecosystem actors.

Third, there is abundant room for advancing research and development efforts to escape the data monopoly of automotive OEMs. Other market participants (e.g., suppliers, repair shops, insurance companies) heavily rely on the OEMs' data supply and are, therefore, in a disadvantageous position (Martens & Mueller-Langer, 2020). As a countermeasure, car data marketplaces tap into the cloud systems of OEMs, harmonize the data, and resell it to independent service providers. Nevertheless, Otonomo and Wejo, renowned car data marketplaces, are currently facing challenging financial circumstances, as certain OEMs are reluctant to share extensive data or only offer data that may not be inherently valuable to external buyers unless shared across multiple brands (Bloomberg, 2023). Hence, there is a significant need for examining how to establish fair competition between OEMs and alternative service providers. A promising foundation for research endeavors could be the European Commission's regulations for fair data access and utilization, commonly referred to as the Data Act (European Commission, 2022b). Scholars may explore different data governance models and frameworks that can be used to implement the Data Act effectively. Another approach would be to assess the potential impact of the Data Act on the value co-creation between OEMs, independent service providers, and data marketplaces.

Fourth, there are also promising prospects for expanding case study research in the investigated field of ecosystem strategies employed by incumbent firms. Looking ahead, we see great potential in transferring our theoretical models to in-depth studies that specifically emphasize industry contexts other than automotive or other incumbent firms beyond the investigated ones to strengthen our results in terms of general applicability to other contexts. In addition, our work and the majority of other IS research (e.g., Bohnsack et al., 2021; Dremel et al., 2017; Svahn et al., 2017) have emphasized platform ecosystems introduced by Western market companies such as Google and Bosch. Hence, it is essential to acknowledge that the findings may not be directly applicable to other markets due to differences in cultural value, market structure, or consumer behavior. To address this limitation, future case studies could explore cooperation models, notably with Chinese automotive and tech firms that exhibit a prominent global presence and influence. This holds particular relevance due to the necessity for regionalized solutions, exemplified by the governmental restrictions on Google services. Moreover, the country's high affinity for technology and demand for a holistic software experience has resulted in established Western OEMs experiencing a decline in their market share.

Finally, this thesis thoroughly investigates the connected car and its remarkable ability to exchange real-time data with its ecosystem. However, the next revolutionary leap in the automotive industry is already around the corner, known as the “*software-defined vehicle*,” wherein the vehicle’s software takes precedence over the mechanical hardware and mainly controls and executes vehicle functions (c.f., Ohlsen, 2022; Windpassinger, 2022). The research opportunity comes from the ability of car owners to select the features and services they want and thus tailor their driving experience to their individual needs. This provides a valuable opportunity to study user preferences, analyze usage patterns and develop personalized features that improve user satisfaction and engagement. Additionally, researchers and innovators have the distinctive chance to shape this future by exploring new approaches and technologies that improve safety, efficiency, and the overall user experience. However, it is evident that neither incumbent OEMs nor suppliers are really prepared for this paradigm shift and can successfully navigate it in isolation. Notably, significant components of vehicle operating systems or cloud environments increasingly rely on frameworks from major hyperscalers like Amazon, Google, or Microsoft. This circumstance calls for further exploration of collaborative approaches and cooperation to enable incumbents to fill their knowledge gaps and actively contribute to the value creation of software-defined vehicles beyond commodity products. All in all, we encourage scholars to join us in exploring the almost endless possibility of the connected and shortly software-defined dream car.

8.5 The End

In summary, this dissertation paves the way for research and practice to harness the potential of connected car data and co-create value within platform ecosystems. Innovative constructs are introduced, offering a unified perspective on conceptualizing this emerging type of business model. Additionally, we offer design knowledge showcasing the value-creation potential of car data and its instantiation into a prototype artifact. This work also provides strategic guidance to incumbent firms operating in the automotive industry and beyond, assisting them in transitioning their organizational structure toward platform ecosystems. With the number of connected car use cases and corresponding ecosystems growing, we believe that organizations will facilitate the proliferation of automotive data resulting in benefits for both businesses and individuals while also contributing to the broader societal context.

In alignment with the introduction of this thesis, I want to close my work with the words of a visionary in the field of future mobility. The transformative landscape for the next two decades encompasses the evolution from fossil fuels to clean energy, the shift from mechanical to software-centric mobility, and the seamless integration of AI to facilitate smooth transitions between human and machine operators. "*When this software dream car will come to the real world, it will be a bit like a white sheet of paper. It's not good or bad in itself, but it is the largest real-life experiment of AI and humans interacting on a daily basis*" (Koster, 2023b, 10:58). By embracing these paradigm shifts, we can actively contribute to creating a future where environmental sustainability, personalized experience, and road safety go hand in hand, both digitally and physically. Let us drive this innovation in a way that benefits humanity as a whole.

Appendix A

A.1 Supplementary Material Chapter 4

Table A.1.: Sample of connected car business models.

Reference	Business model or company name			
Structured literature review	BM1	Apple CarPlay	BM16	Mercedes Live Traffic Information
	BM2	Audi Connect	BM17	Metromile
	BM3	Automile	BM18	Mojio Force for Fleets
	BM4	BMW ConnectedDrive	BM19	Mojio Motion for Consumers
	BM5	BMW Digital Fleet Solutions	BM20	Mojio Platform
	BM6	BMW Remote Software Upgrade	BM21	Nauto
	BM7	Caruso Dataplace	BM22	Otonomo
	BM8	Caruso Repdate	BM23	Porsche Connect
	BM9	Google Android Auto	BM24	Vinli Fleet
	BM10	Google Android Automotive OS	BM25	Vinli Insurance
	BM11	Google Automotive Services	BM26	Volvo Sensus Connect
	BM12	Google Maps	BM27	VW Car-Net / We Connect
	BM13	High Mobility	BM28	VW We Connect Fleet
	BM14	Mercedes Connect Business	BM29	Zendrive
	BM15	Mercedes me connect	BM30	Zubie
PwC (2020)	BM31	Bliq	BM37	Parkopedia
	BM32	Geotab	BM38	Passport Parking
	BM33	GM Onstar	BM39	Ridecell
	BM34	EasyPark	BM40	Upstream Security
	BM35	Evopark	BM41	Wayray
	BM36	Nexar		
Capgemini (Arif et al., 2019)	BM42	Aeye	BM62	Generali Jeniot Mobility
	BM43	Affectiva	BM63	Goodyear TPMS
	BM44	Airbiquity	BM64	IBM Cyber Security Services
	BM45	ALD ProFleet	BM65	Innovusion
	BM46	Alibaba AliOS	BM66	Innoviz Technologies
	BM47	Allianz BonusDrive	BM67	Karamba Security
	BM48	Arval FleetManagement	BM68	MetaWave
	BM49	Autotalks	BM69	Michelin DDI Driving Score
	BM50	Autox	BM70	Momenta
	BM51	AXA UPTO Fleet Management	BM71	Orange Ocean fleet management
	BM52	Bosch Updates Over-the-Air	BM72	Orange Ocean Geostart
	BM53	Bosch FNOS	BM73	Owlcam
	BM54	Bosch Predictive Maintenance	BM74	Phantom Auto
	BM55	Bridgestone Webfleet	BM75	Pony AI
	BM56	Continental Cyber Security	BM76	SAP E-Mobility
	BM57	Continental ContiConnect 2.0	BM77	Sensetime
	BM58	Continental Vehicle Data Services	BM78	Verizon Connect
	BM59	Cortica	BM79	Vimcar
	BM60	Elektrobit EB Cockpit System	BM80	Wejo
	BM61	Faurecia Aptoide	BM81	ZF Smart Service App

Table A.1.: Sample of connected car business models (continued).

Accenture (Seiberth & Gruendinger, 2018)	BM82	BlackBerry QNX	BM96	MAN Rio
	BM83	Ford SYNC	BM97	Mobileye
	BM84	FordPro Fleet Managemet	BM98	Navigon / Garmin Automotive
	BM85	Glympse	BM99	NIO OS / Aspen
	BM86	Harman AAOS Security Suite	BM100	T-Systems Over-the-air-Update
	BM87	Harman Ignite Store	BM101	Tesla Connectivity
	BM88	Harman SHIELD	BM102	Tesla OTA
	BM89	HERE Marketplace	BM103	TomTom Indigo Digital Cockpit
	BM90	HERE Navigation	BM104	TomTom Marketplace
	BM91	Huawei Harmony OS	BM105	TomTom Navigation
	BM92	Huawei HiCar	BM106	Toyota Insurance Service
	BM93	INRIX Marketplace	BM107	Toyota MyT connected service
	BM94	INRIX OpenCar	BM108	Waze
	BM95	Lamborghini Connect		
Crunchbase (crunchbase.com)	BM109	Aplicom	BM132	KATSANA Holding Sdn Bhd
	BM110	Argus Cyber Security	BM133	KOBA Insurance
	BM111	Arrive	BM134	Koola
	BM112	C2A Security	BM135	Koop Technologies
	BM113	CARFIT	BM136	Motion-S Fleet Optimization
	BM114	CarIQ	BM137	Motion-S Connected Insuance
	BM115	Carmen	BM138	MotorQ
	BM116	CaRPM	BM139	Nonda
	BM117	CarX	BM140	Perseus
	BM118	Consenz	BM141	Phiar Technologies
	BM119	Dashroad	BM142	Pitstop
	BM120	Derq	BM143	Preteckt
	BM121	Drivemode	BM144	SecureThings
	BM122	DRUST	BM145	Sibros
	BM123	Faraday Future Infotainment	BM146	Smartcar
	BM124	Fensens	BM147	Synaptiv
	BM125	Fescaro	BM148	Tantalum Corporation
	BM126	GoFar	BM149	Telenav
	BM127	HAAS Alert	BM150	Teraki
	BM128	HUM	BM151	Viaduct
	BM129	IMS (Insurance & Mobility Solutions)	BM152	Voyomotive
	BM130	Jedlix	BM153	Xee
	BM131	Jooycar LLC	BM154	Xevo
Note: If a company offers different connected car business models, the number of objects may be higher than in the first reference screening due to the objects' splitting.				

Table A.2.: Change of taxonomy due to evaluation, including operations on specific elements.

First taxonomy version before evaluation	Operation*	Second taxonomy version after evaluation
Value for customer	*Rename*	Value for car owner or driver
Safety & security	/	Safety & security
Cost reduction	*Swap*	Cost reduction
Traffic efficiency	*Swap*	Traffic efficiency
Infotainment	*Swap*	Infotainment
/	*Add*	Environmental sustainability
Convenience	*Swap*	Convenience
Data accessibility	*Rename*	Indirect value
Influence of car data	*Rename*	Car data impact on value
Car data core business mode	/	Car data core business model
Car data-enabled business model	/	Car data-enabled business model
Influence of autonomy	*Rename*	Car autonomy impact on value
Enhanced value by autonomy	/	Enhanced value by autonomy
Reduced value by autonomy	/	Reduced value by autonomy
Autonomy not relevant	/	Autonomy not relevant
Data personalization	*Delete*	/
Anonymized data	*Delete*	/
Personal data	*Delete*	/
/	*Add*	Data category
/	*Add*	PII
/	*Add*	Contextual data
/	*Add*	Diagnostic data
/	*Add*	Usage data
/	*Add*	ADAS data
/	*Add*	Application data
Data access	/	Data access
Exclusive access	*Rename*	OEM proprietary access
Central server	*Rename*	OEM-specific cloud or neutral server
OBD2-dongle	/	OBD2-dongle
Retrofit	*Rename*	Other retrofit devices
Smartphone	*Rename*	Smartphone or other non-in-vehicle sources
/	*Add*	Future enabler technology
/	*Add*	Blockchain
/	*Add*	Augmented reality
/	*Add*	Over-the-air architectures
/	*Add*	ADAS technology
/	*Add*	Artificial intelligence
/	*Add*	Cellular networks
Role in ecosystem	/	Role in ecosystem
Service provider	Rename	End-customer solution provider
Platform provider	/	Platform provider
Technology provider	/	Technology provider
Customer segment	/	Customer segment
B2C	*Rename*	Private individuals (B2C)
B2B	*Split*	Fleet providers (B2B)
		OEMs (B2B)
		Third-party providers (B2B)
B2G	*Rename*	Governments (B2G)

Table A.2.: Change of taxonomy due to evaluation, including operations on specific elements (continued).

Data monetization	*Rename*	Data monetization strategy
Selling data	*Split*	Data source & data provision
		Data aggregation & data exchange
Selling analysis	*Rename*	Data analysis & data insights
Selling services	*Rename*	Data application & data service
Revenue model	/	Revenue model
Direct sale	*Rename*	One-time payment
Usage fee	*Rename*	Pay-per-use
Subscription fee	/	Subscription fee
Licensing fee	/	Licensing fee
Transaction fee	*Rename*	Commission fee
On-demand	/	On-demand
/	*Add*	Open source

*Operations: add (insert a new element), rename (change the name of an element), swap (change the order of two elements), split (divide an element into at least two elements), and delete (remove an existing element)

Table A.3.: Recommended number of clusters of 154 connected car business models.

Measure suggested by	Suggested number of clusters (Ward.D2)
Ball and Hall (1965)	3
Caliński and Harabasz (1974)	7
Davies and Bouldin (1979)	14
Dunn (1974)	5
Frey and Van Groenewoud (1972)	1
Halkidi et al. (2000)	5
Hartigan (1975)	6
Hubert and Levin (1976)	14
Krzanowski and Lai (1988)	9
McClain and Rao (1975)	2
Milligan (1981)	5
Rousseeuw (1987)	7
Tibshirani et al. (2001)	2

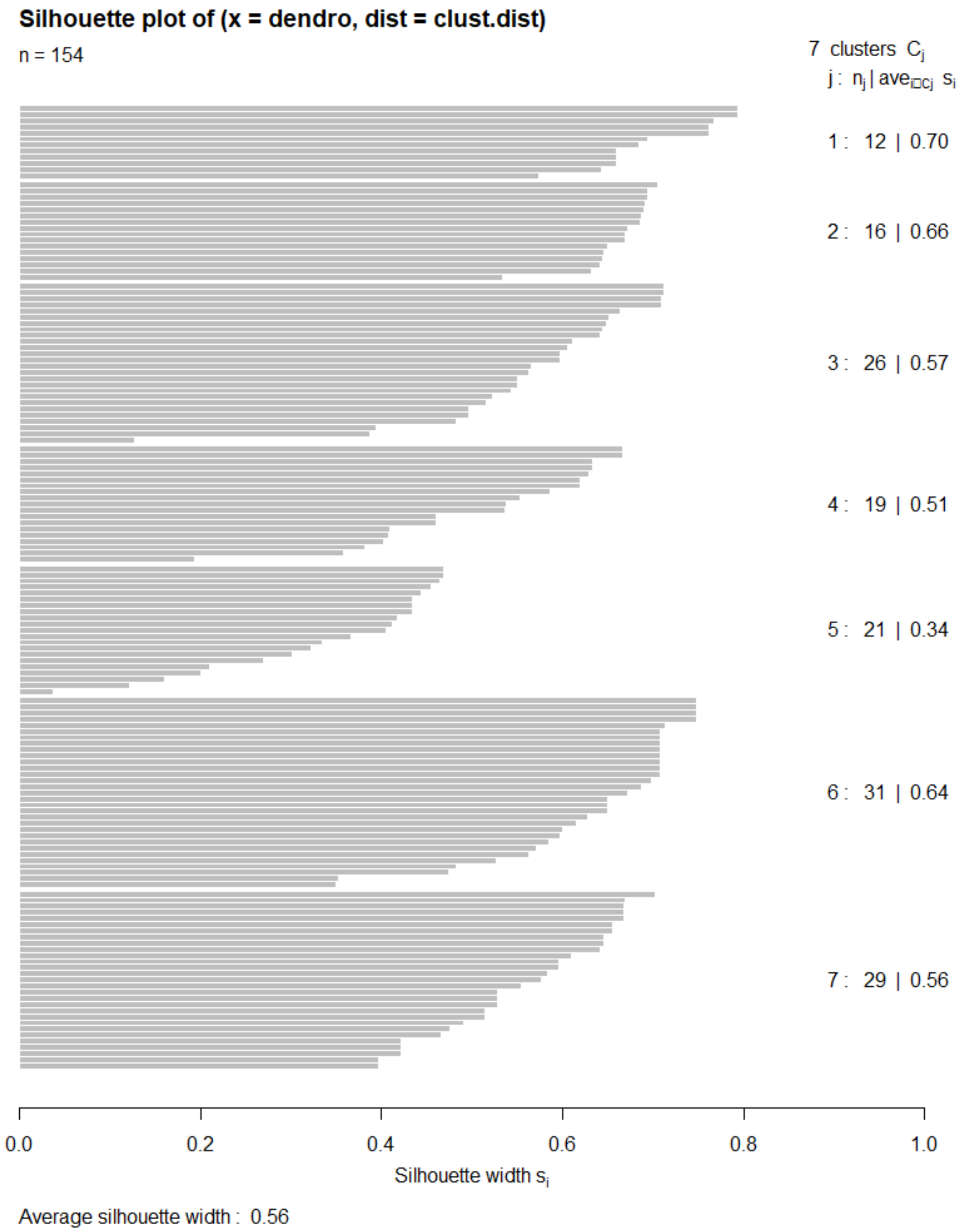


Figure A.1.: Silhouette plot of Ward.D2 partitioning for $k = 7$. Average silhouette width: 0.56.

A.2 Supplementary Material Chapter 5

Figure A.2.: Graphical user interface of the connected fleet management system implemented in Microsoft Power BI.

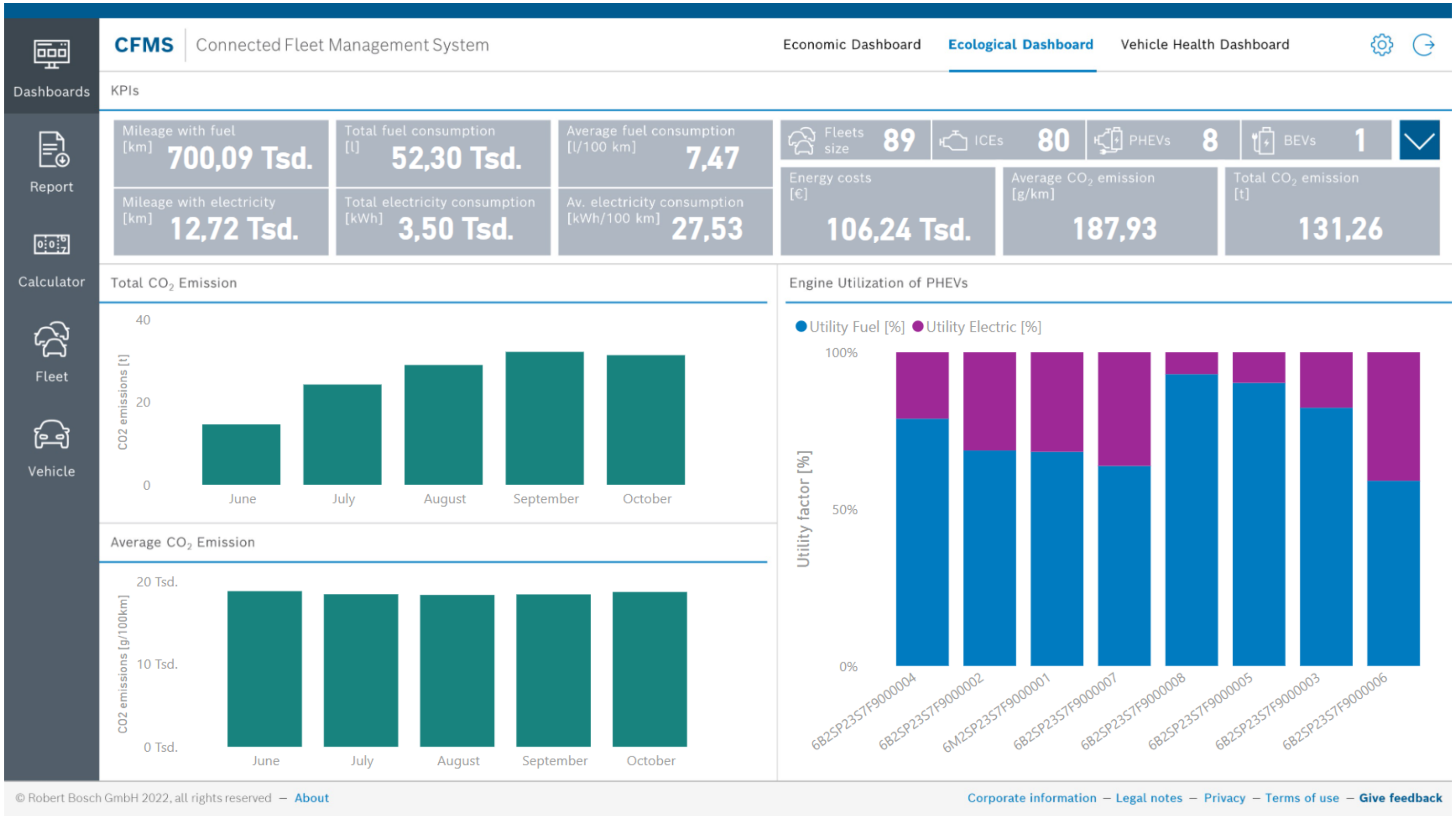


Figure A.2.: Graphical user interface of the connected fleet management system implemented in Microsoft Power BI (continued).

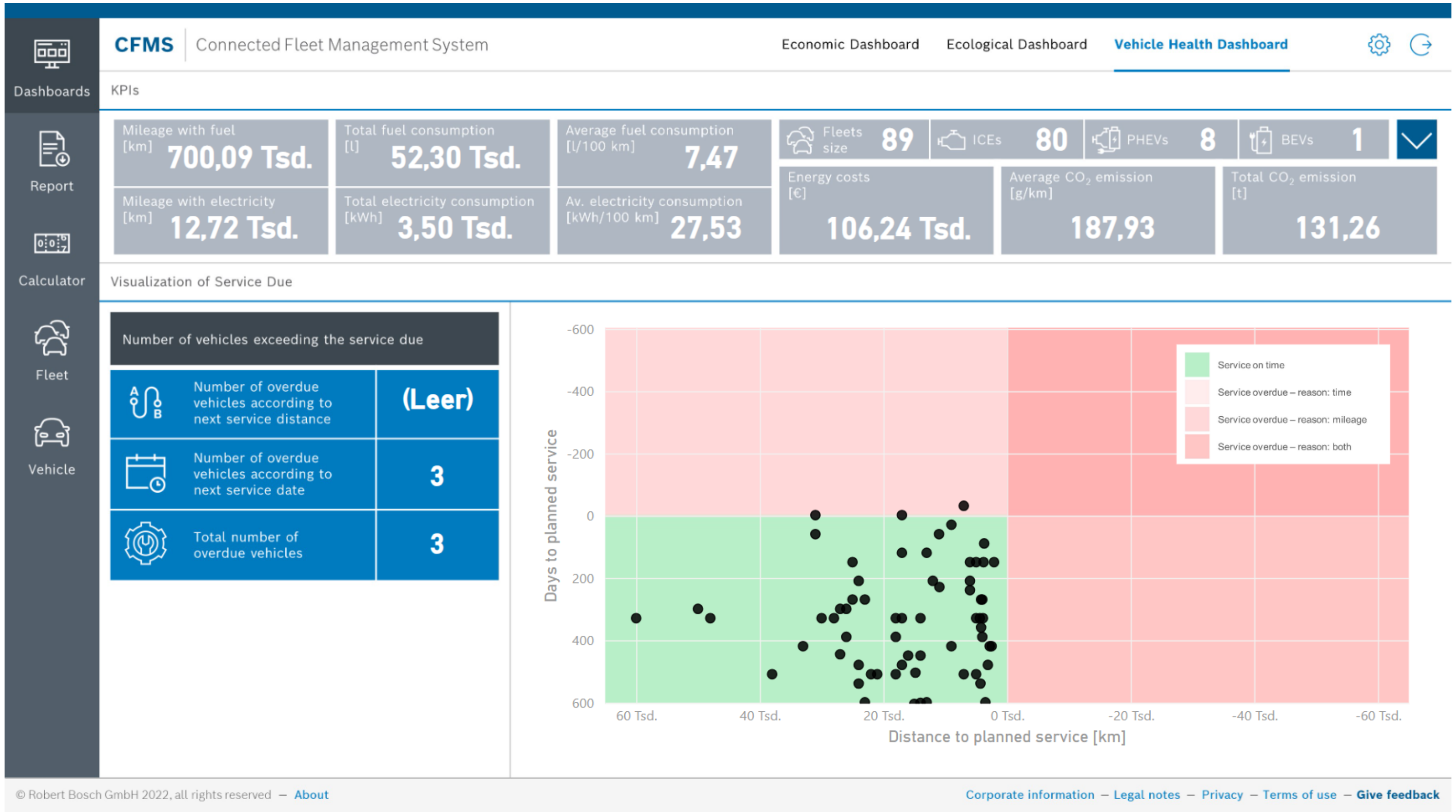


Figure A.2.: Graphical user interface of the connected fleet management system implemented in Microsoft Power BI (continued).

Figure A.2.: Graphical user interface of the connected fleet management system implemented in Microsoft Power BI (continued).

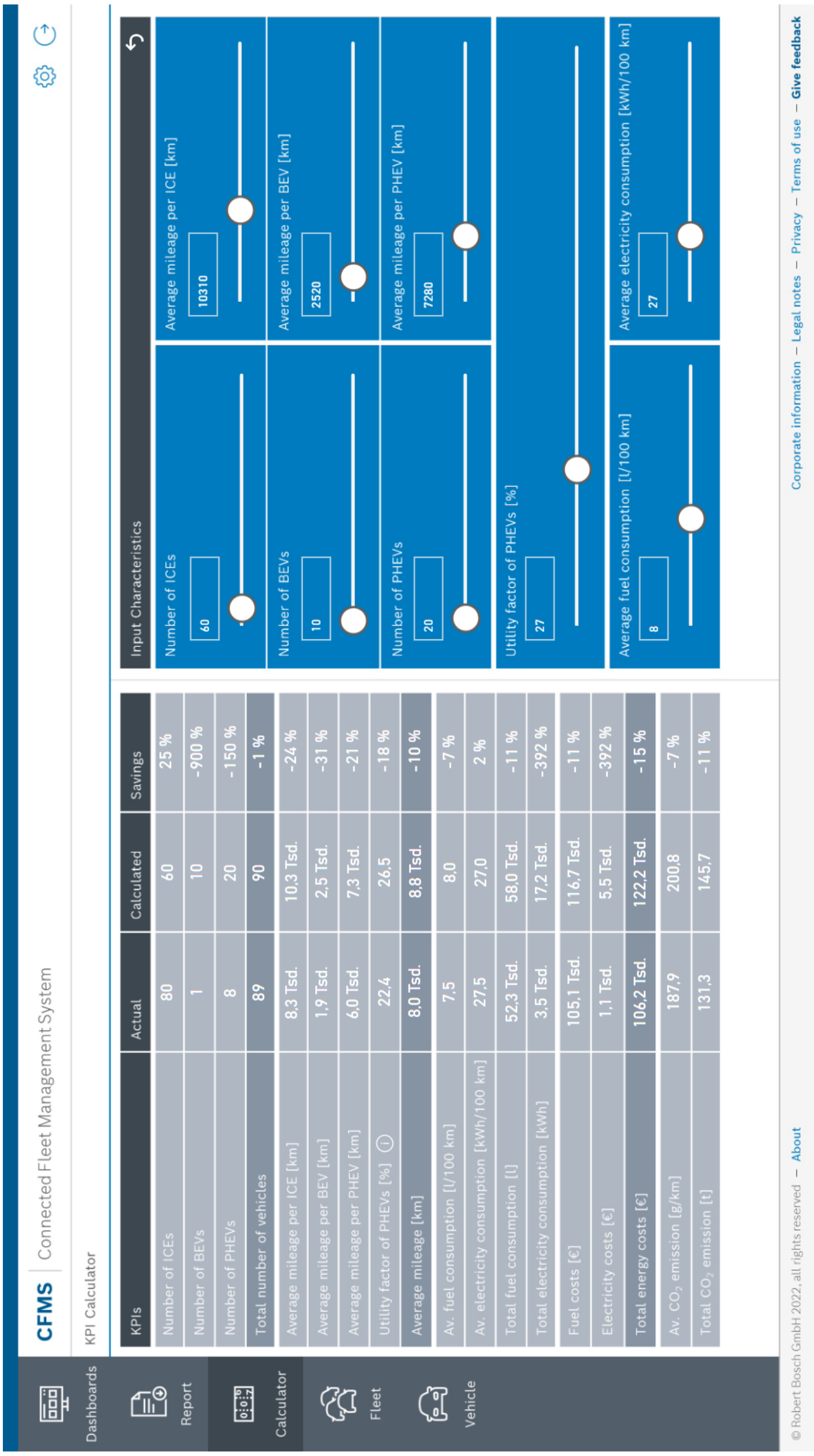


Figure A.2.: Graphical user interface of the connected fleet management system implemented in Microsoft Power BI (continued).

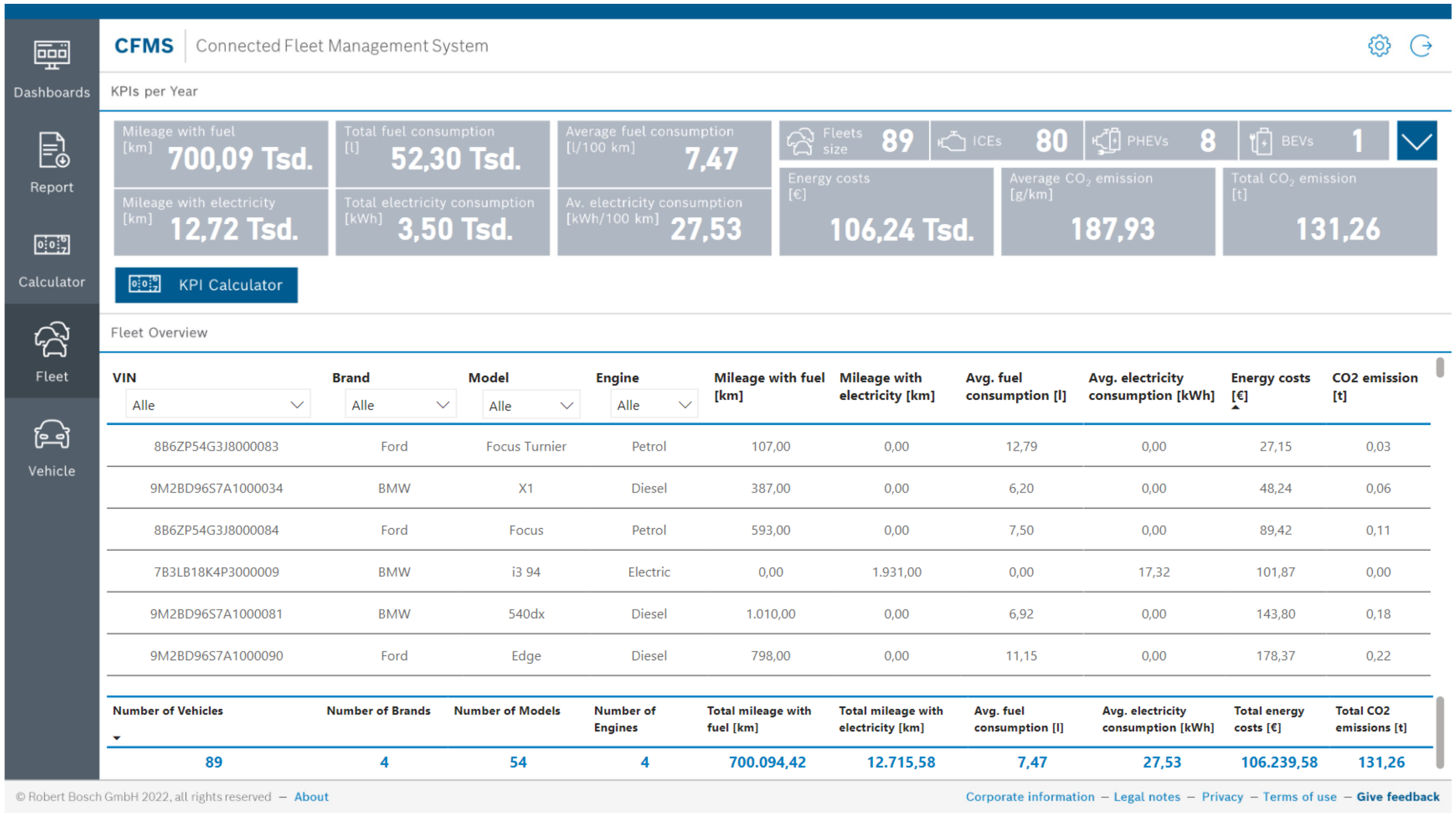


Figure A.2.: Graphical user interface of the connected fleet management system implemented in Microsoft Power BI (continued).

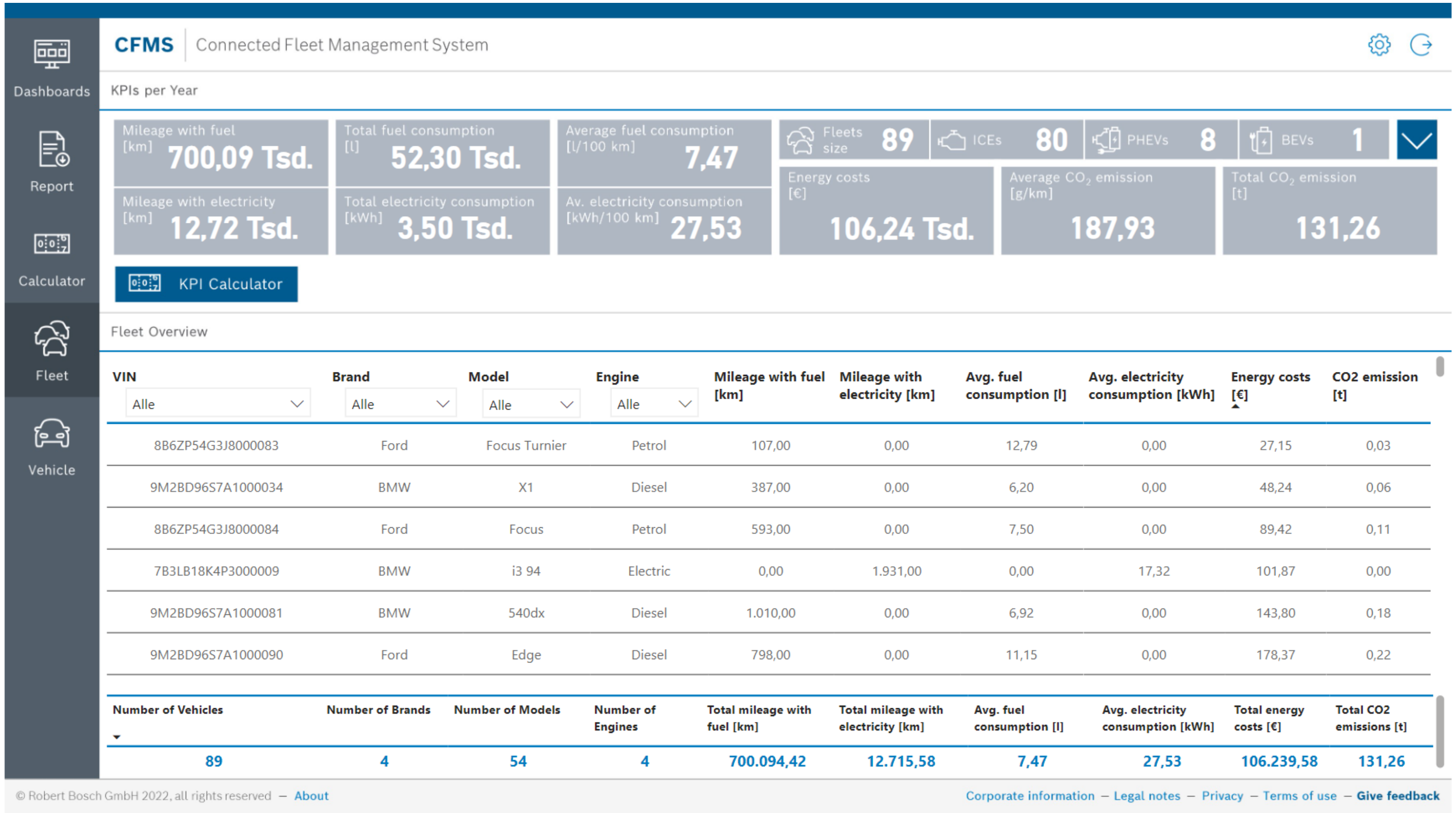


Figure A.2.: Graphical user interface of the connected fleet management system implemented in Microsoft Power BI (continued).

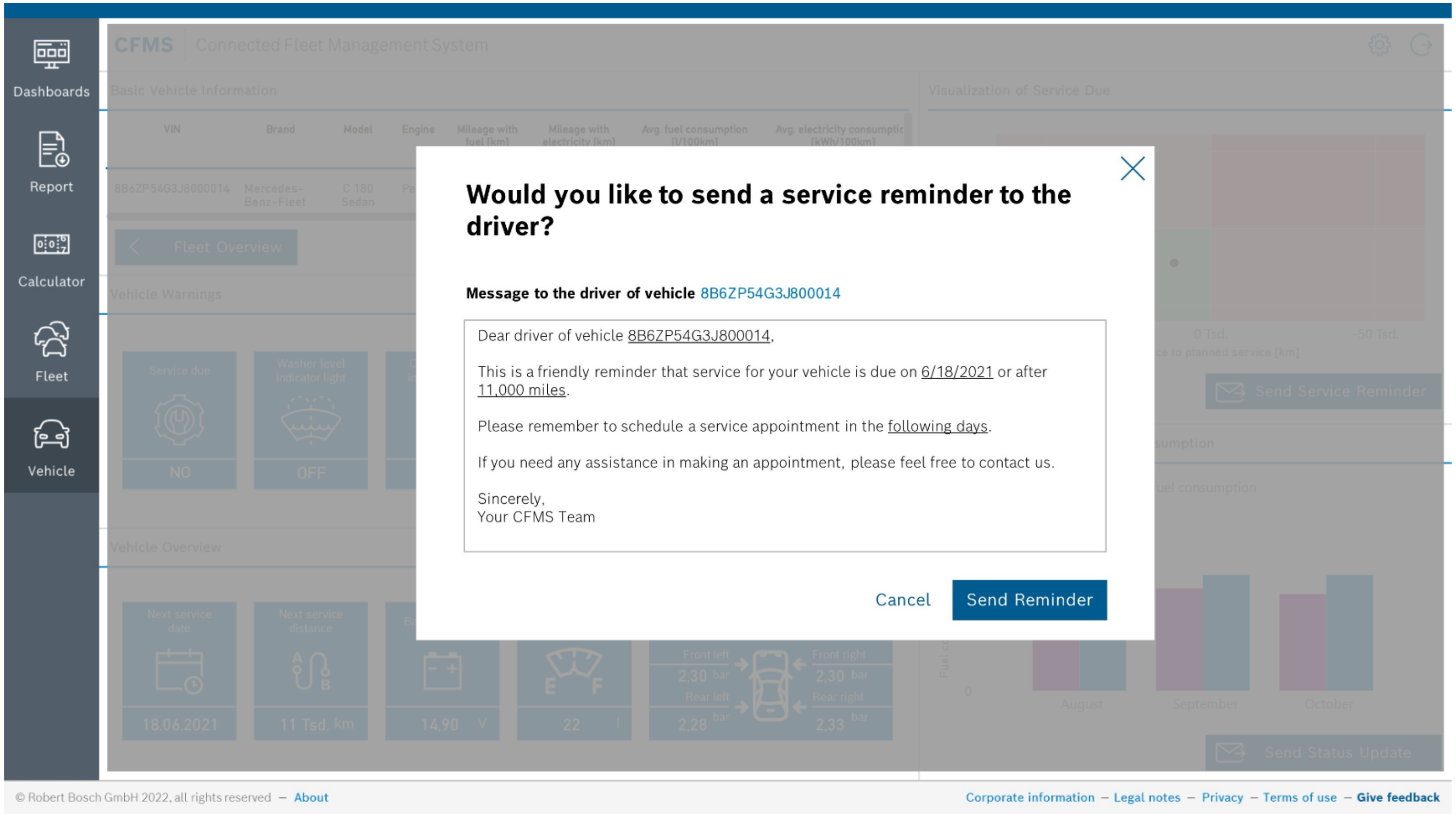


Figure A.2.: Graphical user interface of the connected fleet management system implemented in Microsoft Power BI (continued).

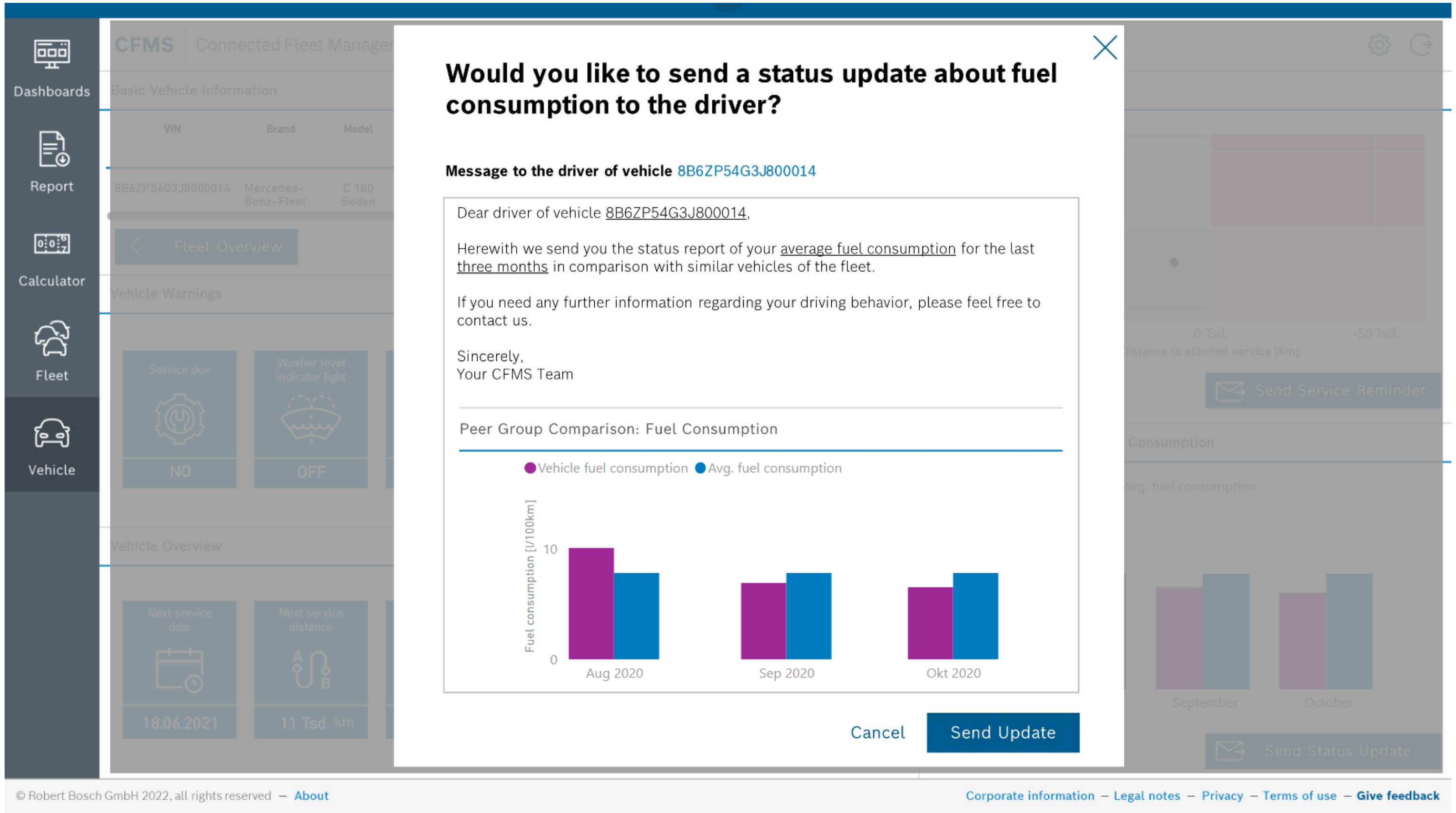


Figure A.2.: Graphical user interface of the connected fleet management system implemented in Microsoft Power BI (continued).

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Declarations

Eidesstattliche Versicherung

gemäß §13 Absatz 2 Ziffer 3 der Promotionsordnung des Karlsruher Instituts für Technologie für die KIT-Fakultät für Wirtschaftswissenschaften

1. Bei der eingereichten Dissertation zu dem Thema *“Monetizing Car Connectivity: Business, Platform, and Ecosystem Strategies to Capture Value from Connected Cars”* handelt es sich um meine eigenständig erbrachte Leistung.

2. Ich habe nur die angegebenen Quellen und Hilfsmittel benutzt und mich keiner unzulässigen Hilfe Dritter bedient. Insbesondere habe ich wörtlich oder sinngemäß aus anderen Werken übernommene Inhalte als solche kenntlich gemacht.

3. Die Arbeit oder Teile davon habe ich bislang nicht an einer Hochschule des In- oder Auslands als Bestandteil einer Prüfungs- oder Qualifikationsleistung vorgelegt.

4. Die Richtigkeit der vorstehenden Erklärungen bestätige ich.

5. Die Bedeutung der eidesstattlichen Versicherung und die strafrechtlichen Folgen einer unrichtigen oder unvollständigen eidesstattlichen Versicherung sind mir bekannt.

Ich versichere an Eides statt, dass ich nach bestem Wissen die reine Wahrheit erklärt und nichts verschwiegen habe.

Karlsruhe, den 16.07.2023

Felix Sterk (M.Sc.)