



# Unlocking the value from car data: A taxonomy and archetypes of connected car business models

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## Abstract

The automotive industry is relocating from viewing cars as standalone products to an all-encompassing ecosystem built around connected cars enabling data-driven business models. The vastly increasing amount of data collected by connected cars grants a unique driving experience for its users while providing companies operating in the automotive industry access to valuable information and, ultimately, cost and revenue benefits. In this article, we develop an empirically and theoretically grounded taxonomy of data-driven business models in the connected car domain to explore the impact of car connectivity and data availability on business models. Building on this, we conduct a cluster analysis revealing seven business model archetypes for the connected car domain: data platforms, location-based services, fleet management, diagnostics and maintenance, driving analytics, cyber-physical protection, and connected infotainment. Our findings advance the theoretical knowledge of data-driven business models, provide researchers with a systematic analysis of connected car-enabled business models, and enable decision-makers to identify strategic opportunities for leveraging connected car technology to enrich their business portfolios.

**Keywords** Business models · Connected cars · Data monetization · Taxonomy · Archetypes · Cluster analysis

**JEL Classification** O3 · L8

## 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). Consultancies with deep industry expertise (i.e., Bertonecello et al., 2016; Seiberth & Gruendinger, 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

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vehicle-to-infrastructure communications and to enable cooperative intelligent transportation systems (Kerber & Gill, 2019; Sterk et al., 2022a). Car data is personal, high-volume, high-velocity, and highly diverse data that is often combined with contextual data such as weather or location data to develop new services (Kaiser et al., 2021; Soley et al., 2018). The integration of digital technologies into cars as physical products is gradually changing the dynamics of the automotive sector (Bohnsack et al., 2021) and driving 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”<sup>1</sup> operating system, to which numerous OEMs have signed up, including Volvo, Renault, GM, and Ford (Legenvre et al., 2022).

Connected cars provide a unique setting to test and extend existing theories and empirical insights on business models (Cichy et al., 2021). Equipped with telematics control units and connected to OEM 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). Regardless of make and model, they already generate massive amounts of valuable data, not only about the cars themselves, but also about their environment through various sensors (e.g., to measure temperature, humidity, or position), which are also of interest to various ecosystem representatives (e.g., suppliers, repair shops, or insurers) (Sterk et al., 2023a). Although research directions related to connected cars, and in particular data sharing mechanisms and associated privacy concerns, have recently received attention (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 so far. Particularly, the current literature lacks a structural analysis that explicitly examines the anatomy, such as stereotypical patterns (i.e., archetypes), of connected car-enabled business models, hereafter referred to as connected car business models (Sterk et al., 2022b). Indeed, the specifics of designing empirical business model classifications require further research (Groth & Nielsen, 2015; Lambert, 2015). Classifying digital 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., 2021).

As a step toward 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 better specify their key features, ultimately supporting decision-makers in their entrepreneurial activities to leverage connected car data. Therefore, we pose the following research question:

**What are the key characteristics and archetypal patterns of data-driven business models in the connected car domain?** To address this question, we follow a sequential research design comprising two phases. In the first phase, 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’s (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 phase, 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 gives an overview of how companies use digital technologies in the connected car domain. Second, we introduce a taxonomy and a set of archetypes that extend existing literature DDBMs and establish a unified language for analyzing, classifying, and configuring connected car business models. These tools, which represent high-level business model configurations, structure the body of knowledge in this emerging field and facilitate a detailed and systemic exploration of the diverse business models present in the connected car landscape (Glass & Vessey, 1995). Our contributions are also of practical significance, as decision-makers can use our taxonomy and archetypes as strategic management tools for developing, evaluating, and benchmarking business models in the connected car sector,

<sup>1</sup> <https://developers.google.com/cars/design>

thereby fostering innovation and strategic advancement within this industry. In conclusion, our work not only fills a highly relevant research gap but also acts as a catalyst for future research and development in this 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 research approach. The “**Results**” section presents a business model taxonomy and corresponding archetypes for the connected car domain. The “**Discussion**” section discusses implications, limitations, and future research opportunities. Finally, the “**Conclusion**” section provides a summary and conclusion of our work.

## Related work

### 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 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). In addition to these existing DDBM-related taxonomies, we also acknowledge the existence of several other taxonomies that bear the label “digital”; however, given the scope of our research, our focus has remained on taxonomies that are characterized as data-driven, in line with our research objectives focused on DDBMs in the connected car domain.

Several articles (Gimpel et al., 2018; Müller & Buliga, 2019; e.g., Passlick et al., 2021) go beyond merely designing taxonomies and identify 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. For example, Hunke et al. (2022) identify and conceptualize four generic archetypes of analytics-based services: (1) making data usable to customers, (2) delivering data-based insights, (3) providing data-based recommendations, and (4) enabling novel ways to conduct business.

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.

### 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 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).

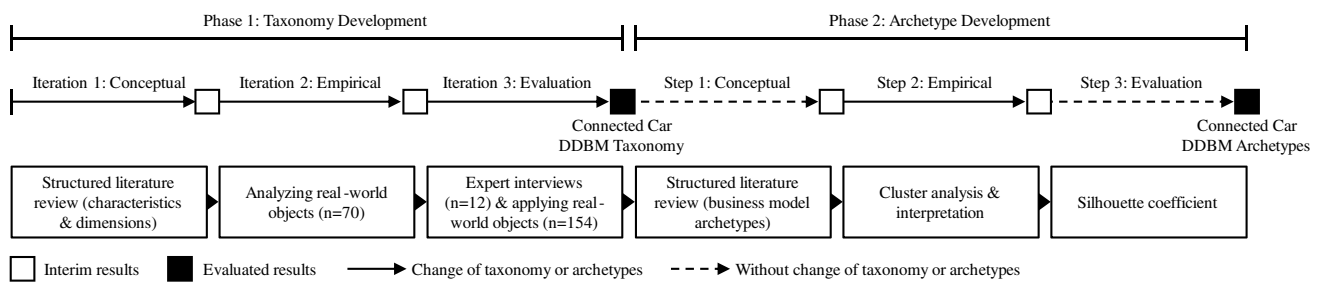
**Table 1** Overview and categorization of existing DDBM-related taxonomies

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 startup firms	Hartmann et al. (2016)	C&E	Yes
	Analytics-based services	Hunke et al., (2019, 2022)	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	Wunderlich et al. (2013)	E	No
Manufacturing	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
FinTech	Smart machines in the mechanical engineering industry	Scharfe and Wiener (2020)	C&E	No
	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 marketplaces	Data marketplaces in the automotive industry	Bergman et al. (2022)	C&E	Yes

\*Methodological approach: *C*, conceptual; *E*, empirical; *C&E*, conceptual and empirical

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., (2017a, 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 onboard 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 car data to independent service providers (Kaiser et al., 2021;



**Fig. 1** Research design of the two consecutive phases

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.

Our research addresses a noticeable gap in the existing body of knowledge regarding data-driven business models (DDBMs) in the connected car domain. In this work, we refer to these “connected car business models” as the rationale for leveraging modern vehicles’ advanced connectivity capabilities and collected data to offer innovative solutions (e.g., real-time data analytics, remote vehicle management, and personalized in-car services) and generate new revenue streams and customer value.

Although various aspects of the automotive data value chain have been explored in previous research, a synthesized consolidation of existing knowledge in this area is still lacking. We aim to fill this gap by introducing a specifically designed taxonomy and archetypes. These tools will effectively synthesize the prevailing knowledge and facilitate a structured pathway for future research efforts in this area. In line with recent calls within information systems (IS) research for more dynamic participation in discussions surrounding the emergence of connected, autonomous, shared, and electric (CASE) vehicles, our research seeks to make a meaningful contribution (Ketter et al., 2022). Through our research, we aim to help shape a smart, sustainable mobility ecosystem that benefits users, mobility providers, and the broader environment. Our contribution is positioned as a first but important step in this evolutionary trajectory of IS research, aiming to cultivate and critically evaluate DDBMs that embody a harmonized balance of profitability, customer value, and overarching sustainability within the mobility domain (Ketter et al., 2022).

Lastly, the connected car is a key facilitator of DDBMs in general for 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 sector, 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.

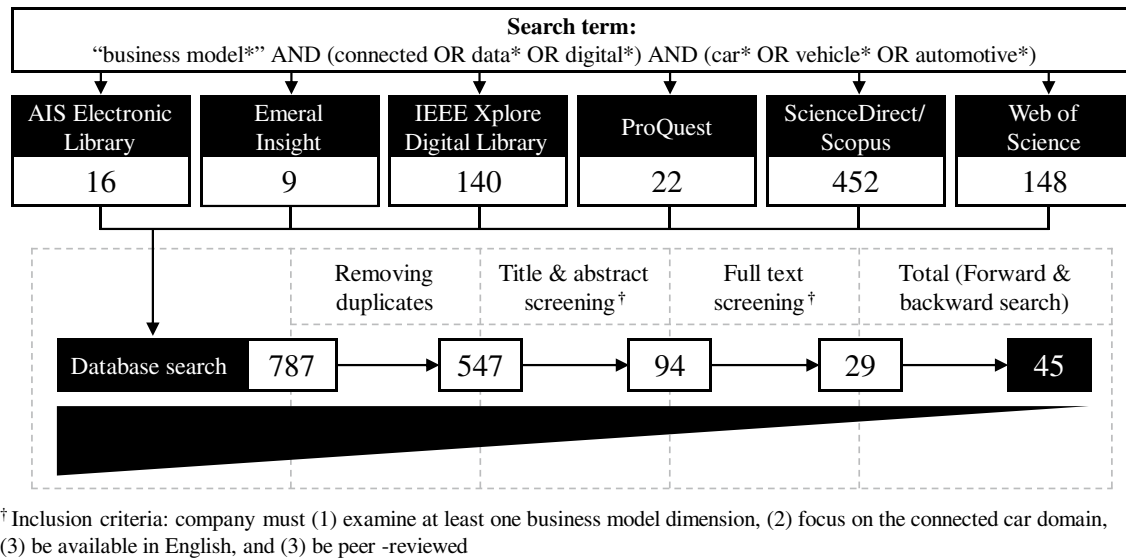
## Research design

Our research follows a sequential research design to provide a taxonomy and archetypes of data-driven 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, which is particularly suitable for the relatively unexplored area of classifying connected car business models (Gimpel et al., 2018; Hunke et al., 2022; Weking et al., 2020). Our research design comprises two major sequential phases (Fig. 1), each with three steps, adopting the structure of previous studies (e.g., Weking et al., 2020). In the first phase, 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 phase, we build on the results of the first phase to identify and evaluate archetypes by conducting a cluster analysis (Kaufman & Rousseeuw, 1990) and interpreting the results.

### Phase 1: Taxonomy development

In the first phase of our research design, we focused on developing a taxonomy for the connected car domain, using the methodological guidelines of Nickerson et al. (2013). We defined our meta-characteristic as “key distinguishing features of connected car-enabled business models” representing a specialized subset of data-driven business models. This definition reflects the overarching purpose of the taxonomy and forms the basis for its components. All proposed dimensions must be a consequence of this meta-characteristic





**Fig. 2** Literature search process

and help describe the structural differences observed in such business models. Guided by this meta-characteristic, we adopted Al-Debei and Avison’s (2010) “V<sup>4</sup> business model framework” and used the V<sup>4</sup> concepts (i.e., value proposition, value architecture, value network, and value finance) as meta-dimensions in our taxonomy. Ensuring that each dimension in the taxonomy corresponded to one of these concepts facilitated a structured taxonomy formulation closely aligned with our meta-characteristic. We also established ending conditions to define when the iterative taxonomy development process would end, following the conditions suggested by Nickerson et al. (2013) (Table 8 in the Supplementary information). With these foundations in place, we proceeded with the taxonomy development and evaluation process in three iterations.

### Iteration 1: Structured literature review (conceptual)

In our initial iteration, 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 Webster and Watson (2002) and Vom Brocke et al. (2009). The literature base is established by querying various interdisciplinary research databases<sup>2</sup> to identify articles that

match our search term<sup>3</sup> in title, abstract, or keywords. Our initial search yielded a total of 787 studies, of which 547 remained after removing duplicates (see Fig. 2). To assess their relevance to our study, we analyzed the title and abstract of each article, 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. Subsequently, a thorough review of the full texts of the 133 remaining articles was conducted based on these criteria. 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.

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; Martens

<sup>2</sup> AIS Electronic Library, Emerald Insight, IEEE Xplore Digital Library, ProQuest, ScienceDirect/Scopus, Web of Science.

<sup>3</sup> “business model\*” AND (connected OR data\* OR digital\*) AND (car\* OR vehicle\* OR automotive\*).

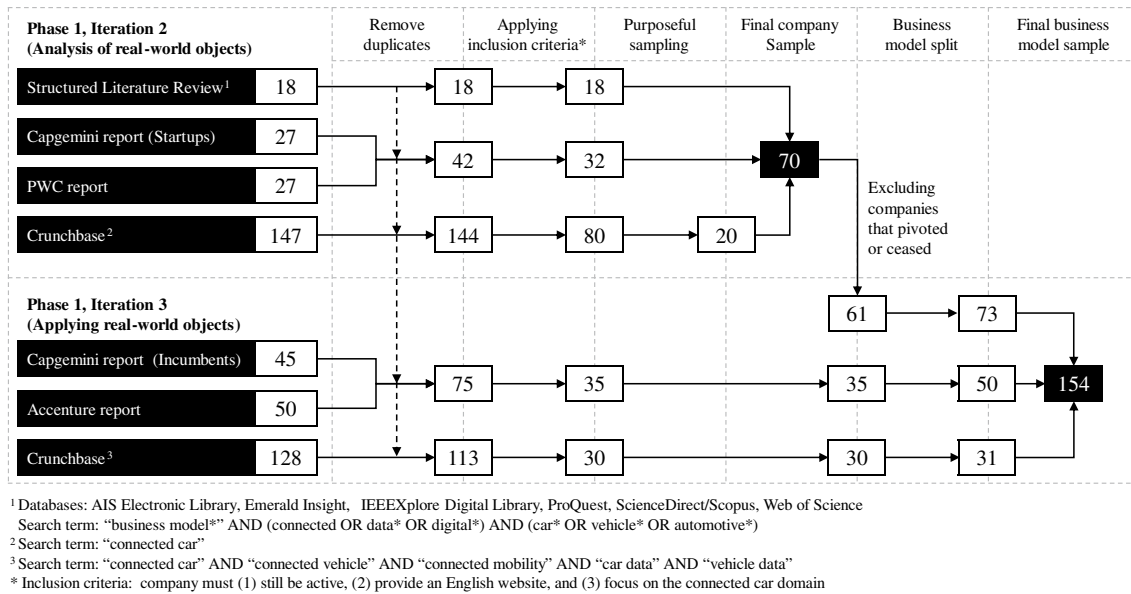


Fig. 3 Company and business model selection process in Iterations 2 and 3 of the first phase

& Mueller-Langer, 2020), *role in ecosystem* (Kaiser et al., 2021; Kaiser et al., 2017a, b; 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.

**Iteration 2: Analysis of real-world objects (empirical)**

In the next iteration, 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., 2017a, 2017b, 2021; Rahman & 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. To achieve this balance, we applied a purposive sampling approach (Bryman, 2016) to the 80 companies sourced from Crunchbase. Our screening aimed to select a diverse subset of 20 connected car companies based on the variety of their business model descriptions and the comprehensiveness of their website information, which led to the exclusion of 60 companies. Figure 3 gives a detailed overview of our company selection approach, and Table 8 in the Supplementary information 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 suggesting theoretical saturation. According to Nickerson et al. (2013), the ending conditions were met (Table 8 in

**Table 2** Overview of interviewees with background, role, institution, and expertise

Background	Role	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

the Supplementary information), and the taxonomy development process was terminated.

### Iteration 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 iteration of the first phase, 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 (Table 2). We used a semi-structured approach based on the suggestions of Myers and 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 12 interviews were conducted by two authors using video-conferencing software, lasted on average 38 min, and were recorded and transcribed, and then analyzed. 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.

In the next step, we used MaxQDA software to employ 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 (Table 3). More details on the taxonomy operations on specific elements and the taxonomy's changes after the evaluation can be found in Table 9 in the Supplementary information.

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 Iteration 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 (Seiberth & Gruendinger, 2018), which identified 50 additional incumbent firms. We also queried Crunchbase with an extended search term<sup>4</sup> and obtained 351 startups, of which we excluded 223 that had not received funding.

<sup>4</sup> "connected car\*" OR "connected vehicle\*" OR "connected mobility" OR "car data" OR "vehicle data".



After removing duplicates and comparing the remaining companies to those included in Iteration 2, we were left with 188 companies. When reviewing the companies' websites, we applied the three inclusion criteria from the previous iteration, 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 Iteration 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 3 depicts the overall selection process, and the final business model sample is presented in Table 8 in the Supplementary information.

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, which served as a codebook for provisional coding (Hunke et al., 2022; 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' (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.

## Phase 2: Archetype identification

In the second phase of our work, we identified a set of business model archetypes as 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.

### Step 1: Structured literature review (conceptual)

The initial step of our second phase 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* ( $n = 4$ ) (Martens & Mueller-Langer, 2020), and *connected cars* in general ( $n = 4$ ) (Bohnsack et al., 2021). In the subsequent iterations of this phase, 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.

### Step 2: Cluster analysis and interpretation (empirical)

In the next step, 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 (Table 8 in the Supplementary information). 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., 2022; Remane et al., 2016; 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 cutoff 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 10 of the Supplementary information. 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 & 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 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 (Table 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.

### Step 3: Silhouette coefficient (evaluation)

In the final step of the second phase, 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 6 in the Supplementary information shows the corresponding silhouette plot, with an average width of 0.56 for the sample of  $n=154$ .

## 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, our "Results" section focuses on the second artifact, the business model archetypes.

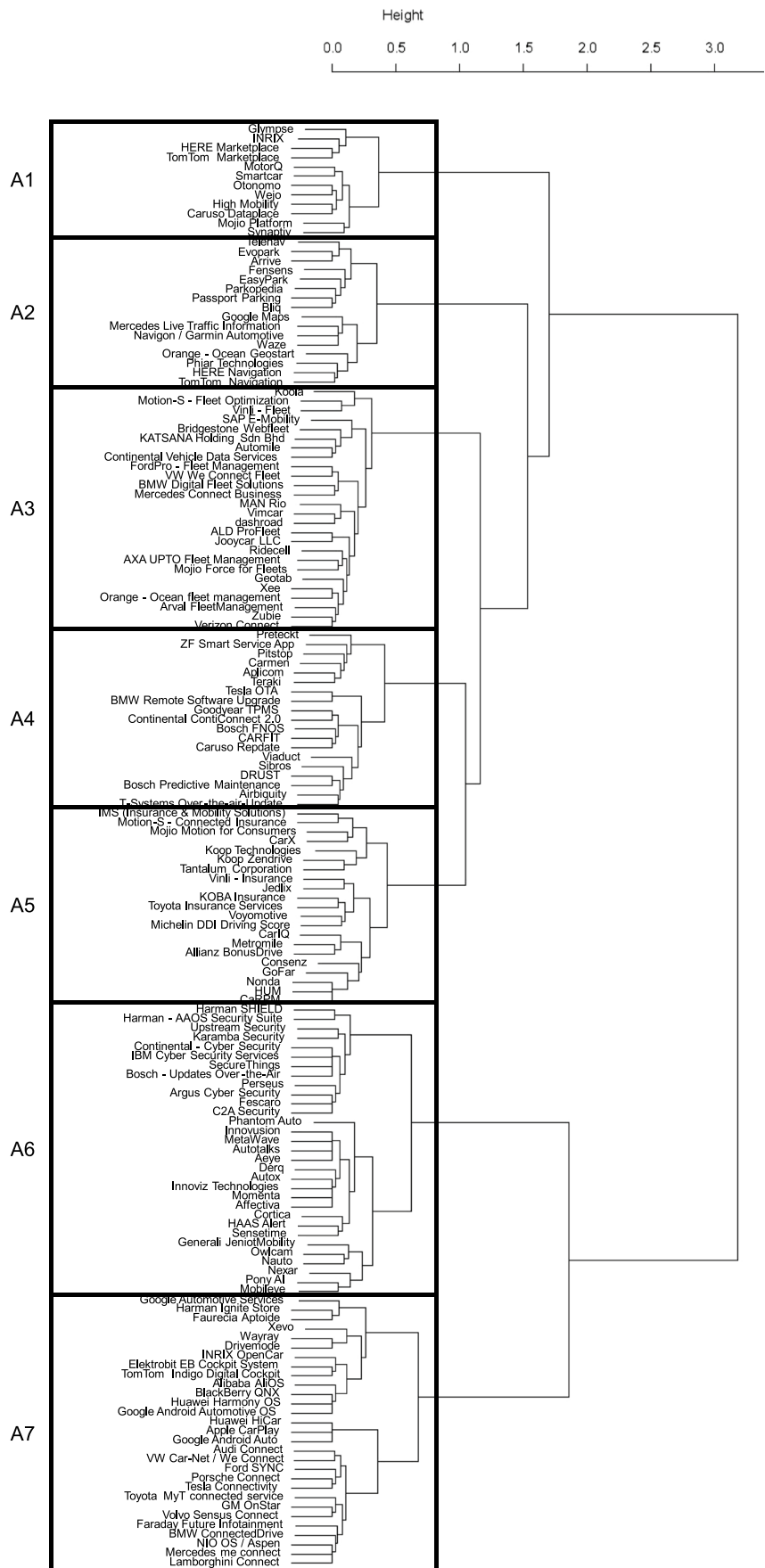
### A taxonomy of connected car business models

Our research's first interim result is a taxonomy of connected car business models comprising ten dimensions with 48 corresponding characteristics Table 3 provides an overview of the complete taxonomy in the form of a morphological box, and Table 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 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 3 indicate the iteration in which dimensions or characteristics were added or last revised.

### 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 (Table 5). By analyzing the companies in the seven different cluster groups and the corresponding

**Fig. 4** Results of Ward.D2 clustering visualized by a dendrogram with seven cluster groups



**Table 3** Taxonomy of data-driven business models in the connected car domain

	Dimension	Characteristic							E/N*
Value Proposition	Value for car owner or driver <sup>3</sup>	Safety & security <sup>1</sup>	Cost reduction <sup>1</sup>	Traffic efficiency <sup>1</sup>	Infotainment <sup>1</sup>	Environmental sustainability <sup>3</sup>	Convenience <sup>1</sup>	Indirect value <sup>3</sup>	N
	Car data impact on value <sup>3</sup>	Car data core business model <sup>2</sup>			Car data-enabled business model <sup>2</sup>				E
	Car autonomy impact on value <sup>3</sup>	Enhanced value by autonomy <sup>2</sup>		Reduced value by autonomy <sup>2</sup>		Autonomy not relevant <sup>2</sup>			E
Value Architecture	Data category <sup>3</sup>	PII <sup>3</sup>	Contextual data <sup>3</sup>	Diagnostic data <sup>3</sup>	Usage data <sup>3</sup>	ADAS data <sup>3</sup>	Application data <sup>3</sup>	N	
	Data access <sup>1</sup>	OEM proprietary access <sup>3</sup>	OEM specific cloud or neutral server <sup>3</sup>	OBd2-dongle <sup>1</sup>	Other retrofit devices <sup>3</sup>	Smartphone or other non-in-vehicle sources <sup>3</sup>		N	
	Enabler technology <sup>3</sup>	Blockchain <sup>3</sup>	Augmented reality <sup>3</sup>	Over-the-air architectures <sup>3</sup>	ADAS Technology <sup>3</sup>	Artificial intelligence <sup>3</sup>	Cellular networks <sup>3</sup>	N	
Value Network	Role in ecosystem <sup>1</sup>	End-customer solution provider <sup>1</sup>		Platform provider <sup>1</sup>		Technology provider <sup>2</sup>		N	
	Customer segment <sup>2</sup>	Private individuals (B2C) <sup>3</sup>	Fleet providers (B2B) <sup>3</sup>	OEMs (B2B) <sup>3</sup>	Third-party providers (B2B) <sup>3</sup>	Governments (B2G) <sup>3</sup>		N	
Value Finance	Data monetization strategy <sup>3</sup>	Data source & data provision <sup>3</sup>		Data aggregation & data exchange <sup>3</sup>		Data analysis & data insights <sup>3</sup>		Data application & data service <sup>3</sup>	N
	Revenue model <sup>1</sup>	One-time payment <sup>3</sup>	Pay-per-use <sup>3</sup>	Subscription fee <sup>1</sup>	Licensing fee <sup>1</sup>	Commission fee <sup>3</sup>	On-demand <sup>2</sup>	Open source <sup>3</sup>	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: <sup>1</sup> phase 1, <sup>2</sup> phase 2, or <sup>3</sup> phase 3

cross-table results, we conceptualized the clusters through detailed descriptions and 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 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 (Table 8 in the Supplementary information).

**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 (Martens & Mueller-Langer, 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** Definitions of taxonomy dimensions and characteristics

<b>Value for car owner or driver</b>	<i>What are the direct benefits for the car owner or car driver?</i>
Safety and 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
<b>Car data impact on value</b>	<i>What is the impact of car data on the main value proposition?</i>
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)
<b>Car autonomy impact on value</b>	<i>What is the impact of the car's autonomy on the main value proposition?</i>
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	Car autonomy does not affect the value proposition
<b>Data category</b>	<i>What are the required types of data to enable the business model?</i>
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
<b>Data access</b>	<i>Which technical gateways enable acceding the required data for the company?</i>
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 <sup>a</sup>
OBD2-dongle	A dongle is plugged into the onboard 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
<b>Enabler technology</b>	<i>What are the key technologies to enable the business model?</i>
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)
Cellular networks	Business model is enabled by cellular networks (e.g., 5G)
<b>Role in ecosystem</b>	<i>Which role does the company play for the other network actors?</i>
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)
<b>Customer segment</b>	<i>To whom does the company provide its offerings?</i>
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)
<b>Data monetization strategy</b>	<i>How does the company capture monetary value from the data?</i>
Data source and data provision	Company operates as car data source and provider
Data aggregation and data exchange	Company operates as car data aggregator for data exchange



**Table 4** (continued)

Data analysis and data insights	Company provides car data-based analysis and insights
Data application and data service	Company provides car data-driven applications and services
<b>Revenue model</b>	<i>How does the company generate revenue or income from each customer segment?</i>
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

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, Telnav (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 Need" (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

**Table 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 %



**Table 6** Summary of the identified archetypes

ID	Archetype	Distinguishing characteristics	Typical applications
A1	Data platforms	<ul style="list-style-type: none"> <li>• Operating as a data platform provider in the automotive ecosystem</li> <li>• Making car data available for third-party service providers at scale</li> <li>• Accessing data directly from the OEM and acting as a neutral server</li> </ul>	Car data marketplaces, contextual data providers
A2	Location-based services	<ul style="list-style-type: none"> <li>• Delivering end-customer value through navigation or parking services enhancing overall transportation efficiency</li> <li>• Collecting data by mobile mapping vehicles equipped with remote sensing systems</li> <li>• Exploiting contextual data such as external road and environmental conditions to create real-time maps</li> </ul>	Navigation systems, parking applications
A3	Fleet management	<ul style="list-style-type: none"> <li>• Addressing fleet providers, logistics service providers, and mobility service providers as customer segment</li> <li>• Delivering end-customer value primarily in the areas of driving safety, cost reduction, and traffic efficiency</li> <li>• Accessing data commonly by means of retrofitted OBD2-dongles</li> </ul>	Fleet management systems, digital driver logbooks
A4	Diagnostic and maintenance	<ul style="list-style-type: none"> <li>• Analyzing diagnostic data such as trouble codes to offer proactive and predictive maintenance</li> <li>• Providing value not only to end-customers but also to aftermarket players such as car dealers or workshops</li> <li>• Utilizing over-the-air architectures to do incremental remote updates and repairs in future scenarios</li> </ul>	Remote diagnostics services, predictive maintenance services
A5	Driving analytics	<ul style="list-style-type: none"> <li>• Analyzing car usage data for monitoring driving patterns and behavior</li> <li>• Reducing cost through pay-as-you-drive tariffs or recommendations for fuel-efficient driving</li> <li>• Providing driving assistance and driver tutoring to increase road safety</li> </ul>	Usage-based insurance tariffs, applications for driving style suggestions
A6	Cyber-physical protection	<ul style="list-style-type: none"> <li>• Delivering end-customer value by ensuring occupant safety and cybersecurity</li> <li>• Enabling data-driven business models by providing crucial and secure connected car technologies</li> <li>• Harboring huge future potentials, for instance through over-the-air driver assistance system updates</li> </ul>	Cybersecurity solutions, driver assistance systems
A7	Connected infotainment	<ul style="list-style-type: none"> <li>• Delivering end-customer value via in-car infotainment applications</li> <li>• Providing a standardized platform that enables in-car third-party applications on the head unit</li> <li>• Increasing value through car autonomy, e.g., by watching virtual reality films or playing video games</li> </ul>	Digital cockpit solutions, infotainment operating systems

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

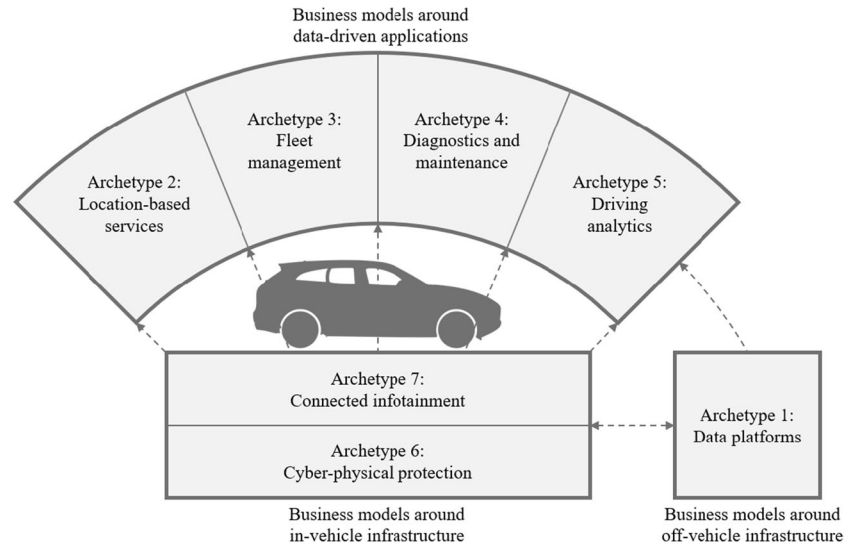
driving data can become vulnerable targets for hackers. For this reason, newly developed or upgraded software components undergo rigorous testing procedures to ensure a high level of cybersecurity. For example, Fescaro (BM125) offers cybersecurity testing to OEMs to detect and handle vulnerabilities. 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 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

**Fig. 5** Visualization of archetypes and their relationships



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.

## Discussion

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., 2022b). As a result, research to date 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 through two successive phases. 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 phase, a cluster analysis (Kaufman & Rousseeuw, 1990) was performed to identify seven connected car business model

archetypes by interpreting and evaluating the corresponding clusters.

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 Fig. 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).

## 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 provide theoretical and empirical implications to inform future research. The connected car provides a unique setting to examine and extend existing theory and evidence on business models for connected device data (Cichy et al., 2021). Unlike currently existing taxonomies that focus primarily on data, connectivity, or the IoT in general, our taxonomy stands out as the first to focus specifically on the connected car.

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 within it. Throughout its development, we ensured both theoretical rigor and practical relevance by using input from the existing literature corpus and industry-specific real-world objects (i.e., 154 connected car business models). Our taxonomy represents an analytical theory, following Gregor (2006), that classifies the specific dimensions and characteristics of connected car business models by summarizing commonalities in discrete observations. Thus, our research contributes to structuring the body of knowledge in the emerging field of connected cars and smart mobility in IS research and enables a more systematic description and analysis of such business models (Glass & Vessey, 1995).

Second, the corresponding archetypes can serve as a starting point for understanding higher-level business model configurations in the connected car domain. Moreover, the empirical findings of our study extend the knowledge of data monetization by presenting seven established configuration options for business models in the connected car domain. Based on typical configurations of characteristics across all dimensions included in our taxonomy (Table 5), these archetypes provide initial insights into 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).

Third, 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.

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.

## Managerial implications

Our research offers 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 (Table 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.

## 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.

Finally, while our work is focused on connected cars, the next revolutionary leap in the automotive industry is already on the horizon, known as the "software-defined vehicle," in which vehicle software takes precedence over mechanical hardware and primarily controls and executes vehicle functions (cf.,

Ohlsen, 2022; Windpassinger, 2022). The increasing reliance on large technology companies such as Amazon, Google, or Microsoft for vehicle operating systems and cloud environments highlights the need for research into collaborative strategies and alliances (Sterk et al., 2023b). However, entirely new business models are also emerging around the software-defined vehicle, thanks to the unified software architecture that can be addressed fully remotely, going far beyond the current limited remote capability of connected cars. This creates a need for future research in taxonomy development and archetype identification dealing with the successor of the connected car, for which our work can serve as a starting point.

## Conclusion

Our study explores the potential of connected cars in the area of business model innovation using vehicle data. We contribute two artifacts to the field: a taxonomy and seven archetypes for connected car business models. This research extends the existing body of knowledge on data-driven business models and connected cars by providing a comprehensive examination of such 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. For decision-makers, these tools can facilitate a smoother transition and enable companies, especially startups, to quickly adapt and excel in this fast-moving industry. In addition, our research benefits established companies by providing clear guidance on how to overcome challenges and update their strategic approaches. 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.

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