Data-Driven Business Models from an Internal Automotive OEM Perspective: Categories and Challenges

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Research Paper

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Abstract. The automotive industry is undergoing a profound shift driven by digitalization, prompting the emergence of data-driven business models (DDBMs). As the original equipment manufacturers (OEMs) have already realised a number of DDBMs, their role in the traditional automotive industry is of great interest. This study investigates DDBMs within the European automotive sector, addressing two key objectives: a categorization of existing internal OEM DDBMs and internal OEM challenges. Interviews were made with sixteen automotive experts from four OEMs and two OEM suppliers, working in DDBM-related departments. Hence, five internal OEM DDBM categories were identified: Technical, Product Optimization, Marketing Analysis, Selling Raw Data, and Customer Services. The seven detected challenges that hinder DDBM development include legal constraints, technical complexities, organizational culture, and data knowledge gaps. These findings were guided by theoretical contributions to DDBMs in Information Systems (IS) and practical contributions such as DDBM advices for OEMs.

Keywords: data-driven business models, automotive industry, interview series, market-based view

1 Introduction

The continuously growing importance of digital technologies such as cloud computing, mobile technology, or the Internet of Things lead towards a digitized world. This also affects primarily physical industries (Hanelt et al., 2015), including the automotive industry. Historically, the business models (BMs) in the automotive industry concentrate on producing and selling physical goods like the car itself and product-related services like the after-sales market, e.g. selling replacement parts. However, the transformation of the car into a "computing unit on wheels" (Bernhart & Alexander, 2020) and its integration into an automotive ecosystem that includes other road users, vehicle manufacturers, service developers, and traffic infrastructure (Kaiser et al., 2021; Li et al., 2014) has opened up new possibilities for car manufacturers to develop new BMs (McKinsey, 2018). These BMs seem to be necessary in the future, since car ownership is expected to decline, and car-sharing is predicted to increase in popularity (Bertoncello et al., 2016). Therefore, car manufacturers must find new ways to remain competitive. In this context, data-driven business models (DDBMs) based on the vast amount of data produced by connected cars represent a promising solution and can create new revenue streams (McKinsey, 2018).

Despite the digital potential in the automotive industry, the core industrial product, the car itself, cannot be digitized completely (Piccinini et al., 2015). Hence, data-driven services will play an additional role (Kaiser et al., 2019). Although there is a need to create DDBMs in the automotive industry, most incumbent car manufacturers struggle when it comes to building and creating DDBMs (Hodd et al., 2019). Furthermore, IS literature has not adequately explored the topic of connected cars and therefore car data and DDBMs (Ketter et al., 2023; Sterk et al., 2024). In addition, Ketter et al. (2023) call for a better understanding of DDBMs in the mobility domain, e.g., the automotive industry. This was the motivation to investigate an internal view from the automotive industry, as the field of DDBMs is developing very fast and internal development is years ahead of market maturity. For a better understanding of DDBMs in the automotive industry, this study focuses on a categorization of the DDBM market within the automotive industry. Since emerging areas such as DDBMs do not come without problems, there is a great interest in the challenges involved in creating DDBMs. Furthermore, the focus was set on an internal OEM perspective, since most authors in this field such as Sterk et al. (2024) or Kaiser et al. (2021) focus on the ongoing ecosystematization of the car.

Thus, this paper addresses the following two research questions: *What are the distinct categories of DDBMs present within the European automotive OEMs?* and *Which challenges do the European automotive OEMs face regarding DDBMs?*

To answer these questions with an internal industry view, an exploratory interview study containing 16 semi-structured interviews with experts working in the domain of DDBMs development in the European automotive industry, which were subsequently coded following Glaser and Strauss (1967) and Grodal et al. (2021), was conducted.

2 Conceptual Background

2.1 Digitalization and Data in the Automotive Industry

Historically, the automotive industry has been a hardware-producing industry with the car at its center of product development. In recent years, digital transformation has also influenced incumbent industries like the automotive industry, e.g. with increasingly improved microprocessors or broadband communication (Yoo et al., 2010). Literature on digital transformation in the automotive industry discusses different aspects. (Chanias & Hess, 2016) investigated strategies for digital transformation in the automotive industry and showed, that digital transformation begins with multiple organizational activities from a bottom-up perspective. Digital transformation in the automotive industry creates new roles for value creation (Riasanow et al., 2017).

In addition to the digital transformation in the automotive industry and hence also of the car, the technological advantages of big data and the interconnected DDBMs also influence the automotive industry. According to a study made by Gissler (2015), all new cars will become connected in 2025. A connected car is equipped with hardware and software to connect the car to a cloud, which enables the OEMs to collect data from sensors (Kaiser et al., 2021). Hence, the amount of car data will grow rapidly. One prominent example of the role of data in the automotive industry is autonomous driving, where data is the key to this technology. Data can also be used inside the OEM to improve organizational performance (Akter et al., 2016); (Dremel et al., 2017). In general, OEMs try to leverage their collected car data by improving their offers for customer needs (Stocker et al., 2017). Following a study made by McKinsey (McKinsey, 2018), car-generated data has the potential to be worth up to 750 billion USD by 2030. This indicates, that the role of data in the automotive industry will play a dominant role in the future. Having a look at European OEMs, data is already recognizable in either data-driven services like 'Mercedes me' (Daimler, 2024) or 'First notification of loss' by Audi (AUDI AG, 2024). Hence, the potential of upcoming data brings also other companies on the track of car-data usage, leading to an additional value stream next to the traditional manufacturing of cars.

2.2 Data-Driven Business Models

Digitized cars lead to an extended amount of car data. To create value out of the car data, OEMs need a guiding architecture, i.e. a Business Model.
According to Sorescu et al., (2011), there is no commonly accepted definition of BMs. However, one definition proposed by Osterwalder and Pigneur (2010) describes a business model as the way how an organization creates and captures customer value by addressing customer relationships and channels, value proposition, resources, revenue and cost, and activities and partners. The creation of customer value is considered the core component of a business model (Fielt, 2014), and the value proposition is a critical aspect of it (Demil et al., 2015). In addition, BMs can be characterized as reflections of realized strategies (Casadesus-Masanell & Heilbron, 2015) and representations of how organizations create value (Teece, 2010). Now, with upcoming advantages of big data namely big data analytics and big data algorithms (Chen et al., 2012; Günther et al., 2017), new DDBMs occur (Hartmann et al., 2016). The value of DDBMs can be e.g. an improvement of business processes and decision-making (Woerner & Wixom, 2015) or the direct or indirect realization of value (Akred & Samani, 2018). In terms of value proposition of DDBMs, several papers exist, e.g. Kühne and Böhmann (2019) which provide a data insight generator, that links data to value proposition. Overall, the study of Hartmann et al. (2016) pioneered the understanding and realization of DDBMs with a focus on start-ups. They defined DDBMs as a business model relying on data as a key resource (Hartmann et al., 2016; Homner et al., 2024).
Furthermore, by analyzing literature on existing business model frameworks and data-related disciplines, (Hartmann et al., 2016) created a framework for DDBMs which contains six key dimensions: data sources, key activity, offering, target customer, revenue model, and specific cost advantage. Each dimension is subdivided, e.g. data sources unfold into ‚internal' and ‚external data', and characterizes a DDBM (Hartmann et al., 2016). Other authors used this framework and the research on DDBMs to

understand how companies innovate and develop DDBMs in consecutive phases, such as the ideation phase (Alfaro et al., 2019; Chen et al., 2017) and the realization phase (Lange et al., 2021). Both phases are interesting for incumbent firms since DDBMs are not core products of such firms.

Regarding the automotive industry, OEMs and new stakeholders in the market, (e.g. start-ups) try to gather valuable information out of the car generated data and built new business models upon that data (Kaiser et al., 2021; Nischak & Hanelt, 2019). Due to the OEMs exclusive access to the car generated data, it is hard to get for third-party service providers such as start-ups (Sterk et al., 2024). Nevertheless, data marketplaces like Otonomo exist, acting as neutral intermediaries where multi-brand car data is sold to independent service providers (Martens and Mueller-Langer, 2020) and research on DDBM archetypes of such data market-places is done. In the creation of DDBMs, different stakeholder types in data ecosystem (S. Oliveira et al., 2019) such as Data-Source, Data-Facilitator and Data-User exist (Schroeder, 2016; Wiener et al., 2020). Bellin et al. (2024) focus on the Data-Facilitator in an automotive industry-related case, showing the strong depencence of the Data-Facilitator on the Data-Source, i.e. the OEMs.

Hence, this research contributes to the body of knowledge by adding an internal OEM perspective on categories and challenges of DDBMs in the automotive industry, which is underrepresented in the current literature as the cited authors focus on an ecosystem perspective. Furthermore, “much of our current literature [on DDBMs] is conceptual, not empirical” (Markus, 2017), thus this study also contributes to this research stream.

3 Method

3.1 Case Description

The field of DDBMs is relatively new in the automotive industry and has not been studied extensively so far. Therefore, an exploratory interview study was conducted to create an understanding of this research field (Klein & Myers, 1999; Yin, 2018). The case selection followed a theoretical sampling approach by Glaser and Strauss (1967) and was planned, following the five components of case studies by Yin (2018). The idea of investigating DDBMs and showing their status-quo in the automotive industry was inspired by the concept of DDBMs as proposed by Hartmann et al. (2016) on a high level. This work theorizes in an inductive approach on a micro level (Birks et al., 2013). To fullfil the research goal, the case must be the automotive industry. Due to feasibility, OEMs and digital companies working as suppliers as representatives for the automotive industry were chosen. To gain comparable results regarding data regulations, customer behavior, and legal situation the European market was investigated. Hence, four different European OEMs were chosen, and two digital companies that create data-driven solutions for the OEMs.

All OEMs, as well as digital companies want to stay anonymous, so key facts about them will be presented by cumulating all OEMs information. Therefore, a detailed description of each company cannot be provided. All OEMs have their headquarters in

Europe and are commonly known since they have a long tradition in the car manufacturing business and have existed at least for more than 80 years. Together, they sell in total more than 15 Million vehicles worldwide and over 8 Million in Europe, with a total market share in Europe of more than 25% (Carsalesbase, 2022). They all act globally, supply the volume or premium segment and have at least more than 100,000 employees worldwide. The digital companies have existed for at least 20 years and have at least more than 100 employees.

3.2 Data Collection and Analysis

Interview data was collected through a series of 16 semi-structured interviews in German or English conducted between April and September 2022 (see Table 1). The interview durations ranged from 32 minutes up to 67 minutes with a median of 43 minutes. Fifteen out of sixteen interviews were conducted online, e.g. via Microsoft Teams, and one in person. The requirements for the interviewees were, that they are working in a department (at an OEM or a related supplier company) that at least deals with data or ideally with DDBMs in the automotive industry, have at least 2 years of work experience in the field of DDBMs and have a company affiliation of at least 2 years. The interview guideline focused on the DDBMs in the automotive industry and the challenges in realizing them.

Table 1. Details on interview Partners.

Expert Tag	Role Description	Company	Duration
A	Engineer	OEM 1	40 Min
B	Big Data Developer	OEM 2	41 Min
C	Head of DDBM Development	OEM 1	37 Min
D	Big Data Developer	OEM 1	58 Min
E	Big Data Developer	SUP 1	32 Min
F	DDBM Strategy Developer	OEM 1	63 Min
G	DDBM Developer	OEM 1	56 Min
H	Head of DDBM Controling	OEM 1	43 Min
I	Head of DDBM Finance	OEM 2	60 Min
J	Technical DDBM Developer	OEM 2	33 Min
K	DDBM Purchaser	OEM 3	62 Min
L	DDBM Purchaser	OEM 1	55 Min
M	DDBM Developer	SUP 2	41 Min
N	DDBM Strategy Developer	OEM 4	33 Min
O	Technical DDBM Developer	OEM 1	67 Min
P	Technical DDBM Developer	OEM 1	43 Min

To prepare for the semi-structured interviews, a guideline was formulated in accordance with the recommendations provided by King et al. (2019). The guideline consisted of three main categories, that addressed questions about business models and DDBMs in the European automotive industry in general ("*What data driven business models do you have in Europe?*"), the design of DDBMs for the European market and their value

proposition ("*What is the value proposition for the customer?*") and the development of DDBMs in the automotive industry ("*How was the data-driven business for the European market model developed?*").
The interview guidelines had to be approved by the labor union at some OEMs in advance. They prohibited recording the interviews, to guarantee privacy and anonymity of the interviewees. Therefore, notes were taken during the interviews. The aim was to transcribe the interviews manually as close to 'word by word' as possible (inspired by shorthand writing), with a focus on interesting statements, which serve as citations after translation from German to English. Subsequently, the interviews were sent back to the interviewees for further amendments or corrections. Following the approach by Glaser and Strauss (1967), three subsequent coding cycles were used: open coding, axial coding, and selective coding. Hereby, this research followed the active categorization framework for theory development proposed by Grodal et al. (2021) and analyzed the transcripts in three subsequent categorization cycles. This method was chosen, because it ensures a high rigor regarding coding. At the beginning of the first attempt, a large number of first-order open codes were identified in a line-by-line coding process. Subsequently, codes were dropped, merged, split, and revised (Grodal et al., 2021). By relating and contrasting the final codes, resulting in axial coding delivered a deeper understanding of the fundamental phenomenon (Corbin & Strauss, 2015). These categories were linked to the research questions, to perform the final step: selective coding. Here, the axial codes were categorized into 'core categories' (Corbin & Strauss, 2015). The coding led to two results: DDBM categories and DDBM challenges. Exemplary for the whole coding process, an example is shown in Figure 1.

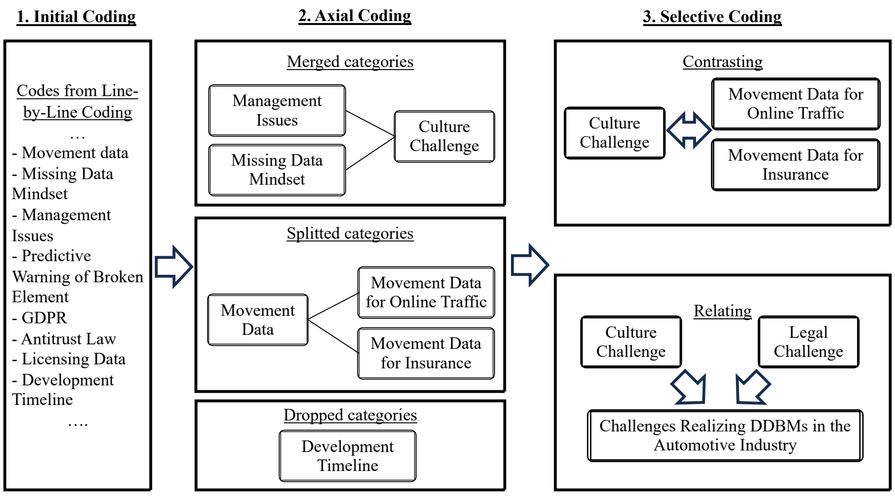

Figure 1. Illustration of coding with the resulting challenge "Culture" as well as two codes ("Movement data for online traffic" and "Movement data for Insurance" resulting in the DDBM Category "Customer Service". Combination of Glaser and Strauss (1967) and Grodal et al. (2021). Every step was followed by iterations.

4 Results

4.1 DDBM Categories at Automotive OEMs

Based on the statements of the 16 interviewees, five categories were identified for DDBMs in Europe: Technical, Product Optimization, Marketing Analysis, Selling Raw Data, and Customer Services. In order to delimit from studies that deal with the eco-systematization like Sterk et al. 2024 or Kaiser et al. 2021, the observed DDBMs in this study occur from an internal OEM perspective and only exist on the basis of vehicle data. While a permanent connection is not technically necessary for all DDBMs and hence not a basic requirement for all DDBMs, they must be able to establish a connection regularly (seconds to monthly).
In Table 2, an overview of these DDBM categories is shown. The existing models vary by category, with some already available to customers and others still in the planning phase. Since the subcategory name would release too much detail about the DDBM itself, the substitute 'PLANNED' stands for subcategories which are not released yet and therefore cannot be mentioned.

Technical: These DDBMs focus on in-car features highly valued by customers and driven by technology. They primarily utilize data sourced from within the vehicle. Complementary data, like map information, relies on a mobile connection. If unavailable, an internal data source like a map version serves as backup. All data processing remains internal, ensuring the service operates independently. The value proposition centers on data-driven services that address customer needs, whether end-users or businesses. For example, in the sub-category predictive maintenance, customers are alerted to potential component failures (*'The plan is to report to the customer: 'Your component may break in the next 100 km' - A.*'), allowing proactive workshop visits to prevent breakdowns.
Product Optimization: The main objective of these DDBMs is to optimize the car as a product. Therefore, data is extracted from the car and processed outside the car in a backend system, where it is analyzed what kind of features or components such as control elements are used and how often they are used. Given the substantial size of OEMs, other company-departments can also be considered as customers, making this an internal OEM DDBM. Consequently, this study includes this DDBM, with the engineering departments acting as the customer, referred to as "B2E" (Business to Engineering) in this study. (*'Our [DDBM] is quite special since we have internal customers. We analyze usage behaviour regarding [control element] for them [Note: the engineering department]' - E*). The value proposition is in the analytical insights provided, influencing future vehicle designs. Rarely used features may be omitted, while frequently used controls will receive special attention. The analytics service is sold internally, with the engineering-department paying a license fee to the analytics-department.
Marketing: Marketing DDBMs in the automotive industry have two primary objectives: to optimize campaigns and gather market feedback on car-specific topics. This DDBM relies solely on external data from customer feedback forms, online sources,

and subscriptions. Similar to "Product Optimization" DDBMs, it is used by internal retail departments, termed "B2R" (Business to Retail) in this study.
The value proposition is analytical insights, such as assessing campaign effectiveness and developing recommendations based on subscription and crawled data. The analytics service is sold internally, with retail departments paying a license fee to use it.
Selling Raw Data: This DDBM is exclusively focused on selling automotive-specific raw data, either anonymized (e.g., anonymized movement data) or personalized (e.g., individual driving behavior), sourced from within the vehicle. The value proposition is providing third parties access to this data, enabling new services and DDBMs.
The financial model is multifaceted, with data sold via subscription fees, usage fees, licensing, renting, or asset sales. However, determining the final price and achieving effective monetization remains challenging.
Customer Services: Customer Services represent a highly diverse category within DDBMs, unified by their exclusive focus on direct customer benefits. Consequently, the data required for these DDBMs is equally varied. The primary data source is derived from within the vehicle, supplemented by complementary data, such as online crawled data. The value proposition of these services lies in their customer-oriented nature, offering data-based services that directly enhance customer experience, such as providing real-time traffic information. The DDBMs examined in this study were all financed through a license fee per vehicle.

4.2 Challenges for OEMs regarding DDBM Development

The implementation of DDBMs inside the OEMs is not without challenges. The evolving market towards DDBMs endangers the automotive OEMs' market power. The main reason according to interviewees is that the OEMs face problems regarding the development of DDBMs. Having examined internal organizational resources, the findings from the interviews were analyzed and seven major challenge types were identified. Furthermore, the challenges are linked to the DDBM categories developed in 4.1 and are presented in Figure 2.
Legal: Creating a DDBM in the European automotive industry has legal boundaries that entail development efforts and hinder using the full potential. Interview partners stated, that the GDPR (General Data Protection Regulation) legislation entails development effort. According to the interviewees, this applies in particular to DDBMs where personalized data is required, i.e. Customer Services, Selling Raw Data and Marketing Analysis. Furthermore, the antitrust law and the law against unfair competition were mentioned as challenges regarding the use of the full potential of data. One interview partner stated: *'Something has to change in the legislation so that the automotive industry also makes progress here. ' - C.*
Technical: The law situation leads to a technical challenge. Due to the anti-trust law, technical standardization of e.g., data formats in the automotive industry is hard to establish. This impedes data customers to create industry-wide DDBMs, according to interviewee F: *'For a potential customer it is difficult, he gets many different data formats/contents/frequencies from each OEM. ' - F.* The challenge is valid for all DDBMs but interviewees mentioned that it is especially hard for the DDBM "Selling Raw Data", since a missing standard hinders a customer to integrate all the required raw data easily

into their product. The DDBM category “Technical” is also affected, since the missing standard forces intermediate steps, before data analysis for “predictive maintenance” or “replacing constructional elements” can be done.

Data Centralization: Interviewees highlighted the issue of missing data centralization and an unfavorable company structure for DDBM development within OEMs. Data exists in various departments, from sales to R&D, and is not centralized, e.g., in a 'data lake'. One interviewee noted: *'At the beginning, there is the problem that data is in small silos. ' - I.* This lack of centralization leads to unstructured DDBM development and lost synergy effects. This issue affects all DDBMs, but especially those related to "product optimization," where incomplete data can lead to incorrect analysis results.

Culture: The main challenge identified in the interview data is the organizational culture at OEMs. Interviewees noted the unrecognized value of DDBMs and called for more proactive management: *'The leadership needs to do more in the direction [of DDBMs].' - C*. However, a manager from the same OEM stated: *'It [digitalization and DDBMs] has been anchored in the corporate strategy for several years. ' - B*. This disparity suggests a lack of consensus on DDBMs within the company, echoed by interviewees from other OEMs. Consequently, a unified DDBM mindset in the automotive industry is absent, making DDBMs' importance unclear. This ambiguity can deter data experts, as one interviewee questioned: *‘How can we as a company get into these mindsets that are attractive for experts?’ - I.* The lack of data experts, resulting in missing knowledge about data in the automotive industry, was identified as a challenge affecting all DDBMs discussed in section 4.1.

Data Knowledge: Interviewees mentioned that knowledge about, e.g., data analytics is missing. Frequently brought up by interviewees a reason for this mindset is surely the car industry itself, exemplary: *‚Because we come from engineering hardware and not from data topics and products. ‚ - E.* In the classical engineering hardware world, constructional elements and Key Performance Indicators (KPIs) like several sold units are important and data plays a subsidiary role. This challenge is also a problem occurring in all DDBMs from 4.1 as the interviewees stated this challenge in the interviews.

Monetization of DDBMs: Another challenge identified in the interview data is the monetization of DDBMs and the resulting risk of disaffection of the management: *‘You can’t say that the risk [realizing a DDBM] is too high because I can’t see it, I can’t calculate it, etc. ‚ – C.* Since monetization and therefore the economic value of DDBMs is hard to estimate, it is challenging for decision-makers to bring these DDBMs to market. In conclusion, OEMs become late penetrators for DDBMs since they only take the economic risk if someone else has already shown that the market demands it. This challenge is a problem for all externally sold DDBMs, i.e. interviewees mentioned this challenge for the categories “Technical”, “Selling Raw Data” and “Customer Services”.

Data Volume: The last identified challenge was the role of data volume. Here, the equation applies: more cars lead to more data: *'As a smaller brand that does not yet have so many cars in the market, it is very difficult to gain a foothold [in DDBMs].' - K.* A high amount of data yields to better DDBMs and therefore a higher economic value, especially for the DDBM “Selling Raw Data”.

Table 2. Details on the occurring DDBM categories. Design inspired by Endres et al. (2019). Elements taken from Hartmann et al. (2016) and own ones.

	Technical	Product Optimization	Marketing	Selling Raw Data	Customer Services
Sub-Categories	Predictive Maintenance; Autonomous Driving; Replacing Constructional Elements	Usage Analysis of Features; PLANNED	Analyzing Subscriptions; PLANNED	Sensor Data; Anonymized Data; Personalized Data	Online Traffic; Insurance; Map Making; Seamless Integration; PLANNED
Data Sources	Anonymized Car-data	Anonymized Car-data	Anonymized and Personal Car-data	Anonymized and Personal Car-data	Anonymized and Personal Car-data
Key Activities	Data Aggregation and Predictive Analytics	Data Aggregation and Prescriptive Analytics	Data Aggregation and Prescriptive Data Analytics	Data Aggregation, Data Generation, Data Processing	Data Aggregation, Data Generation, Data Processing, Data Visualization
Value Proposition	Data-Based Services	Analytics Information	Analytics Information	Automotive-specific Raw Data	Data-based Services with Focus on Direct Customer Benefits
Target Customer	B2C and B2B	B2E (Business-to-Engineering, Internal Use)	B2R (Business-to-Retail, internal use)	B2B, B2C	B2B, B2C
Revenue Model	Single Payment per Car	Internal Costs	Internal costs, License Fee	Asset Sale, Lending/Renting/Leasing, Licensing, Usage/Subscription Fee	License Fee
Provider	OEM, Tier1, Start-Ups	OEM	OEM	OEM, Tier1	OEM, Tier1, Tier2, Start-Ups

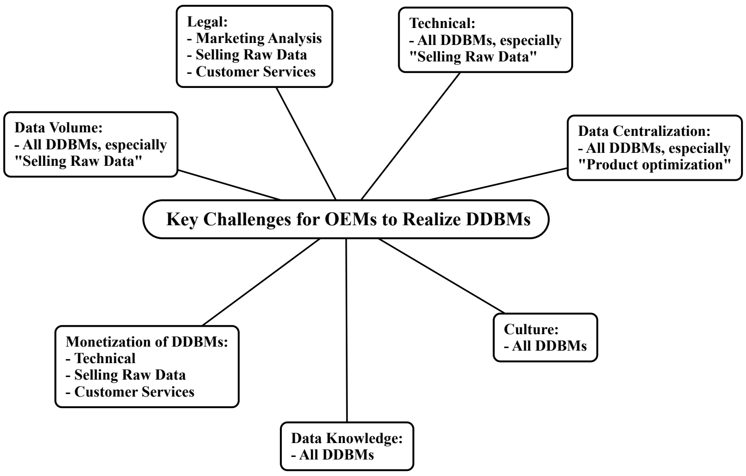

Figure 2. Key Challenges for OEM DDBM development and their linked categories.

5 Discussion

5.1 Implications for Theory

Given the holistic approach of DDBMs in the automotive industry, the presented results carry three theoretical implications. First, the study contributes to the emphasized call to better understand DDBMs in the mobility domain by Ketter et al. (2023). Categories were created for existing DDBMs in the automotive industry based on empirical data and showed their market characteristics. Additionally, taking into account Sterk et al. (2024) this study contributes to the topic of connected cars in IS with an internal OEM perspective. All presented DDBMs depend on automotive data, accessible solely through the connectivity of the vehicle, i.e. a connected car.

Second, our findings show that the framework from Hartmann et al. (2016) needs to be extended or rearranged. For example, a physical product such as a car and its sensors can act as internal and external data sources. It depends on whether the data is personalized and therefore customer-provided or if it is anonymized and can therefore be tracked. This distinction holds paramount significance, particularly within the DDBM category of 'Customer Services'. Within subcategories such as 'insurance' or 'online traffic', the initial consideration does not predominantly lie in discerning between internal and external data sources, rather, the primary differentiation centers on the classification of data as 'personalized' or 'anonymized'. Hence, the 'data sources' dimension by Hartmann et al. (2016) must be rearranged for the automotive industry towards a distinction between 'personalized' and 'anonymized' before it comes to 'internal' or 'external' data sources.

Third, referring to Markus (2017), this work adds an empirical study to the literature on DDBMs.

5.2 Implications for Practice

This study also offers implications for practitioners. First, this study shows that DDBMs are emerging in the automotive industry. Existing categories include Technical, Product Optimization, Marketing, Selling Raw Data, and Customer Services. B2B or B2C DDBMs like Technical, Selling Raw Data, and Customer Services generate additional revenue, while internal DDBMs like Product Optimization and Marketing optimize internal processes. Product Optimization is especially promising, as detailed usage analysis of features can lead to a more optimized car.
Second, this study identifies challenges for OEMs that they need to solve in order to maintain their market power in a market that is changing towards DDBMs, namely Legal, Technical, Company Structure, Cultural, Data Knowledge, Monetization of DDBMs, and Data Volume. These challenges are similar to the findings of Lange et al. (2021) but are described in this study in the context of the automotive industry, while Lange et al. (2021) investigated them in a broader context.

6 Conclusion, Limitations, and Future Work

In this study, an exploratory interview study was conducted to investigate the DDBMs in the mobility domain, e.g., the automotive industry. Therefore, 16 automotive experts spread over four OEMs and two OEM suppliers were interviewed, working in departments that deal with DDBMs. The interviews were guided by the question of how DDBMs within the market of the European automotive industry can be categorized as well as which challenges the European automotive industry face regarding DDBMs. Hence, five DDBM categories in the automotive domain were found: 'Technical', 'Product Optimization', 'Marketing Analysis', 'Selling Raw Data', and 'Customer Services' and seven challenges that the automotive domain deals with: legal, technical, company structure, cultural, data knowledge, monetization, and data volume. Furthermore, three This distinction holds paramount significance, particularly within the realm (DDBMs) of the category of 'Customer Services'. contributions to the theory occured. First, this study responded to a current call from Ketter et al. (2023) by emphasizing a better understanding of DDBMs in the mobility domain, e.g. the automotive industry. Second, this study shows that the framework from Hartmann et al. (2016) needs to be reworked for the automotive industry. Third, by contributing an empirical study to the literature. However, this study has limitations. For this study only four different European OEMs were interviewed. Hence, interviewing more OEMs inside Europe is beneficial to verify the results. This lowers subjectiveness in the results, even though it was tried to analyze the data as objectively as possible. Also interviewing experts outside Europe (e.g., Asian or American OEMs) would add new characteristics to the results of the study in the future. Furthermore, repeating the study as soon as data intensive technologies such as Large-Language-Models are established in the automotive industry, adds new characteristics.
Since this study deals with an internal OEM perspective, it is of great interest to investigate the whole ecosystem with other data suppliers and other competitors from outside the automotive industry. This extends the challenges from an internal OEM perspective to challenges that occur on a data ecosystem level.

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