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Research Article

# Conceptualising value creation in data-driven services: The case of vehicle data

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ABSTRACT

The creation of data-driven services generates new value streams, leading to the emergence of new actors and ultimately to new market configurations. In the automotive industry, the data generated by vehicles during use paves the way for new types of data-driven services. Based on interviews with eleven prominent experts of the Central European automotive industry, we identify key actors in establishing vehicle data-driven services and their data sharing relationships. We illustrate both in a conceptual multi-actor model for value creation in vehicle data-driven services and evaluate it in the context of six real-life cases. Our study adopts an ecosystem perspective and marks an important step towards the systematic design of a conceptual multi-actor model for vehicle data-driven value creation that can help to guide next research endeavours in data-driven service development.

## 1. Introduction and motivation

The ongoing transition towards a digitalised world also affects primarily physical industries (Hanelt, Piccinini, Gregory, Hildebrandt, & Kolbe, 2015). Due to its long tradition in catering to a basic human need – mobility, the automotive domain stands out in particular (Piccinini, Hanelt, Gregory, & Kolbe, 2015). Traditionally, businesses within the automotive domain were geared towards offering goods (e.g. selling manufactured vehicles as the main product) and product-related services (e.g. selling spare parts and conducting maintenance work). However, digitalisation has led the automotive industry to think differently, as vehicles become increasingly connected and capture a lot of data about themselves and their environment (Swan, 2013, 2015). This captured vehicle data eventually paves the way for new types of data-driven services (Bridgelall, Lu, Tolliver, & Xu, 2018; De Winter, Dodou, Happee, & Eisma, 2019; Pillmann, Wietfeld, Zarcula, Raugust, & Alonso, 2017; Pütz, Murphy, Mullins, & O'Malley, 2019).

Consequently, vehicles are increasingly becoming part of an automotive ecosystem that includes not only drivers and passengers but also other road users, vehicle manufacturers or service developers. Connected vehicles enable the possibility to develop data-driven services such as remote vehicle diagnostics or interactive trip analytics (Kuschel, 2008; Papatheocharous, Frecon, Kaiser, Festl, & Stocker, 2018). Thus, the digital transformation offers new players outside the automotive sector the opportunity to enter this traditionally closed ecosystem (Athanasopoulou, Bouwman, Nikayin, & de Reuver, 2016). Among those, we find major companies like Tesla, Google, or Apple (Wittmann, 2017) and start-ups like vin.li and Zendrive.com who create data-driven services related to digital asset tracking, vehicle health or driving safety (Stocker, Kaiser, & Fellmann, 2017). Yet, it remains a challenge for those start-ups to translate their technical innovations into commercially successful product offerings.

Despite these disruptive changes caused by digitalisation, the core industrial product of the automotive industry, the vehicle, cannot be digitised entirely (Piccinini et al., 2015). Instead, it will be complemented by both traditional and data-driven services (Kaiser, Festl, Pucher, Fellmann, & Stocker, 2019). Declining revenues from vehicle sales can be compensated by additional income from the monetarization

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of vehicle data (Bertoncello et al., 2016; Davenport, Pacheco, & Priestley, 2020; Seiberth & Gründinger, 2018). However, it remains no less of a challenge for incumbent companies in the automotive industry to fully embrace such digital innovation (Svahn, Mathiassen, & Lindgren, 2017).

*Data-driven services* are services that support customers' decision-making processes by providing data and analytics to create value for the customer (Schüritz, Farrell, Wixom, & Satzger, 2019). The provision of data-driven services is often, but not necessarily, accompanied by a physical product equipped with sensors for digital connection to other products and information systems-IS (Beverungen, Lüttenberg, & Wolf, 2018; Tomiyama, Lutters, Stark, & Abramovici, 2019). Although this digital transformation in the automotive domain is underway (Kuhnert, Stürmer, & Koste, 2018; McKinsey, 2016), little is known about the most relevant actors and their data sharing relationships to deliver value-added services based on exploiting vehicle data. Especially in the advent of big data, it is even more important than ever to understand the characteristics of data-based or data-driven value creation (Lim et al., 2018; Schüritz et al., 2019).

We put our focus on the automotive domain as their industrial-age core product cannot be digitized completely (Piccini et al., 2015). Furthermore, automotive is one of the most important industries related to non-digital artefacts (i.e. vehicles) (Henfridsson, Mathiassen, & Svahn, 2009). It is, however, worth noting that the automotive sector has begun to experiment with vehicle telematics solutions and connected car initiatives since a few years (Svahn et al., 2017).

The primary goal of our research is to investigate ways through which (small and big[1]) vehicle data can spawn new data-driven services and to provide a framework to structure and evaluate vehicle data-driven value creation. We argue that improved knowledge about key actors and their data sharing relationships will contribute to a better understanding of vehicle data-driven value creation. Accordingly, a fundamental starting point for our research is to map those actors that will have a crucial role in data sharing and then design how data sharing relationships can connect them. Thus, our paper addresses the following three research questions:

- *Which actors play a key role in vehicle data-driven service generation?*
- *How do data sharing relationships connect those actors to enable value creation?*
- *How can a conceptual model illustrate both actors and their data sharing relationships?*

The identification of the most relevant ecosystem actors provides the foundation for better understanding their data sharing relationships and interdependencies, allowing us to design a conceptual model of data-driven value creation. Conceptual models are abstract representations of some subject matter, which serve to promote communication and common understanding between stakeholders, thereby improving the prospects for successful information system development and use (Wand & Weber, 1993). Conceptual models are mostly of a graphic nature and usually contain a visual arrangement of modelling constructs in the form of graphical symbols and text (Bera, Soffer, & Parsons, 2019). Besides supporting communication, they contribute to a better understanding of a particular domain and provide input for the information systems design process (Wand & Weber, 2002).

[1] Although big data and big data analytics are definitely important, we would like to emphasize that we do not focus on research on the adoption on big data analytics. Many vehicle data-driven services are based on "small data" (using only a few data points of a single signal): For instance, services that can detect safety critical situations inside a vehicle and forward this information to operational organizations like emergency services do not rely on big data analytics. In many cases, a few data points from a few signals are sufficient to generate a data-driven service with high added value as for instance mentioned by the interviewed data marketplace provider.

The theoretical gap addressed in our paper is the lack of conceptual models that can unravel the underlying value chain (actors and data sharing relationships) when establishing vehicle data-driven services. We thereby address the calls of researchers (Parvinen, Pöyry, Gustafsson, Laitila, & Rossi, 2020) to closely examine data-driven value creation and ecosystems (Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015). Our designed conceptual model aims to link actors with specific steps within the data value chain. Thereby, it seeks to help organisations that choose to become part of the automotive ecosystem to better understand their role, relationships, and opportunities for data-driven service provision better. Thus, our model supports the design of vehicle data-driven services by introducing the most relevant actors, and data flows, ultimately leading to data-driven value creation. As of now, the model preserves the different perspectives of key actors while addressing the research gap that key concepts and relations regarding data-driven value creation are nowadays insufficiently explored, as we observe it in the research on vehicle data-driven services. As to these arguments, they are grounded in our research within the large-scale research project EVOLVE funded by the European Commission in the Horizon 2020 framework programme involving 19 key partners from 11 European countries from the automotive, big data, cloud and high-performance computing worlds aiming at better exploitation of big data.

The remainder of this paper is structured as follows: Section 2 presents the framework that guided our research approach and paper structure. Section 3 embraces the theoretical foundations of this paper. After this, in Section 4, we elaborate on the data collection including results from eleven expert interviews and their sketching activities. These views are unified and serve as the basis for our conceptual model presented in Section 5. We provide the results of the final evaluation of our model in Section 6, and discuss our findings in Section 7 before we summarise and conclude our paper in Section 8.

## 2. Research framework and paper structure

We address the lack of conceptual models that can unravel the underlying vehicle data value chain (actors and data sharing relationships) in establishing data-driven services. Our research framework is guided by the design-science paradigm (Hevner, March, Park, & Ram, 2004), with its three research cycles (Hevner, 2007): *relevance cycle*, *design cycle*, and *rigor cycle* (Fig. 1). Design-science extends "the boundaries of human and organizational capabilities by creating new and innovative artifacts" (Hevner et al., 2004). In our case, the innovative artifact is the conceptual model for *value creation in vehicle data-driven services.* This research framework allowed us to obtain the different perspectives of key stakeholders (researchers, users, clients, sponsors, and practitioners) while studying complex problems.

As part of the relevance cycle (Section 3), we conducted a literature review of well-regarded scientific electronic databases extended through backward and forward search regarding our application context (value creation in vehicle data-driven services) and theoretical lens (ecosystems). Existing theory on the value of data-driven services and data value chains was used as theoretical input within the design phase.

In the design cycle, we first took a participatory approach to build a practice-based, conceptual model, capturing the individual views of eleven experts from the automotive domain on value creation in vehicle data driven services. We complemented our interviewing approach with simple graphical design activities, letting experts draw sketches on key actors and their data sharing relationships (Section 4). We consolidated the individual expert views in a conceptual model of value creation in vehicle data-driven services, applied conceptual modelling (Wand & Weber, 2002) inspired by the concept of data value chains (e.g. Curry, 2016; Faroukhi, El Alaoui, Gahi, & Amine, 2020; Latif, Saeed, Hoefler, Stocker, & Wagner, 2009) and presented our artifact: a unified conceptual model for the data value creation process consisting of three parts, (i) actors involved, (ii) key ecosystem actors and (iii) data sharing

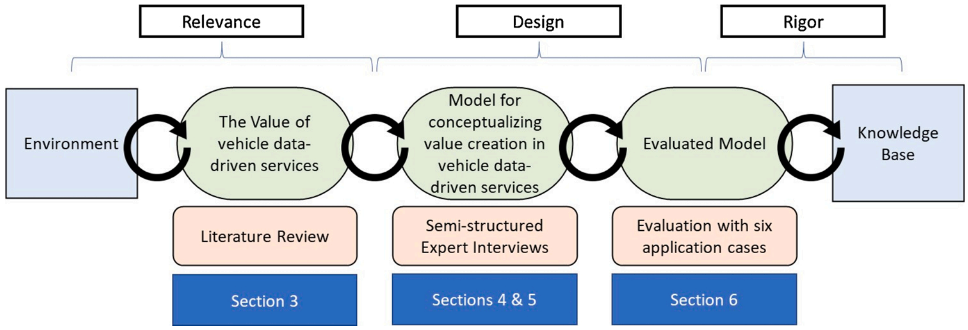


**Fig. 1.** Research Approach and Paper Structure.

relationships between the actors. We established proof-of concept before we proceeded to evaluating our model with real-life cases (Sections 4 and 5).

In the rigour cycle (Sections 5 and 6), we performed conceptual model evaluations by applying our model to in total six real-life application cases enabled by vehicle data and established its proof-of-value. After each design, we conducted an evaluation of the model that resulted in model revision. This resulted either in a change in model actors, a change in data-sharing relationships, or a change in both, while the general structural design of the model remained unchanged. Our paper only includes the sixth evaluation of our model within a real-world case, the development of a data-driven service for road surface quality detection to underpin its practical applicability.

## 3. Theoretical foundations

This section places our research in the context of the relevant existing literature. First, we illustrate the concept of data-driven services in the automotive domain and the rationale behind it. Second, we take a look at the literature on ecosystems which we use as a theoretical lens for our study.

Table 1 shows how research on data-driven services is steadily increasing. In total, we identified 222 papers published since 2011 in established scientific electronic databases as AISeL, ScienceDirect, Scopus, IEEE Xplore and ACM DL (Falagas, Pitsouni, Malietzis, & Pappas, 2008; Gusenbauer & Haddaway, 2020). More than 36 % of these papers were published in 2019.

We included articles that used the following terms: "value creation" or "value", and "data-driven services", or "data-based services", and "automotive", or "vehicle", or "car", or "mobility". We added further papers on the value of data-driven services in general and on vehicle data-driven services in particular by applying backwards and forward search. In what follows, we thematically discuss the main concepts from a representative sample of 48 of the retrieved papers on the value of (vehicle) data-driven services.

### *3.1. Value of data-driven services*

In the last two decades, the service sector has seen an unprecedented development, also due to the expansion of the application of Information and Communication Technologies – ICTs (Berkley & Gupta, 1994; Rai & Sambamurthy, 2006) and the subsequent digital transformation of businesses and society (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013; Chesbrough & Spohrer, 2006; Lim et al., 2018; Lusch & Nambisan, 2015; Spohrer & Maglio, 2008). Among the different available definitions, we adopt here the concise summary provided by Spohrer and Maglio (2008, p. 241) defining *service* as "pay for performance in which value is coproduced by client and provider". This is true, for example, when considering information intensive services (IIS) where the "value is created primarily via information interactions, rather than physical and interpersonal interactions, between the customer and the provider" (Lim et al., 2018, p.121). Moreover, these services rely on the data that generate the information driving the activities, making them valuable for the final customer (Azkan, Iggena, Gür, Möller, & Otto, 2020; Kumar et al., 2013; Maass, Parsons, Purao, Storey, & Woo, 2018). Consequently, value creation based on data should take into account the data value chain as well as key factors, such as for example the data, the data source, data collection, data analysis, information delivery, information on the user, the value in information use, and the provider network (Lim et al., 2018, p.122).

Taking these issues into account, the role of data and information value (Attard & Brennan, 2018; Batini, Castelli, Viscusi, Cappiello, & Francalanci, 2018; Brennan, Attard, Petkov, Nagle, & Helfert, 2019) is a central challenge in the competitive scenarios emerging from digitalisation, in particular for understanding what concerns the evaluation of the information capacity suitable to allow companies to the create and capture value by digital assets and data-driven services (Batini et al., 2018). Furthermore, according to Dedrick (2010) researchers have framed the impacts of the IT on environment as first-order (impacts of ICT hardware during the product lifecycle), second-order (impacts of ICT on other processes such as transportation or industrial production), and third-order effects (changes in lifestyles and economic structures). The latter are relevant when considering the increased use of the media's transformative potential of 'green' IS on the demand side, encouraging practices such as, e.g., carpooling and ridesharing applications coupled with the Internet of Things (Malhotra, Melville, & Watson, 2013).

Moreover, scholars from computer science and IS have also questioned, which business models could be suitable to capture the value of data-driven services (Lim et al., 2018; Schüritz & Satzger, 2016; Schüritz, Seebacher, & Dorner, 2017; Zolnowski, Anke, & Gudat, 2017; Zolnowski, Christiansen, & Gudat, 2016). These contributions complement the questions advanced in the field of technology management (Hartmann, Mohamed, Niels, & Andy, 2016; Sorescu, 2017) about the role of data-driven services in business model innovation. Additionally, IS scholars have investigated the antecedent factors of value creation in connection with the big data analytics phenomenon (Günther, Rezazade Mehrizi, Huysman, & Feldberg, 2017; Mikalef, Pappas, Krogstie, & Pavlou, 2020; Surbakti, Wang, Indulska, & Sadiq, 2020; Wiener, Saunders, & Marabelli, 2020). Central questions concern the big data analytics capabilities that companies require to a) enhance organisational performance (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Wamba et al., 2017), b) create business value (Conboy, Dennehy, &

**Table 1**
Search results (all fields) in AISeL, ScienceDirect, Scopus, IEEE and ACM (2011-2019).

| Year\ Database | AISeL | ScienceDirect | SCOPUS | IEEE Xplore | ACM DL |
|---|---|---|---|---|---|
| 2011–2013 | 1 | 3 | 3 | 2 | 1 |
| 2014–2016 | 8 | 15 | 7 | 5 | 4 |
| 2017–2019 | 54 | 56 | 35 | 16 | 12 |

O'Connor, 2020; Grover, Chiang, Liang, & Zhang, 2018; Wamba et al., 2015), and c) enable service innovation (Lehrer, Wieneke, vom Brocke, Jung, & Seidel, 2018), as well as d) which barriers may prevent their adoption.

For example, Dremel, Herterich, Wulf, Waizmann, and Brenner (2017) discuss in a case study of AUDI how traditional manufacturing organizations can introduce big data analytics and master related organizational transformations. Dremel, Herterich, Wulf, and Vom Brocke (2020) identify big data analytics (BDA) actualization mechanisms from a revelatory case of a vehicle manufacturer. Akter et al. (2016) aim at improving the organizational performance of a company through big data analytics and proposes a hierarchical model. Grover et al. (2018) explore the success of big data analytics projects with respect to creating strategic business value, i.e., by addressing intra-organizational aspects. Lehrer et al. (2018) propose a theoretical model of big data analytics service innovation developed from multiple cases from insurance, banking, telecommunications, and e-commerce that have all implemented big data analytics. Mikalef, Pappas, Krogstie, and Giannakos (2017) recommend that more attention should be paid to the organizational changes that big data analytics brings and how big data analytics should be adopted strategically. Mocker and Fonstad (2017) discuss AUDI's challenges towards the sharing economy and how AUDI has transformed its organizational structure, processes, and architecture. Svahn et al. (2017) address, how incumbent firms embrace digital innovation proposing the Volvo case study and identifying four concerns, but focusing on the perspective of the vehicle manufacturer, only. Wamba et al. (2015) emphasize a lack of empirical research to assess the potential of big data and provides both a literature review and case studies to present an interpretive framework to analyze the different perspectives of big data as well as a taxonomy to better understand the role of big data in value creation. Wamba et al. (2017) propose a big data analytics capability model, extend previous research by examining the direct effects of big data analytics on firm performance. Woźniak, Valton, and Fjeld (2015) introduce a practical example for big data value creation from Volvo and share the story of building a big data service for the automotive industry in a case study. These papers focus heavily on the big data analytics phenomenon and the strategic and organizational capabilities required to create value from big data analytics. They all take a single-actor (i.e., micro) perspective.

### 3.2. Data-driven services based on vehicle data

The recent advances in computing infrastructure, including the Internet of Things (IoTs) as well as the data generation/processing capabilities in products, have boosted the development of data-driven services. However, those who generate and collect the data are not necessarily those who develop and provide data-driven services. The systematic use of the data generated in connection with vehicle use happens in practice within complex actor-networks and ecosystems. Vehicle data paves the way to enabling novel data-driven services (Stocker et al., 2017) and with the current increase in connected vehicles this data can finally be exploited. Connected vehicles are equipped with hardware and software to connect them to the cloud, collect data from sensors (e.g., the vehicles speed, acceleration, and steering wheel angle at a certain time), and send these data to the vehicle manufacturers' servers; this allows obtaining insights on, e.g., driving pattern analysis or estimated time of arrival in the case of fleets. Thus, an ecosystem for such services emerges (Dhungana et al., 2016; Venkataram, 2019).

In general, vehicle manufacturers seek to leverage the value of the data collected through their vehicles to better meet customer needs (Kaiser, Stocker, Festl, Lechner, & Fellmann, 2018; Stocker et al., 2017). According to Gissler (2015), all new passenger vehicles sold in 2025 will be connected, forcing vehicle manufacturers to define their role and determine where they can best benefit from connectivity. Volkswagen, Daimler and BMW all recently announced major investments in data-driven services like "Volkswagen We", "Mercedes me" or "BMW CarData" (BMW, 2020; Daimler, 2020a, 2020b; Volkswagen, 2018). However, there are also approaches for vehicle data collection and use in data-driven services that bypass vehicle manufacturers. These are the ones pursued by tech start-ups such as dash.by, vin.li, or pace.car who bring their own solutions into vehicles (to create a gateway to sensor data) and thereby compete with the activities of vehicle manufacturers in vehicle data collection (Stocker et al., 2017).

Also, emerging data marketplaces, such as caruso-dataplace.com, high-mobility.com or otonomo.io, provide another approach to leverage vehicle data (Pillmann et al., 2017). Data marketplaces are digital platforms on which data products are traded, acting as neutral intermediaries, and allowing others to sell their data products (Spiekermann, 2019). The aim of vehicle data marketplaces is to make available vehicle data collected by different brands of connected vehicles, vehicle manufacturers, fleet operators and other data providers to interested data-driven service developers directly or indirectly through a single point of access.

### 3.3. Theoretical lens: the ecosystem concept

In general, an ecosystem describes the relationships and interactions between living organisms and their environment (Briscoe & De Wilde, 2006; Schulze, Beck, & Müller-Hohenstein, 2005). To differentiate an artificial ecosystem from a natural one, some authors add further attributes to the term to qualify it, e.g. software ecosystem, business ecosystem or digital service ecosystem (Immonen, Ovaska, & Kalaoja, 2015). However, a commonly agreed definition does not yet exist.

Considering the field of strategy as relevant for the focus of this research on the automotive industry, an early definition has been provided by Teece (2007, p. 1325), who considers an ecosystem as "the community of organisations, institutions, and individuals that impact the enterprise and the enterprise's customers and supplies" including "complementors, suppliers, regulatory authorities, standard-setting bodies, the judiciary, and educational and research institutions". Focusing on modularity and coordination for different types of complementarities (in production vs. in consumption), Jacobides, Cennamo, and Gawer (2018) have proposed a consolidated perspective on the ecosystem concept. They define it as "a set of actors with varying degrees of multilateral, non-generic complementarities that are not fully hierarchically controlled" (p. 2264). Furthermore, Adner (2016, p. 40) define an ecosystem as "the alignment structure of the multilateral set of partners that need to interact in order for a focal value proposition to materialise". Considering 'partners' in the automotive industry, while Original Equipment Manufacturer (OEM) traditionally exerted a strong influence on ecosystems, this configuration is currently challenged by the digitalisation characterising new breeds of quantified vehicles and new actors on the market (Stocker et al., 2017).

Nischak, Hanelt, and Kolbe (2017) emphasise that three components are essential elements of digital business ecosystems: value exchange (innovation, information, products/services), resources (digital and non-digital) and actors (organisations, individuals, societies). This definition can be adapted and specialised for digital automotive ecosystems. Similar to a digital business ecosystem, a digital automotive ecosystem contains actors that in this case are original equipment manufacturers (OEM), data intermediaries or data service providers, for example. These actors have access to resources, such as data and infrastructure, for generating, transmitting and storing data. Leveraging these resources, the actors participate in value exchanges by providing or consuming data.

Nevertheless, research on digital automotive ecosystems is still limited. Particularly in connection with vehicle data and the process of creating data-driven services, the literature repeatedly refers to data-based business ecosystems (Curry, 2016; Kitsios, Papachristos, & Kamariotou, 2017; Nachira, Dini, & Nicolai, 2007). For instance, Immonen, Palviainen, and Ovaska (2014) outline the open data ecosystem from a business viewpoint and define ecosystem actors such as application users, data and service providers, application developers and infrastructure providers along with their role in the data-based ecosystem. Also, in many cases the authors refer more to technical ecosystems (e.g. Kolbe, Kubler, Robert, Le Traon, & Zaslavsky, 2017; Gerloff & Cleophas, 2017; Kuschel, 2008; Martínez de Aragón, Alonso-Zarate, & Laya, 2018). In these technology-oriented perspectives, an analysis of the business relations enabled through the digitalisation of the vehicle and the feasibility of new data-driven services is largely missing.

Researchers focusing on the exploration of actors and relationships between actors have often taken a different perspective, e.g. describing automotive engineering as an automotive ecosystem of interacting organisations (Knauss & Damian, 2014), or presenting a strategically motivated approach to discover business models in traditional industries and apply them to the mobility sector without empirically substantiating their findings (Remane, Hildebrandt, Hanelt, & Kolbe, 2016). Researchers have also used data from automotive investment and partnering activities to better understand the ecosystem: Riasanow, Galic, and Böhm (2017) have used data from crunchbase.com to derive roles, design the automotive value network, and discuss the model with five experts. Nischak and Hanelt (2019) have used data about alliances, joint ventures, mergers and acquisitions along with network visualisation techniques for a longitudinal analysis of the automotive ecosystem. Although vehicle data paves the way to ecosystem-building activities, none of the reviewed articles contains a focus on vehicle data-based ecosystems.

## 4. An expert perspective on the value of vehicle data-driven services

The literature review showed that actors and their data sharing relationships were only marginally considered with regard to the development of services based on the data generated by connected vehicles. Also, the majority of the reviewed contributions do not address the specifics of vehicle data-driven ecosystems, which we aim to elicit by conducting interviews with eleven automotive domain experts with an average professional experience of more than 16 years, all of them being opinion leaders for the Central European market.

### 4.1. Data collection

From May 2018 to December 2018, we have conducted in-depth interviews with experts from the Central European automotive industry. More specifically, we combine two instruments, capturing automotive experts' general views on value creation in vehicle data-driven services by conducting semi-structured interviews, and then aiming towards gaining a deeper understanding of the data-driven value creation process through experts' graphical models of actors and data sharing relationships. Two of the authors conducted the interviews and the fieldwork, while the other three authors acted as critical and reflexive actors (Gioia, Corley, & Hamilton, 2013) during the monthly online meetings for discussing the material added to the emerging corpus of interviews, memos, and archival documents.

According to findings of Scholte, van Teeffelen, and Verburg (2015) from ecosystem research, expert-based approaches hold the potential that experts can be asked to express their own opinions and values starting with what they find important, while in-depth (unstructured or semi-structured) interviews can be used to gain a deeper understanding on ecosystems. Interviews have been used in the past by previous related research (e.g. Beverungen, Müller, Matzner, Mendling, & Vom Brocke, 2019; Riasanow et al., 2017) to conceptualise service (eco)systems. However, we argue that conducting interviews alone may not be sufficient to gain a deep understanding of the complex data-sharing relationships of identified actors. Therefore, we complemented our interviewing approach with simple graphical design activities to let experts visualise the value creation process from their perspective.

Involved experts had on average more than 16 years professional work experience (cf. Table 2) and included large industries (e.g. automotive manufacturers), small and medium enterprises (e.g. data marketplaces, suppliers, and data-driven start-ups), public authorities and automotive research organisations. Due to the reputation of the experts, it sometimes took months before an appointment was possible. Interviews lasted between 60−90 min and were divided into several parts:

- *Part 1*: We covered the experts' background, professional experience, and attitude towards using data-driven applications.
- *Part 2*: We asked them to describe vehicle data-driven services they knew and have already used to judge their experience better.
- *Part 3*: We showed experts an existing ecosystem model from the media domain built by Gordijn, Petit, and Wieringa (2006) and asked them to attempt to sketch their view on vehicle-data driven value creation, which we assumed to be a cognitively challenging task. To guide experts, we asked them to start their personal design process by first naming relevant actors before designing data-sharing relationships. Finally, we asked them to describe the changes they expect in the digital automotive service ecosystem over the next 5 years.

We have conducted in total eleven expert meetings, four of them face to face with experts who were using pen and paper to sketch their views (experts 2, 3, 8, and 9). The seven remaining meetings were conducted online, using a video conferencing service with screen sharing enabled. For the virtual meetings, we prepared a special online document for ecosystem design in which the experts had to list the relevant actors before linking them with data sharing relationships. In total, eight experts gave their consent to have their voices recorded during the meeting, while the remaining three experts refused recording, due to strict automotive confidentiality policies.

In the following section, we present and discuss the various ecosystem models designed by the experts, with a detailed example from expert No. 3 and a summary of all other experts.

**Table 2**
Information on the background of the experts involved in the design process.

| Expert No. | Organisation | Expert profile | Work Exp. |
|---|---|---|---|
| 1 | Public authority | Responsible for a metadata service for accessing vehicle data | 23 yrs. |
| 2 | Automotive research | Research manager dealing with vehicle data and data-driven services | 25 yrs. |
| 3 | Automotive research | Senior data scientist involved in vehicle data analytics projects | 9 yrs. |
| 4 | Automotive research | Senior researcher involved in projects with vehicle manufacturers that deal with data-driven services | 5 yrs. |
| 5 | Provider of data-driven service | Senior manager of a provider o f vehicle data services | 14 yrs. |
| 6 | Public authority | Representative in international committees in charge of a vehicle data provision service | 26 yrs. |
| 7 | Data marketplace provider | Leader of a national research project on data marketplaces | 21 yrs. |
| 8 | Provider of data-driven services | Senior consultant involved in development of vehicle data-driven services | 7 yrs. |
| 9 | Automotive and software engineering | Owner and managing director of an automotive engineering service company | 24 yrs. |
| 10 | Provider of data-driven services | Senior developer of vehicle data-driven services | 5 yrs. |
| 11 | Vehicle manufacturer | Head of a data-driven service department | 19 yrs. |

### 4.2. Case vignette

We present the output of one expert interview as a case vignette. This is a representative example to illustrate that all experts have a particular context from their field of expertise, but an excellent overview of the automotive and mobility sector in general.

Expert 3, Frank, doctor of technical mathematics, has more than 9 years of experience as a senior data scientist for an industrial research company. He was jointly responsible for the development and operation of a data-driven service based on Floating Car Data (FCD), which is used by a traffic control center to provide information for road users, traffic planners, and state governments. Therefore, Frank has a particular view on the sharing of vehicle data, which is characterized by his own working context.

Stakeholders relevant to Frank are decision-makers, infrastructure providers, vehicle manufacturers, suppliers of vehicle manufacturers, road users, data intermediaries, traffic news offices and traffic management. Frank identified several data-sharing relationships between these actors and presented them as connecting lines on the drawing board (cf. Fig. 2). As a data scientist, Frank began designing the ecosystem around *'data'* that is the basic ingredient for data-driven services: *"The problem that I have is that this data is separated. Data packets go from the data intermediary to the road user, and that does not necessarily have to be the same data that the road user sends somewhere else."* During this design process Frank also starts to explain and interpret what he has achieved so far in the ecosystem model, related to different *actors*, their needs and relationships in the ecosystem: "*Infrastructure providers would like to [get data from vehicle manufacturers], but they don't get it [the data]."* Therefore, infrastructure providers, as service users, appear to be actors that would benefit greatly from data on vehicle movements and would even start collecting such data by using stational roadside units to detect passing vehicles, e.g. to measure and predict traffic flows. However, their willingness to pay other actors for vehicle data is still questionable: "*This is still in the making, that infrastructure providers really pay data intermediaries for data",* and adds, *"INRIX, TomTom, or HERE – these are the classic [data intermediary] players."*

Data intermediaries emerge as *new players* who are beginning to establish a powerful position within the ecosystem. *"These are institutions that penetrate the market from outside and deal a lot with data. They are rather atypical. What is now very immanent in this system is that someone enters the traffic data market that actually has nothing to do with it originally."* Other new players are about to enter the market for data-driven service generation and are seeking cooperation with existing players. Some actors seem to have developed their own *practices to gather data* for decision making, e.g. traffic planners are used to collect their own data manually, instead of cooperating with other players: *"... traffic planning is still a point, but now they are still outside. These would already be relevant, but they now usually collect the data using standard methods."* Infrastructure providers started to make their data available to traffic planning and management: *"Vehicle measuring stations on the motorways belong to the infrastructure provider who makes the data available to traffic management. [...] They would also make this data available to the decision-makers, which would be classic loop-data."* The cooperation of actors outside the closed automotive ecosystems will only slowly take shape. There is still a lack of cooperation at national and European level, which would benefit both policy makers and traffic managers. "*Decision-makers, infrastructure providers and traffic management - which is often the same institution - have to join forces and network at least at European level in order to achieve a critical mass in order to represent the interests of data intermediaries, who currently have a very high power."*

In summary, from expert 3's view point, the main actors for the design of data-driven services are data intermediaries (10 relationships), road users (7 relationships), traffic management (4 relationships) and infrastructure providers (4 relationships). Among decision makers, traffic management, road operator and traffic planning, four actors have been identified who are related to or usually funded by national authorities reflecting the research background of the expert.

### 4.3. Summary of the individual design processes of the remaining experts

This sub-section summarises the results of the individual design activities of the remaining experts. Since their sketches are space-consuming, we present only the sketches of the experts No. 5 and 6. We are aware that each expert argues from his or her own perspective, also depending on the organization in which the expert is employed, so there are discrepancies in the interview statements. The aim of the empirical data collection, however, was to gain an overview as complete as possible of the actors and data exchange relationships.

*Expert 1* was responsible for a metadata service to access vehicle sensor data and identified the vehicle (driver) as the main actor transmitting generated vehicle data via a telecommunication provider to either the OEM, a private- or a public data platform provider. A metadata provider, an actor in which he is personally involved, could provide the interface to a service provider or road operator to search and automate access to vehicle data.

*Expert 2* understands the ecosystem as a network of relationships between actors around a data marketplace. Data collection is mentioned several times and seems to be an unresolved problem, as expert 2 is uncertain who is currently deciding on data sharing: The expert assumes that data could be shared with a service provider without the knowledge of vehicle users. A total of 11 actors were included in the ecosystem sketch, 10 of which were connected with data sharing relationships. The eleventh actor, the vehicle user, "*does not receive any data, but actually only the services*". Main actors are OEM (7 links), vehicle owner (5 links), service provider (3 links), vehicle (3 links) and data marketplace (3 links).

*Expert 4* was involved in several large-scale projects with vehicle manufacturers, mentions six actors and adds that there are literally data sharing relationships between them all. The expert adds that a user can generally pay for services either "*with data or with money*". Furthermore, the expert argues that the data marketplace will be a "*closed platform [of OEMs]*", as the "*access to useful vehicle data is too critical to be open*",

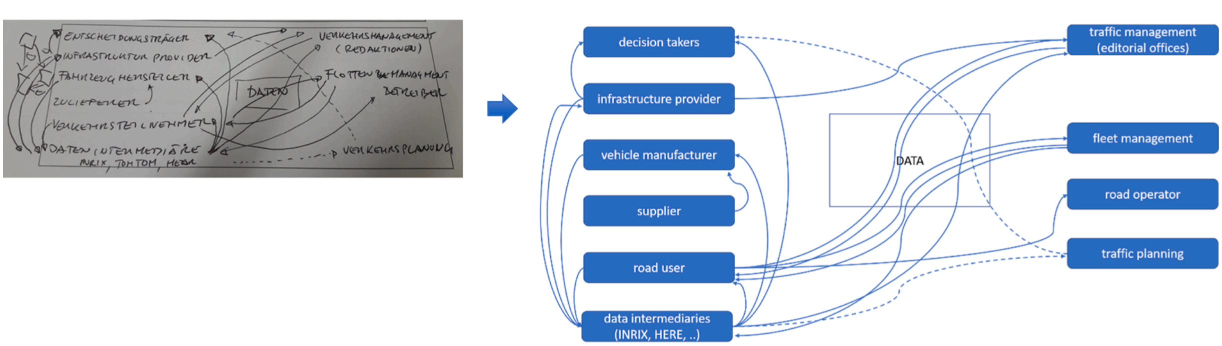


**Fig. 2.** Expert 3 hand drawing and digitized vehicle data-driven service sketch.

meaning that the information could be exploited to launch a cyber-attack on vehicles.

*Expert 5* (cf. Fig. 3) is a senior manager of a vehicle service provider, designs an in-depth model and presents the vehicle as a central actor that passes on vehicle data to seven actors. The expert mentions an external influence through national and European regulations to positively influence OEMs to provide access to vehicle data for innovative service developments of other actors. The expert concluded by saying that "*trust is the key to the whole ecosystem*".

*Expert 6* (cf. Fig. 3) sketches a data value chain from the vehicle driver via a data enricher, to a service provider who provides a service to the OEM, who in turn provides a service to any service user such as workshops, statistic services, enablers such as data marketplaces, insurance companies, or public authorities.

*Expert 7* is involved in the development of a data marketplace and has sketched a data flow from the OEMs to a data market provider that makes the data available to potential buyers and service developers. The expert describes "*while* the *OEM servers will host the data, the data markets will only do the contracting and data access and will be able to mesh data [from different data providers]*" and predicts that "*data markets will succeed and take hold [in the ecosystem]. Many of them are just beginning, and some successful ones will survive*".

*Expert 8* is a consultant who sketches the model based on his own experiences in developing data-driven services with SMEs and public authorities. The main actor is "data", which can be interpreted as a data platform or portal, but automotive (as data supplier) and infrastructure providers (who receive data from three other actors) play an important role, too. The actor 'automotive' (a synonym for car/vehicle manufacturers) "*also retrieves the data for own services, which is probably the main application for car manufacturers*". Service providers, IT infrastructure providers and academic research are all relevant players in service provision, with access to the data remaining the key element.

*Expert 9* is the managing director of an automotive company and did not sketch direct data-sharing relationships but mentioned eleven actors. He sees OEMs in a stronger position, which is suggested by the statement that "*start-ups will disappear when larger players [such as OEMs] enter the [service] market*". He doubts that external players will enter the value chain between the data source and the data enricher, because "*data should not simply be passed on to external parties, [..], CAN data must be interpreted correctly*". He argues that "*the balance of power between technology companies vs. OEMs vs. public authorities will be crucial [for the future of the data-driven service ecosystem], and a balanced situation would be best*" for all stakeholders.

*Expert 10*, who is employed by a service provider, mentioned eight ecosystem actors. Vehicle data flows logically through the gateway provided by a gateway provider to a data platform provided by a hosting provider, to a service provider, and then to customers and fleet operators. The expert mentioned several data-sharing relationships during the interview but did not sketch them explicitly. The expert also mentioned the EU as an external influencing factor.

*Expert 11* is head of service development at a vehicle manufacturer and outlined three different actors in two different scenarios depicting the dominant role of vehicle manufacturers in the ecosystem. In the first scenario, where a customer uses a service from the OEM, the vehicle user allows data access, "*the consumer has the right to say no*", and pays the OEM for the service, which provides the technical infrastructure such as the mobile connection installed in the vehicle. The OEM in turn provides vehicle data to a contractually bound service provider and provides the vehicle user with the developed service. In the second scenario, the vehicle user buys a service from a third-party service provider and thus grants the service provider access to vehicle data. Due to strict European data protection legislation the vehicle user can "*already decide, which parties can be granted access to the data*". The service provider, in turn, uses the OEM's technical infrastructure, such as the mobile connection installed in the vehicle, and pays the OEM for its use, which the expert underlines by the statement that "*vehicles are equipped with more expensive technology to enable data sharing*".

The statements made by the eleven experts clearly show the influence of their own work on the designation of key actors and data sharing relationships. Experts working in the classic automotive industry (e.g. experts 9, 10 and 11) see the vehicle manufacturer in a dominant role in the data-driven service ecosystem, while scientific actors and those working in service development take a more differentiated view on the ecosystem.

## 5. A conceptual model for value creation in vehicle data-driven services

### 5.1. Design process

We have used two data sources, interview statements and expert sketches, to derive key actors and their data sharing relationships. We carefully examined the transcribed interviews and the individual conceptual models sketched by experts and extracted terms that had been used to describe the different actors. We ended up with a list of 90 terms, some of which were mentioned more than once, and were finally able to identify 64 different actors. As experts tend to use different terms, levels and descriptions for the same type of actors (e.g. 'OEM', 'automotive manufacturer', and 'vehicle manufacturer') we have renamed some actors in order to create a consistent terminology for our conceptual model. Another challenge was the distinction between specific actors, such as cloud service providers, and providers of data-driven services to end-users. As a result, one group of actors was referred to as 'provider of cloud computing services', while another one was referred to as 'provider of data-driven services. We then categorised individual actors into groups and placed terms such as 'AI provider', 'cloud provider', and

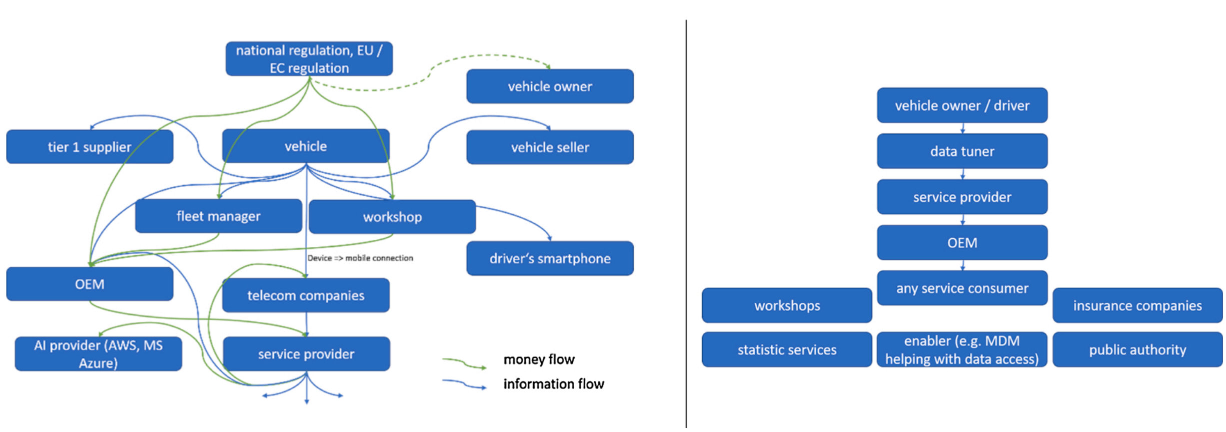


**Fig. 3.** Digitized vehicle data-driven service sketches of experts 5 (left) and 6 (right).

'database provider' into the actor group 'platform provider'. After the ninth expert interview, it became apparent that no previously unknown actors were named by the experts who could not be classified into the actor groups described below. Following the principle of theoretical saturation (Saunders et al., 2018), we therefore judged our sample to be complete. As a result, the cleaned set included 25 actor groups. In order to make the actor groups more tangible for our model design, we identified the six highest ranked actors named by the experts and classified them into groups (Table 3).

We built our first conceptual model on the expert interview statements and their model sketches. We thereby carefully examined transcribed interviews and their sketched models and extracted terms (actors, actor roles, types of data sharing relationships) to create a consistent terminology for the conceptual model (cf. Table 3). We then designed the first conceptual model of a unified model using only the main actor groups from the consolidated actor group list and upon the reviewed literature, thus establishing proof-of-concept (Nunamaker, Briggs, Derrick, & Schwabe, 2015). In a further design step, we linked actors with data supply and data consumption activities to outline the data transformation process. The process from data supply to data use is often referred to in the scientific literature as the data value chain (Curry, 2016; Kaiser et al., 2019; Latif et al., 2009; Miller & Mork, 2013). Our first design of a conceptual model was inspired by structuring approaches that linked actors with data transformation steps (Latif et al., 2009).

After each design, we conducted an evaluation of the model that resulted in a model revision, either in a change in model actors, a change in data-sharing relationships, or a change in both, while the general structural design of the model remained unchanged. We carried out a total of six such iterations of the model in order to evaluate it against the individual views of the engaged automotive experts and against several real-life use cases of value creation in data-driven services. In doing so, we follow the suggestions of design researchers such as Gregor and Hevner (2013) to use case studies as a technique for conceptual model evaluation. With regard to Sonnenberg and vom Brocke (2011) and Venable, Pries-Heje, and Baskerville (2016), our evaluation can be seen as an ex-post evaluation, while we referred to the evaluation criteria model completeness, fidelity with real-world phenomena, internal consistency, level of detail and robustness as published by March and Smith (1995). In our ex-post evaluations, we also demonstrated the usefulness of the model to describe value creation in data-driven services, establishing proof of value (Nunamaker et al., 2015).

Using our designed conceptual model to describe value creation referring to concrete vehicle-data driven services led to several improvements of the model. We have already included the vehicle user as an essential element in the first conceptual model. However, as we found that many vehicle data-driven services are not enabled by vehicle data alone, but also use contextual data such as weather data or aggregated traffic data that obviously cannot be provided by the vehicle user alone, we added the actor role 'contextual data provider' in a second design iteration to the model to refer to actors providing other data as part of the value creation process. Furthermore, we have learned from several cases that the main beneficiary of vehicle-data driven services can be the vehicle user, e.g. by offering services such as intelligent parking while driving. However, vehicle data can also lead to services whose beneficiaries go beyond the vehicle user, e.g. by providing a dynamic map of traffic density to urban traffic managers. Hence, we have added the actor role 'other consumers' in a third iteration of our model. For space reasons, we will only show the final evaluation of our model with an exemplary real-life application case in Section 6 of our paper.

**Table 3**
Top ranked actors (left) and actor groups (right).

| Top ranked actors from expert interviews (N = 64) | Quantity |
|---|---|
| OEM | 7 |
| Service provider | 6 |
| Infrastructure provider | 3 |
| Public authority | 3 |
| Road operator | 3 |
| Vehicle | 3 |
| [58 further actors] | 1–2 |
| **Top ranked actor groups (N = 25)** | **Quantity** |
| Vehicle manufacturer | 10 |
| Data marketplace | 9 |
| Vehicle data service provider | 9 |
| Vehicle user | 7 |
| Consumer | 6 |
| Platform provider | 5 |
| [19 further actor groups] | 1–4 |

### 5.2. Conceptual model description

The presented conceptual model is a result of iteratively designing a conceptual model. In our design process, we performed six iterations of the model, to evaluate it against the views of the interviewed automotive experts and against several real-life application cases of value creation in data-driven services. Existing theory on value of data-driven services (cf. Section 3.1) and data-driven value chains (e.g. Curry, 2016; Faroukhi et al., 2020; Latif et al., 2009) was used as theoretical input within this design phase. Our structural design of the model was informed by Latif et al. (2009), referring to entities that can act as ecosystem roles connected by data sharing relationships, i.e. consuming or providing data. Fig. 4 shows the metamodel of our conceptual model. It outlines that each participating entity (i.e. organisations or persons) can act in one or more actor roles, thereby either providing data to the data-driven value creation process, consuming value-added data, or doing both (if more than one role is taken by the same ecosystem entity).

Participating entities can be individuals, organisations or organisational units that can take on one or more of the following actor roles: vehicle users as primary data providers, contextual data providers offering additional data for service design, vehicle manufacturers that can exploit access to vehicle sensors, gateway providers collecting vehicle data with their own equipment, data marketplace or portal providers allowing access to data via their application programming interfaces (APIs), data-driven service providers, and finally vehicle users as well as other consumers. We will now take a closer look into these ecosystem actor roles and illustrate their data sharing relationships.

A *vehicle user* is a professional or private actor that decides to provide *vehicle data* (i.e. data generated while vehicle operation by sensors and electronic control units) to be used in data-driven services in any format and in any level of aggregation to the related *vehicle manufacturer* directly, or to other actors via a *gateway provider* indirectly. Vehicle users must give their consent to the sharing of vehicle data to other ecosystem actors.

A *contextual data provider* is any organisation that has additional contextual data that is relevant to the provision of data-driven services and is willing to share this data for service development. Examples of contextual data providers are companies that can provide geodata, weather data, traffic data or map data, but also governmental actors that publish open data.

A *vehicle manufacturer* is an actor that develops, manufactures, and maintains vehicles as its main industrial product. Vehicle manufacturers have equipped vehicles with advanced sensors that collect and process a wealth of data to ensure the driving function, optimize the vehicle's internal functions and facilitate safety. Most vehicle manufacturers have equipped their latest vehicles already with telematics software and connectivity to allow use of the data generated in data-driven services. Various types of vehicle dynamics data such as vehicle speed, acceleration, rotation, position as well as other data such as information on fuel, battery, service, and window status, wheel rotation, or steering wheel angle can be provided at different sampling rates.

A *gateway provider* is an actor that collects either raw or processed

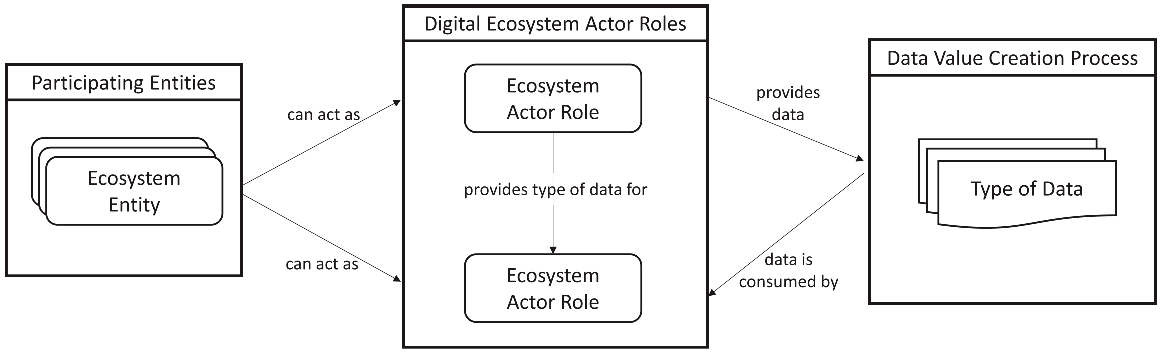


**Fig. 4.** Metamodel of our conceptual model: Participating entities, digital ecosystem actor roles and types of data in the data-driven value creation process.

vehicle data or other contextual data such as weather data or map data for the development of data-driven services. Gateway providers may collect vehicle data through deploying a data capturing device connected to the vehicle's on-board diagnostics interface (OBD), to the controller area network bus (CAN), or through the use of a dedicated independent sensor and connectivity device. Besides, vehicle dynamics data can also be collected by the gateway provider using a special sensor kit that is not connected to the vehicle's bus systems or a mobile application installed on a smartphone which captures data from smartphone sensors while the vehicle is moving.

A *data marketplace, platform or portal provider* is an actor that receives data from various vehicle manufacturers, contextual data providers, and/or gateway providers and performs data harmonisation, transformation, and storage activities, either with the distinct purpose of selling service-specific vehicle data and/or service-relevant data from third parties (*marketplace, platform*) to enable the development of data-driven services, or to provide such data for free (*portal*). Data market place providers may provide data to the developers of data-driven services who only need to integrate once via their APIs, instead of having to enter into many different relationships with OEMs and other data suppliers, while at the same time having to deal with diverse (and changing) data formats.

A *provider of data-driven services* is an actor that consumes service-specific (vehicle) data from a data marketplace or data portal provider and provides consumable service data to a service user, which in turn may be either a vehicle user or another consumer, i.e. any other type of end-user or organisation wishing to consume a data-driven service enabled by vehicle data and probably enriched with other contextual relevant data. Vehicle data service providers ultimately offer data-driven services, such as road surface quality detection, harsh driving detection, or predictive maintenance.

Finally, both *vehicle users* and *other consumers* may be consumers of data-driven services offered by data-driven service providers. As the final actor in the data-driven value chain, these professional or private actors are end users and main beneficiaries of the entire data transformation process. Examples of data-driven services are road surface quality detection (consumed by municipalities or a road infrastructure managers) or harsh driving detection (consumed drivers to improve their driving style or by insurance companies to provide a 'pay as you drive' insurance that calculates the insurance premium based on the driving style).

Actors provide and consume different types of data within the data value creation process. First, in order to comply with data protection regulations such as the General Data Protection Regulation (GDPR) in Europe, vehicle users should grant access to the data their vehicle generates before *vehicle data* may be used in services. *Contextual data* relevant for the development of a particular data-driven service, such as weather data, traffic data or data on accident hotspots, are provided by providers of contextual data for the data value creation process. This data can be provided as *raw vehicle/contextual data* (e.g. as data that is measured and collected directly from vehicle sensors without any kind of pre-processing) or as *processed vehicle/contextual data* (i.e. including some kind of data cleaning, transformation, resampling and conversion into a data format that is better suitable for service development). Service-specific *vehicle/third party data* is provided by a data marketplace, platform or portal provider that has been transformed from raw or processed vehicle data into a form that can be used by data-driven service developers within data-driven services. Finally, *consumable service data* is provided by data-driven service developers to vehicle users and third parties within provided applications (services), creating value for the end-users.

The conceptual model, as shown in Fig. 5, outlines individual actors and their steps in vehicle data-driven value creation. The value concept we used in the model is added value for the data consumer. From the perspective of end-users, consumable service data is the most valuable data. Therefore, end users may be willing to provide monetary or non-monetary consideration for this type of data.

## 6. Evaluation

We evaluated our conceptual model (the artifact) ex-post by applying it to six *real-life cases* such as designing a *data-driven service for road surface quality detection*, to identify actors and data sharing relationships as shown in Fig. 6. After each design, we conducted an ex-post evaluation (Sonnenberg & vom Brocke, 2011; Venable et al., 2016) of the model that resulted in a model revision, either in a change of model actors, a change of data-sharing relationships, or a change of both, while the general structural design of the model remained unchanged. The presented case is the sixth and final evaluation of the model and based on real experiences of two authors working on the project mentioned in the introduction. After this last evaluation, the model remained stable.

A *data-driven service for road surface quality detection* can be envisaged by the municipality of a city, responsible for a road network (e.g. the City of Vienna with a road network of 3.000 km). The municipality operates a vehicle fleet and has an infrastructure management department which orchestrates road maintenance work. Thus the municipality acts as *vehicle user (collecting fleet operation data)* and *other consumer (consuming road surface quality data)* in this case (orange background colour in Fig. 6).

Our model indicates drivers from the municipality fleet as data creators who can opt in to deliver service-relevant data such as vehicle speed, acceleration, rotation and position. Furthermore, map data from a contextual data provider (Map provider, orange font colour) must be used for georeferencing detected road surface quality from recorded vehicle data. Vehicle data can be captured directly by vehicle manufacturers in case they already operate vehicles in this city that can capture and transmit those data, which requires special contracts with selected manufacturers. Vehicle data can also be collected via gateway providers that provide devices for installation in vehicles equipped with

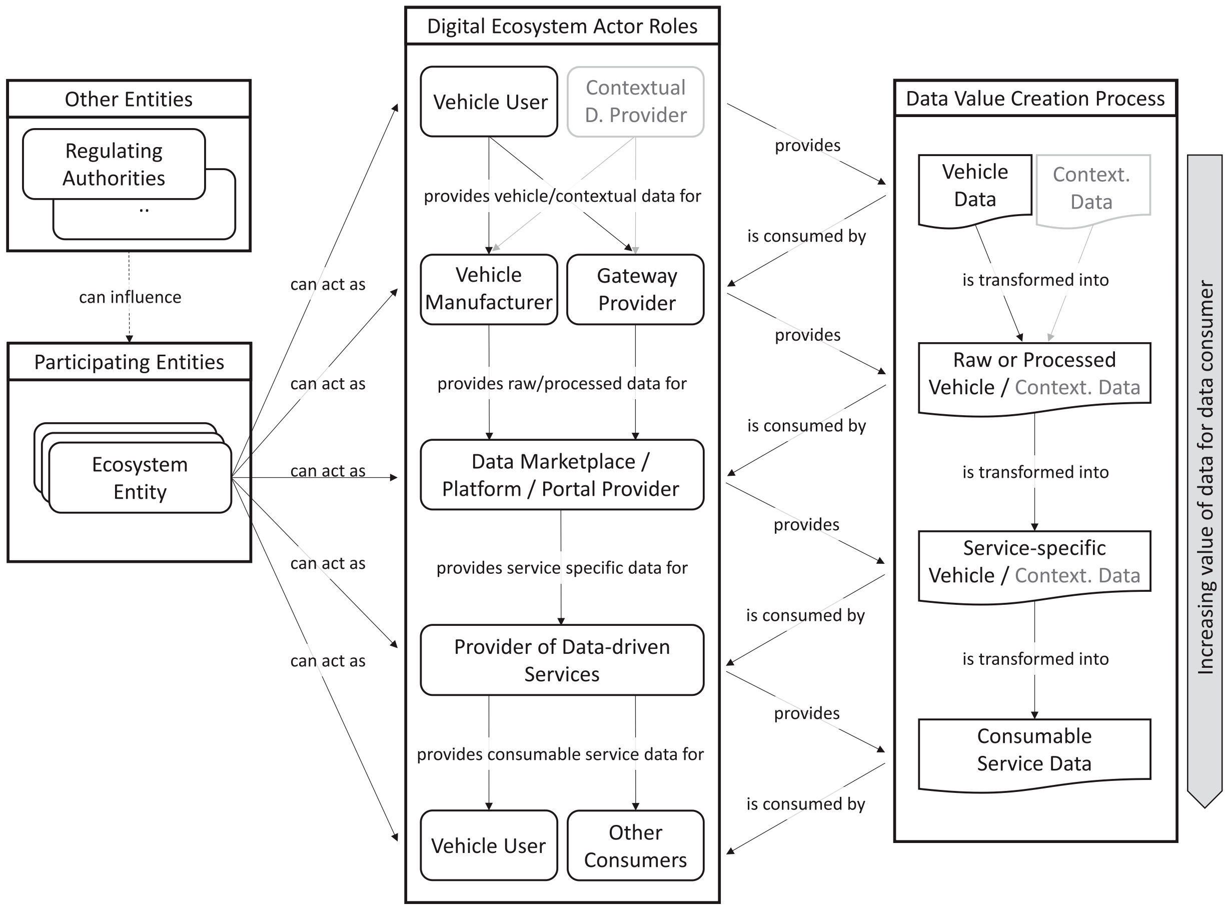


**Fig. 5.** A conceptual model for value creation in vehicle data-driven services.

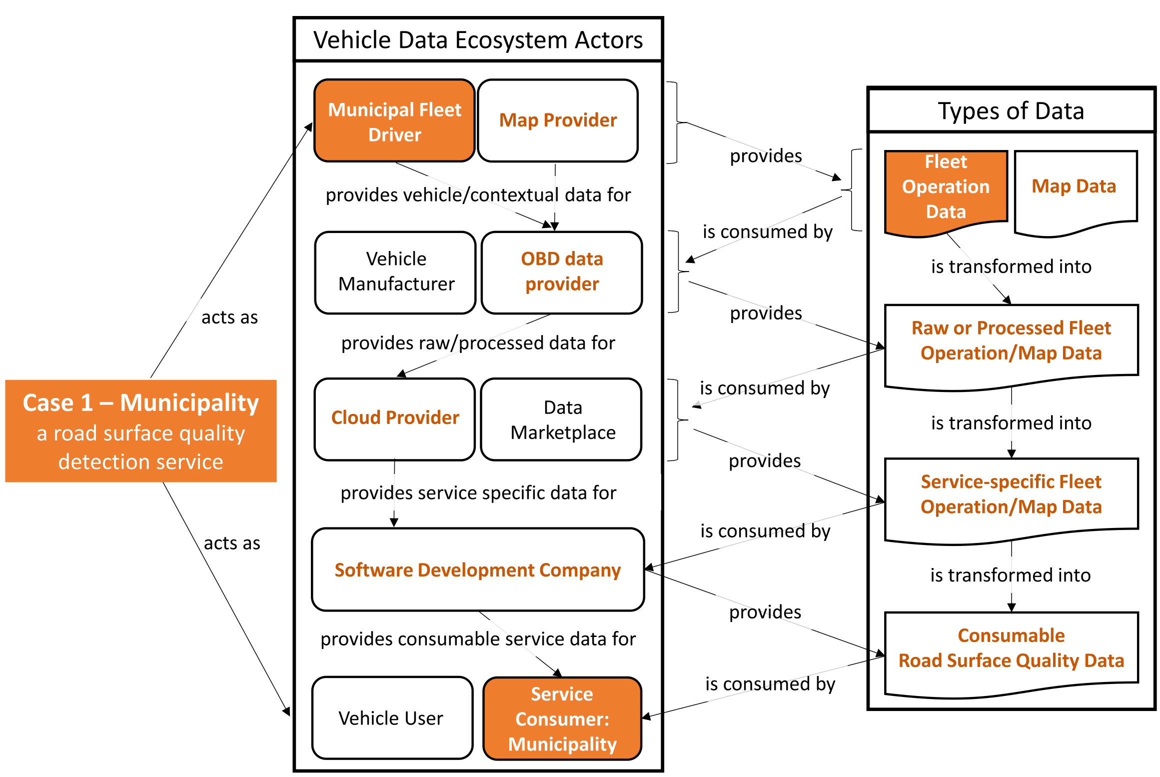


**Fig. 6.** Actors and data sharing relationships in the design of a data-driven service for road surface quality detection.

the necessary sensors, which presupposes that a sufficient number of gateways are installed in vehicles moving in the area where road surface quality is to be measured. A municipality may already operate own fleets with different vehicle brands, consisting of all employees' business vehicles. In this case, the municipality may form a business relationship with a gateway provider (OBD data provider, orange font colour) to support the data collection by equipping all vehicles in the fleet independent of their brand with gateways. Vehicle operation data being collected could be prepared for further processing and then either be made available to the provider of the data-driven service (a company in charge of developing the road surface quality detection service) by a platform/portal provider or a data marketplace ideally in combination with corresponding map data from a map provider. As the provider of the data-driven service already cooperates with the cloud provider AWS (orange font colour), AWS is also chosen as platform provider. Finally, a contracted software development company (orange font colour) is responsible for developing the road surface quality detection service and takes vehicle data and map data required for service provision, applies a data processing approach, extracts events indicating a particular road surface quality such as potholes from identified deviations of the processed vertical acceleration and pitch together with their positions (vehicle data), and visualises the geographic position of identified potholes in a web dashboard (using map data) to create value for the service consumer, the infrastructure management department of the municipality (orange background colour). In addition, the software development company prepares a table with prioritised repair lists and interaction possibilities to investigate the worsening or improvement of road surface quality for the infrastructure management department.

This real-life application case illustrates the complexity of developing a road surface quality detection service and shows the usefulness of our model for better understanding the roles of concrete ecosystem actors and their data sharing relationships in the development of a vehicle data-driven service.

## 7. Discussion

Vehicles are increasingly equipped with advanced sensors to ensure driving functionality, optimise the vehicle's functions, and facilitate safety and comfort through increased automation such as providing adaptive driving assistance systems (Stocker et al., 2017). Moreover, most vehicle manufacturers have additionally equipped their latest vehicles with advanced software and connectivity to make use of the data generated and to provide additional services to drivers. The data generated during vehicle use can enable new types of data-driven services addressing many interesting use cases (if drivers opt in to vehicle data sharing) that go far beyond supporting the operation of vehicles, especially through intelligent linking of vehicle sensor data with other contextual data such as weather data or data on the traffic situation. This raises the important question of which ecosystem actors can and will contribute to use cases that can only be implemented if data is shared between multiple actors.

### *7.1. Implications for theory*

The theoretical gap addressed in our paper is the lack of conceptual models that can unravel the underlying value chain (actors and data sharing relationships) when establishing vehicle data-driven services. In this paper, we have therefore presented a novel conceptual model that includes multiple actors and their data sharing relationships (i.e. in terms of a data value chain) that are relevant for vehicle data-driven value creation. As such, our multi-actor model shows data and information flows as a series of data sharing and data transformation steps that are needed to finally generate value and useful insights to service consumers, establishing proof-of-concept (Nunamaker et al., 2015). Following Baskerville, Baiyere, Gregor, Hevner, and Rossi (2018) we present a novel and useful conceptual model and thus generate a significant contribution. While previous research in (big) data has shown a clear focus on data users (Wiener et al., 2020), we also emphasize the importance of data providers and intermediaries and their interactions in a multi-actor model, thus extending the perspective to the ecosystem where the value creation is enacted. Consequently, we emphasize that data-driven value creation in the automotive ecosystem must be achieved through collaboration among various stakeholders, thus contributing to the debate on realizing value from (big) data (cf. Günther et al., 2017) by stressing a multi-actor perspective.

Several researchers in the field of information systems have also been engaged in the study of value creation from big data because big data is a comparatively new phenomenon and the organizational implications of big data are of great interest to them (e.g., Akter et al., 2016; Dremel et al., 2017, 2020; Grover et al., 2018; Lehrer et al., 2018; Mikalef et al., 2017; Svahn et al., 2017; Wamba et al., 2015, 2017). However, they focus on the impact of big data analytics on the level of an individual organization (e.g., on organizational performance, strategic business value, strategic use, organizational change, or required organizational capabilities) and exclude the network and ecosystem perspectives for creating data-driven services. They focus on an intra-organizational (i.e., micro) perspective, whereas we want to look at value creation in a multi-actor ecosystem (i.e., macro) perspective. While their research specifically targets the big data phenomenon, we want to emphasize that value can also be created from services enabled by the exchange of small data between actors.

Several studies investigate how vehicle usage data can lead to novel services, such as location-based services for carsharing vehicles (Wagner, Willing, Brandt, & Neumann, 2015), predictive maintenance of connected vehicles (Gerloff & Cleophas, 2017), or eco-feedback on driving behaviour (Bätz, Gimpel, Heger, & Wöhl, 2020). Yet, these studies focus rather on data analytics approaches to exploit vehicle data than on the data ecosystem perspective. Also considering the state of the art gaps discussed in previous sections, we argue that our proposed conceptual model would allow relevant actors to be identified and mapped in order to eventually achieve periods of stability and change (Nischak et al., 2017, p. 17) and the interactions that ultimately lead to the envelopment (Eisenmann, Parker, & Van Alstyne, 2011) of other emerging digital business ecosystems. Furthermore, our model indicates choices for how the value chain can evolve and, above all, which other actors are needed, because the development of a data-driven service and the selection of suitable actors is a decision-making task.

Our model shows that actors are involved in a multi-party data value creation process to ultimately provide sustainable data-driven services to service customers such as vehicle drivers and therefore contributes to a better understanding of vehicle data-driven value creation in general. Based on our interviews with experts, all of whom have a connection to vehicle data-driven value creation and some of whom are developing these vehicle data-driven services themselves, we have learned that the successful development and provision of data-driven services in the automotive domain and thus the successful monetisation of vehicle operation data will require new partnerships between individual ecosystem actors, as no actor will bear the service development risk alone. We argue that our conceptual model provides a solid understanding of the ecosystem actors and their role in data sharing and in the creation of data-driven services, thus supporting strategic decisions, e.g., in terms of partnerships and sourcing. In doing so, we are contributing to research on data monetization, responding to the call by Parvinen et al. (2020) for a better understanding of the role of data aggregators and refiners in data monetization, how they create value and how different parties can capture it.

We have developed our model empirically, drawing on the knowledge of automotive domain experts who have an average of more than 16 years of professional experience in the mobility industry. Laying emphasis on actors that have a stake in data generation and sharing, we differ methodically from the approaches of other researchers who study ecosystems in the mobility domain, including Riasanow et al. (2017)

using crunchbase.com data to visualise the current automotive ecosystem in a generic value network, Remane et al. (2016) focusing on the identification of business model types of start-ups, or Kolbe et al. (2017) creating an IoT framework and focusing on semantic interoperability.

Our background is in the field of data-driven service development in the automotive domain, and we stress that our conceptual model is inspired by research on data-driven value creation published by Curry (2016), Miller and Mork (2013), or Latif et al. (2009). Our concept of connecting automotive ecosystem actors with data sharing and enrichment processes is new. We understand our model as a descriptive tool that shows the process towards providing a data-driven service from both an actor and a data perspective. Furthermore, we believe that our presented research is also helpful in better describing and classifying existing data-driven services. Our model can support ecosystem actors to better recognise and understand their interdependencies with other actors or even to understand what interdependencies exist at all.

It is worth mentioning that actors within the ecosystem for vehicle data-driven value creation are different from the classical actors within the vehicle supply chain. For instance, although vehicle manufacturers (OEMs) are heavily dependent on original equipment suppliers in the supply chain, these Tier-1 (module or system suppliers) and Tier-2 (component suppliers) are not specifically addressed in our model. However, they have an indirect relevance within the creation of vehicle-data driven services: First, they can supply the vehicle telematics device to the vehicle manufacturer, which enables data acquisition and data transfer to the manufacturer's backend servers. However, suppliers do not have a direct role within the process "from data to service", as they do not have direct access to the vehicle data transmitted by their supplied telematics units to the vehicle manufacturer. Second, suppliers may act as service developers providing not only hardware but also data-driven services to vehicle manufacturers. If suppliers choose to do so, they are included in the model in the actor role "Provider of data-driven services". We have deliberately avoided an actor role "supplier" in the model. For example, Tier-1 Robert Bosch GmbH not only designs vehicle telematics devices but also offers data-driven services, such as road condition-based services (Bosch, 2020a) or Connected Horizon (Bosch, 2020b). The development and provision of both services can be well described by the use of our model, and both cases served within the conceptual model evaluation process. Third, suppliers can act as users of a data-driven service, and in this case, are included in the model as "other consumers". A prominent example case is the provision of a data-driven service for ECU health, that is made available to suppliers. This service can help suppliers to monitor the functionality of ECUs they have designed and delivered to vehicle manufacturers and that are installed in the vehicle by the OEM. Suppliers can also take advantage of driving style recognition or environmental condition monitoring services that will both help them to improve their ECU designs as well.

### *7.2. Implications for practice*

In addition, we see several implications of our work for business practice. Based on a specific role of an ecosystem actor, we have shown in the evaluation that our conceptual model is useful to practitioners to better understand their own position in the ecosystem.

For example, a manager responsible for digitalisation can identify which actors are relevant to provide data-driven services. In addition, service developers may recognise the special role of a vehicle user, without whose consent to the provision of collected data the development of a data-driven service will not be possible. Vehicle manufacturers may be able to better communicate their own position in the value chain as the one who can technically store, interpret, and forward generated vehicle data. The manufacturer may recognise that a scaling provision of certain data-based services will only be possible if other actors are granted access to the vehicle's bus information systems or if the manufacturer stores, transmits and makes vehicle data available to others via its own datacentre.

Start-ups interested in producing data-driven services may realise that they can also turn to data marketplaces that have already signed contracts with vehicle manufacturers and do not need to negotiate individually with each manufacturer to access the necessary data. The provision of vehicle data to data marketplaces can also lead to new ways for vehicle manufacturers to monetise vehicle data, namely when others use it to develop services that generate value independent of their core product, the vehicle. Those who wish to design data-driven services can better identify the key players in the ecosystem they need to deal with, and those who want to be part of the service delivery process can better understand who they need to work with. Since one of the first decisions for organisations seeking to monetize vehicle data is to figure out, where to play in the value chain (Hood, Hoda, & Robinson, 2019), we consider the knowledge contained in our model to be a significant contribution.

### *7.3. Limitations*

In our concept phase, we tried to generalise the expert's individual mental models on data-driven value creation in order to eliminate individual perspectives as much as possible. Furthermore, we have involved eleven experts from Central Europe in the data collection, who also work together with specific players in the automotive ecosystem and thus contribute their own views. All interviewed experts are opinion leaders for the Central European market (the location of some of the largest vehicle manufacturers in the world), and therefore we believe that the interviewed experts represent an impressive amount of knowledge. The interviews and individual sketching activities of the experts showed that there was a consensus on many important patterns (i.e., on the roles of the actors and their data sharing relationships). This seems to show that our sample is appropriate for our research purpose. It is also worth noting that two of the authors have been working in the automotive sector for eight years each. Their contextual bias is mitigated by closely involving the other three authors in the research process in order to adopt an external and critical perspective, and by reflecting the results of the design process with them, so that "the higher-level perspective necessary for informed theorising" is maintained (Gioia et al., 2013, p. 5). Finally, we have evaluated the model in total six times ex-post by applying it to real-life cases, establishing proof-of-value (Nunamaker et al., 2015). Furthermore, we established proof-of-use by successfully applying the model in a research proposal that was granted with funding.

## 8. Conclusion

In this article we adopt an ecosystem (i.e., macro) perspective and propose a novel conceptual, multi-actor model for value creation in vehicle data-driven services consisting of ecosystem actors and their data sharing relationships, establishing proof-of-concept. We thereby illustrate how different key actors such as vehicle users, manufacturers, data marketplaces, and service providers have to engage in data sharing relationships to create value from vehicle data (i.e., data that is collected by the vehicle's sensors) and other relevant contextual data. We evaluated our model ex-post by applying it to six real-life application cases, such as the development of a vehicle data-driven service for road surface quality detection, which we also present in our paper, establishing proof-of-value.

The theoretical gap addressed in our paper is the lack of conceptual multi-actor models that can unravel the underlying value chain (actors and data sharing relationships) when establishing (vehicle) data-driven services and consider an ecosystem perspective. Many of the researchers cited have focused on the perspective of a single organization, with an emphasis on deciphering the phenomenon of big data analytics and its implications at the intra-organizational (i.e., micro) level. As our evaluation has shown the conceptual model contributes to a better understanding of the (data-driven) value creation logic and reveals critical actors and their data sharing activities that ultimately lead to created value.

While we designed our conceptual model as a high-level model to reduce the complexity of the whole automotive ecosystem and focus on vehicle data provision and use, we are aware that our model cannot represent and explain all relevant aspects, value flows and power relations. We have focused on the data value chain and have therefore only included the most important actors in terms of data sharing. Nevertheless, we see numerous practical implications as our model could be used as a governance and/or creativity tool to influence data sharing regulation (e.g., to better understand the dominant role of the OEM in enabling vehicle data-driven services) or even for the design of data-driven services outside the automotive domain. In addition, at an academic level, we see our research as a first contribution to the systematic design of a multi-actor model for vehicle data-driven value creation in the automotive sector that can help to guide next research endeavours in data-driven service development.

Finally, we expect our paper to have further implications on research such as becoming a structuring tool to design, compare and/or analyse cases of data-driven service development, or simply help future researchers to better understand potentials and pitfalls in the development of data-driven services. We even believe that the presented model is transferable to other domains where non-digital artefacts are the core product that generate data during use (such as the aircraft industry), although proving this claim would go beyond the scope of this paper. Going after this claim, however, may spur future research endeavours.

## CRediT authorship contribution statement

**Christian Kaiser:** Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization, Project administration. **Alexander Stocker:** Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision, Funding acquisition. **Gianluigi Viscusi:** Writing - original draft, Writing - review & editing. **Michael Fellmann:** Methodology, Writing - original draft, Writing - review & editing, Visualization, Supervision. **Alexander Richter:** Conceptualization, Methodology, Formal analysis, Writing - review & editing, Supervision.

## Declaration of Competing Interest

The authors report no declarations of interest.

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