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Why Even Participate? Actor Engagement in Automotive Data Ecosystems

Pepe Bellin
FAU Erlangen-Nürnberg, Germany, pepe.bellin@fau.de

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Research in Progress

Pepe Bellin[1]

[1] Friedrich-Alexander-Universität Erlangen-Nürnberg, Nürnberg, Deutschland

Abstract. Transforming vehicle data into actual value propositions remains a challenging endeavor. Consequently, there is a growing recognition in the car industry that collaboration among various stakeholders is essential to leverage value from data, leading to the emergence of automotive data ecosystems. However, it remains unclear why actors participate in these ecosystems, especially when co-creating and realizing value from vehicle data is complex and challenging. Through a multi-case study involving 12 interviews, we provide preliminary insights into why actors engage in automotive data ecosystems. We contribute to the literature by illustrating how the context influences engagement in these ecosystems. We also add to the understanding of Original Equipment Manufacturer (OEM) dispositions, further unpacking the automotive data ecosystem and its actors.

Keywords: data ecosystems, actor engagement, automotive domain, data-driven service

1 Introduction

OEMs are sitting on the "new oil"—vehicle data—yet transforming this resource into actual value propositions remains challenging (Hartmann et al. 2016; Hanelt et al. 2015). Despite being frontrunners in equipping vehicles with sensors and having access to a rich data basis, the automotive industry struggles to develop economically sustainable business models based on data (Fruhwirth et al. 2018; Sterk et al. 2022). For example, the downfall of Wejo, until now the largest car data platform, highlights the practical challenges of merely selling car data (Roth & Fontecchio 2023). This challenge of developing value propositions based on car data is possibly due to several industry characteristics. For one thing, the entire automotive industry stems from an engineering background, leading to significant knowledge gaps in data processing and analytics. Cars are still primarily considered as tangible objects of mobility, not as intangible objects of data (Bohnsack et al. 2021). For another thing, OEMs act as dominant actors and gatekeepers of vehicle data, creating substantial barriers to innovation (Bellin et al. 2024). Due to the highly competitive nature of the industry, these OEMs demand high returns on their investments and thus further complicate the development and implementation of

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profitable data-driven business models (DDBM) (Hanelt et al. 2015). As the single OEM approach is failing, there is a growing understanding in the automotive industry that various stakeholders are needed to leverage value from data (Kaiser et al. 2021). Major automotive initiatives like Catena-X (European Data Space) demonstrate, that it requires plenty of actors to generate, exchange, analyze, and sell car data. Among others, IT infrastructure companies, domain experts, and data providers are needed, to transform car data into profitable value propositions (Schroeder 2016). As a result of these collaborative multi-actor arrangements, we can observe the rise of automotive data ecosystems (e.g., Stocker et al. 2017; Heinz et al. 2022; Otto & Jarke 2019).

Business information systems (IS) scholars started to address this emerging phenomenon too. Research on automotive data ecosystems agrees that it demands various stakeholders to co-create and realize value from vehicle data (Kaiser et al. 2021; Sterk et al. 2024). For example, along the data value chain various external stakeholders exchange resources (Chen et al. 2012), but internal stakeholders like employees also need to engage to develop business models from car data (Förster et al. 2022). Hence, IS literature agrees that it requires various resources (Günther et al. 2017; Alaimo et al. 2020) and actors (Wiener et al. 2020) to develop profitable data-based value propositions (Hunke et al. 2022; Schüritz et al. 2019). However, it remains unclear why actors participate in automotive data ecosystems in the first place – especially if creating and realizing value from vehicle data is such a challenging and complex endeavor. To understand how value propositions from car data emerge, the automotive data ecosystem and its actors need to be further unpacked (Kaiser et al. 2017). Against this backdrop, we ask the following research question:

Why do actors engage in automotive data ecosystems?

To answer this question, we conducted a multi-case study with two automotive data ecosystems, comprising 12 interviews so far. To conceptually grasp the context and motives of the participating actors, we use the concept of actor engagement as a theoretical lens (Chandler & Lusch 2015). With this study, we contribute two themes, which (preliminarily) explain why actors engage in automotive data ecosystems. Our first theme covers the competition and regulatory aspects, while the second theme puts forward the role of the OEM. With our results from two case studies, we contribute to the literature by showing how the organizational context and the disposition of OEMs determine the engagement of actors in automotive ecosystems (Heinz et al. 2022).

The rest of this research-in-progress paper is structured as follows. Section 2 provides the research background on automotive data ecosystems and actor engagement. Section 3 outlines the research design. Section 4 presents the preliminary results of the study. Section 5 includes the contributions of our findings as well as limitations and next steps.

2 Research Background

Automotive Data Ecosystems. The advent of connected cars has spurred the emergence of automotive data ecosystems (e.g., Stocker et al. 2017). In such narratives, the quantified car becomes the platform for emerging data ecosystems

(e.g., Kaiser et al. 2019; Otto & Jarke 2019; Lusch & Nambisan 2015), providing soil for an entire portfolio of business models (Sterk et al. 2024). The key resource of such DDBMs—data—comes from multiple sources, both inside and outside the vehicle. Local vehicle data includes speed data or driving patterns; while contextual or vehicle-to-everything data is more heterogeneous and includes, for example, upcoming hazards, or traffic signals (Soley et al. 2018, Siegel et al. 2017). In this context, the vehicle data gives rise to a portfolio of related data-based services, ultimately leading to an entire automotive data ecosystem (Adner 2017; Jacobides et al. 2018).

We consider the data ecosystem as a socio-technical system that simultaneously represents both a business ecosystem centered on a value proposition (Adner 2017), and a platform ecosystem designing interactions between actors (Hein et al. 2020). The central actors in data ecosystems are data providers, facilitators, and users (Schroeder 2016; Wiener et al. 2020; Chen et al. 2012). Specifically for automotive data ecosystems, IS scholars have identified various stakeholders: OEMs, vehicle users, contextual data providers, regulators, service providers, technology providers, and different customer segments such as individuals or governments (e.g. Kaiser et al. 2021; Stocker et al. 2017; Sterk et al. 2022). In this regard, IS scholars agree that it requires different resources (Günther et al. 2017; Alaimo et al. 2020) and actors (Wiener et al. 2020) to jointly develop profitable value propositions based on vehicle data (Hunke et al. 2022; Schüritz et al. 2019). Thus, there is further agreement that creating and realizing value from vehicle data is a challenging and complex endeavor (Heinz et al. 2022). So, despite these challenges, why do actors engage in vehicle data ecosystems?

At first glance, one might argue that the nature of these ecosystems drives engagement: they require the interaction of multiple partners to realize a value proposition (Adner 2017; Thomas et al. 2022). Only a naive thinker would assume that it is that simple. Much research on IS development has revealed the complexity of user participation (e.g., Wang et al. 2020, He & King 2008), and studies on platform participation highlight the importance of actor types and the role of governance (e.g., users vs. complementors). In the emerging and spare literature on data ecosystems, researchers often draw on capital-inspired theories and suggest that certain conditions must be met for actors to engage and collaborate in ecosystems (e.g., Danatzis et al. 2022, Kude et al. 2012). From our brief overview, we conclude that actor engagement is a complex phenomenon that yet cannot be explained by the existing literature on data ecosystems (Heinz et al. 2022).

Actor Engagement. Knowing why actors engage is the first step to understanding value co-creation in automotive data ecosystems (e.g., Storbacka et al. 2016; Benz et al. 2021). By applying the lens of actor engagement, we take this step and ask why OEMs, suppliers, or IT providers participate despite the challenges involved. Actor engagement focuses on both external connections (context) and internal dispositions (agency) to conceptually grasp the context and motives of the participating actors (Chandler & Lusch 2015). This dual focus allows us to explore not only the external factors influencing actor participation, such as competitive pressures and regulatory environments, but also the internal motivations and psychological states that

drive actors to engage in these ecosystems (Brodie et al. 2019). The external connections, or context, of an actor, are made up of temporal connections, defined as "a repository of exchanges from the past that continually influence actors in the present time" (Chandler & Lusch 2015, p. 5), and relational connections, defined as "actors take on social roles, or sets of practices, that connect them" (Chandler & Lusch 2015, p. 5). Moreover, engagement is determined by the agency or the actor's internal dispositions. Dispositions refer to a psychological state and are linked to the actor's past, present, or future (Brodie et al. 2011).

3 Research Design

To empirically investigate actor engagement in the context of the automotive data ecosystem, a qualitative case study was chosen as a research design (Yin 2018). The approach of a qualitative case study is particularly suitable, as the complexity of an investigated phenomenon can be captured (Eisenhardt 2021). We chose a multi-case design with two automotive data ecosystems as research subjects. Based on our socio-technical interpretation of data ecosystems, we applied purposive sampling and selected two cases in the automotive industry: Dart and Amo. The Dart ecosystem, launched in 2021, aims to enhance transparency, efficiency, and sustainability in the automotive supply chain by developing a platform for sovereign data exchange. Amo is a private automotive data ecosystem that uses car, weather, and map data to develop new DDBMs for vehicles and provide services to the public sector, including authorities and contractors. While both instances function as platform and business ecosystems simultaneously, Dart primarily represents a platform ecosystem, and Amo represents a business ecosystem.

Data Collection. As part of the case studies, semi-structured interviews were conducted with actors of both ecosystems (Miles & Huberman 1994). In preparation for the semi-structured interviews, a guideline was developed based on the recommendations of King et al. (2018). The interview guide represents a synthesis of actor engagement (e.g., *What is your motivation for participating in the data ecosystem?*) and data ecosystems (e.g., *Could you please describe your previous experience with the data ecosystem?*). The guideline was adapted for each interview to consider the characteristics of the participants (King et al. 2018). All participants were provided with an information sheet on the study in advance. Based on this approach, 12 interviews were conducted between April 2023 and January 2024. The interviews had an average length of 44 minutes and ranged from 17 to 57 minutes. Information about the participants is listed in Table 1. All interviews were recorded. Researchers' notes or thoughts were put down using memos in a global research diary. The recorded interviews were transcribed and anonymized. The final transcripts served as the foundation for the data analysis.

Data Analysis. As the research of this study is still in progress, the transcripts were analyzed with precoding (Saldaña & Omasta 2016). Using the software MAXQDA, our

preliminary analysis followed this process. First, we coded the interviews based on three data ecosystem participants: Data User, Facilitator, and Provider (Schroeder 2016). For each actor type, we then applied the actor engagement framework by Chandler & Lusch (2015). This method allowed us to determine the disposition and relevant context for each participant. Finally, we grouped these codes into engagement themes where the disposition and context were aligned. Next, the preliminary results of our analysis are presented.

Table 1. Interviewees of the automotive data ecosystems Dart and Amo.

Dart			Amo		
ID	**Description**	**Role**	**ID**	**Description**	**Role**
D1	Car Manufacturer #1	Project Manager	A1	Car Manufacturer #2	Product Manager
D2	Supplier #1	Project Manager	A2	IT Provider #3	Product Manager
D3	Supplier #2	Project Manager	A3	IT Provider #3	Head
D4	Supplier #3	Head	A4	IT Provider #3	Presales Consultant
D5	IT Provider #1	Sales Manager	A5	Business Customer #1	Head
D6	IT Provider #2	IT Architect	A6	Public Customer #2	Coordinator

4 Preliminary Results

Theme 1: A Challenge called GAFAM. The GAFAM companies (Google, Amazon, Facebook, Alphabet, and Microsoft) are seen as major rivals in the automotive industry. In both ecosystems, US competitors are perceived as dominating the data business landscape. Many automotive companies already use infrastructure from the GAFAM companies, and thus have a temporal connection, which they interpret as a threat: „We have a real problem with the hyperscalers. We create dependencies, which no one wants to have" (D5). Hence in this theme, the actor engagement is mainly driven by a context with a competitive nature. But also policymakers and their activities can be placed in the contextual realm. For example, a participant in the Amo ecosystem highlights the importance of current EU regulations and thus legitimizes the participation in the data ecosystem: „But the EU in particular, with its Data Act, has now recognized that an enormously useful and profitable ecosystem could emerge here" (A3). Even further, the public sector sponsors automotive data ecosystems: „We had the government funding beforehand, which was good, then you have a certain intrinsic motivation" (D2). Besides the context consisting of regulators and US rivals, the actors are also inspired by the success of the GAFAM companies. There is a strong wish to replicate this success in the automotive sector. However, the OEMs fear losing their current powerful position in the industry to their US rivals, which know from experience how to dominate such data ecosystems: "And once someone owns the platform, they won't let go of it. And these giants won't do that anytime soon. They know exactly where the treasure lies and how to turn it into money" (A3).

Theme 2: Leveraging the Quantified Car. By engaging in automotive data ecosystems, the OEM seeks to increase their profitability. However, the OEM is incapable of leveraging the car data internally but still wants to create and realize value through data-driven services: "Almost all data recipients receive raw data from us. […]

They then use this data, add their know-how or what-so-ever, but sometimes also a combination with other data points, and then create the actual product" (A1). In the past, similar constellations have proven successful for the OEM. By providing the vehicle data to external data facilitators, the car manufacturers were able to provide data-driven services to their customers and had positive market feedback. Consequently, the OEMs are mainly motivated by the hopes for future business development. Participation in automotive data ecosystems is an opportunity to develop innovations and to capture value, without having the capabilities available internally: „But essentially it boils down to the question: How can we create additional business opportunities?" (A1).

5 Contributions, Limitations, and Next Steps

Contributions. Within this research-in-progress, we conducted a multiple case study, unpacking the engagement motives of actors in two automotive data ecosystems. Our findings address the gap identified by Heinz et al. (2022), highlighting the need for more insights into actors' engagement in data ecosystem initiatives. Against this backdrop, we contribute two themes of actor engagement: First, strong competition from US companies drives actors to participate in automotive data ecosystems. Second, the opportunity to co-create and capture value based on car data is particularly significant for OEMs, who are unable to achieve this independently. Complementing the internal perspective by Förster et al. (2022), we further show that the organizational context is an equally important reason to consider for actors in automotive ecosystems, for example, if policymakers like the EU support data ecosystems (Kaiser et al. 2021). Finally, we are contributing to the understanding of the role of OEMs in automotive data ecosystems. By holding and providing vehicle data, car manufacturers act as major resource integrators (Schüritz et al. 2019; Kleinaltenkamp et al. 2012), and thus, determine the co-creation of data-driven services. OEMs need to be considered particularly in automotive data ecosystems, for example by recognizing their disposition of increasing the profitability of a car (Bellin et al. 2024).

Limitations and Next Steps. This research-in-progress has several limitations. First, the analysis of our results is still in a preliminary state (Saldaña & Omasta 2016). Consequently, the next step of our study is to analyze our data more rigorously (i.e., first analyzing the Dart and Amo cases separately, writing single case reports, and finally developing a cross-case analysis). Second, our current data collection is limited to data providers and facilitators, while data users are underrepresented (Schroeder et al. 2016). To understand the latter actor type and hence data ecosystems more fully, a second interview iteration is planned. With this approach, we hope to increase our internal validity and enable further triangulation (Yin 2018). Lastly, due to the space limit only selected results were reported. By developing our study further, we hope to expand our results section and thus provide more findings to the reader.

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