

# Actualizing Big Data Analytics Affordances: A Revelatory Case Study

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## Abstract

*Drawing on a revelatory case study, we discuss four big data analytics (BDA) actualization mechanisms: (1) enhancing, (2) constructing, (3) coordinating, and (4) integrating, which manifest in actions on three socio-technical system levels, i.e., the structure, actor, and technology levels. We investigate the actualization of four BDA affordances at an automotive manufacturing company, i.e., establishing customer-centric marketing, provisioning vehicle-data-driven services, data-driven vehicle developing, and optimizing production processes. This study makes important theoretical contributions in advancing our knowledge on how BDA value can be realized; it also has specific practical implications in that it guides practitioners in BDA adoption.*

**Keywords:** Big data analytics; affordance theory; socio-technical approach; organizational transformation; organizational benefits; affordance actualization.

## Introduction

In the digital age, data are leveraged increasingly to derive insights and make decisions. As a result, the ability to collect, store, transform, and build causal or predictive models from data (data analytics) becomes a competitive factor in many contexts, as it drives how value is created (Davenport et al. 2012; Davenport and Kudyba 2016; Dremel, Herterich, et al. 2017; McAfee and Brynjolfsson 2012). While, in the past, data were available mainly in small quantities and bound by experimental contexts, technological advancements allow the generation of digital traces in high volumes, velocities, and varieties. Against this background, the capability in terms of managing and making sense of big data has grown rapidly in importance for both society and the economy over the last several years (Galliers et al. 2017; Günther et al. 2017; Loebbecke and Picot 2015; Wulf et al. 2017). Beyond enabling data-driven decisions in marketing and customer research, big data analytics (BDA) has transformed increasingly the value propositions of product and service businesses by augmenting the functionality of physical products (Henke et al. 2016; Luckow et al. 2015; Opresnik and Taisch 2015) and affording individualized services (Lehrer et al. 2018).

The “value” of BDA, however, is highly dependent on the socio-technical context and rooted in the strategic goals of an organization (Sharma et al. 2014; Troilo et al. 2017). We consider BDA to be a socio-technical phenomenon which rests on the interplay of: (1) technology “to gather, analyze, link, and compare large data sets”, (2) analysis “to identify patterns in order to make economic, social, technical, and legal claims from large datasets”, and (3) a data-driven culture, which represents “the belief that large data sets offer a higher form of intelligence and knowledge that can generate insights that were previously impossible” (Boyd and Crawford 2012, p. 663).

While extant research indicates the importance of organizational learning in the realization of BDA value (Gupta and George 2016; Mikalef, Boura, et al. 2018), it is largely unknown which organizational actions contribute to realizing BDA value. Organizational learning characterizes an organization’s concerted efforts to enhance existing capabilities and develop novel ones (Crossan et al. 1999; March 1991). Initial scholarly evidence suggests learning broadly applies to an organization’s socio-technical system (STS) on the actor level (e.g., employee-level competencies) (Debortoli et al. 2014), the structure level (e.g., organizational structures) (Slinger and Morrison 2014), and the technology level (e.g., technological infrastructure) (Hashem et al. 2015). Further, initial evidence suggests that realizing BDA value requires the alignment of a firm’s BDA-related socio-technical entities (BDA alignment), including the alignment of strategic plans, experts, and tools (Akter et al. 2016; Ghasemaghaei et al. 2017; Wamba et al. 2017); an integrating theory which explains the constituents and outcomes of BDA alignment, however, is still missing.

In summary, in spite of a growing body of practitioner reports (e.g., Bughin et al. 2010; Henke et al. 2016; Manyika et al. 2011) and academic literature (e.g., Baesens et al. 2016; Chen et al. 2012) on selected socio-technical aspects of BDA, scholars struggle in theorizing the value realization of BDA (Baesens et al. 2016; Mikalef, Pappas, et al. 2017; Tambe 2014; Wamba et al. 2015). Thus, the existing body of knowledge on BDA is still in a nascent stage and lacking empirical evidence and theoretical foundations with which to illuminate how an organizations’ actions lead to the realization of BDA value (Günther et al. 2017).

In Information Systems (IS) research, the concept of affordances has gained momentum in terms of exploring the value of digital technology (Leonardi 2012; Robey et al. 2012; Strong et al. 2014; Volkoff and Strong 2017). Recent works have introduced the concept of affordance actualization as a means by which to explore the process of realizing the value of digital technology and analyze affordances on an organizational level (Strong et al. 2014; Volkoff and Strong 2017). Accordingly, to address the lack of a theory on the realization of BDA value, we raise the following research question:

*RQ: “How do actions which modify an organization’s socio-technical system contribute to actualizing BDA affordances?”*

We present the results of a revelatory, in-depth case study on the actualization of BDA affordances at a leading global automotive manufacturing company. The revelatory case study involved the collection and analysis of data from 31 key informant interviews triangulated with rich internal case material. Our qualitative data analysis demonstrates the organizational actions required for the process of the actualization of four affordances: (1) customer-centric marketing, (2) provisioning vehicle-data-driven services, (3) data-driven vehicle developing, and (4) optimizing production processes. Our results indicate that the actualization of BDA affordances demands four kinds of orchestrated organizational actions (i.e.,

*enhancing, coordinating, constructing, and integrating*). Our discovery of these mechanisms at the structure, the actor, and the technology levels of a company's STS extends, in particular, prior research on BDA alignment by distinguishing organizational actions of intellectual, social, and operational BDA alignment. Further, this discovery extends the current knowledge on how a company develops BDA capability by eliciting two modes of organizational learning, incremental and radical learning, on the individual level as well as the organizational level. These findings motivate and inform further research which explores different modes of BDA alignment and organizational learning in the realization of BDA value.

The remainder of the article is structured as follows. In the background section, we introduce key concepts and relate them to the extant body of knowledge. In Section 3, we present our research approach, comprising the illustration of the case context, data collection, and data analysis. Section 4 illustrates our results by presenting our identified BDA affordances briefly and detailing their actualization. In Section 5, we integrate our research findings theoretically against the background of our uncovered actualization mechanisms. Section 6 discusses the implications for theory, implications for practice, and limitations. Section 7 concludes our research study.

## Background

In the following section, we discuss the theoretical framework used to analyze the realization of BDA value. In this framework, we integrate affordance theory with STS theory. Affordance theory allows us to conceptualize the action potential which results from big data technologies on an organizational level. STS theory, in turn, enables us to frame value realization as the process of a recursive shaping of social and technical entities (Leonardi 2012; Orlikowski 2000; Orlikowski and Scott 2008). In the next subsection, we introduce our affordance theoretical lens and discuss prior literature on BDA value. In the subsequent subsection, we explain our STS-theoretic perspective on value realization and describe prior literature related to the implementation of BDA.

### ***An Affordance-Theoretic Perspective on Big Data Analytics Value***

To study the perceived value potential of BDA, we use affordance theory as our theoretic lens. In IS research, affordance theory is employed broadly to conceptualize the action possibilities which a technical artifact – in our case, big data technologies and tools – affords an actor through its materiality (i.e., constituent materials of a technical artifact) (Leonardi 2012; Robey et al. 2012).

Gibson (1986) first coined the term “affordance” as part of his research in perceptual psychology to explain the behavior of actors (e.g., animals or people) in regard to their environment. According to Gibson (1986), an actor interacts with a physical object due to its value in a specific-use context (e.g., a bed to lay down upon) rather than its qualities (e.g., a bed is horizontal, constructed out of wood, and knee-high). “What we perceive when we look at objects are their affordances, not their qualities” (Gibson 1986, p. 134). Hence, any affordance needs to be perceived before it can be actualized by an actor (Chemero 2003; Gibson 1986). Affordances are prerequisites to an action which are not required to be performed or actualized (Stoffregen 2003; Strong et al. 2014). Depending on the relationship between the actor and environment, an affordance is perceived “relative to the posture and behavior of the animal [or the actor] being considered” (Gibson 1986, pp. 127–128). In the subsequent development of affordance theory, the relational character of “affordances” was further underlined (cf. Chemero, 2003; Hutchby, 2001). Affordances stem, accordingly, from the properties of the environment and actor as well as from their relationship (Hutchby 2001) and can be seen as an emergent property of an actor-environment system (Stoffregen 2003). Affordances may change depending on the context (i.e., constraints of and the relationship between the actor and environment), though the material properties do not (Gibson 1986; Hutchby 2001; Leonardi 2012). IS scholars use affordance theory to elaborate on and investigate the consequences of IT artifact use in organizations (Majchrzak and Markus 2012; Markus and Silver 2008; Mettler and Wulf 2018) and the related organizational changes (Leonardi 2011; Volkoff and Strong 2013; Zammuto et al. 2007).

Affordances may not only be analyzed on an individual level, but also on an organizational level. Strong et al. (2014), for example, study the implementation of an electronic health records system in a multi-site

medical group and investigate the affordances which relate to group-level goals. Accordingly, Strong et al. (2014, p. 74) refer to an affordance as “an organizational affordance to the extent that the potential actions enabled are associated with achieving organizational-level immediate concrete outcomes in support of organizational level goals.” In our research, we regard affordances as organizational-level action possibilities stemming from the material properties of IS artifacts and the socio-technical characteristics of an organization as well as from their recursive interrelationships (Markus and Silver 2008; Strong et al. 2014; Zammuto et al. 2007).

From an affordance-theoretic perspective, BDA technologies and tools provide the means to process, store, and collect a vast volume of data characterized by variety, variability, and velocity (van den Broek and van Veenstra 2015; Constantiou and Kallinikos 2015; Goes 2014). These technologies enable a flexible handling of incomplete, inconsistent, ambiguous, heterogeneous, and agnostic data (Constantiou and Kallinikos 2015). On this technological basis, affordances (i.e., BDA value potential) on the *task level* emerge, such as the improvement in decision-making processes, products, and services (Davenport 2014; Markus 2015; Woerner and Wixom 2015). The actualization of BDA affordances, in turn, results in BDA value.

Prior literature on BDA value distinguishes the following value categories (Wamba et al. 2015, p. 239): “creating transparency” (e.g., Bärenfänger et al. 2014), “enabling experimentation to discover needs, expose variability, and improve performance” (e.g., Chen et al. 2017; Tiefenbacher and Olbrich 2015), “segmenting populations to customize actions” (e.g., Bughin et al. 2010; Kowalczyk and Buxmann 2014), “replacing/supporting human decision making with automated algorithms” (e.g., Markus 2015; Newell and Marabelli 2015; Woerner and Wixom 2015), and “innovating new business models, products, and services” (e.g., Constantiou and Kallinikos 2015; Duan and Cao 2015; Loebbecke and Picot 2015). Only one prior study, to the best of our knowledge, uses an affordance-theoretic perspective in order to study BDA value (Lehrer et al. 2018). Lehrer et al.’s analysis focuses on how the technological features of BDA stimulate business to consumer (B2C) service innovation and does not focus on the processes through which affordances are actualized.

Mapping the field of BDA value through extensive, systematic literature reviews, Mikalef, Pappas, et al. (2017) and Wamba et al. (2015) highlight the lack of empirical research and call for further research on the phenomenon of interest in order “to understand the mechanisms and processes through which big data can add business value to companies” (Mikalef, Pappas, et al. 2017, p. 1). Moreover, the current body of knowledge is dominated by either conceptual or technologically focused studies (Troilo et al. 2017; Wamba et al. 2015).

### ***A Socio-Technical Perspective on Big Data Analytics Value Realization***

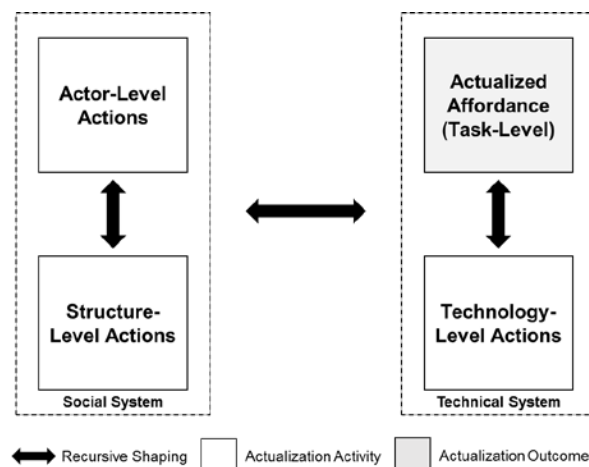
While the concept of affordance is well-established in IS research at an individual level only, the study of technology-induced organizational change requires theoretical extensions to the affordance concept which allow a description of the interdependencies between aggregated technologies and larger social collectives (Robey et al. 2013). For this reason, several researchers articulate the need for further theory which supports the study of affordance actualization at the organizational level (e.g., Bygstad et al. 2016; Volkoff and Strong 2017). For example, Volkoff and Strong (2017) acknowledge the need to build “mid-range theories of IT implementation and IT-enabled organizational change that focus on specific technologies and specific organizational goals” and call for research that “seeks to identify mechanisms for organizational change.” The actualization of affordances in organizations is influenced by several social and technical factors, such as employee expertise, organizational processes and procedures, controls, boundary-spanning approaches, and social capabilities (Zammuto et al. 2007). Thus, studying the actualization of affordances at the organizational level requires a broad recognition of the socio-technical context of an organization which may “stimulate [...] actualization in a variety of ways” (Bygstad et al. 2016, p. 87).

Against this background, Strong et al. (2014) introduce a model for the actualization of organizational affordances which includes organizational goals, the organizational context, and goal-directed actions. An extension of this actualization model considers actions, intended and unintended outcomes, as well as adjusted actions (Tim et al. 2017). While these works introduce key concepts with which to study actualization, they consider actualization activities as a unidimensional construct; they lack a granular

perspective in terms of which adjustments of the organization (which we conceptualize as a STS) influence affordance realization and thus form part of the actualization process.

In our theoretical model, we complement the affordance perspective with STS theory to distinguish actualization activities analytically by capturing which modifications of the STS affect the realization of affordances. STS theory is a well-established perspective in IS research which, still today, is employed frequently to study technology-induced organizational change (e.g., Bygstad et al. 2010; Durkin et al. 2015; Lyytinen and Newman 2008; Seidel et al. 2013). STS theory distinguishes the social system and its socio-technical entities *actors* and *structures* as well as the technical systems and its socio-technical entities *tasks* and *technologies* (Bostrom and Heinen 1977; Leavitt 1965). *Actors* are, among other things, characterized by capabilities and a shared culture, *structures* are characterized by project organizations and institutional arrangements, *technology* by tools and technological platforms, and *tasks* by the processes which are required to fulfill work or the delivery of services (Bostrom and Heinen 1977; Leavitt 1965; Lyytinen and Newman 2008).

STS are inherently dynamic; they evolve through a recursive shaping of social constructs and technical infrastructure (Orlikowski 2000; Orlikowski and Scott 2008). The organizational adoption of novel technologies entails changes in an organization's social system (e.g., new roles, modified organizational structures, and changes in cultural norms). Such modifications, in turn, enable the realization of technology affordances (Leonardi 2012). As a technical system changes, the social system adjusts "to damp out the impact of the innovation" (Keen 1981, p. 25). As a consequence, an STS is subjected continuously to incremental and punctuated changes to one or more of its socio-technical entities (Lyytinen and Newman 2008). Framing a STS as a "complex web of mutual causality" (Trist 1981, p. 13) allows us to conceptualize the process of actualization as modifications to socio-technical entities which result in realized action potentials.



**Figure 1. Affordance Actualization Model (adapted from Leavitt 1965; Bostrom and Heinen 1977; Leonardi 2012)**

Figure 1 summarizes our theoretical model. Affordances are action potentials at an STS's task level. Affordance actualization consists of a recursive shaping of socio-technical entities, which is reflected in the organizational activities related to modifying entities at the structure, actor, and technology levels. Structure-, actor-, and technology-level actions then lead to the actualized affordance at the task level.

Interpreting BDA as a socio-technical phenomenon and studying the actualization of BDA affordances through an STS lens allows us to detail the socio-technical antecedents of value realization. The current body of knowledge on BDA, according to Mikalef et al. (2017), focuses largely on the technical aspects and characteristics of big data and pays little attention to "the organizational changes they entail and how they should be leveraged strategically" (Mikalef, Pappas, et al. 2017, p. 1). Though several authors (e.g., Gupta and George 2016; Mikalef, Framnes, et al. 2017; Mikalef, Pappas, et al. 2017) adopt a dynamic capability perspective to provide first conceptual works toward the development of a "BDA capability," there is no theory on *how* organizations realize value from BDA (Günther et al. 2017). More precisely, how perceived affordances are actualized through organizational actions is unknown. Recent studies on BDA suggest that

actualizing BDA affordances involves actions which affect an organization's socio-technical entities at the *structure, actor, and technology levels*.

Because BDA poses novel structural challenges, such as the allocation of analytical knowledge and capabilities and new functional interrelationships between business units and the IT unit, an organization needs to perform *structure-level actions*; examples include the establishment of new organizational structures and work methods in order to support and grow cross-departmental collaboration (Constantiou and Kallinikos 2015; Kiron et al. 2012; Miranda et al. 2015; Porter and Heppelmann 2015). Against this backdrop, the implementation of a dedicated BDA unit is proposed in order to implement the organizational frame and acquire and develop the capabilities and knowledge with which to actualize BDA affordances (Davenport 2014; Davenport and Harris 2007; Porter and Heppelmann 2015; Sharma et al. 2014), especially when trying to monetize big data (Woerner and Wixom 2015). In addition, several authors find that the use of agile methods for data science projects, such as Scrum, Crisp, and Kanban, contributes to the success of BDA projects (e.g., Saltz, Crowston, et al. 2017; Saltz, Shamshurin, et al. 2017).

*Actor-level actions* address the development of novel employee capabilities (e.g., business acumen, and analytical and technical capabilities) and the creation of a commonly shared mind-set concerning the role of data as a critical success factor (Boyd and Crawford 2012; Cao and Duan 2014). The culture of the company, which is characterized by the beliefs and practices of the individual employees, should reflect that the use and analysis of data are critical for improving firm performance (Boyd and Crawford 2012; Cao and Duan 2014). Prior research shows the significant effects of a data-driven culture on competitive advantage (Cao and Duan 2014) as well as on a company's ability to innovate products (Duan and Cao 2015). The development of advanced employee skills in data science methodologies is an additional critical success factor, particularly for companies which digitize their business models (Ghasemaghaei et al. 2016; McAfee and Brynjolfsson 2012).

*Technology-level actions* address the implementation of BDA technology and tools, such as Hadoop clusters or in-memory databases (Hashem et al. 2015). Organizations are confronted with an unprecedented *volume* of data, and key benefits arise from large-scale integration and processing (Gölzer et al. 2015; Marton et al. 2013). An important source of value lies in the exploitation of previously unused data sources, such as text or log data, which has, in some cases, been considered as noise or garbage in the past (Marton et al. 2013; Yoo 2015). As a consequence, the processing of big data necessitates the use of new data base structures, such as HBase, to leverage new data file systems, such as the Hadoop Distributed File System and Google File System, as well as the dynamic allocation of computational resources through solutions such as YARN (Hashem et al. 2015). To this end, new computational approaches to the analysis of data (e.g., machine learning and neural networks) as well as the process of data acquisition (e.g., connection of new data sources through data loggers) are a prerequisite (Yoo 2015). In summary, technology-level actions enable the realization of BDA value through better insights from different, diverse, and new data sources (e.g., social media, wearables, and radio-frequency identification (RFID)) and computational approaches which uncover patterns, correlations, or other previously unknown information pertaining to this data (Duan and Cao 2015).

Summarizing the above aspects, socio-technical entities, among others, are related to data-oriented culture, practices, technologies, and analytical processes (i.e., accessing, examining, aggregating, and analyzing evidence) which need to be adapted in order to actualize BDA affordances (Dremel, Overhage, et al. 2017; Holsapple et al. 2014). The design of the actualization process which consists of STS modifications and how this process links to realizing business value are largely unexplored (Constantiou and Kallinikos 2015; Davenport 2014; George et al. 2014; Günther et al. 2017; Mikalef, Pappas, et al. 2017). The realization of BDA value is by no means assured, and the complex nature of organizational designs challenges the effective use of BDA (Chen et al. 2015; Kowalczyk and Buxmann 2015; Mikalef, Pappas, et al. 2017).

Therefore, there are calls for further research on: (1) "enterprise-wide BDA [...] that maximizes the potential for competitive advantage in different types of industries and for different organizational cultures and governance archetypes" (Abbasi et al. 2016, pp. XX–XXI) and (2) on "the processes and structures necessary to orchestrate [...] resources into a firm-wide capability" (Mikalef, Pappas, et al. 2017, p. 23). In particular, empirical studies on BDA are scarce. Therefore, Günther et al. (2017, p. 192) calls for empirical studies to develop "theories on big data value realization."

Thus, with our research, we pursue the objectives: (1) to theorize on the socio-technical modifications which constitute the actualization of BDA affordances and (2) to explore the interrelationships between actualization activities and BDA affordances.

## Research Design and Method

By drawing on the aforementioned theoretical foundations, this work aims to investigate how affordances related to the BDA phenomenon are actualized in the context of an automotive manufacturing company. We chose an inductive qualitative research design due to: (1) the novelty of the topic and (2) the lack of prior research on BDA and resulting affordances (Eisenhardt 1989; Myers 1997; Sarker 2013; Yin 2008). Specifically, we conducted an in-depth case study of one of the largest automotive corporations worldwide (*AutomotiveGroup*). We chose the automotive industry because harnessing BDA is pivotal to this industry (Deloitte 2015; Luckow et al. 2015; SAS Institute Inc. 2015). Acknowledging the paucity of in-depth empirical work on the actualization of BDA affordances (Günther et al. 2017), we elaborate on the actualization of BDA affordances at *AutomotiveGroup* in a revelatory single case study (Yin 2008). In line with Yin (2008), we opted for a revelatory case study design for two reasons. First, the phenomenon of interest has been inaccessible to previous investigators due to its novelty and due to investigators' limited accessibility to large organizations. Second, the insights can potentially help to better explain the research phenomenon of a company's actualizing BDA affordances.

Table 1 provides an overview of our overall research approach. In what follows, we go into details regarding the case context, data collection, and data analysis.

Methodological Consideration		Illustration
Data Collection		
Selection of Case	The revelatory case was selected based on the ability to study the phenomenon of interest in a real-world-setting with high strategic relevance.	The case organization in the automotive industry represents one of the largest players. Harnessing BDA and driving the corresponding change is reflected in the organization's vision.
Choice of interviewees	Snowball sampling (Myers and Newman 2007) was used to obtain an adequate set of interviewees.	We stopped adding additional interviewees when saturation of a specific perspective was reached.
Conduct of the interviews	A semi-structured interview guideline was developed based on the recommendations of Schultze and Avital (2011).	Interviews were conducted in two rounds. An explorative, open first round allowed us to gather rich information on the overall context and goals of the organization. A more focused second round, targeting mainly affordance actualization, was conducted to obtain additional insights on the actualizations of specific affordances.
Inclusion of multiple data sources	Our findings are rooted in a rich set of data sources, taking into account contextual information and allowing us to capture the complexity of the phenomenon of interest from various perspectives.	Mainly internal documents such as strategic working papers, presentations, and memos were used for triangulation purposes. Besides, publicly available documents were considered.
Validity and/or reliability considerations	To limit bias, we considered various perspectives on the phenomenon of interest by recruiting a broad set of interviewees. The integrity of our data was ensured by working exclusively with recorded and transcribed interviews.	In the interviews, additional questions were asked when a good understanding of the points being made by the interviewees was needed.

Data Analysis		
Data triangulation	182 additional documents were reviewed to triangulate findings derived from interviews.	When condensing insights from the data, we made sure that we looked for converging evidence between multiple sources.
Validity and/or reliability considerations	Throughout the process of analyzing the data, we were aware that interview statements could be subject to the personal biases of interviewees related to their roles and responsibilities.	We were careful with regard to the statements of interviewees. For instance, interviewees in business functions tended to underestimate the required technological implementation efforts.

**Table 1. Research Approach with Illustrations (structure based on Tim et al. 2017)**

### Case Context

BDA can be regarded as the key underlying technology which fuels trends in the automotive industry, such as connectivity, autonomous driving, and car sharing (Deloitte 2015; Luckow et al. 2015; SAS Institute Inc. 2015). In order to be innovative in terms of products and business models, the automotive industry has to master the most dramatic shift in years and draw on BDA to face the challenges of digitization (Dremel, Herterich, et al. 2017; Gissler et al. 2016). Accordingly, organizations in the automotive sector rely heavily on BDA to achieve customer and service orientation (Mocker and Fonstad 2017; SAS Institute Inc. 2015). In this regard, BDA provides the foundation for developing new vehicle-data-driven services and business models (Gissler et al. 2016; Henke et al. 2016; McKinsey & Company 2014; SAS Institute Inc. 2015). As a consequence, the effective actualization of BDA affordances has a strategic impact on the competitive edge of automotive organizations (Deloitte 2015; Luckow et al. 2015). One interviewee described how BDA relates to the growing importance of digitization in the automotive industry as follows:

*“All topics which we take care of through analytics are enablers of better functions for the customer or result in product optimization and, hopefully, a big cost reduction to aid our product development process [...] Moreover, look to other industries that successfully changed their business models and how they work today: Pretty much every successful business model which somehow tries to be [a] digital [business model] uses data as its energy source. That is what we are trying to achieve.” Interviewee A2*

In consequence, the automotive industry being an industry which is affected heavily by data analytics and digital technology (Deloitte 2015; Dremel, Wulf, et al. 2017; Mocker and Fonstad 2017), it serves as an adequate context in which to study the actualization of BDA affordances (i.e., value realization of BDA).

In the course of a research initiative which was kicked off in 2015 with *AutomotiveGroup*, which represents one of the largest multinational automotive manufacturing companies in terms of global sales and market share, we obtained in-depth insights into BDA actualization. *AutomotiveGroup* comprises seven suborganizations which target distinct customer segments ranging from premium sports cars to affordable compact cars: *LuxCar*, *PremiumCar*, *MediumCar*, *MobilityServiceCo*, *TrucksCo*, *CarCo*, and *CommodityCar*. *LuxCar* is a car manufacturer specializing in producing high-performance sports cars, SUVs, and sedans for the luxury segment. *LuxCar* has approximately 25,000 employees world-wide, making an annual net income of approximately USD 2.3 billion. *PremiumCar*, targeting customers in the premium segment, is known for its technological advancement and produces approximately 2 million cars a year while making an annual net income of approximately USD 4.6 billion and employing around 90,000 people world-wide. Moreover, *PremiumCar* serves as the digital innovation leader within the *AutomotiveGroup*. *MediumCar*, which targets the mass market, earns around USD 2.0 billion per year while producing approximately 6 million cars a year with approximately 600,000 employees world-wide. *CommodityCar* employs around 14,000 employees and has an annual output of approximately 400,000 cars per year for a USD 0.1 billion net income. *CarCo* produces approximately 1 million cars a year with its 30,000 employees world-wide while accumulating a profit of USD 0.12 billion per year. *TrucksCo* manufactures high-class trucks and buses for commercial purposes with the help of its 50,000 employees, achieving a profit of USD 0.6 billion per year. Lastly, *MobilityService* acts as one of the biggest mobility and



financial service providers in Europe with its 11,000 employees in order to make a USD 1.8 million profit every year.

### **Data Collection**

In order to obtain in-depth qualitative data, exploratory interviews served as primary source and were conducted with managers at *AutomotiveGroup*. Specifically, because the focus of our investigation lies in the actualization of BDA affordances, we selected managers and senior executives responsible for BDA within *AutomotiveGroup* for the interviews (see Table A1 in Appendix A). Interviews were conducted in two rounds. The objective of the first interview round was to explore BDA affordances broadly and gain an understanding of the affordances and their socio-technical contexts. Thus, the first round of interviews had a rather explorative character and included representatives of *AutomotiveGroup*'s seven suborganizations. Interview partners were selected in such a manner as to gather contextual information and cover a broad variety of roles and responsibilities with regards to BDA. The second interview round, which focused on deriving insights into affordance actualization, zeroed in on *AutomotiveGroup*'s suborganization *PremiumCar* for two main reasons. First, in the initial interview round, we learned that *PremiumCar* acts as the innovation leader in the *AutomotiveGroup*. Even though other suborganizations perceived similar action potentials with regard to BDA, they did not start the actualization of the perceived affordances. *PremiumCar* was the only suborganization which tackled broadly the actions required to realize the value related to BDA. Second, because the actualization activities for different affordances are complex and interrelated, our focus on *PremiumCar* allowed us to study actualization activities with sufficient depth. Prior to conducting the interviews, an interview guideline was developed following the work of Schultze and Avital (2011) (see Appendix A). Based on the respective knowledge of the interviewees and the interview context, additional questions were asked. In particular, we conducted 31 interviews within *AutomotiveGroup*. Table A1 in Appendix A provides an overview on the two interview rounds which highlights the interviewees' roles. Interviews were conducted by two senior researchers and lasted between 25 and 108 minutes. They were transcribed based on audio recordings, resulting in 410 pages of text. In addition to the interviews, internal documents and publicly available data (182 documents in total) were used to corroborate findings.

### **Data Analysis**

To analyze the gathered case data, we follow the well-established recommendations of Straus and Corbin (1990). Specifically, we pursued a step-wise coding which consisted of open, axial, and selective coding in order to elaborate on the actualization of affordances and their required organizational actions and actualized outcomes.

In the open-coding stage, codes emerged through case write-ups and summaries which were used to condense the transcripts and obtain an initial overview of all case data (Yin 2008). Codes were initially developed inductively due to the novelty of the topic. In the axial coding stage, we condensed the data based on the dimensions of the affordance and STS theories (see Figure 1). Along the dimensions of *technology* and *task*, we identified relevant aspects of the technical system. Our analysis regarding the social system was structured along the *actor* characteristics and *structural* aspects of the organization. We aggregated emerging codes to identify reoccurring themes. Selective coding allowed us to finally sharpen our focus on the relations between the identified concepts. Specifically, we identified organizational actions which related to affordance-specific socio-technical modifications on the structure, actor, and technology levels. During coding, we continuously corroborated the detailed insights derived from analyzing the interviews by constantly comparing and triangulating these insights with the results obtained from analyzing the internal (e.g., internal presentations) and external case material (e.g., public statements).

In order to analyze the data and manage the collected data in a systematic way, we used ATLAS.ti as our computer-assisted qualitative data analysis software. Over the three coding stages, a total of 396 codes were generated.

## Results

In the following section, we present briefly the four BDA affordances which we identified in the initial interview round. Thereafter, we detail the actions required for the actualization of these four affordances at *PremiumCar*.

### **Affordances of Big Data Analytics**

**Affordance 1: Establishing Customer-Centric Marketing.** This affordance is characterized by the organizational goal of improving marketing effectiveness through personalized customer interactions, which is enabled by analyzing traces of digital and nondigital customer interactions. *CarCo*, for example, uses A/B testing to improve the design of the online car configurator and predict customer preferences early on in the configuration process. *CommodityCar* tracks its customers' behaviors across different online platforms and, based on this data, calculates customer profiles which support the dealer's preparation of personalized sales offers:

*"We join data either from touch points like [our] car configurator [...] to generate customer journeys, and [...] we combine this with social media data [...] to optimize the targeting of the customers." Interviewee E1*

*PremiumCar* tracks the behavior of its customers on its digital touch points in real time, particularly on its different homepages and the car configurator. This enables the assessment and measurement of sales funnel efficiency in real time. Moreover, *PremiumCar* uses socio-demographic and behavioral customer data (e.g., purchase history) for lead management, which has already resulted in an increase in the lead conversion rate by 10 percent in Spain and France.

**Affordance 2: Provisioning Vehicle-Data-Driven Services.** This affordance is characterized by the organizational goal of improving customer offerings through vehicle-data-driven services which complement the vehicle manufacturers' core products. *TrucksCo*, for instance, produces commercial trucks with which their customers transport goods. Using predictive maintenance, *TrucksCo* tries to reduce truck breakdowns and outage times:

*"In particular, we focus on a predictive maintenance service [...] we use the onboard connectivity to transfer the data, and we provide remote and predictive maintenance services to the customers." Interviewee C1*

*MediumCar* works on integrating car location data with real-time traffic information, such as traffic light data. Based on this information, *MediumCar* would like to enhance its navigation services. *PremiumCar* works on fleet management services which use car location information to optimize route scheduling, support energy-efficient driving, and identify security-related incidents, such as theft.

**Affordance 3: Data-Driven Vehicle Developing.** This affordance targets analyzing the data acquired through on-road tests and vehicle usage data in order to improve vehicle safety and functionality. *TrucksCo*, for example, tries to establish a feedback loop from the actual truck usage to the requirement definitions for future truck systems and functionality improvements:

*"We [try] to define [the functions of] our brake based on large-scale customer usage data." Interviewee G1*

The R&D department at *PremiumCar* leverages BDA to ensure the safety of new car models based on on-road test data. In doing so, *PremiumCar* identifies anomalies such as misconfigurations in the electric braking system.

*"In research and development, we analyze an immense amount of data to improve our cars and safeguard their functioning." Interviewee B1*

Additionally, *PremiumCar* increases the coverage of tested car functions constantly. This is particularly important for testing (semi-)automatic driving features, which require a great number of test scenarios.

**Affordance 4: Optimizing Production Processes.** This affordance aims at leveraging production and sensor data for the optimization of production processes. In particular, the focus lies on leveraging a smart factory approach which involves creating a highly accurate virtual representation (digital twin) of the entire production facilities and using real-time data to minimize production costs. *MediumCar*, for instance, undertakes several steps to avoid production down times, such as a near real-time identification of failures in screwing processes and the predictive maintenance of production facilities:

*“Big data analytics helped [MediumCar] to minimize blackouts in production. That is to predict when a machine might break down in advance.” Interviewee L1*

CarCo tries to optimize its rate of production through aligning the production and sales processes:

*“Based on car configurations [...] we can make predictions of sales opportunities [...] this enables sales and product development [...] [to analyze] which car components and configurations will actually be sold more, so [they] can better plan supply and production.” Interviewee E1*

PremiumCar conducts automatic car disposition planning to improve yard management and uses energy analytics to reduce its facilities’ energy consumption. Through a proactive analysis of errors during the production process, PremiumCar also tries to reduce waste.

*“If you realize an error of the press shop at the final step of painting or the final montage, a lot of value creation already has taken place.” Interviewee M2*

Table 1 provides an overview of the four affordances, associated organizational goals, and examples from the interviewed suborganizations.

Affordance	Organizational Goal	Examples
Affordance 1: Establishing Customer-Centric Marketing	Improvement of marketing effectiveness through personalized customer interactions	<ul style="list-style-type: none"> <li>• Improve design of car configurator through A/B testing</li> <li>• Personalize sales offers through customer profiling based on click data</li> <li>• Increase lead conversion rate through analysis of socio-demographic data and purchase history</li> </ul>
Affordance 2: Provisioning Vehicle-Data-Driven Services	Improvement of customer offerings	<ul style="list-style-type: none"> <li>• Reduce outage time of trucks through the use of predictive maintenance</li> <li>• Improve navigation services with traffic light data and high-resolution traffic information</li> <li>• Provide fleet management and security services based on car location information</li> </ul>
Affordance 3: Data-Driven Vehicle Developing	Improvement of car safety and functionality	<ul style="list-style-type: none"> <li>• Improve brake system functionality based on usage data</li> <li>• Identify anomalies during on-road tests</li> <li>• Increase the coverage of on-road tests</li> </ul>
Affordance 4: Optimizing Production Processes	Decrease in production costs	<ul style="list-style-type: none"> <li>• Near real-time identification of failures in screwing processes</li> <li>• Predictive maintenance of production facilities</li> <li>• Demand-adaptive production of cars</li> <li>• Reducing production costs through improved yard, energy, and error management</li> </ul>

**Table 1. Affordances, Organizational Goals, and Examples**

### Actualization of Affordances

In the following section, we describe essential organizational actions and explain how they contribute to actualizing the four BDA affordances at PremiumCar. We provide an organizational chart for PremiumCar and a complete list of all affordance-related organizational actions which we discovered in Appendix B.

#### Actualization of Affordance 1: Establishing Customer-Centric Marketing

**Structure-level actions:** Within the marketing unit, analytics efforts had been scattered. The associated lack of a managed development of analytical capabilities and the lack of knowledge exchange between employees in analytics projects had resulted in the marketing unit’s inability to support BDA projects. In order to channel the establishment of analytical capabilities within the marketing unit and centralize marketing activities, the chief of marketing ordered the installation of a marketing analytics subunit.

*“We decided on the management level that we want to move towards doing things independently in order to develop BDA knowledge and skill in house. In particular, with the topic data, we will have a competitive edge and will face a problem if our external providers know more than we do, as they might sell the same [services] to our direct competitors.” Interviewee I2*

Starting off as a small group, this subunit extended its headcount to approximately 20 people on two management levels. The marketing analytics subunit is now responsible for marketing-related data analytics topics as well as a dedicated BDA strategy which enables customer-centric marketing. It has initiated several BDA projects, including sales forecasting and the analytical design of car configuration packages based on online configuration data, as well as a data quality program. Further, the marketing analytics subunit took over the project lead for a marketing analytics service initiative at the marketing unit. This initiative involves consolidating the requirements of the different stakeholders (i.e., subunits of the marketing unit, car dealers, and car importers) and managing service implementation. The installation of the marketing analytics subunit led to a bundling of know-how and a managed development of analytical capabilities within the marketing unit.

The marketing unit's BDA projects are not carried out by the marketing analytics subunit exclusively, but also involve the IT analytics subunit and *PremiumCar's* independent analytics subsidiary, which bundles data science knowhow. However, not having the adequate governance instruments in place meant that *PremiumCar* had risked a misalignment of the three organizational entities. As a consequence, a joint steering committee was established which is responsible for BDA project portfolio management and prioritization:

*"We meet up on a weekly basis in a steering committee to align all our efforts from [the analytics subsidiary], [the IT analytics subunit] and [the marketing analytics subunit]. With four managers, two for our unit, we have to align our strategic goals and discuss the main challenges we are facing, may it be a business issue or a technological one." Interviewee C2*

This steering committee includes the head of and a product manager from the marketing analytics subunit, the head of and a product manager from the IT analytics subunit, and the head of the analytics subsidiary. Thus, it provides a joint platform for coordinating BDA projects which support customer-centric marketing at *PremiumCar*.

**Actor-level actions:** *PremiumCar* had had considerable difficulties in attracting new recruits with much-needed data science competencies due to two reasons. First, the hierarchical structure of a large corporation is unattractive for young potential recruits searching for self-actualization. Second, *PremiumCar's* company headquarters are located in a mid-sized city which is less attractive to young adults. In order to introduce a new means of attracting data scientists, *PremiumCar* founded an innovative start-up-like analytics subsidiary in a big city nearby.

*"The data scientists in the [analytics subsidiary] have substantial independencies because they can focus on and design the analytics methods and approaches without having to handle the day-to-day business. Being located in a more influential city, the analytics subsidiary is far more attractive to the rare talents we try to recruit for our analytics projects." Interviewee E2*

The subsidiary can design its own business processes (such as employee recruitment) without having to comply with the bureaucratic processes of *PremiumCar*. The introduction of the analytics subsidiary helped *PremiumCar* to attract data scientists and increase its capability of establishing BDA-driven customer intelligence.

In the IT unit, analytical capabilities had been scattered because the IT unit is organized into organizationally and physically separate subunits following the departmental structures of *PremiumCar's* business units. As a consequence, the IT unit had limited capability to design and operate big data infrastructures. To bring together all of the BDA experts, *PremiumCar's* IT unit established a big data competence center which cuts across the individual IT subunits.

*"The implemented competence network mainly targets employees in the IT subunits. In our company, we faced initially a serious issue with experts on analytics in the IT unit. The big data competence center was a first step to bring together all existing and future experts to share their expertise across the IT unit and, consequently, to be a partner for units like the [marketing analytics] subunit." Interviewee A2*

In particular, it organizes synchronization meetings in which IT unit's current technological solutions are discussed. Further, it operates a document space for knowledge exchange between the big data experts. This led to a substantial increase in the analytical capabilities of the IT unit and the ability to act as a respected partner of the marketing analytics subunit in BDA projects.

**Technology-level actions:** When the marketing analytics subunit was founded, it was confronted with greatly disintegrated legacy business intelligence (BI) infrastructures. As a consequence, the marketing analytics subunit was unable to implement BDA scenarios which required a sophisticated analytics infrastructure. Consequently, in order to store and analyze customer-related data centrally, a centralized marketing BDA platform was set up:

*“We implemented, in collaboration with the IT unit, Teradata as the data warehouse with the SPSS modeler as an analytics solution and Tableau as visualization software to unify the technological stack used in marketing.” Interviewee C2*

This BDA platform provided the capabilities required to conduct advanced BDA projects based on customer data.

Not only the infrastructure, but also the customer data had been scattered across the marketing unit, which had resulted in the inability to aggregate rich customer information. As a consequence, the marketing analytics unit initiated the integration of customer data in the marketing BDA platform.

*“The biggest challenge was the fact that no one paid attention to what happens with the data and what has emerged over the last five, six, seven years of operational systems. There existed very few individual examples with both a clean logic and a clean data model and an appropriate link with other systems.” Interviewee A1*

Customer data from approximately 230 data sources, such as online customer platforms and car dealer systems, were copied little by little into the centralized storage. Integration further involved the matching of schemas and customer identifiers. This action supported the access to and full exploitation of different customer data sources.

The analytics experts in the marketing unit had traditionally compiled analysis results manually into static reports owing to the lack of a reporting and visualization platform. This static reporting and lack of automation had resulted in heavy manual workloads and constant issues with outdated customer data. In order to enable dynamic reporting and to increase the level of automation, the marketing unit introduced a Tableau-based infrastructure which supports dynamic dashboards. Users can now adjust data views dynamically and conduct analyses themselves.

*“We built now a Tableau server through which we deliver our analytics service [...] Previously, data snapshots were used and sent as dashboards via mail, for instance, as PDFs or sometimes as offline Tableau dashboards. Now, we integrate these dashboards step-by-step.” Interviewee C2*

The introduction of the Tableau-based infrastructure decreased significantly the data scientists’ repetitive and manual labor and improved the supply of customer information to *PremiumCar’s* marketers.

Table 2 summarizes the key actions used to establish a customer-centric marketing approach at the structure, actor, and technology levels.

Structure Level	Actor Level	Technology Level
<ul style="list-style-type: none"> <li>- Constructing a marketing analytics subunit</li> <li>- Aligning marketing analytics subunit, the IT analytics subunit, and the analytics subsidiary through a steering committee</li> </ul>	<ul style="list-style-type: none"> <li>- Recruiting data scientists, big data architects, and visualization experts in a start-up-like analytics subsidiary</li> <li>- Newly bringing together big data experts in the IT unit through a big data competence center</li> </ul>	<ul style="list-style-type: none"> <li>- Implementing a Teradata- and Tableau-based technological infrastructure</li> <li>- Integrating customer and dealer data from dealer systems and customer portals</li> <li>- Delivering dynamic analytics services through a Tableau solution instead of offline dashboards</li> </ul>

**Table 2. Actions of Establishing a Customer-Centric Marketing**

## Actualization of Affordance 2: Provisioning Vehicle-Data-Driven Services

**Structure-level actions:** The development of vehicle-data-driven services had required the collaboration of the R&D unit, which manages the vehicle-embedded systems and vehicle data, and the marketing unit, which has customer expertise and manages the development of customer services. However, these two units traditionally had limited interactions:

*“At first, it proved difficult to get hold of vehicle data, as our vehicles were not able to send data and, even more importantly, we were not collaborating until then with the R&D unit.” Interviewee E2*

Consequently, the marketing analytics subunit and the R&D unit joined forces by installing a joint task force. This task force was responsible for defining use cases for vehicle-data-driven services and initiating first pilots. Establishing this collaboration was an essential prerequisite for the subsequent actions taken to collect and store centrally vehicle data as well as to implement vehicle-data-driven services.

Early initiatives to implement vehicle-data-driven services had faced two major obstacles. First, there had been very limited technological capability with which to collect vehicle data because the tracking of vehicle sensors had been limited to a few maintenance-related car incidents. Second, the embedded systems in different vehicles had used inconsistent data models and identifiers, which had prohibited an integrated use of sensor data from different vehicle models. As a consequence, the marketing analytics subunit used its strategic budget to finance two projects in order to overcome these obstacles:

*“To finance our first projects with the R&D unit, we were in the lucky position that we had been granted a strategy budget from our top management to heavily push forward our joint analytics efforts.” Interviewee F2*

The first project addressed the equipping of vehicles with data loggers; the second project targeted building an integration architecture to enable the analysis of vehicle-sensor data across different models. The marketing analytics subunit’s funding of these two projects was a key structure-level action because providing access to vehicle data represented a crucial actualization step toward vehicle-data-driven services.

**Actor-level actions:** *PremiumCar* had used sequential processes initially to develop vehicle-data-driven services, which had led to insufficient coordination between product managers and data scientists. In order to improve the interworking of product managers from the R&D unit and the data scientists from the analytics subsidiary, *PremiumCar* introduced the scrum process. The iterative nature of scrum helped to streamline the explorative design of vehicle-data-driven services and service implementation.

*“We have to develop a flexibility and agility in regard to our releases. Instead of two major releases, we need – as is characteristic for agile approaches – high-frequency micro releases [...] Scrum is one possibility to achieve this and to get our product management and the developing team together.” Interviewee N2*

All involved data scientists update each other and the respective product manager in a brief daily scrum call. Projects consist of weekly sprints. Each sprint represents a one-week development cycle within which data scientists explore specific user stories. These actor-level actions improved the collaboration between product managers and data scientists and reduced significantly the risk of misguided efforts in terms of implementing vehicle-data-driven services.

It had been clear to *PremiumCar*’s R&D unit from early on that the development of digital vehicle-data-driven services, comparable to engineering vehicle technology, would determine eventually *PremiumCar*’s competitive market advantage. However, the R&D unit had lacked data science experts with the data-processing skills which are indispensable for vehicle-data-driven services. For this reason, *PremiumCar* had relied heavily on external analytics consultants. In order to establish in-house competence in developing BDA applications in the R&D unit, *PremiumCar* introduced co-coding for projects with external analytics consultants.

*“We use co-coding to avoid being dependent on the analytics knowledge of external partners [...] that way we make sure that we develop the required analytics know-how within our company.” Interviewee N2*

Through this action, the analytics competencies of the R&D unit’s employees improved substantially. Today, the R&D unit develops vehicle-data-driven services largely independently of company-external support.

**Technology-level actions:** New cross-unit collaborations at *PremiumCar*, such as between the R&D unit and the marketing unit, resulted in BDA scenarios which required the integration of large and diverse data sources and high processing capabilities. Because the individual units had historically been satisfied with dedicated-purpose BI infrastructures, no infrastructure could meet these new requirements. In order to address these demands, the IT unit implemented a central BDA platform which is open to all of *PremiumCar*'s units. It is designed as an on-premises platform which supports large-scale analyses and reporting. For large-scale analyses, it covers the entire Hadoop ecosystem, including cluster storage, Spark, and the support of diverse analytical programming languages such as SQL, R, and Python. For visualization purposes, the platform includes the Tableau and SAP BusinessObjects server.

*"The platform receives data from our cars, production data (this means we try to connect our robots from the assembly lines), diagnosis data from our dealerships [...] we try to consolidate our data streams across the company with the platform."* Interviewee S2

This platform represents a fundamental enabler for the development of vehicle-data-driven services and supports, among others, the exploration of remote maintenance, fleet management, and advanced navigation scenarios.

Traditionally, the logging functionality of the vehicle-embedded systems had been limited to a fault memory which logged few maintenance-relevant events. This data had been transferred to *PremiumCar*'s systems very sporadically when dealers read out this fault memory during maintenance services. Vehicle-data-driven services, such as predictive maintenance, however, rely on detailed and up-to-date sensor data, which were not logged at that time. In order to capture a broad array of sensor data and transfer it to the central BDA platform on a regular basis, *PremiumCar* decided to mount data loggers in new vehicles.

*"Together with R&D, we have to lay the technological foundation for accessing vehicle data. [...] At first, we absolutely had to build in data loggers within our vehicles to allow the over-the-air-transfer of data."* Interviewee E2

The data loggers are connected to the vehicles' data transmission system and thus allow an instant over-the-air transfer of sensor data. Having access to this rich vehicle data at near real-time in the central BDA platform improved substantially *PremiumCar*'s ability to explore and design innovative vehicle-data-driven services.

Table 3 summarizes the key actions taken to provision vehicle-data-driven services at the structure, actor, and technology levels.

Structure Level	Actor Level	Technology Level
<ul style="list-style-type: none"> <li>- New collaborating of the marketing analytics subunit and R&amp;D unit</li> <li>- Central funding of marketing-R&amp;D analytics projects</li> </ul>	<ul style="list-style-type: none"> <li>- Improving the interworking of product managers and software developers with scrum</li> <li>- Co-coding with external partners</li> </ul>	<ul style="list-style-type: none"> <li>- Constructing a cross-unit Hadoop platform</li> <li>- Improving the exchange of data between vehicles and the analytics platform with car data loggers</li> </ul>

**Table 3. Actions of Provisioning Vehicle-Data-Driven Services**

### Actualization of Affordance 3: Data-Driven Vehicle Developing

**Structure-level actions:** Owing to a lack of capabilities related to the analysis of large volumes of data and the use of a scalable infrastructure, *PremiumCar*'s R&D unit had been unable to cope with the sheer amount of data a car produces during an on-road test. During such tests, a single vehicle produces more than one gigabyte of data per second. Collaborations with external analytics providers had proved difficult because the sensor data which the in-car systems produce are highly specific.

*"We at R&D collaborated initially with a lot of external partners...but we had to realize that it is really difficult to find a partner who could deliver components which work properly and take the domain-specific internal car systems into account."* Interviewee R2

As a consequence, the R&D unit had only been able to analyze very specific errors and safeguard limited and clearly defined car functionalities. In order to help expand the coverage and depth of on-road tests, the R&D analytics subunit was installed. This subunit is responsible for the analysis of sensor signals, bus

system signals, and overall product test data before the actual start of production. In addition, the subunit took over the task of conceptualizing a technological infrastructure for vehicle sensor data analyses. Establishing this R&D analytics subunit was a key structure-level action because the combination of analytical capabilities and vehicle electronics expertise is indispensable for data-driven vehicle developing.

The R&D unit is organized in a decentralized fashion into several vehicle-component-specific R&D subunits with historically developed work structures. Owing to an initial skepticism within some of these vehicle-component-specific R&D subunits, the R&D analytics subunit struggled initially to gain access to information about all relevant vehicle-data sources. In order to ensure the R&D analytics subunit's access to relevant vehicle data sources, the R&D unit introduced a standardized data approval process. Chief data stewards now serve as representatives for their R&D subunits and have the power to authorize access to the data sources for which the respective subunit is responsible. The approval process also includes stakeholders from the legal unit (with particular expertise related to privacy issues) and from the IT unit (with particular expertise related to technological topics).

*“Every department has to nominate a chief data steward. Supported by a purchased data management software tool, we will implement a quick process to ensure the access to data.” Interviewee A1*

The process to gain access to data sources requires that the project leader fills in a data request online. The stakeholders involved in the approval process (e.g., system and data owners) have the right to object to a data access request. If, within 1 week, no objection is made, the data access request is approved automatically. This data approval process facilitates significantly data-driven vehicle developing through avoiding project setbacks because of a lack of access to data.

**Actor-level actions:** The R&D unit had been faced with a shortage of employees who combined vehicle engineering knowledge with profound analytical capabilities, both of which are required for vehicle-data-driven engineering.

*“In particular, when we look at cars, the domain-specific knowledge is key. You are just not able to analyze any data of the car without having a proper understanding of the car itself [...] our cars are technically very complex.” Interviewee O2*

In order to equip domain experts in R&D with analytical capabilities, the R&D unit began to take part in *PremiumCar's* company-wide BDA education program. This program consists of five modules which are separated into three levels (i.e., basic, advanced, and expert). The first module, digital business, focuses on an overview of methods and approaches (e.g., CRISP-DM, a modeling approach for data mining, and design thinking, an interdisciplinary innovation methodology) as well as portfolio management. The second module, data architecture, covers relational and nonrelational database systems. At the expert level, the foundations of SAP HANA and Hadoop on Hortonworks are addressed. The third module, data analytics, comprises methods with which to structure and cleanse data as well as foundations in R and Python. Machine learning and artificial intelligence, which comprise the fourth module, cover supervised and unsupervised learning methods as well as neural networks. The last module, data strategy, illustrates strategic trends in analytics and data governance. This education program improved significantly the ability of engineers in the R&D unit to participate in data-driven vehicle developing.

Initially, the conceptualization of a dedicated analytics platform had been done by the R&D analytics subunit, which had, however, turned to the IT unit for help with scalability issues it could not resolve. But the IT unit had initially been unable to resolve these issues owing to a lack of expertise in building and maintaining BDA platforms. The IT unit reacted consequently to the R&D unit's new technology demands and recruited BDA platform architects.

*“For us, it is crucial that we have the manpower to evaluate the technological solutions available on our own and to choose the best suitable technological stack for our use cases [...] in this regard, [the IT unit] took a huge step forward and hired platform architects to bring our endeavor forward.” Interviewee R2*

After recruiting platform architects, the IT unit and R&D analytics subunit could collaboratively provide the needed employee-level skill set for data-driven vehicle developing independently of external support.

In addition to using sensor data from on-road tests, *PremiumCar* further had started to inform vehicle development with customer-generated vehicle usage data which was transferred to *PremiumCar's* central systems over-the-air. Historically, sensor data from *PremiumCar's* sold vehicles had only been transferred



through secured access methods to central systems in the rare event of car maintenance being done at PremiumCar’s repair shops. For this reason, employees in the IT in-car subunit very rarely had had contact with security experts in the IT security subunit. The extension of the vehicles’ functionality to transfer usage data over-the-air required a further intensification of the collaboration between the car and IT security experts. Therefore, regular meetings between both subunits’ security experts were set up in order to align their current data-related security issues.

*“Initially, our vehicles and our IT landscape had to be seen as disjoint systems. They only interacted in rare cases, such as in the case of maintenance work [...] accordingly, both the vehicles and the IT landscape were separately secured [...] Today, however, the IT security experts and in-car security experts work closely together, as we are otherwise not able to look at all aspects of security throughout the chain from the car to our IT landscape and vice versa.” Interviewee N2*

The active exchange between the car and IT security experts supports data-driven vehicle developing through ensuring end-to-end security measures.

**Technology-level actions:** An immense amount of data is produced during an on-road test which requires the use of hard drives within the test vehicle for storage. These hard drives are collected and the respective data is stored within an existing data storage system in the R&D unit. However, the R&D analytics subunit had lacked an adequate analytics infrastructure with which to process and analyze this high volume of data with advanced analytics methods.

*“During on-road tests, our test cars produce more than a gigabyte of data. [...] Though we have the technological infrastructure and processes to collect and store the data, we had to extend our technological landscape to allow analyzing these high volumes of data.” Interviewee R2*

In order to enhance the existing data storage system with analytics components, the R&D analytics subunit initiated the implementation of a Hadoop-based analytics platform for vehicle test data analysis. This platform includes Spark and a Hadoop distribution of MapR as analytics engines. It supports interactive programming through Jupyter and Python. This platform provided the R&D analytics subunit, for the first time, with the technological means by which to exploit fully the collected test data for data-driven vehicle developing.

Table 4 summarizes the key actions taken for data-driven vehicle developing at the structure, actor, and technology levels.

Structure Level	Actor Level	Technology Level
<ul style="list-style-type: none"> <li>- Constructing an R&amp;D analytics subunit for car usage data</li> <li>- Using a standard data approval process</li> </ul>	<ul style="list-style-type: none"> <li>- Improving employee BDA competencies through a central education program</li> <li>- Recruiting platform architects for the IT unit</li> <li>- Establishing a closer exchange between security experts from the IT in-car and IT security subunits</li> </ul>	<ul style="list-style-type: none"> <li>- Constructing an R&amp;D Hadoop platform for on-road test data</li> </ul>

**Table 4. Actions of Data-Driven Vehicle Developing**

**Actualization of Affordance 4: Optimizing Production Processes**

**Structure-level actions:** With regard to managing the production facilities’ IT systems, the production unit had historically collaborated with the manufacturers of the production machines and not with the IT unit. In its efforts to implement a smart factory approach, the production unit required a competent partner who supported the implementation of a secured digital twin of the production facilities. Because the IT unit had by then developed considerable knowledge in managing big data infrastructures, the production unit decided to collaborate with the IT unit.

*“We started to collaborate heavily with the IT unit as they built an analytics platform for [PremiumCar]. The IT unit supports us with the toolset on which we can work and also takes care of all the licensing issues you face when you use enterprise solutions.” Interviewee O2*

In the course of this novel collaboration, the chief of production and the chief information officer hosted a hackathon. The goal was to connect to skilled and creative data scientists. The hackathon led to 18 use cases, of which 12 were followed up on within the production unit. Overall, the IT unit's analytical capabilities contributed substantially to implement the technological infrastructure and generation of innovative use cases for a smart factory approach.

A plethora of digitization efforts had been scattered across *PremiumCar's* production unit and had been insufficiently aligned to improve *PremiumCar's* production processes in a sustainable manner. In order to improve the structural support for its digitization efforts, the production unit implemented a board of digital officers. Each subunit within the production unit nominates a digital officer who is responsible for his/her subunit's digitization efforts and consolidating these efforts at the production unit level.

*"Besides coordinating our digitization efforts, which are mostly analytics topics, they try to avoid redundancies within the production unit. They have to find answers to: "Which data do we need from which production site? What should our system landscape look like over a five- or ten-year time horizon?" Interviewee O2*

The committee not only prioritizes digital topics, which are mostly analytics topics, and grants budgets, but also instructs subunits within the production unit to take over tasks. This structure-level action improved significantly the management of analytics efforts within the production unit, leading to an avoidance of redundancies and ensuring strategic prioritization when optimizing production processes.

**Actor-level actions:** Because analytics experts at the individual production subunits had traditionally focused on optimizing their specific production steps, there was a lack of knowledge exchange and collaboration among the analytics experts at the production unit. In order to ensure employee-level collaboration and bring together analytics experts, the production unit launched a social community. This social community uses an enterprise social software in order to communicate and exchange information and further hosts information exchange meetings on a regular basis.

*"Our analytics efforts are supported by regular workshops within our production unit which are organized by a colleague from another subunit. He actively pushes our social community in order to ensure collaboration and a common understanding in regard to our analytics efforts at the production unit." Interviewee P2*

Through this social community, the production unit improved the sharing of best practices among analytical-savvy engineers in terms of optimizing production processes.

The smart factory efforts at the production unit had been struggling with strong opposition from middle-level managers. Many managers feared losing decision-making competencies and a devaluation of their domain-specific skills owing to increased production automation. For these reasons, they had been reluctant to change their established work practices. In order to educate these managers and receive their buy-in, the production unit hosted a series of data awareness workshops.

*"We offer data awareness workshops on the management level. But you always have to consider that you will not reach all employees through the management or top-down approach. Thus, you have to complement it with bottom-up approaches." Interviewee O2*

These workshops were complemented by events in which employees of the decentralized units presented their initial success with applying BDA to achieve smart factory approaches. Through achieving commitment on the management level, additional projects and, particularly, more capacities could be acquired when optimizing production processes with smart factory approaches.

**Technology-level actions:** In order to implement a full digital representation of its production facilities, *PremiumCar's* production unit had to gain access to the data of all of the production machines. Access to the data from many of *PremiumCar's* production facilities, however, had not been feasible initially as, in the majority of the cases, no digital interfaces existed. In order to establish digital connections, the production unit decided to build dedicated interfaces and leverage company-internal platforms owing to the operational criticality of these interfaces.

*"If we are not able to connect to our machines using protocols such as OPCUA, we enable our machines to connect to our LAN- or WLAN-infrastructure and try to access the data using different approaches [...] for instance, screen scraping." Interviewee M2*

Establishing these interfaces enabled the production machines to be read out on a regular basis. The digitization of interfaces to production facilities allowed, for the first time, the unified and centralized access

to previously untouched data points and thus was a precondition for the data-driven optimization production processes.

While it had been possible for some production subunits to manage local production facilities digitally, the global distribution of *PremiumCar's* production facilities around the world required a central solution in order to collect and store production data from across the globe. Owing to the inability to integrate production data on a global scale, *PremiumCar* had not been able to leverage synergies through a global optimization of, among others, yard management, energy management, and error management. In order to integrate the data from the world-wide production facilities (e.g., data from KUGA robots, press shop, or other production facilities) into the company-wide BDA platform, the production unit initiated the implementation of a data lake.

*“Our production unit is dominated by the continuous improvement process mindset. Thus, we try to support as well as we can the process of connecting data from all of our production facilities to our technological infrastructure and making the data analyzable. [...] We are producing across the globe, which makes it even more challenging.” Interviewee B2*

Based on these data, 300,000 screwing processes, for instance, were analyzed to identify proactively errors in early car production phases, thus avoiding cost-intensive repairs in later production phases. The data lake at the production unit was a key technology-level action because providing accessibility to the global production data represented a crucial actualization step toward optimizing production processes.

Table 5 summarizes the key actions taken for optimizing production processes at the structure, actor, and technology levels.

Structure Level	Actor Level	Technology Level
<ul style="list-style-type: none"> <li>- New collaborating between the production and IT units</li> <li>- Improving structural digitization support through a board of digital officers in the production unit</li> </ul>	<ul style="list-style-type: none"> <li>- Establishing a social community for BDA in the production unit</li> <li>- Offering a data-awareness program for management-level employees</li> </ul>	<ul style="list-style-type: none"> <li>- Digitizing interfaces to production facilities</li> <li>- Implementing a data lake for the production unit</li> </ul>

**Table 5. Actions of Optimizing Production Processes**

## Discussion

We conducted a revelatory case study at *AutomotiveGroup*, one of the largest automotive corporations worldwide, in order to study the actualization of BDA affordances, which has been identified as lacking a research base (Günther et al. 2017; Mikalef, Pappas, et al. 2017; Wamba et al. 2015). We have identified four BDA affordances, namely: 1) establishing customer-centric marketing, 2) provisioning of vehicle-data-driven services, 3) data-driven vehicle developing, and 4) optimizing production processes, and we gathered detailed information on affordance actualization at the structure, actor, and technology levels.

Analyzing the actions taken, we see evidences for four underlying mechanisms used by *PremiumCar* to advance affordance actualization: *enhancing*, *constructing*, *coordinating*, and *integrating*.

- *Enhancing* refers to the further development of a company’s socio-technical entities.
- *Constructing* refers to the implementation of novel socio-technical entities.
- *Coordinating* refers to improving the interworking of socio-technical entities.
- *Integrating* refers to establishing novel interfaces between socio-technical entities.

We refer to these mechanisms as “actualization mechanisms,” and we have detailed specific actions on the structure, actor, and technology levels which refer to each mechanism as we found them in the data in Table 6.

Actualization Mechanism	Structure Level	Actor Level	Technology Level
Enhancing	Further development of structural entities:	Further development of employee competencies:	Further development of information technologies:

	<ul style="list-style-type: none"> <li>- Using a standard data approval process</li> <li>- Improving structural digitization support through a board of digital officers in the production unit</li> </ul>	<ul style="list-style-type: none"> <li>- Improving employee BDA competencies through a central education program</li> <li>- Co-coding with external partners</li> <li>- Offering a data-awareness program for management-level employees</li> </ul>	<ul style="list-style-type: none"> <li>- Constructing an R&amp;D Hadoop platform for on-road test data</li> <li>- Delivering dynamic analytics services through a Tableau solution instead of offline dashboards</li> </ul>
Constructing	Installing novel structural entities: <ul style="list-style-type: none"> <li>- Constructing a marketing analytics subunit</li> <li>- Constructing an R&amp;D analytics subunit for car usage data</li> </ul>	Hiring employees with novel competencies: <ul style="list-style-type: none"> <li>- Recruiting data scientists, big data architects, and visualization experts in a start-up-like analytics subsidiary</li> <li>- Recruiting platform architects for the IT unit</li> </ul>	Implementing novel information technologies: <ul style="list-style-type: none"> <li>- Implementing a Teradata- and Tableau-based technological infrastructure</li> <li>- Constructing a cross-unit Hadoop platform</li> </ul>
Coordinating	Improving the interworking of structural entities: <ul style="list-style-type: none"> <li>- Aligning marketing analytics subunit, the IT analytics subunit, and the analytics subsidiary through a steering committee</li> <li>- Central funding of marketing-R&amp;D analytics projects</li> </ul>	Improving the interworking of employees: <ul style="list-style-type: none"> <li>- Improving the interworking of product managers and software developers with scrum</li> <li>- Establishing a closer exchange between security experts from the IT in-car and IT security subunits</li> </ul>	Improving the interfacing of information technologies: <ul style="list-style-type: none"> <li>- Improving the exchange of data between vehicles and the analytics platform with car data loggers</li> <li>- Implementing a data lake for the production unit</li> </ul>
Integrating	Installing novel collaborations between structural entities: <ul style="list-style-type: none"> <li>- New collaborating of the marketing analytics subunit and R&amp;D unit</li> <li>- New collaborating between the production and IT units</li> </ul>	Generating novel collaborations between employees: <ul style="list-style-type: none"> <li>- Newly bringing together big data experts in the IT unit through a big data competence center</li> <li>- Establishing a social community for BDA in the production unit</li> </ul>	Establishing novel interfaces between information technologies: <ul style="list-style-type: none"> <li>- Integrating customer and dealer data from dealer systems and customer portals</li> <li>- Digitizing interfaces to production facilities</li> </ul>

**Table 6. Actualization Mechanisms and Exemplary Organizational Actions**

The first mechanism is *enhancing*. *PremiumCar*, for instance, formalized the data approval process within the R&D unit and introduced the role of digital officers in the production unit; both actions represent structural-level enhancements. At the actor level, *PremiumCar* launched an education program and implemented alternative mechanisms to further develop employee capabilities. At the technology level, *PremiumCar* improved its IT systems, among others, by enhancing a storage system for on-road test data with analytical system components and improving reporting technologies with dynamic Tableau dashboards. Through these actions, *PremiumCar* developed further the company's socio-technical entities in order to actualize BDA affordances, which we refer to as the actualization mechanism *enhancing*.

The second mechanism is *constructing*. *PremiumCar*, for instance, constructed analytics subunits in the marketing and R&D units, which are actions taken on the structure level. At the actor level, *PremiumCar* recruited data scientists to its analytics subsidiary and increased substantially the headcount of big data platform architects in the IT unit. At the technology level, *PremiumCar* introduced novel technologies, most notably a central BDA platform based on Amazon Web Services and Hadoop, as well as a Hadoop-based analytics platform in the R&D unit. Through these actions, *PremiumCar* implemented novel socio-technical entities in order to actualize BDA affordances, which we refer to as the actualization mechanism *constructing*.

Results provided by *enhancing* and *constructing* provide insights for the ongoing discussion on organizational learning. Specifically, we interpret instances of the *enhancing* mechanism as evidence of

incremental learning. Similarly, we interpret instances of the *constructing* mechanism as evidence of radical learning. This, we argue in the following, extends the current knowledge of how firms develop BDA capability.

The sparse research on BDA capability development accentuates the fact that a firm's intensity of organizational learning represents a determinant of BDA capability (Gupta and George 2016; Mikalef, Boura, et al. 2018). In their empirical validation of the BDA capability construct, Gupta and George (2016) consider the intensity of organizational learning as a formative factor for BDA capability, measured with several items which describe the perceived ability of a firm to search for, acquire, assimilate, and apply relevant knowledge. While these results assert the importance of organizational learning for BDA capability, there has been, to the best of our knowledge, no prior research on *how* firms develop BDA capability through organizational learning. The organizational learning literature distinguishes two polar learning mechanisms (Edmondson 2002; Lavie 2006; Miner and Mezias 1996). Incremental learning refers to the improvement of an established capability through the modification of the individual building blocks of this capability, for example, by optimizing an operational routine. Radical learning refers to the reframing of a situation and acquisition of novel capabilities, for example, by hiring employees with competencies in a novel and sought area. Furthermore, learning in organizations takes place at the individual level (i.e., novel employee knowledge) as well as at the organizational level (i.e., novel organizational structures and technological capabilities) (Crossan et al. 1999; Kim 1993).

In *PremiumCar's* actualization of BDA affordances, incremental learning at the employee level manifests in actor-specific instantiations of the *enhancing* mechanism. An example of incremental learning at the individual level is the employee education program because it signals an enhancement of employee competencies. Incremental learning at the organizational level manifests in structure- or technology-specific instantiations of the *enhancing* mechanism. The introduction of a standardized data approval process in *PremiumCar's* production unit, for example, is evidence of incremental learning at the organizational level because it represents a structure-specific enhancement of the (previously informal) data approval practices.

Radical learning at the employee level manifests in actor-specific instantiations of the *constructing* mechanism. An example of radical learning at the individual level is the recruitment of data scientists with competency profiles, which *PremiumCar's* employees did not match, for the start-up-like analytics subsidiary; this action signals the construction of novel employee competencies. Radical learning at the organizational level manifests in structure- or technology-specific instantiations of the *constructing* mechanism. The installation of a novel marketing analytics subunit, for example, represents radical learning at the organizational level because it entailed the construction of a new structure-specific entity.

To summarize our discussion of the first two mechanisms *enhancing* and *constructing*, our case study demonstrates that *PremiumCar* conducts incremental and radical learning on the individual and organizational levels to actualize BDA affordances. By detailing how *PremiumCar* improved incrementally socio-technical entities through *enhancing* and how *PremiumCar* radically introduced novel socio-technical entities through *constructing*, we provide a link to the extant literature on organizational learning (Edmondson 2002; Lavie 2006; Miner and Mezias 1996) and contribute to an understanding of *how* firms develop BDA capability.

The third mechanism is *coordinating*. *PremiumCar*, for instance, improved the structure-level alignment of the marketing and IT units with a steering committee which brings together key stakeholders for the marketing analytics service initiative. At the actor level, *PremiumCar* introduced scrum in order to align the work of product managers and software developers. At the technology level, *PremiumCar*, among other actions, improved the exchange of sensor data between vehicles and a central analytics platform with the use of car data loggers. Through these actions, *PremiumCar* intended to improve the interworking of socio-technical entities in order to actualize BDA affordances, which we refer to as the actualization mechanism *coordinating*.

The fourth mechanism is *integrating*. *PremiumCar*, for instance, introduced the collaboration between the R&D unit and the marketing analytics subunit in order to support the development of vehicle-data-driven services on a structure level. At the actor level, a newly created big data competence center, for example, brought together big data experts who were distributed across the IT unit. At the technology level, customer data owned by the car dealers were newly integrated with customer data collected through *PremiumCar's* web platforms. Through all of these actions, *PremiumCar* intended to establish novel interfaces between

socio-technical entities in order to actualize BDA affordances, which we refer to as the actualization mechanism *integrating*.

Insights related to *coordinating* and *integrating* contribute to the existing body of knowledge by providing a detailed understanding of how firms align BDA-related socio-technical entities and thus extend the currently limited body of knowledge on BDA alignment.

Many prior studies take a resource-based perspective on the constituents of BDA capability and discuss tangible, intangible, and human resources (e.g., Gupta and George 2016; Mikalef, Pappas, et al. 2017; Mikalef, Boura, et al. 2018). The actualization mechanisms *enhancing* and *constructing* are congruent with this resource-based perspective on BDA capability for the following three reasons. First, enhancing and constructing socio-technical entities at the technology level addresses the formation of tangible resources, such as data, infrastructure, and software. Second, enhancing and constructing structure-level entities addresses the formation of intangible resources, such as business analytics governance and prioritization of business analytics investments. Finally, enhancing and constructing actor-level entities addresses the formation of human resources with a focus on, for example, technical knowledge and analytical skills. However, the results of our research show that actualization is not merely a result of providing individual socio-technical entities through *enhancing* and *constructing*. Actualization further requires the coordination and integration of these entities. With this finding, we address the open research question as to how BDA resources must be aligned in order to reach sustainable performance effects (Wamba et al. 2017).

Our findings support the results of prior researchers who have highlighted the importance of aligning BDA-related socio-technical entities (Mikalef, Boura, et al. 2018; Mikalef, Krogstie, et al. 2018; Tallon et al. 2013) and enrich the present understanding of how alignment is implemented in different alignment dimensions, as follows. Prior IT alignment research distinguishes several alignment dimensions, including intellectual, social, and operational alignment (Chan and Reich 2007; Gerow et al. 2015). *Intellectual BDA alignment* deals with how business strategy is supported by BDA strategy (cf. Gerow et al. 2015). Based on a general assessment of how BDA plans align with the companies' objectives and support the companies' direction, Akter et al. (2016) empirically show that intellectual BDA alignment moderates the impact of a BDA capability on firm performance. Our case study's structure-level actions, which we allocate to the mechanisms of *coordinating* and *integrating*, detail the understanding of *how* firms actualize BDA affordances through achieving intellectual BDA alignment. The installation of a committee which steers jointly the marketing and IT units' analytics activities, for example, led to a shared understanding of the BDA objectives and priorities which facilitated the actualization of customer-centric marketing. *Social BDA alignment* denotes a state in which BDA employees and employees from other business functions understand and are committed to the business and BDA mission and objectives (cf. Chan and Reich 2007). Wamba et al. (2017) consider social BDA alignment as a subconstruct in their operationalization of BDA capability. They measure the general level to which BDA experts and line people exchange information and coordinate joint work and refer to it as BDA coordination. Our case study's actor-level actions which we allocate to the mechanisms of *coordinating* and *integrating* introduce a fine-grained perspective on how firms increase social alignment in their efforts to actualize BDA affordances. The introduction of a social community platform, for example, fueled the personal exchanges between analytics experts in the production unit and, in this way, supported the actualization of optimizing production processes. *Operational BDA alignment* refers to the alignment of business infrastructure and processes with BDA infrastructure and processes (cf. Gerow et al. 2015). Ghasemaghaei et al. (2017) address operational BDA alignment and empirically show that the fit between BDA tools and data, between BDA tools and people, as well as between BDA tools and tasks, moderates the impact of data analytics use on firm agility. Our case study's technology-level actions which we allocate to the *integrating* and *coordinating* mechanisms represent further actions in support of operational BDA alignment beyond a focus on BDA tools and thus broaden the understanding of how firms implement operational BDA alignment. The integration of customer data from dealer systems and *PremiumCar's* online platforms in Affordance 1, for example, led to an increased alignment of customer analytics systems to *PremiumCar's* customer-facing business processes and thus facilitated the actualization of customer-centric marketing.

To summarize the insights achieved through our work for the ongoing BDA alignment discussion (Akter et al. 2016; Ghasemaghaei et al. 2017; Wamba et al. 2017), our study leads to the rich discovery of actions which represent *integrating* and *coordinating* mechanisms on the structure, actor, and technology levels.

This discovery extends the currently limited knowledge on how firms achieve BDA alignment, particularly in the intellectual, social, and operational dimensions of alignment.

In sum, we conclude that companies actualize BDA affordances through enhancing, constructing, coordinating, and integrating socio-technical entities. The case study also highlights specific actions *PremiumCar* has taken regarding each mechanism on the structure, actor, and technology levels so that, overall, a balanced portfolio of actions has been created. These mechanisms and the identified actions characterize conjunctively the “recursive shaping” of socio-technical entities (Leonardi 2012; Orlikowski 2000; Orlikowski and Scott 2008).

## Implications

### *Implications for Theory*

Prior studies on BDA have primarily focused on either the potential value of BDA (Günther et al. 2017; Müller et al. 2018) or on the organizational resources and capabilities for BDA (e.g., Gupta and George 2016; Mikalef, Pappas, et al. 2017). The link between effective applications of BDA and associated organizational preconditions, however, is still omitted in existing research (Günther et al. 2017). This link, however, is essential in creating knowledge on how to generate business value through BDA.

Our work contributes to the current body of knowledge on the value realization of BDA in several ways. We identify affordances which drive automotive manufacturing companies to adopt BDA. Thus, we respond to Abbasi et al.’s (2016) call to study concrete and industry-specific scenarios on how enterprise-wide BDA maximizes the potential for competitive advantage and shed light on how BDA can provide and deliver value in the automotive industry.

Further, we adopt a theoretical perspective on BDA actualization by connecting affordance theory with the STS theory. Inspired by Volkoff and Strong (2013), we study affordance actualization by gaining detailed insights into the adaptation of organizational structure, actors, and BDA technology. In doing so, we identify the organizational actions required to actualize and thus profit from BDA. Our findings contribute to the general IS affordance literature by supporting a better understanding of how configurations of the STS relate to the actualization of affordances, as called for by Zammuto et al. (2007).

Moreover, we respond to Günther et al. (2017), Mikalef, Pappas, et al. (2017), and Wamba et al.’s (2015) call for empirical studies on the realization of BDA value. We contribute an actions-oriented perspective to the currently sparse theory on the organizational-level formation of BDA capability. Our theorization on the BDA affordance actualization represents a type II mid-range theory (“theory for explaining”) (Gregor 2006). With our revelatory case study, we do not aim at generating testable predictions, but, instead, to provide a theory which is “new and interesting [...] to explain something that was poorly or imperfectly understood beforehand” (Gregor 2006, p. 625).

We examine the process of building BDA capability, as called for by Mikalef et al. (2017), and discover four general mechanisms behind how a company actualizes BDA affordances: *enhancing*, *constructing*, *coordinating*, and *integrating*. Our discovery of these mechanisms on the structure, actor, and technology levels of a company’s STS extends particularly prior research on BDA alignment by relating the mechanisms to extant IT alignment theory (Chan and Reich 2007; Gerow et al. 2015) and by distinguishing the organizational actions of intellectual, social, and operational BDA alignment. Further, this discovery extends the current knowledge on how a company develops BDA capability by relating the mechanisms to theories on organizational learning (Edmondson 2002; Lavie 2006; Miner and Mezias 1996) and by eliciting two modes of organizational learning, incremental and radical learning, on the individual level as well as on the organizational level.

### *Implications for Practice*

Despite the increasing application of BDA, it is not well understood how firms actualize BDA affordances successfully. In this research, we uncover structure-, actor-, and technology-level actions resulting in the actualization of four affordances at *PremiumCar*. Our revelatory case study provides actionable inspirations for organizational actions which contribute to the realization of business value through BDA.

The findings suggest that firms should leverage jointly four mechanisms to actualize BDA affordances: *enhancing*, *constructing*, *coordinating*, and *integrating*. As an example of *enhancing*, a company must complement its analytics systems with state-of-the-art BDA technologies to enable scalable analytics, as the enhancement of *PremiumCar's* storage system shows (see Affordance 3). As an example of *constructing*, companies must implement novel structural entities to pool BDA expertise and to create the organizational frame for pursuing BDA initiatives, as *PremiumCar's* marketing analytics subunit shows (see Affordance 1). Firms, however, should not only focus on constructing novel socio-technical entities or on enhancing existing socio-technical entities on the structure, actor, and technology levels. Rather, they should also align these entities by coordinating and integrating them. As an example of *coordinating*, companies must improve the interworking of BDA stakeholders, as the introduction of a scrum process to coordinate product managers and software developers shows (see Affordance 2). As an example of *integrating*, companies must bring together disparate data sources, as the integration of customer data from dealer systems and customer portals shows (Affordance 1).

In summary, our findings can help guide practitioners in crafting their BDA strategies and will be particularly insightful for traditional businesses seeking to profit from BDA, for instance, in form of product or service innovations. The discussed actualization mechanisms can, together with the exemplary actions which we discovered at *PremiumCar* and instantiate these mechanisms (see Table 6), be used as an organizational framework. Companies can map their planned and undertaken organizational actions in order to reflect on the coverage of each mechanism and each socio-technical level. In this manner, our study can provide initial support for a company in developing and transforming its STS to realize value from BDA. Limitations

Due to the interpretive nature of our revelatory case study, we cannot claim that we have explored exhaustively the actualization of BDA affordances. The statements in our interviews could have been interpreted differently by other people. In particular, the fact that we were in intense contact with our case organization between October 2016 and October 2017 bears the risk of inconsistent interpretations of early interviews and interviews conducted at later stages. To take this threat into account, we were careful when analyzing early data and aimed at triangulating findings between multiple data sources. Moreover, throughout the process of analyzing the data, we tried to create clear chains of evidence, considered multiple viewpoints, and involved multiple researchers in data coding and analysis.

Because we used a single case study approach to gain rich, in-depth insight, the generalizability of our findings may be limited. However, we base our empirical findings on well-accepted IS theories and propose four general actualization mechanisms (i.e., *enhancing*, *constructing*, *coordinating*, and *integrating*) which emerged from our case results to support further empirical research.

Our case study can be considered as a revelatory case as our case organization serves as a prime example for the actualization of BDA affordances when similar evidences or emergent theories on the actualization of BDA still need to be developed. Before generalizing our results to a further extent, however, additional research is required to prove that the results of this study also hold true in different contexts and industries.

## Conclusion

The process of realizing value from BDA has long been a Pandora's box for both scholars and practitioners. Insights from our revelatory case study of *PremiumCar* shed light into the actualization of four BDA affordances which address customer-centric marketing, data-driven services and development approaches, and optimized production processes. With regard to our introductory research question of how socio-technical actions contribute to actualizing, our results indicate that the enhancing, constructing, coordinating, and integrating of socio-technical entities conjunctively form the mechanisms which lead to an affordance being actualized. Our socio-technical perspective, which frames actualization as the process of a recursive shaping of social and technical entities (Leonardi 2012; Orlikowski 2000; Orlikowski and Scott 2008), enabled us to discover evidence of incremental and radical learning on both the organizational and individual levels. Further, it allowed us to distinguish three modes of BDA alignment (i.e., intellectual, social, and organizational alignment) which *PremiumCar* leverages.

We foresee three avenues for further research based on the results of this study. First, future research should analyze in other contexts how the four proposed mechanisms have a bearing on the actualization of BDA affordances. Supplementary insights into how these mechanisms' effectiveness is contingent on



factors such as industry, level of digitalization, or size would further increase our knowledge on the actualization of BDA affordances. Second, our findings motivate studies on how incremental and radical organizational learning mechanisms interact and shape the development of BDA capability. Particularly, we require further knowledge on the interrelationship of individual- and organizational-level learning and the combined effects on BDA capability formation. Third, our findings evidence that organizational actions on intellectual, social, and operational BDA alignment contribute to actualizing BDA affordances. Further research should study in greater detail the interrelationships of the different types of BDA alignment and BDA value. Particularly, studies on whether and how the roles of intellectual, social, and operational BDA alignment are contingent on a company's strategic orientation would enhance greatly our knowledge on BDA value realization.

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## Appendix A

### *Interview Protocol*

#### **Interview Introduction**

The accumulating evidence of the potential benefits provide a legitimate reason to consider Big data analytics (BDA) as a sustainable phenomenon rather than a buzzword (Davenport 2014; Davenport et al. 2012). BDA opens up new business opportunities, such as using “real-time information from sensors, radio frequency identification and other identifying devices to understand business environments at a more granular level, to create new products and services, and to respond to changes in usage patterns” (Davenport et al. 2012, p. 22). BDA is based on a continuous stream which delivers real-time data from heterogeneous sources and demands new approaches with which to structure and interpret the gathered data (Davenport et al. 2012). The implementation of BDA poses challenges regarding the development of appropriate organizational competencies (Agarwal and Dhar 2014; Loebbecke and Picot 2015) because the “expanding sea of data [...] is either too voluminous or too unstructured to be managed and analyzed through traditional means” (Davenport et al. 2012, p. 22).

Those challenges originate from the vast amount of data which come in both structured and unstructured forms and from various sources, such as the Web, social media, or the Internet of Things (Bhimani 2015; Constantiou and Kallinikos 2015). This leads to specific and novel implications for organizations on a procedural (e.g., new forms of decision-making), organizational (e.g., new employee competencies), and technological (e.g., new platform and tools) level. Accordingly, the adoption of BDA requires organizational transformations as well as the development of specific analytical (e.g., identification of new patterns) and technological capabilities (e.g., the effective deployment of big data platforms within the current IT landscape) (Chatfield et al. 2015; Davenport 2014; McAfee and Brynjolfsson 2012; Miranda et al. 2015).

In this interview, we aim to get an in-depth understanding of the actualization of BDA affordances. In particular, we focus on required organizational actions as well as their concrete outcomes.

#### **Interview Questions**

The following questions were asked selectively during interviews. If it proved necessary, follow-up questions were asked to gain a deeper understanding. The interviews took approximately 45 minutes. The interviews were recorded if consent was given to enable the anonymized analysis using qualitative research tools.

#### **Introduction and General Information**

1. How long have you been working in your current role and what are your main tasks?

#### **Main Objectives**

2. Which potential benefits (i.e., affordances) led to the adoption of BDA for the OEM which you are related to?
3. What organizational changes have been/are undertaken to achieve these potential benefits (i.e., affordances)?
4. What challenges did the OEM face to profit from BDA?
5. What mid- or long-term goals have been achieved by the OEM with BDA? Which individual, departmental, or company-wide actions were/are necessary to achieve them?

## Detailed Questions

### Social System

6. Please explain how digitalization and, in particular, BDA are anchored in the organizational structure.
7. Why was this design chosen (advantages/disadvantages)?
8. What roles have been created because of BDA and why?
9. What were the success factors for establishing BDA within the company?
10. Which governance mechanisms were helpful for anchoring BDA (e.g., committees, new processes, structures, etc.) (especially regarding the analysis of car data)?
11. What is the role of the IT department in the successful use of BDA?
12. Do collaborations with external service providers take place regarding BDA initiatives and projects?
13. Which capabilities are critical to the successful profiting from BDA?
14. How are these capabilities built up or brought into the company?
15. Are there any classical organizational capabilities that should be developed or modified in particular? Or do certain capabilities gain in importance?
16. To profit from (big) data analytics, should it be anchored in the culture of the company (i.e., a data-driven culture)?
17. Has such a data-driven culture been implemented in the past or is it recognizable? Which characteristics are recognizable?
18. Is the access to the data always possible, or are there any resistant forces recognizable in the company? How is data access guaranteed?

### Technical System

19. What technologies are used in this context and why was this technology chosen?
20. What data sources have been/are used? Are traditional data sources (such as ERP, CRM) used? What are the most valuable data sources and why?
21. How is technological access to relevant data sources ensured (e.g., 5G for car data streams)?
22. To what extent do the findings generated through applying BDA technologies affect organizational decision-making processes?
23. How are the findings passed on to internal or external customers (e.g., provisioned through analytics services or one-off projects/initiatives)?

### What else

24. Against the background of these questions would you like to add something?

## Interview Participants

Interviewee	Role	Years in Role	Interview Details	Suborganization
Round 1. Exploring Affordances				
A1	Group Head of Data Analytics & Strategy	~2 years	Online Meeting, 35 min	AutomotiveGroup, Group Strategy
B1	Head of IT Analytics Subunit	~2 years	Face-to Face, 56 min	PremiumCar
C1	Head of Mobility Services	~1 year	Online Meeting, 30 min	MediumCar
D1	Head of Navigation Systems	~2 years	Online Meeting, 30 min	MediumCar
E1	Head of Digitization Customer Journey	~2 years	Online Meeting, 37 min	CarCo
F1	Head of CRM & Data Analytics	~1 year	Online Meeting, 27 min	MobilityServiceCo

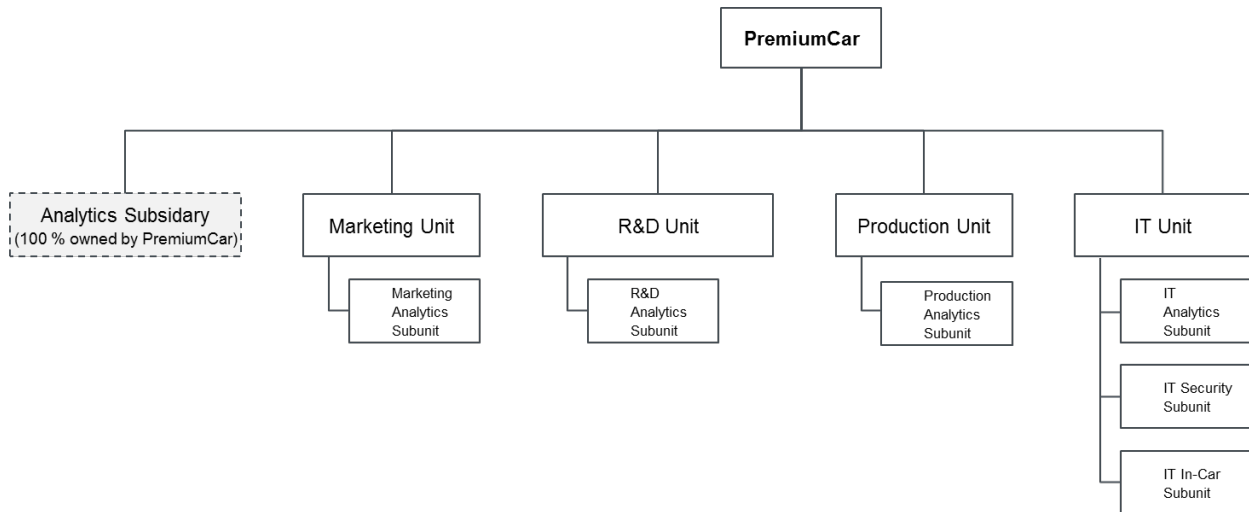
G1	Head of Development Big Data Analytics	~1 year	Online Meeting, 30 min	TrucksCo
H1	Product Owner, Big Data Analytics Platform	~1 year	Online Meeting, 42 min	TrucksCo
I1	Head of Market Intelligence (Data Science & Analytics)	~1 year	Online Meeting, 69 min	CommodityCar
J1	Consultant, Data Analytics	~4 years	Online Meeting, 66 min	LuxCar
K1	Partner Data Privacy Consultancy, Automotive	~8 years	Online Meeting, 45 min	AutomotiveGroup, Privacy Consultancy
L1	Consulting Director IoT/Analytics, Automotive Sector	~6 years	Online Meeting, 20 min	AutomotiveGroup, IT-Consultancy
Round 2. Actualization of Affordances				
A2	Head of Marketing Analytics Subunit	~5 years	Face-to-Face, 60 min	PremiumCar
B2	Head of Big Data Competence Center	~2 years	Face-to-Face, 79 min	PremiumCar
C2	Product Owner, Marketing Analytics Service Initiative	~2 years	Face-to-Face, 79 min	PremiumCar
D2	Product Owner, IT Analytics Subunit	~2 years	Face-to-Face, 35 min	PremiumCar
E2	Product Manager, Car Data #1	~2 years	Face-to-Face, 49 min	PremiumCar
F2	Product Manager, Car Data #2	~4 years	Face-to-Face, 44 min	PremiumCar
G2	Product Manager, Marketing Analytics Service Initiative #1	~4 years	Online Meeting, 44 min	PremiumCar
H2	Product Manager, Marketing Analytics Service Initiative #2	~2 years	Face-to-Face, 44 min	PremiumCar
I2	Product Manager, Marketing Analytics Service Initiative #3	~2 years	Face-to-Face, 63 min	PremiumCar
J2	Product Manager, Marketing Analytics Service Initiative #4	~2 years	Face-to-Face, 42 min	PremiumCar
K2	Manager, Privacy for Marketing Analytics Service Initiative	~1 year	Face-to-Face, 25 min	PremiumCar
L2	Manager, Digitization Strategy	~3 years	Online Meeting, 108 min	PremiumCar
M2	Manager, Digitization of Production Processes	~2 years	Online Meeting, 66 min	PremiumCar
N2	Head of R&D Analytics Subunit	~5 years	Online Meeting, 25 min	PremiumCar
O2	Business Analyst, Production Analytics Subunit	~2 years	Online Meeting, 47 min	PremiumCar
P2	Data Scientist, Production Analytics Subunit	~2 years	Online Meeting, 30 min	PremiumCar

R2	Project Lead, R&D Analytics Subunit	~2 years	Online Meeting, 42 min	PremiumCar
S2	Data Platform Architect, Analytics Subsidiary	~2 years	Online Meeting, 44 min	PremiumCar
T2	Data Scientist, IT Analytics Subunit	~1 year	Online Meeting, 42 min	PremiumCar

**Table A1. Overview of Interviewees**

## Appendix B

### Organizational Chart of PremiumCar



**Figure B1. Organizational Chart of PremiumCar (Simplified Excerpt)**

### Full List of Organizational Actions

Organizational Actions	Empirical Evidence	Affordances	STS Dimension (Actualization Mechanism)
Collocating IT analytics and marketing analytics subunits	<i>"To further improve on our collaboration with the IT analytics subunit, we are now collocated in the same building and on the same floor."</i> Interviewee A2	1	Structure-Level (Enhancing)
Using a standard data approval process	<i>"Every department has to nominate a chief data steward. Supported by a purchased data management software tool, we will implement a quick process to ensure the access to data."</i> Interviewee A1	1 2 3	Structure-Level (Enhancing)
Constructing a marketing analytics subunit	<i>"We decided on the management level that we want to move towards doing things independently in order to develop BDA knowledge and skill in house. In particular, with the topic data, we will have a competitive edge and will face a problem if our external providers know more"</i>	1	Structure-Level (Constructing)

	<i>than we do, as they might sell the same [services] to our direct competitors." Interviewee I2</i>		
Constructing an IT analytics subunit	<i>"Through the creation of the [analytics subunit at IT], we had, for the first time, a unit which was responsible for our IT tasks for all the analytics efforts we took over. Beforehand, it was so difficult to find a supporting partner in the IT unit, as no one really felt responsible." Interviewee A2</i>	1	Structure-Level (Constructing)
Aligning marketing analytics subunit, the IT analytics subunit, and the analytics subsidiary through a steering committee	<i>"We meet up on a weekly basis in a steering committee to align all our efforts from [the analytics subsidiary], [the IT analytics subunit] and [the marketing analytics subunit]. With four managers, two for our unit, we have to align our strategic goals and discuss the main challenges we are facing, may it be a business issue or a technological one." Interviewee C2</i>	1 2	Structure-Level (Coordinating)
Improving employee BDA competencies through a central education program	<i>"We try to educate [that way] our employees and our top management [...] we want to give them an understanding of the world of data at [PremiumCar]." Interviewee L2</i>	1 2 3 4	Actor-Level (Enhancing)
Initiating a top-down cultural change (through strategy implementation and leadership)	<i>"Data analytics is an immense cultural topic because it holds true that data results in knowledge, knowledge is power [...] to share and to provide access to this data is perceived of as a danger or risk by some people [...] Through our top management who put analytics and digitization on their strategic agenda, we could slowly get our colleagues at the marketing unit on board." Interviewee A2</i>	1	Actor-Level (Enhancing)
Ramping up employee knowledge and skills through collaborating with external service providers	<i>"In case we do not have the skills and knowledge, we try to collaborate initially with external providers to learn and to enable ourselves to slowly take care of the projects on our own." Interviewee C2</i>	1	Actor-Level (Enhancing)
Recruiting analytics-savvy and experienced business analysts for the marketing analytics subunit	<i>"Through the management decision to internalize knowledge and skills we had the possibility to slowly grow our capacities at the [marketing analytics subunit]." Interviewee A2</i>	1	Actor-Level (Constructing)
Recruiting data scientists, big data architects, and visualization experts in a start-up-like analytics subsidiary	<i>"The data scientists in the [analytics subsidiary] have substantial independencies because they can focus on and design the analytics methods and approaches without having to handle the day-to-day business. Being located in a more influential city, the analytics subsidiary is far more attractive to the rare talents we try to recruit for our analytics projects." Interviewee E2</i>	1 2	Actor-Level (Constructing)
Leveraging scrum as an agile development process to align employees of marketing BDA projects	<i>"When I first started in my role, I had frustrated employees due to the number of tasks they had to take care of and the lack of transparency of the tasks they worked on. So, we started to implement scrum as an agile method." Interviewee B1</i>	1	Actor-Level (Coordinating)
Bringing together previously distributed marketing analytics experts and consolidating respective marketing analytics projects	<i>"At the marketing analytics subunit, we consolidate all analytics experts and projects of the marketing unit." Interviewee C2</i>	1	Actor-Level (Integrating)
Newly bringing together big data experts in the IT unit through a big data competence center	<i>"The implemented competence network mainly targets employees in the IT subunits. In our company, we faced initially a serious issue with experts on analytics in the IT</i>	1 4	Actor-Level (Integrating)

	<i>unit. The big data competence center was a first step to bring together all existing and future experts to share their expertise across the IT unit and, consequently, to be a partner for units like the [marketing analytics] subunit." Interviewee A2</i>		
Delivering dynamic analytics services through a Tableau solution instead of offline dashboards	<i>"We built now a Tableau server through which we deliver our analytics service [...] Previously, data snapshots were used and sent as dashboards via mail, for instance, as PDFs or sometimes as offline Tableau dashboards. Now, we integrate these dashboards step-by-step." Interviewee C2</i>	1	Technology-Level (Enhancing)
Implementing a Teradata- and Tableau-based technological infrastructure	<i>"We implemented, in collaboration with the IT unit, Teradata as the data warehouse with the SPSS modeler as an analytics solution and Tableau as visualization software to unify the technological stack used in marketing." Interviewee C2</i>	1	Technology-Level (Constructing)
Integrating customer and dealer data from dealer systems and customer portals	<i>"The biggest challenge was the fact that no one paid attention to what happens with the data and what has emerged over the last five, six, seven years of operational systems. There existed very few individual examples with both a clean logic and a clean data model and an appropriate link with other systems." Interviewee A1</i>	1	Technology-Level (Integrating)
Leveraging an existing R&D committee to achieve visibility	<i>"[It] was crucial to take all established stake holders by the hand. You have to clarify that the process before was not the worst one and it made sense, but that you can improve it through analytics [...] So, we took part actively in the R&amp;D committee to push our topic forward." Interviewee E2</i>	2	Structure-Level (Enhancing)
Implementing a centralized committee landscape for data analytics (i.e., analytics board and office)	<i>"We install in every [suborganization] two committees [...]. The first [(the analytics board)] consists of the top management of each suborganization. The second committee, the analytics office, comprises managers of the middle management, who are nominated by their business department heads. These managers represent the business department's interests and make decisions in the name of the respective business departments." Interviewee A1</i>	1 2 3 4	Structure-Level (Constructing)
Central funding of marketing-R&D analytics projects	<i>"To finance our first projects with the R&amp;D unit, we were in the lucky position that we had been granted a strategy budget from our top management to heavily push forward our joint analytics efforts." Interviewee F2</i>	2	Structure-Level (Coordinating)
Supporting joint analytics efforts through top management in the R&D and marketing units	<i>"We received support from both the top managers from the R&amp;D and the marketing unit. That is something you absolutely need for new topics in our company." Interviewee E2</i>	2	Structure-Level (Coordinating)
New collaborating of the marketing analytics subunit and R&D unit	<i>"At first, it proved difficult to get hold of vehicle data, as our vehicles were not able to send data and, even more importantly, we were not collaborating until then with the R&amp;D unit." Interviewee E2</i>	2	Structure-Level (Integrating)
Co-coding with external partners	<i>"We use co-coding to avoid being dependent on the analytics knowledge of external partners [...] that way we make sure that we develop the required analytics know-how within our company." Interviewee N2</i>	2	Actor-Level (Enhancing)
Increasing the employee headcount for car-related analytics topics in the marketing unit	<i>"For us, it helped a lot that our top management not only ensured our financial budget, but also allowed us to recruit new employees for our topics." Interviewee F2</i>	2	Actor-Level (Constructing)

Improving the interworking of product managers and software developers with scrum	<i>"We have to develop a flexibility and agility in regard to our releases. Instead of two major releases, we need – as is characteristic for agile approaches – high-frequency micro releases [...] Scrum is one possibility to achieve this and to get our product management and the developing team together." Interviewee N2</i>	2 3	Actor-Level (Coordinating)
Constructing a cross-unit Hadoop platform	<i>"The platform receives data from our cars, production data (this means we try to connect our robots from the assembly lines), diagnosis data from our dealerships [...] we try to consolidate our data streams across the company with the platform." Interviewee S2</i>	2 4	Technology-Level (Constructing)
Improving the exchange of data between vehicles and the analytics platform with car data loggers	<i>"Together with R&amp;D, we have to lay the technological foundation for accessing vehicle data. [...] At first, we absolutely had to build in data loggers within our vehicles to allow the over-the-air-transfer of data." Interviewee E2</i>	2 3	Technology-Level (Coordinating)
Constructing an R&D analytics subunit for car usage data	<i>"We at R&amp;D collaborated initially with a lot of external partners...but we had to realize that it is really difficult to find a partner who could deliver components which work properly and take the domain-specific internal car systems into account." Interviewee R2</i>	2 3	Structure-Level (Constructing)
Recruiting platform architects for the IT unit	<i>"For us, it is crucial that we have the manpower to evaluate the technological solutions available on our own and to choose the best suitable technological stack for our use cases [...] in this regard, [the IT unit] took a huge step forward and hired platform architects that bring our endeavor forward." Interviewee R2</i>	3	Actor-Level (Constructing)
Establishing a closer exchange between security experts from the IT in-car and IT security subunits	<i>"Initially, our vehicles and our IT landscape had to be seen as disjoint systems. They only interacted in rare cases, such as in the case of maintenance work [...] accordingly, both the vehicles and the IT landscape were separately secured [...] Today, however, the IT security experts and in-car security experts work closely together, as we are otherwise not able to look at all aspects of security throughout the chain from the car to our IT landscape and vice versa." Interviewee N2</i>	3	Actor-Level (Coordinating)
Constructing an R&D Hadoop platform for on-road test data	<i>"During on-road tests, our test cars produce more than a gigabyte of data. [...] Though we have the technological infrastructure and processes to collect and store the data, we had to extend our technological landscape to allow analyzing these high volumes of data." Interviewee R2</i>	3	Technology-Level (Constructing)
Improving structural digitization support through a board of digital officers in the production unit	<i>"Besides coordinating our digitization efforts, which are mostly analytics topics, they try to avoid redundancies within the production unit. They have to find answers to: "Which data do we need from which production site? What should our system landscape look like over a five- or ten-year time horizon?" Interviewee O2</i>	4	Structure-Level (Enhancing)
Constructing a production analytics subunit	<i>"We as a team are responsible for finding ways to improve our production processes through analytical methods [...] Thus, we first try to access the data available to us and, in collaboration with the other [production subunits], identify use cases." Interviewee O2</i>	4	Structure-Level (Constructing)
Top management support for the analytics efforts in the production unit	<i>"Once our top management understood the value of analytics, they supported us as best as they could. For instance, through additional budgets." Interviewee O2</i>	4	Structure-Level (Coordinating)



New collaborating between the production and IT units	<i>"We started to collaborate heavily with the IT unit as they built an analytics platform for [PremiumCar]. The IT unit supports us with the toolset on which we can work and also takes care of all the licensing issues you face when you use enterprise solutions"</i> Interviewee O2	4	Structure-Level (Integrating)
New collaborating of production unit with legal offices to assert privacy aspects	<i>"When we optimize and digitize our production processes, the work our employees are doing in our production assemblies becomes transparent [...] of course, our work council is concerned with the privacy of our employees, so we closely discuss this aspect with our colleagues from legal."</i> Interviewee M2	4	Structure-Level (Integrating)
Offering a data-awareness program for management-level employees	<i>"We offer data awareness workshops on the management level. But you always have to consider that you will not reach all employees through the management or top-down approach. Thus, you have to complement it with bottom-up approaches."</i> Interviewee O2	4	Actor-Level (Enhancing)
Recruiting data scientists and data analysts for the production analytics subunit	<i>"We slowly started to recruit our own personal for analytics topics; in particular, data scientist and analysts like myself [...] our production processes are quite specific and require at some point more than analytical understanding."</i> Interviewee P2	4	Actor-Level (Constructing)
Establishing a social community for BDA in the production unit	<i>"Our analytics efforts are supported by regular workshops within our production unit which are organized by a colleague from another subunit. He actively pushes our social community in order to ensure collaboration and a common understanding in regard to our analytics efforts at the production unit."</i> Interviewee P2	4	Actor-Level (Integrating)
Connecting production data to the central analytics platform	<i>"Even though we implement a dedicated data lake for production, our main goal is to use our central analytics platform."</i> Interviewee O2	4	Technology-Level (Integrating)
Digitizing interfaces to production facilities	<i>"If we are not able to connect to our machines using protocols such as OPCUA, we enable our machines to connect to our LAN- or WLAN-infrastructure and try to access the data using different approaches [...] for instance, screen scraping."</i> Interviewee M2	4	Technology-Level (Integrating)
Implementing a data lake for the production unit	<i>"Our production unit is dominated by the continuous improvement process mindset. Thus, we try to support as well as we can the process of connecting data from all of our production facilities to our technological infrastructure and making the data analyzable. [...] We are producing across the globe, which makes it even more challenging."</i> Interviewee B2	4	Technology-Level (Coordinating)

**Table B1. Complete List of Organizational Actions for the Actualization of Affordances**

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