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How machine learning activates data network effects in business models: Theory advancement through an industrial case of promoting ecological sustainability

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ABSTRACT

A firm's business model accounts for direct and indirect network effects, where the network size is a key enabler of value creation and appropriation. Additional conception of a business network's contribution is provided by a recent advancement of the theory of data network effects, where machine learning is used to analyze large data sets to learn, predict, and improve. The more learning there is, the more value is generated, producing ever more data and learning and creating a virtuous circle. For the first time, this study combines the theory of data network effects with business model theory. The contribution lies in extending a business model's lock-in effects through direct and indirect network effects to encompass data network effects. This paper provides a case study that supports the theoretical advancement and illustrates how this form of machine learning can increase profitability while reducing negative ecological impacts in an industrial context.

1. Introduction

A firm's use of digital technologies enables the activation of direct and indirect network effects (Katz & Shapiro, 1985; Parker, Van Alstyne, & Jiang, 2016) as part of the business model to create and appropriate value (Amit & Zott, 2001). In certain cases, such as the technology firms Amazon, Apple, Alphabet, Facebook, and Microsoft, this value is unprecedented (Parker et al., 2016). Direct and indirect network effects create a certain amount of value depending on the size of the network (Afuah, 2013). That is, the more users of an offering there are, the more valuable it becomes. This value in turn attracts more users, which creates even more value, and so on (Economides, 1996; Farrell & Saloner, 1986; Liebowitz & Margolis, 1994; Sheremata, 2004). In neoclassical economics (Afuah, 2013), this size hypothesis is challenged. The suggestion is that the size assumption should be relaxed and that other network characteristics of a firm's business model also contribute to value creation and appropriation. A recently proposed characteristic relates to actors' ability to conduct experience-based *learning* by means of machine learning techniques. This learning is enabled by the collection of large volumes of data that are analyzed using machine learning techniques (Gregory, Henfridsson, Kaganer, & Kyriakou, 2020). The use of such technologies to perform data analysis enables the identification of patterns in past behavior. Predictions can thereby be made to increase the accuracy of the offerings provided to users. This increased accuracy generates higher perceived value, as illustrated by AI-powered traffic navigation systems, music streaming services, and Internet search engines (Russell & Norvig, 2009; Sivarajah, Kamal, Irani, & Weerakkody, 2017). When the accuracy and success of the data and AI-enabled learning increases, the predictions become more accurate, and subsequently the value of offerings provided to users increases. This value may in turn help to attract additional users. These causal chains of events emerging from positive feedback (Arthur, 1990) are known as *data network effects* (Gregory et al., 2020).

A key question therefore arises: *Can the contemporary conception of a business model, based on the conventional strategic network theory of direct and indirect network effects* (Amit & Zott, 2001; Massa, Tucci, & Afuah, 2017; Zott, Amit, & Massa, 2011) *be extended to account for the newly proposed notion of data network effects?* By answering this question, the purpose of this study is to advance our understanding of firms' value creation through business models that use machine learning technologies.

To answer this research question, this paper presents a unique case study of an industrial firm that has embraced the use of big data and machine learning in its development of dedicated customer service

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packages. This case study offers an in-depth understanding of how firms can create value by modifying the business model architecture to adopt and use machine learning technology and thereby activate data network effects (Foss & Saebi, 2017; Teece, 2010). This case study thereby provides a positive answer to the research question. The study shows how this form of activation of data network effects contributes to the realization of the four business model themes of efficiency, novelty, complementarity, and lock-in (Amit & Zott, 2001). Additionally, the study shows how data network effects boost the economic value of the service offering while reducing negative ecological impacts by lowering CO_2 emissions. This paper thereby contributes to the literature on both business models and sustainable business.

The next section reviews business model theory and the theory of data network effects to target the knowledge gap. A knowledge proposition is derived thereafter, which is subsequently tested in an empirical case study. The research approach and methods are then presented, followed by detailed analysis of the case study. The paper ends by offering a discussion and presenting the conclusions of the study.

2. Literature and theory development

This review starts by recalling the emergence of the notion of the business model. Next, the business model is defined, and the role of the business model themes in value creation and appropriation is reviewed. The focus then turns to the strategic network theory that underpins the notion of the business model. In this case, the discussion centers on the network effects that contribute to the realization of business model themes, particularly lock-in. A limitation of one of the key assumptions of strategic network theory, namely that network effects are driven solely by network size, is then explained. Instead, the conception of data-driven learning in a network is proposed as an alternative source of value creation and appropriation. That argument lays the foundation for the main contribution of this research by integrating the recently proposed data network effects into the notion of the business model. This integration suggests that the business model architecture can be configured to realize data network effects and thereby activate several business model themes.

2.1. The emergence of the business model conception

At least two forces seem to have driven the conception of a firm's business model. One derives from the world of business, where several emerging factors interact, including the development and adoption of novel technologies in manufacturing, transportation, and logistics. Digital technologies accompanied by changes of trade regulation jointly enabled the emergence of global markets (Teece, 2010). The second force is the inability of the existing bodies of theory to account for and explain the radical value created and appropriated by technology-based firms. For example, Apple's market entry into the mobile phone industry cannot be explained using the conventional views in the industrial organization literature (Parker et al., 2016), namely the position view (Porter, 1985) and the resource-based view (Barney, 1991). Apple's successful entry should have been hindered by the high barriers to entry imposed by the incumbent phone makers. These barriers included strong brands, large scope and size, optimized global supply chains, intellectual property, and know-how. The predominant bodies of theory such as the contingency view (Miller, 1988, 1992), position view (Porter, 1985), resource-based view (Barney, 1991; Teece, Pisano, & Shuen, 1997), Schumpeterian innovation (Schumpeter, 1934, 1942), transaction cost economics (Williamson, 1975, 1979, 1983), strategic networks (Doz & Hamel, 1998; Gulati, Nohria, & Zaheer, 2000), and network externalities (Arthur, 1990; Katz & Shapiro, 1985) could at best individually offer a selective and highly limited account of this novel kind of economic value creation and appropriation (Amit & Zott, 2001). Business world experiences of economic value creation and appropriation coupled with these theoretical limitations motivated theorizing that gave rise to the concept of the business model (Amit & Zott, 2001; Massa et al., 2017; Zott et al., 2011). At least two key views of the business model emerged. Under the first view, it is assumed that the business model characterizes a firm and its context, including its performance and performance drivers. According to the other view, the business model is a cognitive filter (or pattern) that characterizes the thinking and decision making of the managers of a firm (Massa et al., 2017). While both views make crucial contributions to the understanding of a firm's value creation and appropriation, the view that the business model characterizes the firm is adopted here because that view enables the conception of value creation from the use of digital technology (Amit & Zott, 2001; Massa et al., 2017)

Following attempts to unify organizational, strategic management, and entrepreneurship theories (Amit & Zott, 2001; Massa et al., 2017; Zott et al., 2011), research has recently converged upon a shared notion of the business model as the "architecture of value creation, delivery, and capture mechanism" (Teece, 2010, p. 172). Here, "architecture" refers to "the functional relations among those mechanism and the underlying activities" (Foss & Saebi, 2017, p. 215) accounting for value creation, delivery, and capture. With this conception of the business model, value creation is regarded as a firm boundary-spanning system of deliberate activities operated by firm-internal and firm-external actors, which are linked with transaction mechanisms to activate one or more value creation themes (Amit & Zott, 2001; Zott & Amit, 2010). The business model construct extends the conventional understanding of a focal firm's value creation and appropriation (Roberts, 2004). Instead of regarding a firm as a standalone entity, either as a bundle of resources (Barney, 1991) or as a chain of activities performed using the firm's resources to enhance its competitive position within its industry (Porter, 1985), the understanding has evolved into something more comprehensive. According to the conventional understanding of a firm, value is created either by a firm's value chain activities (Porter, 1985) or resources (Barney, 1991) on the supply-side of a transaction. By contrast, the business model understanding accounts for the fact that value can be created and appropriated on both the supply side and the demand side of a transaction and that this value is rooted in both resources or actors and activities (Massa et al., 2017; Zott et al., 2011).

2.2. Business model themes

In their groundbreaking work, Amit and Zott (2001) presented four key *business model themes* that make up the design, or configuration, of the business model architecture to create and appropriate value (Amit & Zott, 2001; Kulins, Leonardy, & Weber, 2016; Zott & Amit, 2007, 2008). The actors within the architecture, along with their capabilities, are synchronized with transaction mechanisms and the governance setup to build an activity system of the business model. Such configurations may activate one or more business model themes. The importance of the business model themes lies in the fact that they co-determine variation in the performance of a firm (Amit & Zott, 2001; Sohl, Vroom, & Fitza, 2020). They thereby complement other known product-specific, firm-specific, industry-specific, and country-specific performance conditioners (Hawawini, Subramanian, & Verdin, 2003; McGahan & Porter, 2002; Porter, 1985; Rumelt, 1991; Sohl et al., 2020). The four business model themes are *novelty*, *efficiency*, *complementarity*, and *lock-in* (Amit & Zott, 2001; Zott & Amit, 2007).

The *novelty business model theme* refers to a configuration of the business model architecture that is new to the market in terms of kinds of actors and their activities, types of transaction mechanisms linking actors, interaction patterns, and the overall governance structure (Amit & Zott, 2001; Bouncken, Kraus, & Roig-Tierno, 2019; Lee & Trimi, 2018; Martínez-Climent, Mastrangelo, & Ribeiro-Soriano, 2020). The novelty of a configuration in the market must be relevant to its constituent actors such as customers, suppliers, employees, and other partners. This novelty should target a latent market need. One example is eBay's disruption of the auction market by enabling large-scale trading of low-value items, thereby creating a large new market segment. The *efficiency* business model theme refers to an architectural configuration that enables resource consumption that is lower than that of alternatives in the market (Amit & Zott, 2001). This efficiency can occur through novel configurations of actors, alternative uses of actors, novel activity system setups, and novel transaction mechanisms. An example is Spotify's music streaming service versus Apple's music file downloading solution. The *complementarity* business model theme accounts for architectural setups that have various ways of bundling offerings, activities, resources, and capabilities (Amit & Zott, 2001). Crucially, this combination of assets must be non-trivial so that two or more resources complement each other and additional value is thus generated from their combination. That is, the value of A increases more in the presence of B than in the presence of C (Ennen & Richter, 2010; Milgrom & Roberts, 1994). Amazon exemplifies this theme with both its expansion from books into general retail and then its unveiling of Amazon Web Services. Finally, the *lock-in* business model theme is configured to disincentivize the actors in a business model architecture (i.e., customers, mediators, partners, suppliers, and employees) from migrating to an alternative. Amit and Zott (2001) stress that lock-in can be activated through both *sunk costs* (Parayre, 1995) and *network externalities* (Katz & Shapiro, 1985), such as direct network effects and indirect network effects (Clements, 2004; McIntyre & Srinivasan, 2017). The music provider Spotify again offers an illustration of both of these forms of lock-in. First, when a user creates a large set of playlists, the time invested is a sunk cost because these lists cannot be transferred to an alternative music provider. Second, as the number of actors that use Spotify grows, more sharing becomes possible (sending and receiving), which adds value with respect to a new competitor with a small customer base.

Amit and Zott (2001) stress that the four business model themes are neither orthogonal nor mutually exclusive. Several of them can co-exist. Recent research suggests that a business model can change its themes over time as it co-evolves with external factors (Costa Climent & Haftor, 2020). The business model conception, with its four themes of value creation, rests on an ingenious combination of well-established individual theoretical lenses, namely the Porterian value chain (Porter, 1985), the resource-based view (Barney, 1991), transaction cost economics (Williamson, 1983), Schumpeterian innovation (Schumpeter, 1942), and strategic network theory (Doz & Hamel, 1998; Gulati et al., 2000). The theoretical lens of strategic network theory is the focus of this paper.

2.3. Strategic networks and value creation

A key advancement in the conception of the business model is the incorporation of the strategic network view, together with the other views mentioned earlier. A firm's strategic network is regarded as an inter-actor configuration, where actors are organizations and individuals such as consumers (Freeman, 1979). Strategic networks may take various forms such as alliances, joint ventures, and long-term buyer–supplier relations. Regarded as an alternative to purely market-based or internal hierarchy solutions of governance (Williamson, 1979), strategic networks enable firms to access information and knowledge, customer and supplier markets, technologies, intellectual property, and so on while sharing risks (Anand & Khanna, 2000; Dyer & Nobeoka, 2000; Gulati et al., 2000; Hughes, Cesinger, Cheng, Schuessler, & Kraus, 2019; Katz & Shapiro, 1985; Shapiro & Varian, 1999). A key finding from the strategic network research is that a firm's value creation can center on the strategic network and is therefore *outside* the focal firm as such (Burt, 1992; Doz & Hamel, 1998; Gulati et al., 2000). This idea is contrary to the assumptions of the position-based and the resource-based views, where it is the focal firm that creates value through its value chain or capabilities (Barney, 1991; Porter, 1985). A crucial contribution of strategic network research is the recognition that a firm's value is created not only on the supply side of a transaction (as assumed under the position-based and resource-based views) but also on the demand side (Afuah, 2000; Priem, 2007; Priem & Butler, 2001; Priem, Butler, & Li, 2013). For example, under a business model conception, Google's success is acknowledged as being conditioned by *both* its internal capabilities (e.g., search algorithms) *and* activities conducted by the users of its search engine through the data they produce when they use its algorithms. These data enable further development of those algorithms and thereby search performance. The user of the offering is thus its co-producer.

Amit and Zott (2001) explain how a firm's strategic network can contribute, together with the other views, to the realization of the four value creation themes of the business model. A strategic network can increase the *efficiency of a business model*, such as when key resources are accessed more easily than otherwise. A strategic network can also enable the realization of *complementarities* by linking several actors' assets so that their combination generates additional value (Gulati, 1998). One example of this is when travel agencies provide a bundle of services from accommodation to travel insurance, all provided by different actors. A strategic network can give rise to *novelties*, such as new offerings and new operational setups that disrupt an industry, as exemplified by eBay. Finally, strategic networks constitute a key enabler in the realization of a business model's value creation through *lock-in*. This role of strategic networks stems from their ability to realize network externalities (Arthur, 1990, 1996; Katz & Shapiro, 1985; Shapiro & Varian, 1999). Here, network externalities mean that "the utility that a user derives from consumption of the good increases with the number of other agents consuming the good" (Katz & Shapiro, 1985, p. 424). Thus, the value of a product to a user may originate from the product's benefits, from the other users of the product, or both (Economides, 1996; Farrell & Saloner, 1986; Liebowitz & Margolis, 1994; Sheremata, 2004).

Two kinds of network externalities or effects are typically considered: direct network effects and indirect network effects (Clements, 2004; McIntyre & Srinivasan, 2017). Direct network effects emerge when a user of a product (i.e., a good or service) or platform can interact with other users, thereby generating value for other users (Rochet & Tirole, 2003; Zhu & Iansiti, 2012). A classic example is the telephone network. The more users there are who use this network, the more users there are to be linked to. Thus, more value is offered to these users. A telephone network with two individuals has less value than one with two billion individuals. This value is at the core of social platforms such as Facebook, where users can interact directly with each other by both producing and consuming content. Indirect network effects emerge when the more users of a product or platform there are, the more it attracts a diversity of complementary offerings, thereby increasing the value provided to each user (Boudreau, 2012; Church, Gandal, & Krause, 2008; Clements & Ohashi, 2005). This idea was illustrated when Apple introduced its iPhone and opened the App Store for third party app providers. Apple succeeded in attracting an initial customer base that in turn attracted third party actors to develop and offer a multitude of apps. This offer in turn attracted an even larger customer base, which, once again, attracted more new apps, and so on.

While the outlined strategic network theory accounts for the way that value creation and appropriation functions in a firm's network, Afuah (2013) notes that the current strategic network theory focuses primarily on the role of the *size of a network* for value creation and appropriation. This focus is illustrated by the theory's early development in neoclassical economics: "The benefit that a consumer derives from the use of a good often depends on the number of other consumers purchasing compatible items" (Katz & Shapiro, 1986, p. 822). Afuah (2013) lists several key assumptions of this *network size hypothesis*. Two key assumptions are as follows: (i) every actor in the network can transact equally with every other actor and benefit equally; and (ii) all actors across the network (both providers and receivers) have similar capabilities. Afuah (2013) challenges these and other key assumptions, concluding that *size* is only one of several characteristics of a firm's network that generate value. Other characteristics related to a network's structure and conduct are cited. Examples include the type of ties (weak vs. strong) between actors, the number of roles that an actor plays (producer or consumer), the degree of opportunistic behavior, and the reputation of actors.

2.4. Data network effects

A new type of network effect theory has recently been proposed: the theory of *data network effects* (Gregory et al., 2020). According to this theory, the more a platform or a provider *learns* from the data it collects on users, the more valuable the platform becomes to each user. This theory thus relates an actor's ability and scope to collect, analyze, and *learn* from data to the value creating characteristics of a network that form the foundation for improving offerings. It is at this juncture that the present paper's key contribution comes to light. This paper proposes a modified conceptualization of the business model where, instead of considering the *size of the network* as the only means of value creation, the actors' *scope for data-driven learning* is also considered to be crucial. Unlike traditional network theory, data network theory recognizes that numerous networks and their transactions can generate large volumes of varied data and have a "computer in the middle" (Varian, 2014, p. 1). This endows actors—organizations and their parts—with a certain kind of intelligence (van Gigch & Le Moigne, 1990). The remainder of this paper elaborates on this proposition and investigates it empirically.

An example of a data network effect is Google's search engine, where data come from search content, context, time, place, terms, their permutations, and so on. These data can be analyzed by Google to generate new insights. These insights are then used to further develop and adapt Google's services in general and to personalize and customize offerings for each individual user. This service improvement and personalization convinces users that the services are more valuable, which simultaneously incentivizes existing users to continuing using these search services and attracts new users. This positive feedback loop (Arthur, 1990) is fully automated. Large data sets are gathered and analyzed using machine learning techniques, a type of artificial intelligence (Greenwald & Oertel, 2017; Russell & Norvig, 2009). Similar procedures and tools are used by Netflix's video streaming services, which continuously collect user data, analyze these data to detect patterns, and adjust the video content offered to each user. Music streaming providers, such as Spotify, analyze users' listening habits to generate new playlists, which are customized for each user in a given time and place. Banks collect massive volumes of user data, employing numerous machine learning algorithms to customize offerings for clients and detect and prevent fraud.

In all of these examples, a provider's *AI capability,* hence scope for data driven learning, is the key underlying mechanism for the realization of data network effects. AI capability is "the ability of a platform to learn from data to continuously improve its products and services for each user" (Gregory et al., 2020, p. 12). The key way of improving users' perceived value of a good is through the improvement of *predictions* (Meinhart, 1966). Prediction is the ability to produce information about the future based on information about the past and present (Churchman, 1961). Prediction is crucial because it enables the customization of offerings (both products and means of transactions) to fit the evolving needs and wants of each user. The better the predictions are, the higher the user value and satisfaction will be. Predictions by machine learning algorithms (Greenwald & Oertel, 2017; Russell & Norvig, 2009) are based on learning from examples. This learning typically requires a vast set of examples of various kinds to achieve prediction accuracy. Successful prediction informs providers on how to further develop, adjust, or fine-tune their offerings. Examples include a navigation system's prediction of traffic flows and Facebook's identification of toxic content (e.g., violence, spam, nudity, hate speech, and political misinformation). Continuous use of offerings generates continuous data points. These data points can be continuously analyzed for pattern identification. This pattern identification can then be followed by continuous learning to make more accurate predictions. These predictions can in turn be used for further development and adjustments of offerings to create additional value for users, who become incentivized to continue using the provided offerings. This cycle then repeats. This continuous learning and subsequent improvement of offerings gives rise to a new kind of network externality, where a user's utility of an offering is "a function of the scale of data-driven learning and improvements with AI" (Gregory et al., 2020, p. 5) rather than a function of the total number of users (Afuah, 2013; Katz & Shapiro, 1985). The recent emergence of this new data network effect stems from the novel use of digital technologies to extract insight from large data sets and to capitalize on these to provide complementary offerings and achieve lock-in effects. These technologies have an ever-increasing performance-to-cost ratio through their ability to collect, transfer, store, and process data at an unprecedented rate. Novel machine learning techniques enable data-driven learning. Here, few if any pre-defined rules exist, and the algorithms teach themselves classifications based on the data patterns they identify in the large data sets they operate on (Greenwald & Oertel, 2017; Russell & Norvig, 2009). This recently proposed theory of data network effects has received critical scrutiny (Clough & Wu, 2020) in two areas. One concerns the decentralized nature of platform-based businesses and the challenges they pose to value appropriation. The second is that the relationship between the quantity and quality of the data is only loosely associated with the size of the user base. Both these suggestions seem highly pertinent. However, they lie outside the scope of the empirical study presented here.

2.5. A business model endowed with data network effects

The above discussion explains that firms that succeed in activating data network effects through data-driven learning influence both the actors and the activities of their business models. For example, Uber's machine learning algorithms predict the arrival time of a driver to pick up a rider (Rosenblat, 2018). The better the prediction, the more value is offered to the rider, to the driver, and, therefore, to Uber. In this sense, Uber is equipped with artificial agents. These new kinds of actors, constituted by a set of such algorithms, conduct new kinds of activities within the business model. In this case, these activities are predictions based on continuous machine learning and large sets of data, something that conventional taxi services cannot provide (Rosenblat, 2018). Such predictions enable learning, which in turn influences the behavior of riders who can plan their time more effectively up until the predicted arrival time.

Successfully activated data network effects may thus contribute to activating the business model themes. First, data-driven learning may contribute to activating the *efficiency* theme through the optimization of resource use. This efficiency is possible in the case of both the product that is provided and the transaction that provides the product. One example is how offering an optimized route plan for taxi drivers may reduce fuel consumption. Second, data-driven learning may contribute to activating the *lock-in* theme. Increased data gathering and analysis may provide increased learning that contributes to improved products and transactions, which incentivizes the continued use of these offerings. Amazon pioneered this approach in its book business (Kotha, 1998; Zhu & Liu, 2018). Data on search and purchase behavior is analyzed for pattern identification, enabling learning with regard to both whole customer segments and individuals. Customers are presented with new book titles that offer a better match with their interests than matches made without data-driven learning (Zhu & Liu, 2018). The more these data are collected, the better the learning and prediction and, therefore, the better the offering will be and the more satisfied the customer will feel. Such service offerings disincentivize customers from migrating to competitors that lack such data and therefore cannot provide offerings that are as highly customized. This scenario captures the essence of the lock-in theme (Amit & Zott, 2001). Third, data-driven learning may contribute to activating the *novelty* theme. The first mover initiates data gathering, analysis, learning, and improvements of offerings in a given market sector. As with conventional Schumpeterian innovation (Schumpeter, 1939), this first mover may obtain entrepreneurial rents as long as no competitor imitates or substitutes the offering. In the traditional, no-network-effects world, the entrepreneurial time window is typically inversely proportional to the value of the entrepreneurial rents (Schumpeter, 1942). Accordingly, the greater the rent is, the smaller the time window will be before competitors arrive. In the world of data network effects, however, imitation by competitors can be halted for at least two related reasons. First, the first mover succeeds in acquiring a large enough customer base and activates the lock-in mechanism using any combination of the three network effects (direct, indirect, and data network). Second, followers that attempt to imitate the entrepreneurial firm are hindered by the fact that the first mover has acquired vast sets of data and has learned about its customers. The first mover firm can thus improve its offerings, while imitators lack the data required to do so and cannot initiate their learning. They thus provide inferior offerings. Competitors must follow other market strategies than imitation, such as differentiation or niche (Costa Climent & Haftor, 2020; Porter, 1985).

2.6. The proposition

Based on this discussion, we formulate the following proposition:

A business model architecture configured to realize data network effects contributes to activating the business model value creation themes:

- with regard to *novelty*, when the focal firm is the first in its market segment;
- with regard to *efficiency*, when resource use is reduced through learning and improvements; and
- with regard to *lock-in*, when improvements provide superior offerings.

A core question here is, *what characterizes a business model architecture that achieves data network effects?* Gregory et al. (2020) provide the proposal adopted here. An offering's *user value* is created by its provider's use of machine learning to generate insights from large data sets for learning and the subsequent improvement of offerings. User value is understood here as the user's perception of value from that user's actual use of the offerings. This positive relationship between user value and the provider's ability to learn and improve offerings is moderated by several factors. These factors are *prediction*, *legitimation*, *data stewardship*, and *user-centric design* (Gregory et al., 2020).

Here, AI refers to the numerous machine learning methods used to analyze large data sets of relevant experiences and identify patterns in these data sets. These data sets account for past events and can be used to predict the occurrence of future events (Greenwald & Oertel, 2017; Russell & Norvig, 2009). These hidden patterns can then be used to develop prediction models that generate predictions. An example is provided by Facebook's algorithms that predict what to post, for whom, and when. The success of predictions is conditioned by their *speed* and *accuracy*. If Uber's arrival time to pick up a rider is quick and accurate enough, then the user (i.e., the rider) will perceive positive value. By contrast, if such predictions are inaccurate or slow, the user will perceive lower value and may turn to an alternative.

The next mediating capability is *data stewardship*, which is the ability to ensure the right *quality* and *quantity* for the analysis performed by machine learning algorithms (Agrawal, Gans, & Goldfarb, 2018). Data feed machine learning algorithms for training to develop production models until they produce accurate enough predictions, just as fuel feeds industrial machines (Varian, 2014). The more high-quality data there are, the better the prediction models, and thus the predictions, will be (Simon, 1996), contributing to user value. Experience shows that if data are insufficient for training a given prediction model, or if the data are not of a high enough quality (e.g., not a wide enough range of cases), then inaccurate predictions are generated, reducing their user value (Khoury & Ioannidis, 2014).

User-centric design factors refer to the actual design of the offering that a user uses. The design should reflect the users' needs and wants in a manner that increases the *performance expectancy* and reduces the *effort expectancy* of the offering. This issue is crucial because the data network effects of a business model typically depend on access to large sets of user data derived from users' actual use of the offering (Gregory et al., 2020). Users must be incentivized to engage in interactions and use of the offering so that they generate the necessary use data. For example, Waze, a turn-by-turn navigation service, calculates the traffic speed and road network in real-time from local data, car speeds, time information, and travel directions on mobile phones in cars on the road. Waze is packaged into a well-designed, user-friendly mobile phone app that encourages its users to use it and interact with it. Without such use and interactions, data would not be generated, and the quality of traffic predictions would quickly vanish, along with perceived user value.

The final factor that moderates the positive activation of data network effects is the *legitimacy* of the offerings and the provider. Legitimacy refers to a situation when an action's target audience perceives the action as desirable and appropriate in relation to some relevant social norms, beliefs, and attitudes (Suchman, 1995). Legitimacy is a crucial determinant, and thus a crucial asset, of a social actor's ability to acquire resources (Garud, Schildt, & Lant, 2014). In the case of activating data network effects, the key resource is the ability to generate and access relevant data to improve predictions and thus offerings. To generate such data, the provider of an offering should ensure positive legitimacy in the eyes of the stakeholders of an offering. Legitimacy includes two aspects. First, *personal data* collection, storage, processing, and usage must be regarded as legitimate; second, *transparency* must be provided to stakeholders with regard to the use of machine learning and predictions (Gregory et al., 2020). If stakeholders deem the use of personal data and machine learning legitimate, access to data will not be hindered by a legitimacy crisis, such as that experienced on occasions by Facebook.

We now empirically test the proposition regarding business models endowed with data network effects.

3. Empirical approach and methods

A longitudinal case study was conducted to explore the potential validity of the proposed notion of a business model. The case study explored the use of machine learning algorithms and big data with prescriptive analytics by a large international firm that produces heavy vehicles. The firm, which is headquartered in Northern Europe, is referred to here as VehiCo for anonymity. VehiCo has developed and introduced several services to improve the performance of vehicles for long-haul transportation in Europe. Longitudinal case studies enable the identification of time-conditioned transformations and the effects of these transformations. Such studies can thus reveal underlying mechanisms, such as the business model architecture (Ahuja, 2000; Lindgreen, Di Benedetto, & Beverland, 2020). The choice of this firm follows the purposive sampling approach (Patton, 1990). The selection criteria were the firm's use of machine learning and big data to improve services and comprehensive access to the firm's offerings, documents, and representatives.

The study was pursued for 38 months from February 2015 to June 2018. Both qualitative and quantitative data were collected from VehiCo and three of its customers. In total, 245 interviews were conducted with 86 respondents. Each interview lasted approximately 1 h. The interviewees were representatives from the various functions of VehiCo (R&D, production, marketing and sales, aftermarket, HR, and finance), as well as customer representatives. With these customer representatives, 28 co-traveling sessions were conducted with three customer firms, each featuring a set of vehicles and drivers. Internal archival documents were gathered (approximately 1150 pages). These documents covered strategic and marketing plans, sales forecasts and market intelligence reports, product documentation, and project plans. Quantitative data on the performance of the vehicles and associated services such as fuel consumption and vehicle condition were accessed through a dedicated product information system. All data were transcribed and documented in a research system (ALTAS.ti) for the qualitative analysis. Two researchers analyzed the data, guided by the theorization presented earlier and the proposition for the business model endowed with data network effects. The data were coded descriptively and a-theoretically. They were then grouped into themes (open coding). Thereafter, these themes were condensed into theory-related topics (axial coding) with iterative comparisons between the data and the theoretical categories outlined earlier (Klein & Myers, 1999). This data collection, documentation, and analysis was conducted iteratively throughout the whole research engagement with VehiCo. Saturation was thus achieved such that no new insight was obtained toward the end of the investigation.

4. The case of value-extending services

This section presents and analyzes the case study. First, the business model and context are detailed. Then, the newly developed services that were added to the pre-existing business model are outlined. The services based on the use of machine learning technologies are then detailed. This analysis reveals how this use of machine learning technology activated the data network effects that led to the realization of business model themes. The analysis thereby tests the proposition formulated earlier.

4.1. The business model and context

Manufacturers of commercial road vehicles provide trucks to carry loads on roads for commercial purposes. These vehicles are acquired by commercial road transportation firms. These firms are the customers of VehiCo. VehiCo provides the market with approximately 100,000 heavy vehicles annually. These vehicles are used for various applications, including construction, manufacturing, courier and postal services, petroleum and chemicals, forestry and mining, and retail and long-haul transportation. Long-haul transportation represents the largest and most profitable market segment for VehiCo. Its European market is the focus of the present investigation. VehiCo was established a century ago. Today, it competes with a handful of vehicle providers in the premium segment. It has been the most profitable manufacturer of heavy-duty vehicles in its industry for several decades, with 10% to 13% annual profit. The transportation firms that are the customers of VehiCo and its peers are categorized into three groups: small, medium-sized, and large. VehiCo services all of these groups. However, it deliberately focuses its marketing and sales efforts on small and medium-sized transportation firms because they offer a higher profit. The reason is that most small and medium-sized transportation firms require a large set of services to use their vehicles because they typically lack the internal resources and capabilities (e.g., maintenance and repair) needed to provide such services themselves. Services generate significantly higher margins than vehicles. VehiCo has the largest service business in its industry, and it is renowned for its service innovation, which has quickly been imitated by its peers. The downside of serving small and medium-sized customers versus large fleet owners is the higher transaction costs because a substantially higher volume of transactions is generated by a large set of small and medium-sized customers that require a large set of services.

In terms of service, toward the end of 1980 s, VehiCo launched the first repurchase program. Under this program, a new truck was used for 1–3 years by a first-hand transportation firm, mostly in Western Europe, at which point VehiCo offered the option to buy back the vehicle. VehiCo then renovated and refitted the vehicle and sold it on to a second-hand transportation firm, often in Eastern Europe. This program became highly popular, providing first-hand users with reduced risk by enabling them to predict the cost of ownership and giving second-hand users the opportunity to acquire a high-quality vehicle with warranties at a much lower cost than a new one. As industry peers copied this offering, VehiCo launched new kinds of services. These services encompass new modes of pricing, including leasing, renting, and outcome-based payment (e.g., price per driven kilometer per day of use). Under these modes of pricing, the vehicle itself remains in the ownership of VehiCo and can be resold later in the second-hand market.

As mentioned earlier, VehiCo noted that most small and medium-sized transportation firms lacked the internal technical resources needed to conduct vehicle maintenance and repair activities. This insight was accompanied with the insight that such firms typically also lack dedicated internal HR, IT, and advanced operations management resources. The average profitability of such firms is very low (1–3%) because they operate in a highly undifferentiated market (McK, 2018). In contrast, large fleet companies have the internal resources to optimize their resources. For example, they have dedicated service technicians who conduct vehicle repair and maintenance activities. They also have professional HR personnel to recruit drivers, typically from Eastern Europe because of their lower compensation (and thus costs) than drivers from Western Europe. Finally, large fleet companies have IT and operations management functions to plan for and measure the optimized use of resources such as route-planning and the procurement of batches of vehicles at a discount. All of these factors reduce the costs of operating units with respect to those of small and medium-sized firms, thereby generating higher profitability (5–9%) than that of small and medium-sized firms (McK, 2018).

Given this profile of small and medium-sized customers, VehiCo conceived and developed a set of services to target their specific needs and thus help them increase their productivity. One such solution targeted the fact that a vehicle's fuel cost accounted for approximately 35% of the total operating cost of the vehicle. The remaining cost distribution was spread across vehicle procurement (12%), repair and maintenance (9%), driver compensation (35%), tires (3%), and admin (6%). The high fuel costs stem from the fact that a heavy-duty vehicle operates on average 3,000 h, covering 150,000 km annually (McK, 2018). The fuel reduction was targeted with a new, comprehensive optimization package that also reduced CO_2 emissions. This service package, which is described next, is referred to here as OptiDrive.

4.2. The OptiDrive service package

The OptiDrive service package represented an innovation in its industry, advancing considerably beyond the engine optimization solutions that were common in the industry. This service may be conceived in terms of four stages: *identification* of the customer's needs and wants, *customization* of the offering, *support* for ongoing use, and *return* of the used vehicle. The first stage identified the usage profile of a given customer seeking to acquire one or more vehicles from VehiCo. The first stage was the responsibility of a dedicated team from sales and marketing. It included identification of the intended use scenarios of vehicles in terms of transportation, routes, intended cargo, drivers' experience and skills, geographical access to vehicle workshops, and the customer's customers, including contract types and payment modes. This first stage enabled specification of customized requirements of the vehicle and the kind of training and coaching that would be delivered to the drivers of the vehicle. This training and coaching constituted an innovation for the industry. The vehicle customization phase encompassed the assembly of an optimal vehicle in terms of engine (V6, V8, or V8-power), axle ratio, gear box and tuning, filters, aerodynamic body kit, and other components. This phase also included a customized a maintenance program dedicated to the specific vehicle, its use, and its drivers. This second phase involved the customization of a specific driver training and coaching program based on the profile of the drivers, the vehicles, and the vehicle use. This phase identified the required vehicle and a trained driver. The training covered route-planning, loading and unloading of the cargo, the use of the engine for acceleration and deceleration, the use of the gear box and brakes, as well as understanding truck tuning, maintenance, and driving style for efficient fuel consumption. The third phase included continuous monitoring of the use of the vehicle, its condition, and the driver's driving behavior. These data were collected in real time using nearly 1000 sensors onboard the vehicle. The data were sent to the VehiCo headquarters for analysis. The actual performance was then compared to the desired performance to detect any deviations. The results of this analysis then informed the subsequent service and tuning of the vehicle and the content of the driver coaching sessions for each specific driver. Initially, each driver was assigned a professional driving coach. This coach was provided by VehiCo and followed the driving performance of the driver, providing coaching sessions to the driver, typically via video streaming. The initial coaching sessions were provided first weekly, then monthly, and finally quarterly, as the actual driving behavior developed. The targeted driving behavior was based on data analysis findings with regard to identified best practices. Hence, the targeted driving behavior developed over time as more data were collected and analyzed. Therefore, new coaching sessions were required to transfer those best driving practices to the drivers. The monitoring of the vehicle also enabled analysis for pattern identification and optimization of the use of the vehicle and its fuel consumption. Numerous sensors collected large sets of data on the wheels and tires, various aspects of the engine condition and use, the gear box, oils and their filters, the brakes, and other parts of the vehicle. Once a pre-defined state was reached, a specific vehicle service was planned, booked, and conducted. This service took place in a workshop or on the road. While the driver was resting, a mobile service unit reached the vehicle and executed the planned service. The fourth phase of this package was the return of the leased vehicle to VehiCo. VehiCo then renovated the vehicle and resold or leased it in the second-hand market. The benefits from this OptiDrive service package were striking. The data showed that during a 13-month period, the 48 vehicles considered in this study reduced their fuel consumption on average by between 22% and 26% per truck and driven kilometer, with a corresponding reduction of CO_2 emissions. As fuel costs accounted for approximately 35% of operational costs, this decrease of between a fifth and a quarter directly contributed to the operators' profits, thereby meeting the objective of the service package. The reduction of CO_2 emissions also contributed to meeting the goal of lowering the harmful ecological impacts of industrial operations.

The third phase of the OptiDrive service package (support) provided driver coaching and vehicle services. This support phase is the focus of the remainder of the analysis.

4.3. Big data and machine learning for service provision

The OptiDrive service package included the use of machine learning technology to analyze large sets data. This use of machine learning technology targeted the interpretation of the *error codes* generated by a vehicle. The use of a vehicle alters its condition and eventually leads to deviations between the targeted and actual values of key variables. Examples for an engine include the color, pressure, and density of oil, the value of a turbocharger's supercharging control position, engine coolant temperature, airflow at the engine inlet, and the pressure in the fuel distribution pipe. The use of a vehicle causes wear and tear to its condition, creating deviations between the desired and actual state of the vehicle. Using its many sensors, the vehicle's control systems identified such deviations and flagged them with error codes that were sent to the service function at VehiCo. Such signals often included one or two error codes only. In such cases, service technicians were easily able to interpret these error codes and devise actions to handle them by, for example, scheduling a service, ordering spare parts, consulting a senior technician for advice, and taking a dedicated online training module for service technicians. As the vehicles became increasingly well used, typically after 12–18 months of use, *multiple* error codes became more common. These combinations of 5–15 (and sometimes up to 30) error codes challenged service technicians' understanding of what was actually causing the vehicle to malfunction, although some senior technicians with years of experience could effectively interpret the several hundred error code combinations. To handle these combinations, VehiCo developed a dedicated machine learning solution. This solution is referred to here as ErrorSense, which was used to store all error code data together with the data on both the successful and unsuccessful handling of these cases by service technicians. VehiCo had approximately 300,000 vehicles on the road around the world. Therefore, a large set of data was generated every day from those vehicles and all the service units handling the error codes. The ErrorSense system employed a set of machine learning algorithms to analyze the data and identify patterns. The patterns formed the basis of prediction models. These models combined information about the vehicles, their configurations, their actual use, and the error code combinations, as well as the attempted resolution and whether or not it was successful. The production models were developed by a dedicated team of analysts that continuously calibrated the models and their actual use. At the time of this investigation, ErrorSense could effectively interpret the code combination in 97% of cases, in contrast to less than 14% successful interpretation by a trained service technician. This application of machine learning was regarded as a success for several reasons. For instance, the vehicle services that were provided offered shorter lead-times for services and a higher rate of success (i.e., a well-functioning vehicle). Shorter service lead-times reduced the downtime of vehicles with multiple error codes, which translated directly into productivity and therefore profitability for users. This improved accuracy of error code interpretation and the services it enabled also reduced the warranty costs for VehiCo, which translated into improved profitability. As more combinations of error codes were understood, better repair services were provided. Additional uses of these error code combinations also emerged. First, error codes were included in the customization of the vehicle when ordered by a customer. For example, certain combinations of engine and gear box setups were eliminated because the analysis showed that they malfunctioned frequently, causing multiple errors. Second, the research and development unit at VehiCo used the error code prediction models in the design of new versions of vehicles. The aim was to eliminate these errors and thereby improve the quality of the vehicles. In doing so, VehiCo could reduce the frequency of malfunctioning, helping both the customer and VehiCo itself. The third use was especially relevant in the context of the OptiDrive service package. The collected data, identified patterns, and prediction models were also used to identify vehicle use and services to minimize fuel consumption. For example, such analysis showed that replacing two specific filters with new filters, thereby cutting filter use time in half, contributed substantially to both reducing fuel consumption and eliminating the emergence of certain errors and underlying engine malfunctioning. The vehicles produced by VehiCo were in the process of continuous technical development and improvement. Therefore, their continuous use generated a constant flow of large data sets, providing new insights into the origins of errors, error combinations, and opportunities for reducing fuel consumption.

This application of machine learning technology realized data network effects in the business model of VehiCo. VehiCo was able to collect enough high-quality data to feed the machine learning algorithm and thereby generate prediction models for each case of error code combination. These predictions were made quickly and accurately enough for the given situation. VehiCo was careful to protect the privacy of personal data using specific identification codes for each driver. Meanwhile, customers were generally not interested in the technicalities of the prediction models, which meant that the legitimacy of this service was not challenged. Crucially, however, the customers were satisfied with the benefits of the OptiDrive service package, so the benefit seemed to constitute a key driver for legitimation of the service. This legitimacy is a possible addition to the conception of the business model architecture. Specifically, the legitimacy needed to activate data network effects may be moderated by the benefits that the service provides to its users, in addition to guarantees of personal data privacy and prediction explainability, as suggested by Gregory et al. (2020).

A second key lesson emerged from the investigation of the user-centric design, with its performance expectancy and effort expectancy factors for the moderation of user benefits. In the initial phases of the introduction of the OptiDrive service package, VehiCo produced a dashboard for drivers and the firm's transformation management. This dashboard displayed all of the vehicle's performance indicators, including performance and condition, driver indicators, and error codes and services conducted. Although the initial reactions of drivers and transportation firm managers were positive, this reaction quickly faded because they could not properly digest and use all the information. User experience engineers redesigned the display of indicators. Accordingly, the transportation firm managers were allocated a few aggregate vehicle productivity indicators, and drivers were allocated several other performance indicators. Meanwhile, all the information was channeled to the VehiCo service technicians, who used it for their service work. The information was also sent to VehiCo's research and development engineers, who used it to develop updated versions of the vehicle. This experience shows that the "*user*"—as a category of data network effects and thus part of the business model architecture—should not necessarily be conceived as a *single* human actor, as implied by the original theory of the data network effects (Gregory et al., 2020). Instead, this category should be regarded as a "*use process*" that can be executed by several actors. Hence, the thinking should be in terms of "multi-actor use" instead of "users" with different actors potentially using and benefiting differently from the service provided.

4.4. The activation of business model themes

We now assess the business model themes activated by the realization of data network effects. First, the ErrorSense solution for error handling through machine learning increased the *efficiency* of the business model by boosting productivity in both the transportation firms' operations and VehiCo's service operations. The transportation firms' unwanted vehicle downtime was minimized, and in many cases eliminated. Likewise, VehiCo's service operations increased vehicle use productivity and reduced overall warranty costs as the accuracy of error handling increased drastically and the lead-time for handling and deploying costly resources was reduced considerably. Second, the ErrorSense solution contributed to activating the *novelty* theme of the business model. VehiCo became the first provider of heavy-duty vehicles with capabilities and services that reduced fuel consumption and CO_2 emissions while reducing vehicle failures and the corresponding downtime. The innovative use of machine learning technology enabled a new business model architecture. That is, it included actors constituted by sets of machine learning algorithms. This new business model architecture in turn activated data network effects, which contributed to the activation of the novelty theme of the business model. This approach quickly became well known in the marketplace, attracting new customers to VehiCo and spurring key competitors to announce development programs to imitate this solution. Third, the *lock-in* theme of the business model was activated. The more customers used VehiCo's vehicles, the more data were generated and analyzed with machine learning techniques for error handling predictions. Accordingly, better error handling predictions were made and improved error handling services were thereby offered to each vehicle user. The superior vehicle service performance provided by VehiCo became well-known, attracting new customers and retaining existing ones. Finally, the initial proposition did not posit that the *complementarity* business model theme would be activated by data network effects (see earlier theoretical discussion). The primary concern of data network effects is not to link many actors and their resources, as is the case with regular actor networks. However, in the case of the ErrorSense solution, a different kind of complementarity emerged. Specifically, ErrorSense-based services realized through data network effects became a valuable *complement* to the remaining services and the vehicle itself. Thus, data network effects did also contribute to activating the complementarity business model theme.

5. Discussion and conclusions

Experience shows that some firms succeed in using digital technologies to activate direct and indirect network effects in their business models (Parker et al., 2016). This activation creates and appropriates potentially unparalleled value. Research on the functioning of network effects has thus far focused on how the *size* of a network contributes to value. Recent theorizing, however, has challenged this narrow focus (Afuah, 2013). Instead, a complementary focus on the *learning* conducted by actors in a network has been proposed (Gregory et al., 2020). This learning approach enables the activation of data network effects, where actors in a network generate and collect large volumes of data that are analyzed using machine learning technology for pattern identification and formulation of prediction models. These models are then used to improve the configuration, adaptation, and delivery of offerings. The established conceptualization of the business model and the four themes for value creation and appropriation is based on the size hypothesis of a business model's actor network. We expand this conception by combining the notion of data network effects with business model theory to formulate the following proposition. This proposition is positively confirmed by the present case study.

A business model architecture configured to realize data network effects contributes to activating the business model value creation themes:

- *with regard to novelty, when the focal firm is the first in its market segment;*
- *with regard to efficiency, when resource use is reduced through learning and improvements; and*
- *with regard to lock-in, when improvements provide superior offerings.*

In finding empirical support for this proposition, this study advances business model theory and the explanation of value creation by incorporating data network effects theory. The associated proposition is explored, and empirical support is provided using a business model case study. While the proposition accounts for the activation of three business model themes, the empirical study not only supports the proposition but also confirms activation of the fourth business model theme (i.e., complementarity). The paper details how each of the four business model themes (efficiency, novelty, complementarity, and lock-in) are activated by data network effects. The paper presents a rich case study of a business model that increases the profitably of its key actors while reducing negative ecological impacts. This finding indicates that a business model's activation of data network effects can contribute to several kinds of value. In this case, these kinds of values are economic and ecological.

The exploratory case study presented here makes two additional contributions. First, the proposed category of a "user" that receives value from an offering (a good, a service, or a platform) is too limited because it implies the existence of a single human individual who uses the offering. Our investigation highlights the notion of a "use process," where a set of activities conducted by one or several actors better reflects how the benefits of network effects are appropriated. Finally, the case study suggests that the two factors proposed as drivers of legitimation of offerings derived from big data analysis with machine learning (i.e., personal data privacy and prediction explainability) are complemented by a third factor: the *perceived benefits* of the offering. The more benefits such an offering provides, the more it will be legitimized.

This research targets the new kinds of business operations that occur when a firm's novel use of digital technologies contributes to new forms of value creation and appropriation (Parker et al., 2016). Just as the recent development of various kinds of digital technologies enables the generation, collection, transfer, and analysis of massive volumes of real-time data, machine learning techniques enable the detection of patterns within these data, which can in turn be used to build prediction models. Accurate predictions are highly useful for the provision of offerings with benefits that could not be provided otherwise, as this case shows.

The theoretical and empirical study presented here explains value generation from new uses of digital technologies. This paper presents the first empirical exploration of the here proposed business model conceptualization endowed with data network effects. Much research is needed to provide additional support and development of that conceptualization and to give a detailed understanding of the configuration of the business model architecture needed to activate data network effects. This study is limited to a single case study to test the proposition. There is therefore a need to replicate this study both in other contexts and in a cross-sectional manner. Additionally, the recent suggestion for the advancement of data network effects (Clough & Wu, 2020) with regard to value appropriation (and not only value creation) requires special attention in terms of the conceptual development of the notion of a business model to incorporate the use of data network effects.

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