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# FACILITATING E-MOBILITY THROUGH DIGITAL TECHNOLOGIES – DEVELOPMENT AND EVALUATION OF A DYNAMIC BATTERY-LEASING BUSINESS MODEL

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# FACILITATING E-MOBILITY THROUGH DIGITAL TECHNOLOGIES – DEVELOPMENT AND EVALUATION OF A DYNAMIC BATTERY-LEASING BUSINESS MODEL

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## Abstract

*The electric mobility sector – an important pillar for counteracting climate change – is facing a sluggish market development. In this paper, we present a new dynamic battery-leasing business model that can play a key role in promoting the market introduction of electric mobility. Unlike medium- to long-term approaches for creating additional value from electric vehicles (e.g., demand response or vehicle-to-grid), the business model we propose can be applied in the short run as all necessary prerequisites are already fulfilled. To demonstrate, we proceed in two major steps. First, we design the digital technology–enabled business model that breaks with current business logics by actively involving users in the value generation process. The concept contributes to reducing battery degradation effects and thus increases the residual value of the batteries. Second, we test the underlying hypothesis of our business model – the user's willingness to follow a certain charging guideline in order to extend battery lifetime – using a comprehensive conjoint analysis. Thus, our research demonstrates how information systems can be used to encourage green choices by consumers.*

*Keywords: Electric Mobility, Green IS, Digital Business Model, Conjoint Analysis.*

# 1 INTRODUCTION

Environmental sustainability has become one of the most important challenges for our society in securing an “era of economic growth” (Elliot 2011, p. 198) for our common future. Therefore, governments all over the world have established targets to address climate change (Elliot 2011). The development of renewable power sources and improvements in energy efficiency are key elements for establishing sustainable energy systems (REN21 2015). However, the electric mobility sector – an important pillar of the energy turnaround – is currently behind the target levels formulated some years ago. Germany, for instance, aimed to put one million electric vehicles (EVs) on the roads by 2020. However, the latest forecasts indicate that only half of the original target will be achieved (BMBF 2014). Hence, most markets for EVs are stuck in a deadlock situation with customers waiting for cheaper prices, less uncertainty and an appropriate charging infrastructure, while manufacturers wait for a larger market and charging station operators await more EVs on the streets (Giordano & Fulli 2012). To escape this deadlock, it is clear that more cars are needed on the streets. Rather than paying even higher subsidies or waiting for further advances in battery technology, we argue that sophisticated business models play a key role in promoting the dissemination of electric mobility. To make EVs more attractive for the user, one trend is to financially separate the vehicle and the battery because then the risk related to the residual value of the battery remains with the leasing company. In common contracts, mileage-dependent leasing rates are used (e.g., Renault, Nissan), which is a relatively simple mechanism for residual value estimation. Nonetheless, previous research has shown that the use of different charging strategies has a great influence on degradation effects in lithium-ion batteries (e.g., Lunz et al. 2012), thus directly affecting the residual value of a battery. However, this fact is not considered in traditional battery leasing because in such a scenario, the client has no incentive to take care of the battery’s health status when charging. Consequently, the leasing company charges an additional risk fee.

The diffusion of digital technologies as well as their incorporation in industrial age products such as cars allows for new digital innovations also in these industries (Henfridsson & Lindgren 2005; Yoo et al. 2010). In our case digital technologies offer an opportunity for overcoming the described dilemma of a static leasing model. More specifically, we present a dynamic battery-leasing business model that uses a digital platform for value retention. The business model requires appropriate incentives in exchange for a more desirable charging behavior. We argue that by actively steering the client’s charging behavior, the degradation costs of the battery can be decreased and thus a surplus for both the leasing company and the lessee can be generated. This business model can be an important facilitator for breaking through the current deadlock situation and boosting the use of electric mobility. However, as this concept implies the integration of the consumer, there is one critical assumption underlying our business model: the client is willing to charge his/her vehicle according to a certain charging guideline. Hence, with our research, we investigate the following research questions (RQ):

*RQ1: Could a dynamic business model help to increase the residual value of leased batteries?*

*RQ2: To what degree must lessees be incentivized to adopt battery-friendly charging behavior?*

We proceed in four major sections. First, we review existing research on intelligent charging algorithms and demonstrate that battery degradation can be influenced by its working conditions. Second, we sketch a new dynamic battery-leasing business model that offers clients an incentive to undertake a more desirable charging strategy. Third, we test the client’s willingness to give up flexibility regarding the charging process – the underlying assumption of our business model – by conducting a comprehensive conjoint analysis (CA) among 142 users. Finally, we discuss our results as well as their implications for theory and practice.

# 2 FUTURE ENERGY SYSTEMS AND INTELLIGENT CHARGING ALGORITHMS

The consideration of information technology in addressing environmental issues has been anchored to the IS community over recent years and has resulted in the establishment of a dedicated research branch (vom Brocke et al. 2013). From green IT, concerned with reducing the negative impacts of IT on the environment, to the field of green IS, covering the potential of information systems to contribute to environmental sustainability, a plethora of research has been conducted (vom Brocke et al. 2013; Dedrick 2010). The field of energy informatics has emerged as a particularly promising application area for green IS developments to tackle the challenges of future energy systems by increasing the efficiency of energy demand and supply systems (Watson et al. 2010). The transition from conventional energy production to renewable energy sources requires a means of addressing issues concerning demand response. This area offers great potential for the IS community to develop suitable artifacts for optimization (Melville et al. 2010).

A sustainable energy system that builds upon renewable power sources involves great challenges for the overall system because it is largely based on wind and solar power, which are discontinuous and not completely predictable. Within the mobility domain, several researchers have dedicated their work to the development of intelligent charging strategies for EVs because these "have been proposed as a possible – at least partial – solution to the problem of energy storage" (Brandt et al. 2013, p. 1668). EVs remain idle for at least 96% of the day and therefore possess a great potential to adjust energy consumption (Gu et al. 2013). So-called demand response (DR) systems build on time-dependent electricity prices and the ability of customers to respond to those changes by shifting energy consumption, i.e., charging processes, to off-peak hours (Strbac 2008). Here, research has predominantly focused on charging strategies with the aim of reducing energy procurement costs (e.g., Brandt et al. 2013; Feuerriegel et al. 2012; Schmidt et al. 2015). Going even further, within the bidirectional vehicle-to-grid (V2G) concept, vehicles are used for grid support and therefore must be able to feed electricity into the grid (Lunz et al. 2012). However, due to regulatory, technical and institutional barriers, we are a long way from being able to apply DR programs and V2G operations, particularly for end users (Hoke et al. 2011). For instance, the regulatory requirements of many retail electricity markets are not suitable for such approaches, as they lack the option of real-time pricing or demand that actors offer huge amounts of energy to participate on the ancillary market (Schmidt et al. 2014).

Furthermore, previous research has focused on the degradation phenomena in lithium-ion batteries and respective state of health (SOH) prediction (e.g., Haifeng et al. 2009; Millner 2010). These proceedings reveal that battery lifetime can be strongly influenced by operating conditions, and degradation takes place due to complex conditions of use, depending on a combination of factors such as depth of discharge (DOD), temperature and current (Wenzl et al. 2013). Besides algorithms developed with the single aim of reducing energy procurement costs, there are a variety of investigations that describe intelligent charging algorithms for optimizing the trade-off between energy procurement costs that result from variable prices and battery degradation costs (e.g., Bashash et al. 2010; Hoke et al. 2011; Lunz et al. 2012; Sovacool & Hirsh 2009). These charging algorithms achieve promising results. For instance, Lunz et al. (2012) demonstrate that the degradation costs can be decreased by 21.5% just by smart charging (one-way energy flow) and 28.7% by using vehicle-to-grid (V2G) operation (two-way). Here, the potential savings due to the increased lifetime are twice as high as returns from energy trading (Lunz et al. 2012).

In the long run, IS will be the central element of the energy ecosystem by aligning energy consumption with its generation (i.e., DR and V2G programs). What is missing to date are strategies and business models that are already functional and thereby help achieve a critical mass of EVs on the streets. We argue that a digital technology-enabled business model that helps to cope with the high acquisition costs and uncertainties of today's batteries is a promising approach.

# 3 DIGITAL TECHNOLOGY-ENABLED DYNAMIC BATTERY-LEASING BUSINESS MODEL

In recent years, new digital technologies – comprising information, computing, communication and connectivity technologies (Bharadwaj et al. 2013) – have turned cars into ubiquitous computing environments (Henfridsson & Lindgren 2005). By means of sensors and other digital capabilities, these ubiquitous computing environments themselves have become "smart" and enable the deployment of completely new services and business models (Yoo et al. 2010). The business models of firms are therefore an important locus of innovation (Amit & Zott 2001; Teece 2006), as these technological advances must be employed in proper business models in order to create and capture value (Teece 2010). The business model concept thus serves as an intermediary between technological innovations and the achievement of strategic goals (Al-Debei & Avison 2010).

In the following, we propose a new dynamic battery-leasing business model to overcome the weaknesses of the currently employed static model. The model is grounded on the concept of incentive theories – well known from the multi-disciplinary field of organizational behavior (e.g., Hockenbury & Hockenbury 2003) – and uses digital technologies to deploy them. Within the traditional, static model, the customer has no motivation to treat the battery with care. Employing an incentive approach, positive consumer behavior will be rewarded in order to activate a desired behavior and to eventually establish this behavior as a habit (Rani & Kumar Lenka 2012). This desired behavior counteracts battery degradation, thereby increasing the residual value of leased batteries. The business logic is depicted in Figure 1.

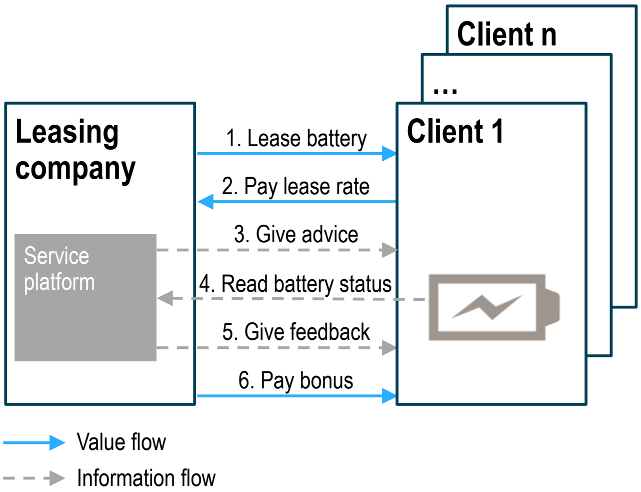


*Figure 1. Business logic of a dynamic battery-leasing business model.*

As with the static battery-leasing business model, a leasing company provides the client with a battery (step 1 in Figure 1) and earns a lease rate as compensation (step 2 in Figure 1). The dynamic battery-leasing business model that we propose enhances several aspects of the static business model by actively involving the lessee in value generation (steps 3–6 in Figure 1). In order to describe the dynamic battery-leasing business model, we apply El Sawy and Pereira's (2013) VISOR framework for digital business models. This framework emphasizes the importance of digital platforms and an active integration of consumers into value creation. The VISOR framework proposes the description of digital business models along five dimensions: *value proposition*, *interface*, *service platform*, *organizing model*, and *revenue model*:

- The *value proposition* of the dynamic battery-leasing model is twofold: First, the lessee is provided with the battery. Second, a bonus is paid to the lessee depending on how well he/she follows the guidance regarding the charging strategy.
- The business model requires two types of *interfaces*. First, a user interface for communication between the client and the service platform. This would typically be an on-board device in the car, the wall box in the garage, or a smartphone. Second, an embedded monitoring interface, which tracks the battery status and all energy-flows to and from the battery.
- The *service platform* can be seen as the heart of the business model and connects the service provider, his customers, and the cars. It thus provides all central functionalities that are necessary to

encourage a desired behavior. First, a charging guideline is implemented within the service platform, which is accessible to the user. Second, the platform – i.e., the backend – aggregates the raw data from the monitoring device (i.e., the monitoring interface) to estimate the battery's residual life and the respective residual value. Third, the client receives feedback regarding his/her charging behavior. Fourth, the premium is calculated based on the client's individual usage patterns.

- The *organizing model* is built around the battery that is leased to the client. The client's role is not limited as a pure and static consumer; instead, he/she is incentivized to follow a desirable charging strategy and thereby actively contributes to value generation by reducing degradation costs.
- The *revenue model* contains a static and a dynamic component. The lessee pays a fixed rent to the leasing company. In addition, a surplus is generated compared to the static battery leasing business model because the applied charging guideline reduces the battery degradation. The lessee receives a part of this in the form of a bonus, and the leasing company keeps the rest.

We argue that this business model creates a positive business case for both the lessee as well as the lessor. The bonus of the client will always be positive, while the profit of the leasing company will be positive if the bonus paid is less than or equal to the increase in residual battery value. Thereby, we neglect the cost for building the IS because the hardware for the frontend is already available in the existing model and the backend will be scalable – and thus marginal – if used by enough customers. However, a necessary precondition for this dynamic battery-leasing business model is the lessee's willingness to follow advice regarding vehicle charging in exchange for a financial benefit. The assumption's validity has not yet been assessed by research; therefore, we evaluate this willingness using a comprehensive conjoint analysis in the next chapter. Furthermore, we intend to gain first indications of the degree to which lessees must be incentivized to adopt a desired charging strategy.

# 4 METHODOLOGICAL APPROACH

As we aim to investigate the idea of a customer-integrating, dynamic battery-leasing concept from a customer's perspective, we conducted a conjoint analysis (CA), which is particularly suitable when investigating customer preferences regarding different attributes at the same time (Orme 2010). In a conjoint experiment, competing product alternatives (stimuli) are displayed to the participants for evaluation; the researchers' interest then is to explore and quantify the underlying value system within a consumer's decision (Johnson 1974). Following a decomposition approach, the utility of a product alternative is determined by its respective characteristics (attributes), which are given several values (levels) (Kuzmanovic et al. 2011). Among the various conjoint variants, we chose the choice-based conjoint (CBC) analysis to be the most suitable approach. In CBC analysis, the preference structure is not determined by ratings or rankings as in the other CA variants but by discrete choice/non-choice decisions. Advantages of CBC include the more concrete and immediate choice tasks that mimic real buying behaviors, which can reduce the high cognitive load of the subjects using an abstract ranking or rating (Orme 2010). Furthermore, CBC allows us to integrate a non-choice option into the choice experiment so that participants are not forced to select unacceptable alternatives (Hildebrandt et al. 2015b).

The identification of proper product attributes and levels has proven to be one of the most critical parts of designing a good conjoint experiment (Orme 2010). Therefore, it is necessary to transform relevant degradation factors into abstract product properties that respondents can visualize, even without any technical know-how. Within the scope of a literature review, various degradation factors could be identified, several of which can be countered by technical developments, e.g., thermal management to actively cool the battery and thus curb the thermal effects on battery degradation (Wenzl et al. 2013). Since technological development is not the focus of our business model, we want to delve more deeply into the factors that can be actively influenced by the user. In that regard, previous research has shown that cycling with high currents, i.e., fast charging, stresses the battery more than average and results in high internal temperatures (e.g., Bashash et al. 2010; Haifeng et al. 2009; Ning et al. 2013) – a circumstance that can be prevented if the user refrains from fast charging. Moreover, a large share of scientific investigations regard degradation as a function of DOD, meaning that the nominal number of cycles decreases exponentially with higher DODs (e.g., Kromer & Heywood 2009; Markel & Simpson 2006; Millner 2010). This implies that high DOD variances can be avoided by regularly connecting the vehicle to the grid instead of only charging when necessary. Applying the frequency of charging in our conjoint experiment has another advantage, as it is a precondition for applying intelligent charging algorithms that foster battery lifetime. Besides these two charging attributes we included a monthly leasing rate in our research design because we aim to conduct a monetary assessment of the charging attributes. To ensure that our price levels were realistic, we used the leasing rates of the Renault ZOE as reference. Assuming an annual mileage of 15,000 km, the monthly leasing rate lies at €86, €96, and €106, depending on the contract duration. Furthermore, we added the value of €76 as we are interested in evaluating monetary incentives. To ensure an understanding among the participants, we provided them with introductory information about EV charging processes, i.e., where and how they can charge. Furthermore, we explained our attributes and the respective levels in detail. The final attributes and levels are displayed in Table 1.

<table>
<tr><th>Attribute</th><th colspan="6">Levels per Attribute</th></tr>
<tr><td>Charging mode</td><td colspan="3">Fast charging is allowed: Using fast charging stations is generally desired (>40 kW; charge time approx. 30 min)</td><td colspan="3">No fast charging: Charging at home or while parked is sufficient, with only a few exceptions (3.7 kW; charge time 6-9 h)</td></tr>
<tr><td>Frequency of charging</td><td colspan="2">As needed: I only connect the vehicle to the grid when the battery charge is low</td><td colspan="2">During longer idle times: I connect the vehicle to the grid whenever possible and I park longer than 1 h</td><td colspan="2">Whenever possible: I connect the vehicle to the grid whenever possible</td></tr>
<tr><td>Monthly leasing rate</td><td>€76</td><td colspan="2">€86</td><td colspan="2">€96</td><td>€106</td></tr>
</table>

*Table 1. Attributes and characteristics for conjoint analysis.*

Each task included three stimuli as well as the “none” option. The number of choice tasks was set to 12 in order to minimize the cognitive load and reduce the dropout rate. The survey was designed using Sawtooth Software SSI Web. In addition to the conjoint experiment, the questionnaire contained questions on selected sociodemographics, mobility behavior and electric mobility in general. Before going online and to assure an adequate understanding of the questionnaire, seven research colleagues participated in a small-scale pre-test. During and after the questionnaire, they had the opportunity to ask questions and make comments. Based on their feedback, the survey and some of our attribute descriptions were reworked. Afterwards, we distributed the link to our online questionnaire in seminars of our university in Germany, in electric mobility Internet forums and to personal contacts.

# 5 RESULTS

Within the survey period, a total of 258 participants were gathered; 116 of these did not complete the questionnaire and therefore had to be excluded. After the exclusion of dropouts, a total of 142 data records remained (completion rate of 55.04%), of which 38.03% were female and 61.97% were male. As a large share of the answers received came from the university’s environment, it is not surprising that 54.93% of respondents were between 20 and 30 years of age and that 62.68% had achieved a university degree. A major part of the sample is composed of students (40.85%), employees (23.35%) and members of civil services (18.31%). Although there might be some justified criticism of our data’s large share of students, we maintain that the chosen target sample is a valid choice for our study. Electric mobility is a relatively new phenomenon in our society, and the dissemination of knowledge is relatively high among our students – a necessary precondition for appropriately evaluating our choice tasks. Furthermore, prior research has stated that student data is suitable for generalizability as this group embodies a substantive part of the target population (Compeau et al. 2012).

With respect to the question of whether they could envisage purchasing an EV, 2.11% replied that they already drive an EV, whereas 3.52% definitively planned to buy one in the near future and 54.93% could generally imagine doing so. However, 9.86% emphasize that the uncertainties of this technology are too great, while 18.31% mention the high acquisition costs and 11.27% indicate other arguments such as range constraints as reasons for the non-purchase. Furthermore, we confronted participants with different ways of funding the purchase of an electric car. In the case that they would buy an electric car, 67.51% would consider the option of buying the car together with the battery, whereas 42.96% could imagine leasing both the car and the battery and 56.34% would want to buy the car and lease the battery separately.

## 5.1 Conjoint Results

For data analysis, a multinomial logit (MNL) model was applied, which is a most frequently used for relating utility scores to choice probabilities (Hill 2013; Orme 2010). Using Sawtooth Software, we conducted a logit choice analysis to estimate the part-worth utilities and the relative importance of all attributes and levels. With regard to the maximum-likelihood principle, estimations for the part-worths are determined in an iterative approach to precisely explain the observed participants' discrete choice decisions (Hildebrandt et al. 2015b). Sawtooth provides us with some statistics describing the goodness of fit. The model achieved a log-likelihood value of −1961.24, which means a difference of 401.01 compared to the null model (log-likelihood: −2362.25), in which all estimates are set to zero (Hill 2013). By multiplying the difference by two, it results in a chi-square of 802.02. Employing the chi-square distribution table, a theoretical value of 18.48 is obtained for 7 degrees of freedom and a significance level of $p < .01$. Because the chi-square of 802.02 is many times larger than this value, it can be deduced that the different attribute levels significantly influence participants' decisions. Another, more intuitive ratio for the goodness of fit is the root likelihood (rlh). A value of 0 indicates that the fit of the solution is pure chance, whereas a value of 1 indicates a perfect fit. In the present case, each choice decision consists of three stimuli plus the "none" option; hence, the rlh for pure chance is .25. The achieved rlh of .32 is above that level but does not constitute an outstanding result.

The part-worth utility is considered to reflect a respondent's preference concerning the attractiveness of a specific attribute level; the higher this value, the more it will be desired by the respondent. The utility value of each attribute consists of the part-worth utilities of all the existing levels. These values will then sum up to zero and, proceeding from that assumption, a negative value signifies a level that the respondent does not favor. The quantified inferences on the overall relevance of an attribute cannot be derived directly because the calculated part-worth utilities for each level are in interval-scaled form (Orme 2010). Therefore, the relative importance is estimated for each attribute to draw conclusions about the influence of the respective attribute on the participants' choice decisions. The results of the logit estimation are indicated in Table 2. It also includes the normalized part-worth utilities for each attribute level as well as their standard deviations and t-ratios. Furthermore, it presents the relative importance for each attribute, which is its span (the absolute difference between the highest and lowest part-worths) divided by the sum of spans of all attributes (Hildebrandt et al. 2015b). Our results indicate that the monthly leasing rate has by far the greatest influence on respondents' choice decisions (relative importance of 73.40%), followed by the charging mode (25.35%). The frequency of charging seems to be comparatively unimportant (1.26%).

A two-tailed t-test was used to answer the question of whether the determined part-worth utilities differ significantly from zero. According to the null hypothesis, the estimated part-worth utilities do not differ significantly from zero. This hypothesis can be rejected at a significance level of 5% in case the t-ratio exceeds the critical value of 1.96 absolutely. In our case, the calculated t-ratios shown in Table 2 indicate that the part-worths of all attribute levels belonging to the charging mode and monthly leasing rate are significantly different from zero. Considering the specific levels, it can be stated that participants largely prefer the option of fast charging and, of course, lower leasing rates. In contrast, the respective t-ratios confirm that the frequency of charging has no significant influence on the choice decisions made by respondents. More specifically, we find indications that clients simply do not care whether they have to connect their vehicle to the grid while parking.

| **Attributes** | **Attribute Levels** | **Part-Worth Utility** | **Std. Error** | **T- Ratio** | **Rel. Im-portance** |
|---|---|---|---|---|---|
| Charging mode | Fast charging is allowed: Using fast charging stations is generally desired (>40 kW; charge time approx. 30 min) | 0.3566 | 0.0320 | 11.14 | 25.35% |
| | No fast charging: Charging at home or while parked is sufficient, with only a few exceptions (3.7 kW; charge time 6-9 h) | -0.3566 | 0.0320 | -11.14 | |
| Frequency of charging | As needed: I only connect the vehicle to the grid when the battery charge is low | -0.0143 | 0.0445 | -0.32 | 1.26% |
| | During longer idle times: I connect the vehicle to the grid whenever possible and I park longer than 1 h | -0.0068 | 0.0451 | -0.15 | |
| | Whenever possible: I connect the vehicle to the grid whenever possible | 0.0211 | 0.0448 | 0.47 | |
| Monthly leasing rate | €76 | 1.0195 | 0.0526 | 19.37 | 73.40% |
| | €86 | 0.4646 | 0.0530 | 8.76 | |
| | €96 | -0.4380 | 0.0618 | -7.09 | |
| | €106 | -1.0460 | 0.0743 | -14.07 | |

*Table 2. Conjoint results.*

### 5.2 Monetary Assessment

The willingness to pay (WTP) represents the maximum price a consumer would accept for the additional presence of a particular feature (Wertenbroch & Skiera 2002). As we are not interested in the WTP but rather how much consumers must be incentivized to adapt their charging behavior in a way that increases battery lifetime. The estimated WTP, according to the theory of economic incentives (Simon 1997), is interpreted as the critical threshold beyond which the granting of monetary incentives exceeds the utility of an attribute. To estimate this threshold, a linear price-utility function is assumed. Using the method of least squares, we calculated the following function:

$$y = -0.071x + 6.460$$

To determine the WTP, we computed the utility's alteration rate resulting from a variation of the leasing rate, which is described by the first derivative of the price-utility function. Only the absolute value of the rate of change is relevant for transforming part-worths in WTPs. More precisely, we defined the level with the lowest part-worth as zero and calculated the (additional) WTP of a certain level by obtaining the span between the part-worth of the respective attribute level and the one with the lowest part-worth and then divided this value by the magnitude of the derivative of the price–utility function. We calculated the relevant monetary threshold for the option in which fast charging is allowed, resulting in a value of €10.05. As the results of our conjoint analysis indicate that the frequency of charging seems to be relatively unimportant to participants, we can infer that the threshold for convincing them to regularly connect the vehicle to the grid is quite low. However, the WTP cannot be computed, as the respective part-worths do not differ significantly from zero.

## 6 DISCUSSION OF FINDINGS

EVs have been reported to be an important module of the future energy system, as they contribute to addressing the problem of energy storage associated with the intermittency of wind and solar power

(Brandt et al. 2013). Besides overcoming the regulatory, technical and institutional barriers that prohibit the application of DR and V2G programs, the dissemination of the decentralized energy stores (i.e., EVs) must be increased massively to boost this potential. However, at the moment, the demand for EVs is still sluggish and we need solutions that address these issues in the short run. In contrast to DR and V2G programs, intelligent algorithms for extending battery life can already be applied because contemporary cars include all necessary on-board systems (Kempton & Tomić 2005).

With our research, we demonstrate how technological advances can be harnessed for business model innovation in order to create and capture value for firms (Teece 2006; Teece 2010). Through the employment of digital technologies, our business model adds to the well-established incentive theory as a dynamic component to the traditionally static model and motivates lessees to adopt a charging behavior that extends a battery's life and residual value. A necessary precondition for introducing the dynamic battery-leasing business model presented is to evaluate users' acceptance of such a concept. To gain insights into their preference structures, i.e., to find out the extent to which users' charging behaviors can be influenced, we conducted a conjoint experiment. We found that the attribute frequency of charging (i.e., how often customers are willing to connect the vehicle to the grid) seems relatively unimportant to the customers. This indicates that minor incentives are likely to be enough to convince consumers to regularly connect their vehicles to the grid. Thus, the degradation effects resulting from high DODs can be avoided and intelligent charging algorithms that counteract battery degradation can come into play. Although the conjoint analysis that we conducted indicates that fast charging is quite important to users, our monetary assessment reveals that the threshold beyond which participants value the monetary incentives higher than the permission of fast charging lies at €10.05 monthly.

A comparison of this value to previous research reveals that these costs are lower than the potential savings, thus indicating that the business model would be beneficial for all parties involved. For example, employing a rural driving profile presented by Brandt et al. (2013) and a DOD-based degradation estimation model, Hildebrandt et al. (2015a) demonstrate that the application of battery-friendly charging strategies may lower degradation costs by almost €318 yearly. Furthermore, considering a yearly mileage of 20,000 kilometers, a smart charging strategy proposed by Lunz et al. (2012) results in savings of €434 compared to uncontrolled charging. Hence, assuming possible savings of approximately €26.5–37 monthly, the financial attractiveness of a dynamic battery-leasing approach is quite given. Going even further, there is still more potential, as discarded batteries could be used in second-life applications. For EV applications, the battery's end of life is reached when the specific performance requirements can no longer be met. However, this does not necessarily mean that the battery is unsuitable for other applications, as there is still 80% of the original capacity available. The digital technology-enabled business model presented here is based on real-time monitoring of the battery's status, which allows for an accurate assessment of further fields of application and the resale of decommissioned batteries for a fair price. This could in turn result in a potential reduction in battery lease payments, thus further driving the sales of EVs.

Thus we strengthen our assumption that dynamic battery leasing might be a promising opportunity to increase the residual value problems of batteries. Furthermore, even though we focused on two specific degradation effects within our empirical study, the business model presented is not restricted to a specific charging strategy and is therefore universally applicable. Indeed, it provides openness towards the integration of future DR and V2G programs, thereby contributing to both decreasing battery degradation costs and supporting grid stability.

Our study thus makes an important contribution to the body of research. We follow Watson et al.'s (2010) call for more research on green IS. Furthermore, we shed light on how digital technology–driven business model innovation can contribute to facing the cost disadvantages of a sustainable technology (i.e, EVs), thus helping to propel the mobility and energy sector towards environmental sustainability. Furthermore, our research shows how the business model concept can be used as an intermediary between technological innovations and the creation of economic value (Al-Debei 2010). Our business model also exemplifies important findings of research on the digital transformation. For instance, it demonstrates how digital technologies are becoming an integral part of physical products and how they serve as a platform for new services and business models (Yoo et al. 2010). Moreover, our research has important implications for practice. We designed a business model that can be used by automotive manufacturers and leasing companies to facilitate the sales of cars and batteries. Our findings suggest that the business model has a positive business case and therefore might be ecologically and economically beneficial. Therefore, we invite practice to test and enhance our business model under real-world conditions.

# 7 LIMITATIONS AND FUTURE RESEARCH

With our research we made a first attempt to pave the way for dynamic battery leasing by conceptualizing a new digital business model and evaluating customers' preferences concerning such a concept. However, our work is not free of limitations. First, our sample includes a large share of students. As described above, we presume that this is an appropriate sample for our analysis; however, it would be interesting to evaluate how EV owners that traditionally buy or lease their batteries would value our concept. These thoughts might be a fruitful direction for further research. Second, when determining relevant attributes and their levels for our study, we had to reduce real-world complexity and focused on two single degradation factors: DOD and current (i.e., fast charging). We are aware that these assumptions are not universally valid, as there is no scientific consensus on the effects of different degradation mechanisms and the interaction effects under complex conditions of use – which is the case for EVs – are not yet fully understood (Wenzl et al. 2013). Furthermore, different battery technologies, i.e., cell chemistries and cell designs, age in different ways. However, the business model presented is not bound to specific factors. If extensive degradation data were available, e.g., for battery manufacturers, it could easily be adjusted. Third, we did not find statistically significant indications for the frequency of charging in our sample data, indicating that clients simply do not care about this attribute. However, due to the lack of significant part-worth utilities, we were unable to assess the magnitude of adequate monetary incentives. We therefore invite scholars to catch up here or to repeat the study with an increased sample size.

# 8 CONCLUSION

With our study, we provide evidence for how digital technologies can contribute to transforming the mobility and energy sector towards environmental sustainability. In this context, we focus on the role of these technologies in developing innovative business models that support the market introduction phase of electric mobility – a sustainable technology itself. In contrast to previous IS research following the energy informatics research stream, we propose a strategy that could be applied in the short term. By introducing the customer-integrating dynamic battery-leasing business model, we present an idea that could help to overcome the residual value problems of traditional leasing contracts. Moreover, the empirical results of our study indicate that users would generally accept such a concept. Furthermore, we provide first insights on how much users must be incentivized to adopt charging strategies that counteract battery degradation.

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