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Measuring customer benefits of full electric vans: an extended compositional approach for commercial applications

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Summary

Climate change and a deterioration of air quality in metropolitan areas result in increasing public debates concerning the electrification of road transport. In this study, customer benefits of full electric vans are analyzed by examining the following research question: What creates customer benefits of full electric vans? We find that range, purchase price, and charging time are the most important product features. In addition, we show that electric vans with a range of at least 200 km and a charging time below one hour offer the highest total benefit for the average van customer in the sample. Regarding the measurement of customer benefits, this work provides a methodological contribution to benefit measurement by applying an advanced compositional approach.

Keywords: Consumers, utility, commercial, EV (electric vehicle), marketing

1 Introduction

According to the 2012 IPCC report, global climate change threatens the physical and economic livelihoods of people throughout the world, as it threatens 20-30% of the world's fauna and flora with extinction [1,2]. Global climate change is caused by rising concentrations of so-called greenhouse gases in the Earth's atmosphere [1]. The greenhouse gases, such as CO_2, are mainly emitted during the combustion of fossil fuels, as used in electricity production and combustion engines. The majority of global CO_2 emissions are caused by the energy and transport sectors. As a consequence, the IPCC report points out that greenhouse gas emissions, especially in the energy and transport sector, must be reduced in order to prevent further global warming [1]. Electric drives are considered as an opportunity to make the transport sector more climate compatible, if the electricity used is generated from renewable energies and not from fossil fuels [3]. In addition to the effects on the climate, electric drives are gaining in importance due to an increasing deterioration in air quality in large cities and metropolitan regions. For example, a purely electrically powered vehicle emits no emissions form the combustion engine locally and thus contributes to an improvement in air quality. Commercial traffic is of particular importance as it is characterized by comparably high mileages and could thus make a large contribution [4,5]. Furthermore, due to its travel profiles (often plannable routes, few exceptions), it is in many cases still suitable for the short ranges of electrically driven vehicles compared to conventional drives [6].

According to [7], customer benefits originate if customer needs are satisfied by the products or services purchased. In order to reach the promising target group of commercial users a profound knowledge of customer needs is indispensable [8]. According to our knowledge previous research exclusively deals with questions concerning the adoption of electric vehicles in the commercial sector in general without differentiating between passenger cars and vans, especially not between different van segments. This work intends to close this research gap by focusing on commercial van customers.

The research question that this paper investigates is the following: What creates customer benefits for full electric vans?

2 Overview of methods and dataset

Section 2.1 provides an overview on the data used before corresponding data collection and analytical methods are described in Section 2.2.

2.1 Data

We carried out a survey and collected answers from 300 fleet managers and decision makers concerning vehicle purchase decisions across all industry sectors between November and December 2017. The link to the survey was only provided to commercial car owners possessing at least one small van (e.g. Mercedes-Benz Citan), mid-size van (e.g. Volkswagen Transporter) or large van (e.g. Fiat Ducato). Owners of camping/leisure vehicles or motorhome variants were excluded due to corresponding non-commercial usage. Survey data was only collected from vehicle owners with cars younger than four years (year of construction 2013 and later). Nearly every second fleet manager and decision maker in our sample is between 40 and 49 years old. In addition, they are predominantly male (about 85 %). Their organisations are mostly (90 %) small and medium-sized enterprises with less than 250 employees. The organisations' fleets count less than 10 vehicles in about 75 % of the sample. The share of the three van segments large, mid-size and small is balanced in the sample. The sample of this work has similarities with samples from previous studies that have also dealt with adoption of electric vehicles in a commercial context [9,10]. The distributions of industry sectors the participating organizations are belonging to, number of employees, and the respondents age and sex distributions look similar.

2.2 Methods

As described above, knowledge on customers' needs is essential when defining the characteristics of a product. A customer's preferences can be used as a measure for customer needs [11,12]. A wide range of methods for measuring preferences is used in marketing research [11,12]. Multi attributive methods for measuring preferences are widely applied. These methods have in common that the considered product is considered as a bundle of attributes. Preferences are used as indicators to explain purchase decisions [11]. Preferences express the extent to which customers consider objects to be desirable [13]. Within this work, customer preferences are measured using a compositional, self-explicated approach [14]:

$$\mathbf{TN}_{m_j,h} = \boldsymbol{w_{j,h}} \cdot \boldsymbol{b_{m_j,h}} \qquad (\boldsymbol{j \in J, m_j \in M_j, h \in H}) \qquad \textbf{(Eq. 1)}$$

$\mathbf{TN}_{m_j,h}$: Part worth value of level m of attribute j for consumer h

$\boldsymbol{w_{j,h}}$: Importance of attribute j for consumer h (stage 2 of the model)

$\boldsymbol{b_{m_j,h}}$: Evaluation of level m of attribute j by consumer h (stage 1 of the model)

$\boldsymbol{J}$: Set of attributes

$\boldsymbol{M_j}$: Set of levels of attribute j

$\boldsymbol{H}$: Set of consumers

This approach is called a weighted self-explicated model which means that both levels 1 and 2 are integrated. We call the model described in Eq.1 basic model.

Such compositional methods are often considered to measure customer preferences less realistically than decompositional methods [13,15]. For low involvement products like consumer goods of private customers this might be a valid argument. However, the particular characteristics of commercial customers can be set against this argument. Due to a higher formalization of the decision process [6,7], we assume that commercial customers break down the product into its attributes, at least to a certain extent, and evaluate the different single attribute levels according to their needs. In addition to the time and cost advantages [14, 12], the "surprising robustness" regarding the validity of compositional procedures is advantageous [16].

Stage 1 of the self-explicated model (cf. Eq. 1) is implemented with a rating scale from 1: "unacceptable" to 5: "completely acceptable" [12]. With regard to further questions in the survey, we used this straightforward method in order to reduce the risk of respondents not fully completing the survey. In addition, rating scales are supposed to have a high validity [17,18]. In the following, a constant sum scale with 100 points is used at stage 2 of the self-explicated model (cf. Eq. 1). This scale has both, a high statistical performance and it guarantees easy applicability. The combination of rating scale at stage 1 and constant sum scale at stage 2 is a proven approach which already has been used in a large number of studies [19-22]. In accordance with the decision criteria identified in existing literature on electric vehicle purchase decisions in the commercial customer segment [24], preferences concerning the product attributes range, purchase price and charging time are collected from the survey participants.

This enables an extension of the self-explicated model of Eq. 1 with regard to the consideration of minimum requirements (barriers [23]) in the purchase decision. In this extended self-explicated model, the part worth value of an attribute is set to zero if the minimum requirements are not met:

$$\mathbf{TN}_{m_j,h} = \begin{cases} w_{j,h} \cdot b_{m_j,h} \;\; \textit{if instance } m \textit{ of attribute } j \geq a_{j,h} & j \in J, m_j \in M_j, h \in H \\ 0 \qquad \textit{if instance } m \textit{ of attribute } j < a_{j,h} & j \in J, m_j \in M_j, h \in H \end{cases} \qquad \textbf{(Eq. 2)}$$

$\mathbf{TN}_{m_j,h}$:	Part worth value of instance m of attribute j for consumer h
$w_{j,h}$:	Importance of attribute j for consumer h (stage 2 of the model)
$b_{m_j,h}$:	Evaluation of level m of attribute j by consumer h (stage 1 of the model)
$a_{j,h}$:	Minimum requirement of attribute j of customer h
J:	Set of attributes
M_j :	Set of levels of attribute j
H:	Set of consumers

With regard to this extension of the self-explicated model, we use the term extended model. In such multiattributive preference models, the total benefit value of a product is calculated by summing up the part worth values of the specific product attributes [10]:

$$\mathbf{u}_{p,h} = \sum_{j \in J} \sum_{m_j \in M_j} TN_{m_j,h} \cdot x_{p,m_j} \qquad (h \in H, p \in P) \qquad \textbf{(Eq. 3)}$$

$\mathbf{u}_{p,h}$: Total benefit value of product p for consumer h

$$x_{p,m_j}: \begin{cases} 1 & \text{if attribute j of product } p \text{ equals instance } m \\ 0 & \text{otherwise} \end{cases}$$

P: Set of products

The total benefit evaluation is carried out on the basis of four basic product types, which are divided into eleven product variants. Basic type A focuses on the total benefit for product variants with a range of 100 km, basic type B on product variants with a range of 150 km, basic type C on product variants with a range of 200 km and basic type D on product variants with a range of 250 km. The variants of the basic types differ in purchase price and charging time.

3 Results and discussion

In this Section the results of the study are described and discussed. In Section 3.1 the part worth values of the tested product attributes are evaluated. In Section 3.2 the results of the total benefit evaluation are presented. In Section 3.3 we critically reflect the methods used in this study.

3.1 Part worth values

Figures 1, 2 and 3 show the average part worth values of the basic model (without explicit consideration of the minimum requirements) and the extended model (with explicit consideration of the minimum requirements) for the product attributes range, charging time and price. As described in Section 2, the part worth values represent the multiplication of the product-specific attribute weight and the valuation of the attribute level. Each respondent was asked to rate product attributes with a maximum value of 100 and a minimum value of 0. Attribute levels were measured on a scale ranging between 1: “not acceptable” and 5: “completely acceptable”. Regarding the extended model, please consider that the part worth values for all four range instances are lower than in the model without explicit consideration of minimum requirements. In this model, the part worth values of the attribute levels below the respondent's specified minimum requirement are set to zero.

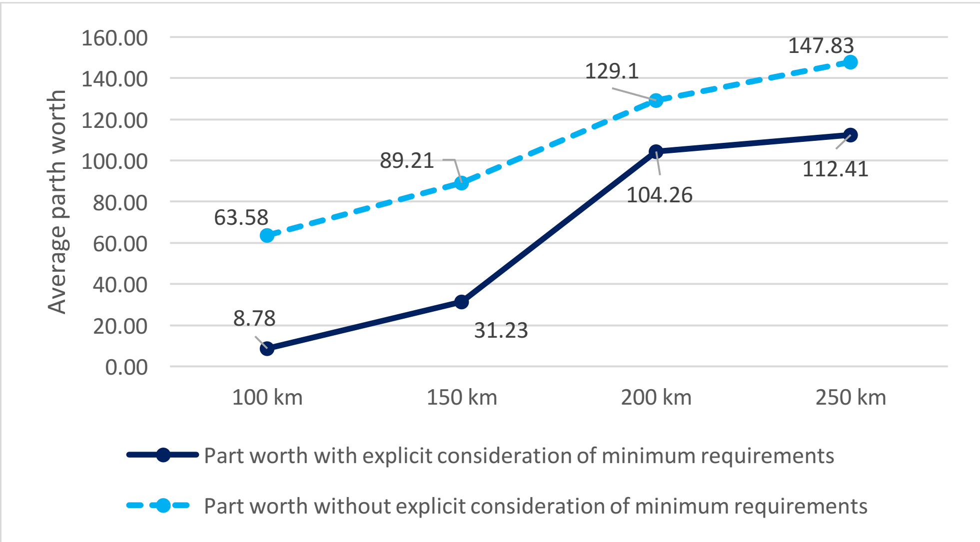

Figure 1: Average part worth values in the basic and the extended model for the product attribute range

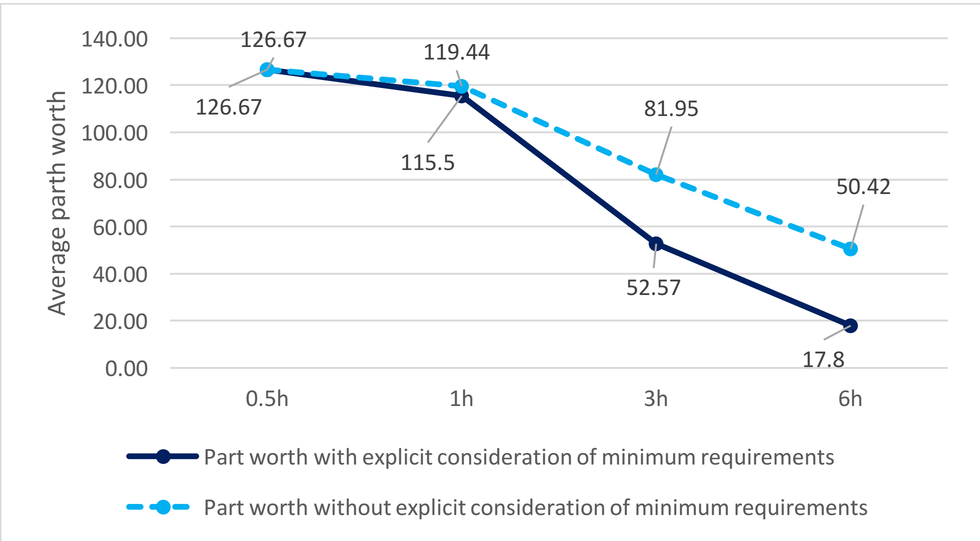

Figure 2: Average part worth values in the basic and the extended model for the product attribute charging time

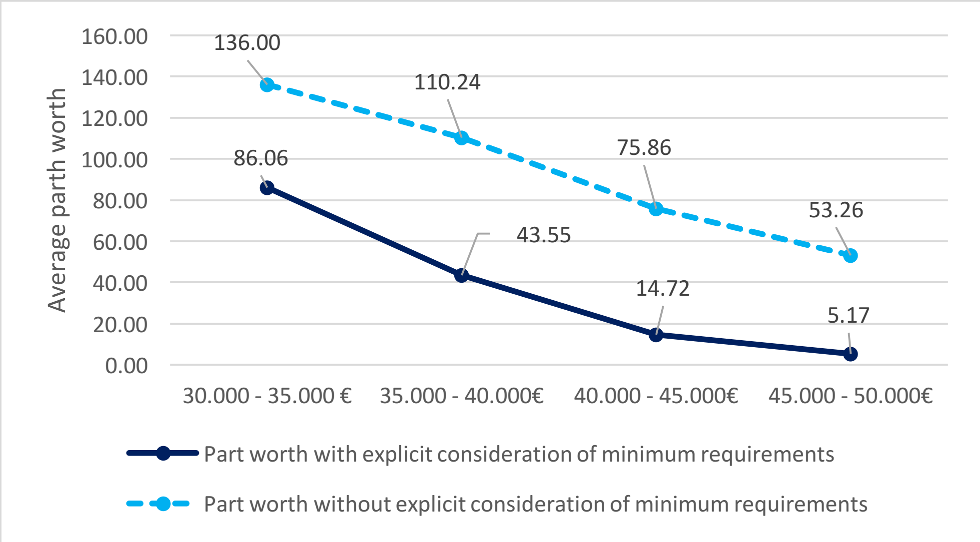

Figure 3: Average part worth values in the basic and the extended model for the product attribute price

Range: As the average values of the extended model for all range instances are below the values of the basic model, minimum range requirements are not met by a significant number of respondents. Regardless of the absolute level of the range specific part worth values, similar trends can be observed in both models. These tendencies are partly more pronounced in the extended model. The biggest average increase of part worth values occurs when increasing range from 150 km to 200 km: At this point, the average part worth value increases from 31.23 to 104.26. For the average respondent, the range of 200 km has more than twice the part worth value compared to the range of 150 km. If range is increased from 200 km to 250 km, the average part worth value only increases by 8.15 (Figure 1).

Charging time: As all the average part worth values of the extended model are below the values of the basic model for charging time and price, corresponding minimum requirements are not met by most of the respondents. The only exception is the average part worth value of half an hour charging time. This charging time fulfils the minimum requirement of all respondents in the sample. As expected, the lowest charging time (0.5 h) is associated with the highest part worth value and the highest charging time (6 h) with the lowest. However, the average part worth value of 1 hour charging time is only slightly lower than that of half an hour (Figure 2).

Price: Regarding the attribute price, the curves show the expected linear relationship between the lowest price range (30,000 - 35,000 €) with the highest part worth value and the highest price range (45,000 - 50,000 €) with the lowest part worth value. For each change of price range, the respective average part worth value almost triples in the extended model. However, between 30,000 and 40,000 €, only a slight doubling of the part worth value can be observed (Figure 3).

3.2 Total benefit values

As described in Section 2.2, we combine the product attributes and their instances into five basic product types, i.e. in total eleven product variants (cf. Table 1). Table 1 shows the average total benefit values of the basic and the extended model sorted by the values of the basic model. In the basic model, the total benefit per product variant ranges between 100 and 500. In the extended model, total benefit values between 0 and 500 are possible. This is due to the fact that part worth values are set to 0 for attribute levels that do not meet the minimum requirements (cf. Section 2.2). In addition to these average total benefits, the extended model with minimum requirements is used. Table 1 additionally shows the share of respondents whose minimum requirements (Min. Requ.) per product variant are met. All requirements for the product variant are met if the minimum requirement is met for each of the three product attributes.

Basic type A (range 100 km):

With regard to the product variants with 100 km, clear preferences for variant A2 ("Low Range DC") with a charging time of one hour compared to variant A1 ("Low Range AC") is observed. The A1 variant thus generates the lowest (model without minimum requirements) and second lowest (model with minimum requirements) average total benefit value of all variants. Similarly, all three attribute levels of variant A1 do not meet the minimum requirements of any of the respondents. Variant A2 meets the minimum requirements of 6.7% of respondents. For a product with a range of 100 km and a purchase price between 30,000 € and 35,000 €, a low charging time of half an hour is required to generate market share.

Basic type B (range: 150 km)

In both models variant B3 ("Mid Range Low Price DC") has the highest average total benefit. Minimum requirements for this product variant are met by 14.3% of the respondents. Variant B1 ("Mid Range DC") has the third lowest total benefit. The three product features fulfil the minimum requirements of 4.7% of the respondents. B2 ("Mid Range AC") on the other hand meets the minimum requirements for only 0.3% of respondents and has the lowest total benefit in both models. The need for fast charging of this basic type becomes particularly evident. B1 generates a higher total benefit despite the higher purchase price and meets the minimum requirements of a significantly higher share of respondents than variant B2.

Table 1: Product variants and their average total benefit values measured in the basic model and the extended model

Product variant	Range	Min. Requ. Range	Price	Price Min. Requ.	Charg. Time	Charg. Time Min. Requ.	$\bar{x}$: Total value Basic Model	$\bar{x}$: Total value Extended Model	All Min. Requ.
D2: "Very High Range Low Price”	250 km	70.0 %	30,000 – 35,000 €	62.3 %	0.5 h	100.0 %	411	325	49.3 %
C4: “High Range Low Price DC”	200 km	70.0 %	30,000 – 35,000 €	62.3 %	0.5 h	96.3 %	385	306	48.0 %
C2: “High Range Mid Price DC”	200 km	70.0 %	35,000 – 40,000 €	38.0 %	1 h	96.3 %	359	263	26.3 %
B3: „Mid Range Low Price DC“	150 km	25.0 %	30,000 – 35,000 €	62.3 %	1 h	62.3 %	345	233	14.3 %
D1: „Very High Range High Price“	250 km	70.0 %	45.000 - 50.000 €	9.0 %	0.5 h	100.0 %	328	244	4.7 %
A2: „Low Range DC“	100 km	10.7 %	30,000 – 35,000 €	62.3 %	0.5 h	23.0 %	326	222	6.7 %
C1: „High Range High Price DC“	200 km	70.0 %	40.000 - 45.000 €	15.0 %	1 h	96.3 %	324	234	8.7 %
C3: „High Range Low Price AC“	200 km	70.0 %	30,000 – 35,000 €	62.3 %	6 h	23.0 %	316	208	2.7 %
B1: „Mid Range DC“	150 km	25.0 %	40,000 – 45,000 €	15.0 %	0.5 h	100.0 %	292	173	4.7 %
A1: „Low Range AC“	100 km	10.7 %	30,000 – 35,000 €	62.3 %	6 h	23.0 %	250	113	-
B2: „Mid Range AC“	150 km	25.0 %	35,000 – 40,000 €	38.0 %	6 h	23.0 %	250	93	0.3 %

Basic type C (range: 200 km)

With regard to the product variants with a range of 200 km, the C4 and C2 variants provide the highest average total benefit, i.e. C4 has the second highest and C2 the third highest of all product variants examined (for both models). The share of respondents whose minimum requirements are met by these two variants is comparably high: 26.3% (C3) and 48.0% (C4). The variants C1 and C3 generate the lowest average total benefits within the type C product variants. For variant C1, the share of fulfilled minimum requirements is 8.7% and for variant C3 it is 2.7%. However, variant C3 has the highest total benefit of all product variants with a charging time of 6 hours. This shows that high ranges and low purchase prices can increase market shares of product variants with longer charging times (AC charging technology). Variant C1 fulfils 8.7% of the samples' minimum product requirements. This indicates a certain willingness to pay for variants with a comparably low charging time as long as the range is sufficient.

<u>Basic type D (range: 250 km)</u>

First, please note that the increase to 250 km does not meet any higher share of minimum range requirements than the 200 km variants (both 70%). In both models the variant D2 ("Very High Range Low Price") has the highest average benefit. In the model with explicit consideration of minimum requirements (extended model) the score is 325, in the model without explicit consideration of the minimum requirements (basic model) the score is 411. This high score is not surprising, as this product variant combines the most advantageous features (highest range, lowest charging time, lowest purchase price). The significantly lower total benefit and share of fulfilled minimum requirements of variant D1 also demonstrates the strong focus of potential customers on the attribute purchase price.

The analyses of the total benefits of the tested product variants show that potential customers have very heterogeneous minimum product requirements. For instance, the three product variants A1, B2 and C3 are equipped with a charging time of 6 hours (AC charging)). Such a charging time meets 23% of the respondents' minimum requirements. However, the 100 km range of the A1 variant are sufficient for around 11% of the respondents, the purchase price of 30,000 - 35,000 € is acceptable for around 63%. At the same time, not a single interviewee meets all three minimum requirements for the attributes of variant A1. Every interviewee who is willing to pay the price wants a higher range or a lower charging time. Similarly, for those respondents who accept the range or charging time of this variant, the purchase price of variant A1 is still too high. The same applies to the B2 and C3 variant. A higher share of fulfilled product requirements can only be achieved by improving the product while maintaining or lowering the purchase price: Variant A2 has the same purchase price and the same range as A1. However, together with the lower charging time the share of fulfilled minimum requirement increases to 6.7%.

The variants C2, C4 and D2 were included in the analysis for reasons of completeness. They combine the most advantageous features (low charging times, high ranges) with low purchase prices. Therefore, they are more likely to be interpreted as an outlook, when battery costs decrease. With these product variants high total benefits can be generated. These variants are interesting for a comparably high share of the respondents (26.3 - 49.3 % fulfilled minimum requirements).

3.3 Discussion of methods

Purchase decisions of a commercial customer are characterized by a higher degree of formalization [7]. The degree of formalization often increases with the size of the organization [6]. The higher formalization and higher rationality within purchase decisions can be seen as appropriate preconditions to use a compositional approach to measure preferences. Compositional approaches are often criticized to present the product in a less realistic way because of the separated evaluation of product attributes. This argument may be true for private customers and consumer products with a comparably low involvement during decision processes. In those purchase decisions decompositional methods (e.g. conjoint analysis) may be more appropriate approaches to measure preferences. According to [14] the applied basic compositional self-explicated method is suitable to measure preferences. In this work we have shown that the extended self-explicated approach developed considering minimum requirements (barriers) can be used to measure customer benefits in electric vehicle purchase decisions.

The survey link was sent to decision-makers from companies that met the following criteria: purely commercial use, all industrial sectors, most recently acquired van not older than 2013 and no camping/leisure vehicles. The sample covers 300 companies. With regard to the sectors represented, the construction industry, the manufacturing and processing industry as well as the service sector and wholesale and retail trade are overrepresented. In addition, the vast majority (90%) of the companies in the sample are small and medium-sized enterprises with less than 250 employees. Accordingly, around three-quarters of the companies in the sample have a fleet with less than 10 vehicles. For these reasons, conclusions regarding product requirements and customer benefits can initially only be drawn for sectors and companies with similar characteristics. Also, the sample is made up exclusively of companies with registered offices in Germany. Accordingly, the results are limited to the German van market. However, depending on commercial usage profiles in other countries, the results might also be applicable to markets outside of Germany.

4 Conclusion & outlook

Range, purchase price and charging times are confirmed as the most important product specific purchase decision criteria during purchase decisions of full electric vans. In our analysis we show that full electric van variants with a range of at least 200 km and charging times shorter than one hour offer the highest total benefits for average van customers within our sample. Our results show that range should be at least 200 km. Charging times should be equal or below one hour in order to be attractive to a larger share of customers. Based on our results, we suggest to include an inexpensive entry-level van variant with a range of 100 km and a charging time of half an hour (Variant A2 "Low Range DC"; range: 100 km; charging time: 0.5 h; purchase price: 30,000 - 35,000 €). For some of the potential customers (~7%) this product variant with a range of 100 km is sufficient. To win these customers, the product must have a low purchase price in addition to a low charging time.

For some potential customers an electrically powered van is only an option in the case of at least 200 km range and the possibility of fast charging. However, these customers are prepared to pay a higher purchase price. Up to about 9% of the sample can be attracted by such product variants (Variant C1 "High Range High Price DC": range: 200 km; charging time: 1 h; purchase price: 40,000 - 45,000 €). In any case, due to the heterogeneous minimum requirements of potential customers, several product variants should be offered to address different customer groups.

This analysis was performed by applying the basic and extended self-explicated model described in Section 2. The extended model was developed by considering electric vehicle specific barriers [23] in the context of commercial electric vehicle purchase decisions. With regard to benefit measurements, this work presents a case study in order to answer how benefit measurements of electric vehicle variants in the commercial context can be implemented. This extension of the basic self-explicated model is relevant if levels of product attributes can not be compensated by other product attribute levels. However, further developing this approach in order to evaluate how services can compensate commercial van customers' minimum electric vehicle specific requirements would be interesting. Furthermore, comparing these results with ex-post evaluations after positive electric vehicle purchase decisions would be interesting. In addition, future research could focus on further quantifying the customer benefits of commercial full electric van customers by integrating further product attributes into the self-explicated model applied in this paper.

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