Understanding charging behaviour of electric vehicle users.

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ABSTRACT

We examined the psychological dynamics underlying charging behaviour of electric vehicle (EV) users. Data from 79 EV users were assessed in a 6-month EV field study. On average, users charged their EV three times per week, drove 38 km per day, and they typically had a large surplus of energy remaining upon recharging. Based on first findings concerning charging style among mobile phone users, we hypothesized that user–battery interaction style (UBIS) is a relevant variable for understanding charging behaviour of EV users. We developed measures to assess UBIS. Results show that it is a relatively temporally stable characteristic which also shows some cross-device consistency. As predicted by our conceptual model, UBIS and comfortable range explain the charge level at which people typically recharged. UBIS was related to users' confidence in their mental model of range dynamics, the utilization of range, and to excess energy from renewable sources. This research has implications for optimizing sustainability of electric mobility systems.

Keywords: electric vehicles, charging, user behaviour, field study

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1 INTRODUCTION

EVs are a promising form of sustainable[1] transportation because of their potential to reduce CO_2 emissions and air pollution (Holdway, Williams, Inderwildi, & King, 2010), mitigate risks associated with peak oil (Hirsch, Bezdek, & Wendling, 2005), and utilize excess energy from renewable sources like wind (Sundström & Binding, 2010). However, these effects are dependent on how an electric mobility system (EMS) is set up as well as how it is used (Franke, Bühler, Cocron, Neumann, & Krems, 2012a; Eggers & Eggers, 2011). Therefore, the user is a critical parameter in the equation specifying the net environmental and economic benefit of an EMS.

Research has shown that it is challenging for users to utilize an EMS in an optimal way. For example, regarding the efficient use of limited energy resources, users have been found to maintain substantial psychological safety buffers in their range utilization (Caroll, 2010; Franke, Neumann, Bühler, Cocron, & Krems, 2012c; Franke & Krems, 2013). This inefficient utilization of precious range resources has an adverse impact on the ecological and economic sustainability of EMS, because battery size is linked to ecological footprint (Hawkins, Gausen, & Strømman, 2012; McManus, 2012) and the affordability (i.e., chance for broad adoption) of EVs (Neubauer, Brooker, & Wood, 2012; Thomas, 2009). Thus, it would be beneficial to avoid wasting substantial shares of usable battery capacity as psychological safety buffer, but how can EV users be supported in the efficient utilization of energy resources?

Findings show that some users adopt more efficient usage patterns than others and certain psychological variables have been found to be related to those individual differences (Franke & Krems, 2013; Franke et al., 2012c; Franke et al., 2012a). These variables may help to inform the development of strategies promoting more sustainable utilization of an EMS. It is therefore important to understand variables underlying individual differences in EMS users' utilization of energy resources, both, in terms of depletion (e.g., trip decisions) and replenishment (e.g., charging decisions) of resources. Previous research in this area has largely focused on the former facet, depletion of resources (Franke et al., 2012c; Franke & Krems, 2013). The present research aims to better understand the psychological dynamics underlying replenishment of resources (i.e., charging decisions).

To this end, a field trial approach was applied in which 79 participants leased an EV for 6 months and provided subjective and objective data. In order to advance the adaptive control of range

[1] With the term sustainability we refer to the "three pillars" model of sustainable development (UN General Assembly, 2005) covering environmental, economic and social facets of sustainability. In particular, EVs must be beneficial for environmental protection and economic development to be considered a sustainable technology. This especially refers to the efficient use of energy and resources.

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resources framework (Franke et al., 2012c; Franke & Krems, 2013), we applied concepts developed through preliminary research on mobile phone users charging style (Rahmati & Zhong, 2009) to the field of electric mobility. We developed measures to assess participants' charging-related user–battery interaction style (UBIS) and analyzed characteristics of UBIS, accordingly. We then examined if UBIS is associated with certain charging patterns. In addition, we examined whether UBIS and comfortable range can account for variance in charging behaviour, and whether there is an association between UBIS and users' confidence in their mental model of range dynamics. Finally, we analyzed the relationship between UBIS and efficient usage of the EMS, with a focus on range utilization and the efficiency of utilizing excess energy from wind.

1.1 Interacting with limited energy resources

To better understand the efficient use of energy (i.e., mobility) resources, we have developed a conceptual model (Franke et al., 2012c; Franke & Krems, 2013), based on principles of self-regulation and control theory (Carver & Scheier, 1998; Fuller, 2011). Our model is similar to the transactional model of stress (Lazarus & Folkman, 1984) in that it proposes a highly subjective appraisal of range resources and a high variance in coping strategies. Indeed, in previous research, we found substantial variance in users' appraisal of objectively similar range resource situations (Franke et al., 2012c; Franke & Krems, 2013) and identified several stress-buffering variables similar to those Lazarus & Folkman (1984) proposed (e.g., internal control beliefs). Rather than focusing on users' individual *appraisal* of available range resources, the present study focuses on individual differences in *coping style* related to charging. Figure 1 depicts the model from the perspective of a single charging decision (i.e., the control loop of user–battery interaction).

The model is based on the premise that whenever users interact with limited energy resources, they continuously monitor and manage the relation between their mobility needs (e.g., distance of next trip) and their mobility resources (e.g., remaining range). This ratio (i.e., the perceived available range buffer) is then compared to the user's preferred range buffer (i.e., the user's comfortable range) which has been shown to vary considerably between users (Franke et al., 2012c; Franke & Krems, 2013). The range appraisal (the experienced discrepancy between available and preferred range resource buffers) leads to a certain degree of range stress (i.e., range anxiety). The more range stress, the more likely the user will apply coping strategies (e.g., drive more economically, charge the car) to resolve the situation. Consequently, the users' comfortable range plays a key role in predicting the likelihood that a user will apply coping strategies (e.g., charging) in a given situation.

Although appraisal of a range situation is an important determinant of users' coping behaviour, we do not assume that this is the only determining factor; rather, we posit that users adopt a preferred coping style when dealing with limited energy resources which we call user-battery interaction style (UBIS). This is based on the observation, that although EV energy resources are limited, experience of subjectively critical range situations is still relatively infrequent (Franke et al., 2012c; Franke & Krems, 2013); therefore, EV users seem to be mostly free to choose how they manage their battery resources in everyday use. In this respect, interacting with EV energy resources is similar to driving a car which is also commonly seen as a "self-paced" task (Elander, West, & French, 1993; Lajunen & Özkan, 2011), that allows individuals to adopt a preferred driving style (Lajunen & Özkan, 2011). Therefore, similar to the common notion driving style we hypothesize that users also adopt a certain coping style to interact with limited battery resources (e.g., EV charging style).

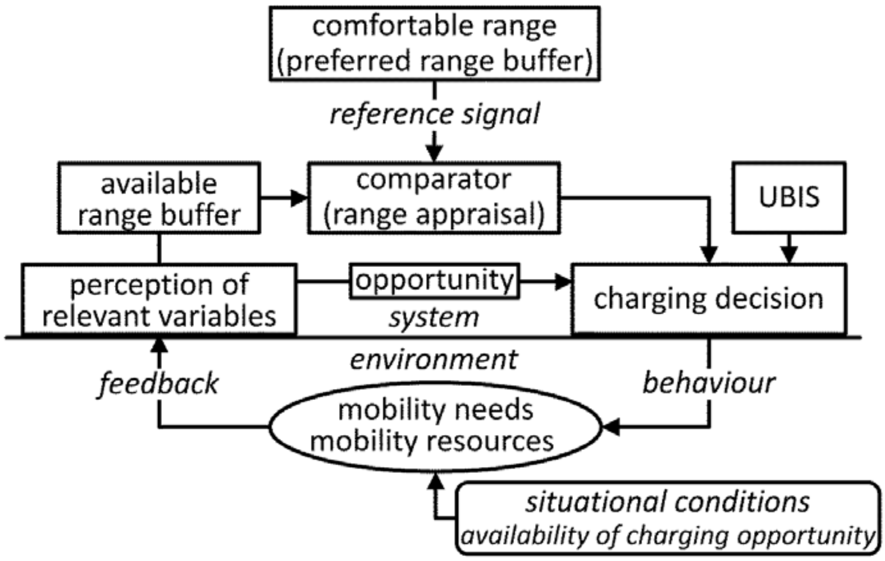

Figure 1. A charging decision according to the adaptive control of range resources model (i.e., the control loop of UBI). The likelihood of charging increases as the salience of a critical remaining range situation increases (available ≤ comfortable range). Users with a lower UBIS will, however, tend to avoid such situations by charging more often than necessary and therefore, they will tend to base their decision on contextual triggers (i.e., the opportunity to charge). In contrast, users with a higher UBIS will tend to base their decision on range resources (i.e., the experienced necessity to charge). Hence, comfortable range affects the control process at an earlier stage (appraisal) while UBIS affects the control process at a later stage (decision on coping behaviour).

1.2 Individual differences in charging style

Most previous research on charging of pure EVs has focused on qualitative descriptions of charging behaviour (see e.g. Caroll, 2010). However, in the field of mobile phones, Rahmati and Zhong (2009) conducted a study with the specific aim of understanding the variables underlying charging behaviour. These researchers have proposed the term “human–battery interaction” (although we prefer user–battery interaction, UBI) to refer to the reciprocal process by which users manage the limited energy resources stored in the battery (Rahmati, Qian, & Zhong, 2007; Rahmati & Zhong, 2009). The term battery in UBI is used in a rather broad sense, referring to the whole energy supply system, including the user interface for controlling and regulating in- and outflow of energy (i.e., energy status displays, power controls, charging interface). Because the objective of the present study is to advance understanding of charging behaviour, we focus solely on the charging-related facet of UBI in the remaining sections.

Based on two small-scale field studies (10 participants over 4 weeks; 14 participants over 4 months) incorporating qualitative interviews and tracking of charging behaviour, Rahmati & Zhong (2009) suggested a classification of users into two user-battery interaction types: Type-a users who are characterised by a low UBI (i.e., unintensive interaction with battery resources) and Type-b users who are characterized by a high UBI (i.e. intensive interaction with battery resources). The typological terminology likely arose from the specific methodology (e.g., qualitative analysis of charging behaviour and subjective data) used in this studies. Herein, low-UBI type was proposed to be marked by flatter (i.e. evenly and broadly distributed) histograms of charge level at start of charge, whereas high-UBI type was visibly indicated by histograms that had a clear peak. In contrast to this typological view, yet consistent with the more common conceptualization of driving style (Elander et al., 1993), we posit that UBI should be conceptualized as a continuum from low to high intensity of interaction with battery resources. We use the term UBI style (UBIS) to better represent our conceptualization. The factors that we expect to predict the development of a certain UBIS as well as the variables that are presumable affected by UBIS are depicted in Figure 2.

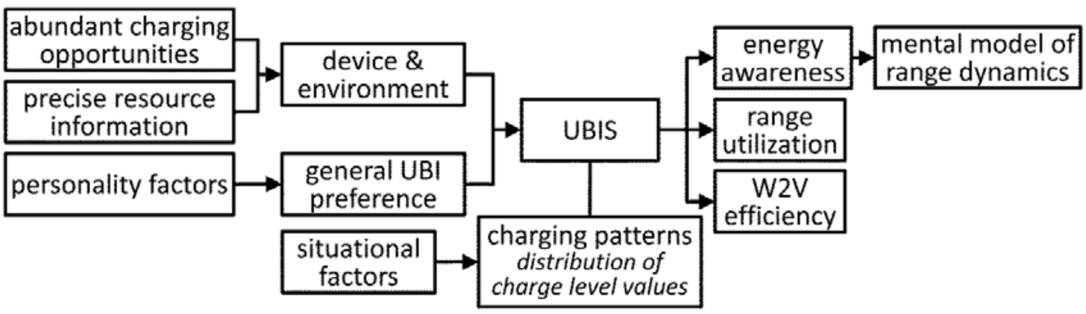

Figure 2. Variables hypothesized to predict the development of a certain UBIS and variables affected by UBIS. The general UBI preference acts as an anchor for the UBIS that users adopt. UBIS is also influenced by characteristics of the device and the environment which limit users’ flexibility in interacting with energy resources. UBIS is a variable on the decision level. It should be visible in behavioural patterns which are however also driven by situational factors (i.e., environmental noise). A high UBIS (i.e., more intensive interaction with battery resources) should lead to (1) more energy awareness and therefore more precise mental models of range dynamics and (2) a higher utilization of range resources but (3) also to a lower wind-to-vehicle (W2V) efficiency (see sections 1.3 and 2.3.7).

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Similar to Rahmati & Zhong (2009), we hypothesize that high vs. low UBIS is the expression of different general resource optimization strategies: while users with a lower UBIS try to reduce their continuous cognitive and perceptual load associated with energy-resource management, users with a higher UBIS try to reduce their motor and partly cognitive load for charging more often than necessary. Consequently, we expect that UBIS has structural similarities to other behavioural or activity-centred styles (e.g., driving style; Kleisen, 2011) as well as to cognitive styles (Zhang & Sternberg, 2005).

This preferred strategy presumably causes users with a lower UBIS to charge their devices regularly based on contextual triggers regardless of charge level (e.g., whenever possible, every evening), while users with a higher UBIS only charge when their subjectively preferred charge level is reached. Thus, it is expected that users with a lower UBIS likely have less awareness of their devices' energy level and consequently develop less precise mental models of battery-level dynamics and their power impact than users with a higher UBIS. A precise mental model of range dynamics supports a generally effective and adaptive interaction with energy resources. Therefore, consistent with Rahmati & Zhong (2009), we hypothesize that users with a lower UBIS will be less likely to take full advantage of available battery resources (i.e. show reduced range utilization). The notion that increased awareness of elements in the environment (i.e., situation awareness) is related to better situation models, and therefore, in the long run, also to better mental models, is common in other areas of human factors research (Endsley, 2000). A mental model in this sense is an internal representation of a physical system that can be used, for example, to derive predictions of system states (Endsley, 2000).

Moreover, UBIS will not only be driven by the personally preferred strategy of interacting with battery resources, but also by characteristics of both the device and the environment. The higher the battery life of a device is in relation to the frequency of encountering charging opportunities (i.e., abundant charging opportunities), the more likely users will adopt a higher UBIS. For instance, adoption of a higher UBIS is more likely in mobile phone use than in laptop use (Banerjee, Rahmati, Corner, Rollins, & Zhong, 2007) and users who lose charging opportunities due to lifestyle changes can change to a lower UBIS (Rahmati & Zhong, 2009). Additionally, a precise and informative charge level indicator is critical for the adoption of a higher UBIS (Rahmati & Zhong, 2009). Related work in the field of refuelling behaviour (Sperling & Kitamura, 1986) has also tentatively proposed that car drivers could be classified into two groups similar to UBIS: (a) people who largely base their refuelling decisions on perceived necessity to refuel and (b) people who focus on external triggers, apart from fuel level (e.g., service, convenient location of refuelling station). Again, people operating in a network with a lower density of refuelling opportunities were less likely to refuel when fuel was running low than individuals operating their vehicles under conditions with more abundant refuelling opportunities.

In sum, after users have adapted to a specific configuration of device and environment demands, we expect UBIS to be relatively temporally stable. Because UBIS is presumed to be an expression of a general UBI preference (see Figure 2), it is also expected to show some cross-device (i.e., cross-situational) consistency. These two propositions are supported by theory and findings in related fields: First, driving style has also been found to be relatively temporally stable (Lajunen & Özkan, 2011) and partly attributable to more general personality traits (Elander et al., 1993; Taubman-Ben-Ari, Mikulincer, & Gillath, 2004). Second, in the extensive literature on intellectual styles (i.e., thinking or cognitive styles; Zhang, Sternberg, & Rayner, 2012), which have also been linked to driving style (Kleisen, 2011), styles are also commonly considered to be relatively temporally stable (Zhang et al., 2012; Kozhevnikov, 2007). Moreover, cognitive styles have been conceptualized as having a hierarchical structure (Zhang et al., 2012; Kozhevnikov, 2007). Hence, there are rather general (i.e., superordinate) styles and rather specific (i.e., subordinate) styles. The more general styles have also been assumed to be more stable than the more specific styles (Curry, 1983). Finally, styles are at least in part a function of general personality traits (Kozhevnikov, 2007; Curry, 1983).

Regarding sustainable interaction with EMS, a higher UBIS is presumed to be beneficial because it is presumably related to a more efficient utilization of limited range resources. Users with a higher UBIS more actively interact with battery resources and may more often exhaust the available range, which has been shown to improve their learning process in dealing with EV range (Franke et al., 2012c; Franke & Krems, 2013; Franke, Cocron, Bühler, Neumann, & Krems, 2012b). Yet, under conditions where a more frequent connection to the power grid would be beneficial (i.e., wind to vehicle charging, see sections 1.3 and 2.3.7), a low UBIS would be preferable from a sustainability perspective.

1.3 Study objectives

The purpose of the present study is to advance understanding of the psychological dynamics underlying charging behaviour and to determine the applicability of the UBIS concept in this regard. Moreover, we aim to examine the relation of UBIS to sustainable behaviour in managing energy resources in an EMS. To this end, the present study provides the first quantitative examination of the characteristics of UBIS and its relationships to other relevant variables.

First, the following research questions were addressed in exploratory analyses: (Q1) How do EV users experience charging? (Q2) How do users charge their EVs under everyday conditions? (Q3) Is UBIS a temporally stable, and cross-device (i.e., cross-situational) consistent characteristic?

Second, the following hypotheses were tested: (H1) Previous research suggests that UBIS can be observed by examining the distribution of charge level at start of charge (Rahmati & Zhong, 2009). In particular, charge level at start of charge should be more equally (i.e., broader) distributed for users with a lower UBIS while it should be more normally (i.e., distinct peak, narrower) distributed users with a higher UBIS. This is a test of criterion validity of the UBIS scale. (H2) This is the main test of our conceptual model in Figure 1. Comfortable range (i.e., user's preferred range buffer) and UBIS (i.e., the tendency of whether a user orients to this level or not), together should explain when people charge their EV. Specifically, our model predicts that the higher users score on these two variables, the lower the charge level at which they typically recharge. (H3) Given their more intense interaction with the energy supply system, we expect users with a higher UBIS to develop more precise mental models of battery-level dynamics and of their power impact. Consequently, we hypothesize that users with a higher UBIS will give estimates of the impact that certain conditions have on range with higher confidence. (H4) Consistent with the proposal of Rahmati and Zhong (2009), we hypothesize that users with a higher UBIS will better exploit full battery capacity, in terms of range utilization. (H5) A major advantage of EVs is that they can use excess energy from renewable sources (e.g., wind) when controlled charging algorithms are applied (Westermann, Kratz, Ifland, & Schlegel, 2010b) such as in the present field trial. As a frequent connection to the grid is beneficial for utilizing excess energy (see section 2.3.7), we hypothesize that the higher the UBIS, the lower wind-to-vehicle efficiency.

2 METHOD

2.1 Field Study Setup

The present research was part of a large-scale EV field trial in the metropolitan area of Berlin, Germany, set up by the BMW Group and Vattenfall Europe, and funded by the German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety. It was part of an international EV field trial (Vilimek, Keinath, & Schwalm, 2012). The EV was a converted MINI Cooper with a 168-km range under normal driving conditions and 250 km under ideal conditions (miniusa.com, 2012). It was equipped with both state-of-charge and remaining-range displays (km). A charge level warning was first displayed briefly at 30% state of charge (SOC) and then constantly below 16 km remaining range (around 10% SOC). The EV had regenerative braking to recover energy during deceleration.

Test drivers had access to a network of 50 public charging stations in the metropolitan area of Berlin, as well as a private home-based charging station (4 h full charge duration at 32 A). The field trial consisted of two consecutive 6-month user studies (S1 and S2) with the same methodology and 40 participants each. For each user, data were collected prior to receiving the EV (T0), after 3 months of driving (T1), and upon returning the EV after 6 months (T2). At each point of measurement, users filled out 1-week travel and charging diaries (T1, T2), and completed a 2- to 3-hour face-to-face interview including questionnaires. Logger data were recorded by the BMW Group and were related to subjective data through personalized keys. Additional details on the field trial methodology are reported in other publications (Cocron et al., 2011; Franke et al., 2012a).

2.2 Participants

Eighty participants were selected from more than 1000 applicants recruited via an online screening instrument that was announced in both print and online media. Requirements for participation in the study were residence in the Berlin metropolitan area, willingness to pay a monthly leasing rate of 400 Euros, to take part in interviews, and to install a private home-based charging box. Additional criteria aimed to increase variance in basic socio-demographic (e.g., age, gender, education) and mobility-related variables (e.g., mileage, vehicle fleet). Despite these efforts our sample was still restricted in variance on basic socio- demographic characteristics compared to the general population of car drivers. The sample can rather be assumed to represent early adopters of EVs in German metropolitan areas. Data collection focused on the main EV user in the household. The 79 users who completed T1 had a mean age of 49 years (*SD* = 9.57), 67 were male, and 59 had a university degree.

2.3 Scales and Measures

All questionnaire items used a 6-point Likert scale from (1) *completely disagree* to (6) *completely agree,* unless otherwise stated. The measures used in the present study are described below in the order of their appearance in the Results section.

2.3.1 Travel and charging diaries

The travel diary was a person-based record of all trips taking place in 1 week (e.g., mode of transport, distance, time, purpose). The average daily distance driven with the EV in a typical week was derived from the T1 travel diary. Data for the 5 workdays (Monday to Friday) were used because users reported that weekend trips were atypical and there were several missing values for weekend days. Complete data were available for *n* = 68 users.

The charging diary was a car-based record of all charging events in 1 week (e.g., charge level in terms of SOC and remaining range, time, location). As the main user of the EV was defined as the unit of analysis for all the analyses, charging events initiated by other users were excluded from the data set. For each main user (1) the number of charging events and (2) the average charge level at start of charge (CLstart) were derived from the T1 charging diary. Data were available for $n = 70$ participants. CLstart values were assessed both in terms of SOC and remaining range, as users could use both indicators to estimate their remaining energy resources. As these score variants were highly correlated ($r = .95$), we combined them with a factor score (CLstartM_CD) for use in regression analysis ($n = 69$ because of missing values in remaining range variable of one user).

2.3.2 UBIS scales

We developed two scales to assess UBIS: UBIS-8 and UBIS-1. Both were administered at T2 in S1 and S2. In addition, UBIS-1 was also administered at T1 in S2. UBIS-8 consisted of four items indicative of a high UBIS (e.g., "I typically charged when the state of charge fell to a certain level") and four items of a low UBIS (e.g., "… a particular timeframe had elapsed ..."). The latter four items (item IDs l1 to l4) were reverse scored so that for all 8 item variables, high numbers indicated high UBIS (for full item texts and item IDs see Appendix A). Data were available for $n = 75$ users. To examine the dimensional structure of the variable set, we conducted a factor analysis using the program FACTOR (Lorenzo-Seva & Ferrando, 2006). Three cases had identical extreme values on two item variables ($z = -2.74$ resp. -2.97). Factor analysis results can be significantly distorted by outliers (Liu, Zumbo, & Wu, 2012). When extracting one factor based on our theoretical expectations using unweighted least squares extraction, factor loadings were partly unsatisfactory (h1 = .68, h2 = .87, h3 = .44, h4 = .83, l1 = .15, l2 = .15, l3 = .20, l4 = .37). Yet, without the three cases mentioned above ($n = 72$), factor loadings were all satisfactory (h1 = .57, h2 = .74, h3 = .37, h4 = .69, l1 = .37, l2 = .45, l3 = .34, l4 = .52). Parallel analysis (Timmerman & Lorenzo-Seva, 2011), however, indicated that two factors best accounted for the data when $n = 75$. Given $n = 72$, both a two factor and a single factor (according to more stringent 95th percentile criterion; Glorfeld, 1995) solution were indicated. In both samples, extracting two factors (promin rotation; Lorenzo-Seva & Ferrando, 2006) led to a clear pattern: items indicative of a high UBIS (h1 to h4) loaded on the first and items indicative of a low UBIS (l1 to l4) loaded on the second factor (all primary loadings > .5, all secondary loadings < .2). The factors correlated weakly ($r = .19$) with outliers included and moderately ($r = .35$) with outliers excluded. Based on this pattern of results, we conclude that it is premature to draw final conclusions on the dimensional structure of the UBIS-8 scale. UBIS could either be conceptualized as comprising (a) one dimension, (b) two weakly correlated dimensions, or (c) two moderately correlated dimensions. As a result, we computed three mean scores: UBIS-8 (all 8 items, Cronbach's alpha =

.70), UBIS-l4 (items l1 to l4, Cronbach's alpha = .72), and UBIS –h4 (items h1-h4, Cronbach's alpha = .80).

UBIS-1 was a single-item measure (see Appendix A). The two endpoints reflected the prototypic description of the two UBISs as proposed by Rahmati and Zhong (2009). UBIS-1 strongly correlated with UBIS-8, $r = .61$, $p < .001$ (UBIS-l4: $r = .43$, $p < .001$, UBIS-h4: $r = .48$, $p < .001$). Data were available for $n = 76$ users. UBIS-1 was also administered at T1 in S2 to test for temporal stability (correlation with UBIS-8: $r = .57$, $p < .001$, UBIS-l4: $r = .37$, $p = 022$, UBIS-h4: $r = .46$, $p = .003$, data available for $n = 40$ users). UBIS-1 was also administered for users' mobile phone (T2 in S1 and T0 in S2, $n = 78$) and combustion vehicles (CVs, only T0 in S2, $n = 39$). For the last two items, users were also asked to indicate battery life in hours/days and range in km, respectively.

2.3.3 Logger data on charging

Charge level variables were also assessed with data loggers in the EV by the BMW Group. We identified charging events by a SOC increase > 12 percentage points between two consecutive trips in order to safely distinguish between charging events and battery recovery. Moreover, charging events were only included in the analysis if they were initiated by the main user[2] and did not occur during the first two months of EV use, as we were only interested in everyday charging behaviour of adapted EV users. Users who had very few available data points (<20) were excluded from the analysis, as we aimed to compute parameters of their individual charge level distributions. Given these constraints, data of $n = 57$ users were determined to be suitable for analysis.

For each user, two parameters of his/her individual distribution of charge level values at start of charge (CLstart) were computed. First, we computed the standard deviation of CLstart values (CLstartSD) because Rahmati & Zhong (2009) proposed that users with a lower UBIS should have a broader distribution (i.e., higher variance) of CLstart values. Second, we computed whether CLstart values were equally or normally distributed (CLstartKS), as Rahmati & Zhong (2009) proposed that user with a lower UBIS should exhibit an equal distribution, while users with a higher UBIS should exhibit a normal distribution (i.e., with a distinct peak) of CLstart values. This was assessed by computing the p-value of the Kolmogorow-Smirnov test (pKS) for equal distribution minus the pKS for normal distribution. Therefore, a higher CLstartKS (i.e., the more the distribution approximates an equal rather than a normal distribution) indicates a lower UBIS and vice-versa. Similar to the charging diary, CLstartSD and CLstartKS were assessed in terms of both, SOC and remaining range. Again, these score variants correlated strongly ($r_{CLstartSD} = .91$, $r_{CLstartKS} = .70$) and were therefore combined

[2] Several users did not use the personalized car keys as prescribed and were therefore excluded from the analysis as charging events by the main user could not be identified for those participants.

using a factor score. Finally, we also computed the average CLstart value for each user (CLstartM_DL) in parallel to the procedure applied to the charging diary data ($r_{\text{CLstartM\_DL}}$.= .96).

2.3.4 *Comfortable range*

The composite variable of comfortable range incorporated three subscores (see also Franke & Krems, 2013). First, the range game assessed the individual range comfort zone using a standardized and ecologically valid scenario (i.e., 60-km trip in a mostly urban area). Participants were asked to report their comfort level for embarking on a trip, according to four items. This was done 10 times with displayed range values between 45 and 90 km in randomized order. The resulting score value represents the lowest range value that users experience as completely comfortable (for further details see Franke et al., 2012c). Second, the 4-item threat scale of the Primary Appraisal Secondary Appraisal (PASA) questionnaire (Gaab, 2009) assessed range threat appraisal for a situation where remaining range and trip distance were equal. Third, the minimum range safety buffer was assessed as the range level below which users were no longer willing to drive the EV. Variables were reverse coded so that high values indicated high comfortable range. A composite score was derived using principal-axis factor analysis (clear single-factor solution, eigenvalue of first factor = 1.62, second factor = 0.81). The three variables had acceptable factor loadings: range game comfort zone = .65, range threat appraisal = .37, range safety buffer = .66. Data were available for n = 73 users.

2.3.5 *Mental model of range dynamics*

Our assessment of users' mental models of range dynamics was based on the conceptual notion that the ability to generate precise situational models in terms of prediction of system states is a valid indicator of a mental model's precision (Endsley, 2000). Users were presented with the following scenario: A range of 100 km was displayed after having driven the last 30 km (the reference distance for the range display in the EV) at an average of 60 km/h in light urban traffic at 10°C ambient temperature, interior heating set at 20°C, and low beam turned on. Users estimated displayed range and reported a confidence rating (0–100%), given that they had driven the last 30 km: (1) without regenerative braking, (2) on the motorway at 120 km/h, (3) without heating, (4) without low-beam, (5) at only 45 km/h, (6) with the radio on. The six confidence ratings had a Cronbach's alpha of .95. This measure was assessed at T1, only in S2, n = 39.

2.3.6 *Range utilization*

To assess range utilization, users were asked to report their longest distance driven with one charge in the periods between T0–T1 (at T1) and T1–T2 (at T2). There was considerable variance in range utilization: M_{T1} = 132 km, SD_{T1} = 37.6, Min_{T1} = 50, Max_{T1} = 245; M_{T2} = 128 km, SD_{T2} = 28.7,

Min_{T2} = 52, Max_{T2} = 212. The correlation of T0–T1 and T1–T2 data was moderately positive, r = .39. A mean score was computed from T1 and T2 data to obtain an estimate of range utilization over the whole trial, n = 77.

2.3.7 Wind-to-vehicle efficiency

The EMS incorporated a controlled charging system to optimize the use of excess energy from wind (wind-to-vehicle). The basic functionality and purpose of the system was explained to the users at T0. This system incorporated an algorithm which regulated energy input during charging to fit the supply curve of excess energy from wind (Westermann, Agsten, & Schlegel, 2010a). In particular, this algorithm shifted the charging processes to the time periods when charging would be most "green" (green windows). Therefore, users were asked to set a standard time of the day (e.g. 8 am) at which the car must be fully charged via a website. They could also set exceptions (e.g. Mon, 01/03/2011, 9 am). If users did not set a standard time a conservative default value was used by the algorithm (7 am). For every charging event, the algorithm optimized the charging (a) to take place in green windows, when the available level of excess-energy from wind was high, and (b) to be completed until the standard time set by users. Users could also use the website to deactivate controlled charging for the current charging event and command the system to charge instantly.

Data on wind-to-vehicle efficiency was collected by partners in the field trial project at the TU Ilmenau (Westermann et al., 2010a). The wind-to-vehicle efficiency score was available for n = 74 users. The information for the score was automatically recorded in the controlled charging system. The amount of energy charged within green windows (i.e., when excess energy from wind was available) was divided by the total amount of energy charged to yield the indicator of wind-to-vehicle efficiency. This was based on the assumption that higher excess energy from wind during charging is associated with a smaller EV ecological footprint. Of course, for users who tend to charge the car frequently with relatively high remaining energy (e.g., users with a lower UBIS), the time slot actually required for charging the battery would be relatively short. Thus, the algorithm could more easily match the required charging time to the green windows. Therefore, a lower UBIS is expected to be associated with more efficient (i.e., sustainable) use of excess energy from wind. However, it could also be possible, that some users are highly motivated to support controlled charging and adjust their behaviour (i.e., charge as often as possible), which could partly determine their UBIS. Yet, our data did not suggest that this potential influence was present in our sample: There was one item in the charging diary that assessed charging motivation. Users were asked to allocate 100 points to five categories ("I want to support controlled charging.", "There is a possibility to charge.", "I need additional range for my next trip(s).", "low battery", "other"). For 60% of recorded charging events, controlled charging did not receive any points (only for 9% >50 points). Moreover, the users average rating of the category was not related to UBIS-8 (r = -.06).

3 RESULTS AND DISCUSSION

3.1 Experience of EV charging

Regarding research question (Q1), results at T1 (n = 79) revealed that most users (87%) agreed (dichotomization of 6-point Likert scale) that charging was easy. However, several users (57%) reported that handling the charging cable was cumbersome. Most users (78%) were not bothered by the longer time required for recharging relative to refuelling a conventional vehicle. Seventy-one percent of users preferred to recharge at a charging station (private or public), rather than refuel their vehicle at the gas station. Although 86% of users agreed that public charging stations were indispensible for charging their EV at T0, only 62% agreed at T1. Taken together, it can be concluded that charging was not a major barrier for users in this study.

3.2 Everyday charging patterns

Regarding research question (Q2), results revealed the following: The average daily distance driven with the EV in a typical week, as assessed with the travel diary, was 38.0 km (SD = 20.4). Interestingly, this number is similar to the average daily distance travelled in German urban areas, 36 km (infas & DLR, 2010). This gives some indication that our sample represented relatively average car users, who drove the EV for similar daily distances as a conventional automobile. The maximum distance that participants were willing to drive with the EV when fully charged was on average 124.9 km (*1st quartile* = 105.0, *3rd quartile* = 140.0, SD = 19.9). Thus, the available range of the EV typically lasted for several days. As the users had daily access to a private charging station, they consequently had abundant charging opportunities. On average, they did not need to charge the EV whenever possible, but could instead adopt their preferred charging style.

Based on the data from the charging diary, the average users reported 3.1 charging events in a typical week (*1st quartile* = 2, *3rd quartile* = 4, SD = 1.5). This self-reported charging frequency is similar to the 2.8 charging events per week, as assessed with car-based data loggers for the present field trial by the BMW Group and also similar to figures found in other countries (Vilimek et al., 2012). Users most often employed their private charging station (83.7% of charging events) and only seldomly public charging stations (4.8%) and normal sockets (11.5%). As depicted in Figure 3, users typically recharged their EV when there was plenty of range left. Sixty-six percent of users on average charged their EV when SOC was > 40% and there was a relatively broad distribution of charge levels.

This pattern suggests that users with a lower UBIS were represented in this sample. Moreover, distinct peaks in the distribution of charge levels were observed just above 30% SOC and just above 15% SOC. Both of these peaks corresponded with the thresholds of the two standard charge level warnings (i.e., 30% and 10% SOC, see section 2.1). This pattern indicates the presence of user with a higher UBIS in the sample. Therefore, the charging diary data indicate that there are some individual differences regarding UBIS within this sample (for a more direct examination, see section 3.4).

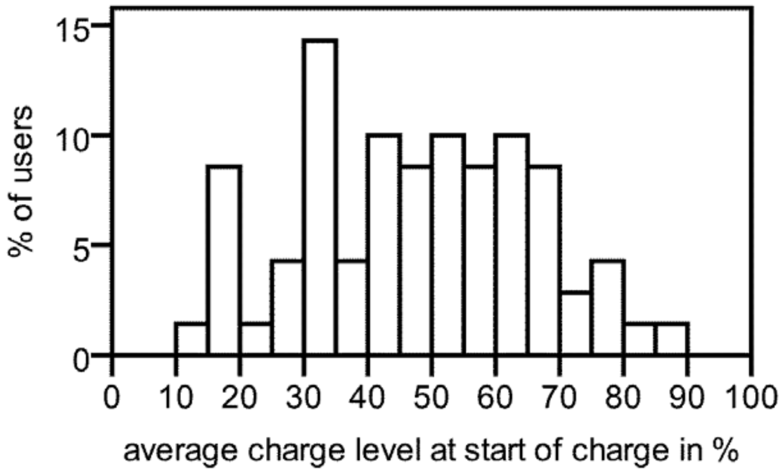

Figure 3. Histogram of users' average charge levels recorded at start of charge. Data come from the charging diary at T1, n = 70.

3.3 Temporal and cross-device stability of UBIS

In order to examine research question (Q3), the UBIS-1 was administered at T1 and T2 in S2, to allow for analysis of temporal stability after adaptation to the EV. Results showed that UBIS can be conceptualized as a relatively temporally stable characteristic over a period of 3 months, $r = .65$, $p < .001$, $n = 39$.

Cross-device (i.e., cross-situational) consistency was tested by examining the correlation between users' response to UBIS-1 for charging their EV (T2) and for charging their mobile phone (T2 in S1, T0 in S2). Charging a mobile phone differs considerably from charging an EV in terms of the device and the environment (e.g., number of charging opportunities, consequences of running out of charge, charge duration, etc.). However, because of the assumed general UBI preference UBIS should still be similar (see also Figure 2). Indeed, there was a significant correlation between the two measures, $r = .24$, $p = .035$, $n = 76$. This finding provides some support for the existence of a general UBI preference variable. Previous research has shown that the everyday battery runtime of a device influences adoption of a particular UBIS (Rahmati & Zhong, 2009). Thus, we also computed the analysis only for those users who had a mobile phone with an experienced everyday battery runtime that was relatively comparable to an EV (i.e., < 4 days of estimated battery runtime). In fact, this led to an increase in effect size, yielding a moderate and again significant effect, $r = .32$, $p = .035$, $n = 45$. The test of cross-device consistency to CV refuelling was not possible because of limited variance on the CV-UBIS-1 (T0 in S2): 88% had a scale value of 5 or 6, which indicates a high UBIS. Yet, this is a relevant result in itself as it again supports the hypothesis that a high density of easily accessible, usable, and fast charging opportunities in a user's operating range is associated with a higher likelihood of adopting a high UBIS.

3.4 Charge level distribution and UBIS

The hypotheses were tested using a series of regression analyses (sections 3.4 to 3.8). Prior to performing the analyses, we examined if assumptions for (multiple) regression analysis were met according to Stade, Meyer, Niestroj, & Nachtwei (2011). Almost all assumptions (e.g., normal distribution and reliability of variables) were satisfactorily met, except for some individual cases that were identified as outliers, residual z-value > |1.96|. Urban and Mayerl (2008) suggested that results should be presented with and without these outliers. To aid readability, results with outliers excluded are presented only if their statistical significance or effect size magnitude differed considerably (e.g., change from a weak to a moderate effect). As we had directional hypotheses, our tests were one-tailed, except for the omnibus test of whole-model fit in multiple regression in section 3.5. Effect sizes were interpreted according to the conventions (i.e., weak effect is r =.10; moderate effect is $r = .30$; strong effect is $r = .50$; Cohen, 1992). All of the regression analyses were conducted with UBIS-8, as it was assumed to be more reliable than UBIS-1 because of its item count (De Gruijter & Van der Kamp, 2008), most comprehensive, and yielded similar results compared to analyses with the subscales UBIS-l4/h4 (we point out all exceptions, see for example in next paragraph). A table that presents a correlation matrix and descriptive statistics of all variables used in confirmatory analyses is included in Appendix B.

In support of hypothesis (H1), a significant relationship between distribution characteristics of users' charge level at start of charge (CLstart) and UBIS-8 was found (see Table 1). Specifically, there was a significant negative relationship between CLstartSD (the standard deviation of users CLstart values) and UBIS-8 (same result for UBIS-l4). When outliers were excluded, a moderate effect size was observed for this relationship. For UBIS-h4, this effect was not present at first, however, in the analysis with outliers excluded, the result was similar to the result for UBIS-8 (moderate effect). In addition, a significant moderate and negative relationship between CLstartKS (the approximation of CLstart values to an equal minus to a normal distribution) and UBIS-8 was obtained, such that higher UBIS-8 was associated with normal distributions (same result for UBIS-l4/h4). This is consistent with Rahmati & Zhong's (2009) hypothesis that charge level at start of charge is more equally (i.e., broader) distributed for users with a lower UBIS while it is more normally (i.e., distinct peak, narrower) distributed for users with a higher UBIS. Therefore, UBIS is observable in charging behaviour and the UBIS concept seems to be applicable for our purposes.

Table 1. *Indicators of (1) a broader (CLstartSD) or (2) more equal than normal (CLstartKS) distribution as predictor for UBIS-8.*

		n		β		*p*		R^2_{adj}	
(1)	CLstartSD	56	*55*	–.25	*–.32*	.032	*.010*	.05	*.08*
(2)	CLstartKS	56	*54*	–.38	*–.47*	.002	*<.001*	.13	*.20*

Note. Results after outlier exclusion are given in italics.

3.5 UBIS and comfortable range as predictors of typical charging behaviour

Consistent with hypothesis (H2), UBIS-8 and comfortable range explained substantial variance in average charge level values at the start of charge, as assessed by the charging diary and the automatically recorded data logs (see Table 2). The two predictors were significant and in the expected direction in both analyses, with UBIS-8 yielding an (almost) strong effect, and comfortable range yielding a (nearly) moderate effect (similar result for UBIS-l4/h4). These results support our model and the hypothesis that UBIS and comfortable range are two key variables that can explain how users decide to charge an EV.

This result also indicates that the 1-week snapshot of self-reported charging behaviour and the more comprehensive data obtained from the automated data logs yielded very similar results. Indeed, both scores correlated highly, $r = .74$, $p < .001$, $n = 53$. This gives some indication that charging behaviour of EV users in the field trial was temporally stable (i.e., can be assumed to be habitual).

Table 2. *Comfortable range and UBIS-8 as predictors of charge level at start of charge as assessed by the charging diary (1) versus the data logger (2).*

		n	R^2_{adj}	*p*	β	*p*	*Part correlation*	*Zero-order correlation*
(1)	UBIS-8	65	.29	<.001	–.49	<.001	–.49	–.49
	Comfortable range				–.27	.006	–.27	–.28
(2)	UBIS-8	54	.37	<.001	–.51	<.001	–.51	–.54
	Comfortable range				–.32	.003	–.32	–.36

3.6 UBIS and users' confidence in their mental models of range dynamics

In support of hypothesis (H3), there was a significant positive relationship between UBIS-8 and confidence in range estimates (similar result for UBIS-l4/h4), yielding an almost strong effect (see

Table 3). As previous literature indicates that range knowledge is related to more efficient utilization of EV range (Franke et al., 2012c; Franke & Krems, 2013), the present result provides support for the hypothesis that a higher UBIS is associated with more sustainable behaviour in the usage of EV battery resources.

Table 3. *UBIS-8 as predictor of users' confidence in their mental model of range dynamics*

n	β	*p*	R^2_{adj}
38	.47	.001	.20

3.7 UBIS and range utilization

Consistent with hypothesis (H4), UBIS-8 was positively associated with the range utilization indicator, yielding a significant and nearly moderate effect (see Table 4). In the analysis with UBIS-l4/h4 only UBIS-h4 yielded a significant moderate effect. In other words, users who rather charged based on the charge level were also more likely to utilize the full battery resources. Therefore, this result lends additional support to the hypothesis that higher UBIS is associated with more sustainable EV battery usage patterns.

Table 4. *UBIS-8 as predictor of range utilization*

n	β	*p*	R^2_{adj}
75	.28	.007	.07

3.8 UBIS and wind-to-vehicle efficiency

As expected from our hypothesis (H5), UBIS-8 was negatively related to wind-to-vehicle efficiency, yielding a significant and, after outlier exclusion, moderate effect (see Table 5). In analysis with UBIS-l4/h4 only UBIS-h4 yielded a significant moderate effect. The relationship implies a goal conflict in terms of which UBIS is related to sustainable behaviour in dealing with the energy resources in the EMS. Implications of this are discussed below.

Table 5. *UBIS-8 as predictor of wind-to-vehicle efficiency*

n		β		*p*		R^2_{adj}	
71	*67*	−.21	*−.31*	.041	*.005*	.03	*.08*

Note. Results after outlier exclusion are given in italics.

4 GENERAL DISCUSSION

4.1 Summary of findings

The present research investigated the psychological dynamics underlying sustainable EV battery charging behaviour. With respect to our research questions, results indicated that: (Q1) Users experienced EV charging as convenient, (Q2) users charged their vehicle about three times a week and typically drove 37 km with the EV per day. Many users typically charged their EV although substantial battery life was remaining and some users typically charged at charge levels that were associated with battery warnings. These findings suggest the presence of individual differences in participants' UBIS in our sample. (Q3) UBIS was observed to be a relatively temporally stable characteristic that also showed some cross-device consistency. Results of hypothesis testing supported our hypotheses: (H1) charging behaviour in terms of distribution parameters of charge level at start of charge was related to UBIS. (H2) UBIS and comfortable range significantly predicted the charge level at which people typically recharged, (H3) higher UBIS was positively related to confidence in range estimates, and (H4) to range utilization, and (H5) higher UBIS was negatively related to wind-to-vehicle efficiency.

4.2 Theoretical implications

The present research gave some indication for the usefulness of our conceptual model in the prediction of users' charging decisions when interacting with limited EV energy resources (see Figure 1). Together, UBIS and comfortable range explained up to 37% of the variance in average charge level at which users charged their EV. In addition, the variables were observed to play largely independent roles in this relationship (i.e., small difference between zero-order and part correlation of predictors) and were also found to be nearly uncorrelated in general (see Appendix B). This supports our conceptualization that comfortable range and UBIS are two clearly distinguishable constructs that affect the control loop of UBI (see Figure 1) at different stages (appraisal vs. decision). While comfortable range is similar to the concept of a preferred safety margin or level of accepted task difficulty (Fuller, 2005) that determines how a situation is appraised; UBIS is a preferred decisional style that either (a) orients the user to a specific safety margin and causes the user to not to fill up resources more often than necessary (i.e., engage in safety-related behaviours) or (b) orients the user to fill up resources more often in order to avoid dealing with the safety margin altogether. Although these two variables explain sizable variance, a substantial amount of unexplained variance remains. For example, variables related to the comprehension of the available range buffer and/or additional situational factors might account for part of the unexplained variance. These should be studied in further research.

Moreover our research indicates that the UBIS concept is an important driver of individual differences in users' utilization of limited energy resources. Indeed, our findings suggest that users have a rather consistent battery charging style over time and across devices. Moreover, consistent with previous research (Rahmati & Zhong, 2009), UBIS exhibits relationships with other variables as expected (charge level distribution, mental model of range dynamics, resource utilization). However, given that this is the first quantitative study on UBIS, additional research is needed before drawing firm conclusions from our results. For example, researchers should more directly test whether there is indeed a general UBI preference and future studies should examine which personality factors are drivers of this variable. Some potentially related personality variables could, for example, be: (1) Trust as a facet of agreeableness (Costa, McCrae, & Dye, 1991), because a higher trust in battery resource displays (i.e., the resource estimation algorithm) could lead to higher reliance on this information (i.e., a higher UBIS). (2) Locomotion and assessment (Kruglanski et al., 2000) because these variables are also partly associated with the tendency to avoid cognitive versus motor load. (3) Need for cognition (Cacioppo & Petty, 1982) because this variable is associated with higher acceptance of cognitive load. Moreover, a controlled study of the influence of environmental factors on adoption of a specific UBIS (e.g., the impact of differentially precise battery status displays) would improve understanding of the stability of UBIS.

4.3 Practical implications

Taken together, the results of (H3) to (H5) suggest the emergence of a possible goal conflict. While a higher UBIS seems favourable for sustainable utilization of range resource (H3, H4), it seems unfavourable for sustainable utilization of excess energy from wind (H5). It is difficult to weigh these effects in terms their impact on net sustainability of an EMS. When controlled charging is *not* incorporated in an EMS, a higher UBIS is clearly favourable. When controlled charging is applied in an EMS, a higher UBIS is both, favourable (H3, H4) and unfavourable (H5). A solution to this dilemma could be to introduce and promote controlled charging only after the critical EV adaptation period. Previous research suggests that much of the users' adaptation to range is completed within the first 3 months of EV use (Pichelmann, Franke, & Krems, 2013). It is during this period that range skills, habits and the individual range comfort zone are established. This critical period lays the foundation for efficient range utilization. Consequently, adoption of a higher UBIS should be promoted during these early months of EV use so that users more actively interact with battery resources. Only after the adaptation phase, the more frequent and regular charging patterns should be promoted as they support the utilization of excess energy from wind.

How could the adoption of a specific UBIS be supported? As shown previously (e.g., see Figure 2), UBIS is not just a function of the person, but also of the device- and environment-related characteristics. A more precise and informative battery indicator and perception of abundant charging opportunities will promote the adoption of a higher UBIS. Rahmati and Zhong (2009) point to the appeal of adaptive charge level displays that increase their precision with lower SOC values. Such displays could reduce *perceived* range depletion and thereby encourage users to wait until they really need to charge. Also, informing users about the location of safety charging spots (i.e., accessible charging opportunities near planned routes that can be used for charging in case of emergency) appears to be a helpful strategy for promoting awareness of the abundance of charging opportunities. Finally, previous research on how users deal with limited EV range showed that prior knowledge regarding EV technology can lead to increased competent range (Franke & Krems, 2013). Given the feedback principles that we assume in our model, knowledge may not only be an outcome but also a predictor of a high UBIS. Frequent and regular charging should only be promoted after users have adapted to range. Although monetary incentives are mostly discussed as motivators to comply with controlled charging (Ifland, Exner, & Westermann, 2011), other motivating factors like intrinsic motivation to use green energy for EV charging appear promising, based on users' responses in the present study (Franke et al., 2012a; Rögele, Schweizer-Ries, Zöllner, & Antoni, 2010). Accordingly, employing elements of gamification and competiveness likely represent attractive options in this respect.

4.4 Critical evaluation of study findings and further research needs

Our study results are based on a specific sample of early adopters of EVs, who only represent one segment of all future EV users. However, we assume that the factors underlying the charging behaviour of this group are not fundamentally different from other groups of users, because (1) an influence of socio-demographic characteristics on charging style seems unlikely, and (2) the mobility patterns of users in our sample were relatively similar to those usually found in German urban areas in terms of daily distance travelled. Yet, our sample might be restricted on relevant personality variables as time of adoption is known to be related to personality characteristics (Rogers, 2003). Consequently, the distribution of UBIS values could be different in other samples, as personality is assumed to be a driver of UBIS. Yet, this should not have a substantial influence on the obtained relationships between variables.

Additionally, the present research was conducted using one specific EMS with one specific EV. This control of the device & environment factor (see Figure 2) was helpful for the present research, as it limited variance associated with extraneous variables. Regarding generalizability, we expect that our results would be similar for other EVs, as the key characteristics of the device, the range of around 170 km and a precise charge level display, are similar to those of other EVs. However, under conditions where the charging network is much less dense (e.g., no daily charging opportunity), or in a sample solely made up of users who approach the objective range limit on a daily basis (e.g., 160 km daily driving distance), results may be different and our proposed theoretical concepts might be less applicable.

In conclusion, we view our research as a first step in achieving a better understanding of everyday charging behaviour in EV users. UBIS seems to be a useful concept in this regard that deserves further research attention. For instance, we believe that a fruitful research agenda could focus on an examination of UBIS from the perspective of the proposed analogy to driving style. Moreover, battery life has also re-emerged as a major usability concern in mobile phones with the rise of smartphones (Rahmati & Zhong, 2009). Hence, we argue, in parallel to other current research (Lundström, Bogdan, Kis, Olsson, & Fahlén, 2012), that it is important to further explore similarities between these two mobile systems and to test the transferability of proposed solutions to the transport domain, for example how to represent energy availability in mobile settings.

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6 APPENDIX

Appendix A

The UBIS-8 scale.

		Im nächsten Abschnitt geht es um **typische Auslöser für das Starten eines Ladevorganges**. Mein Ladeverhalten lässt sich am besten so beschreiben, dass ich **typischerweise geladen habe, wenn…** *The next section is about **typical triggers for starting a charge**. To describe my charging behaviour best, I would say that I **typically charged when**…*	stimmt gar nicht *completely disagree*	stimmt weitgehend nicht *largely disagree*	Stimmt eher nicht *slightly disagree*	Stimmt eher *slightly agree*	stimmt weitgehend *largely agree*	Stimmt völlig *completely agree*
h1	1	... die Batterie leergefahren war. *… the battery was discharged.*	☐	☐	☐	☐	☐	☐
l1	2	… sich irgendeine Gelegenheit zum Laden bot. *… there was any opportunity to charge.*	☐	☐	☐	☐	☐	☐
h2	3	... ich zu wenig Reichweite für meine nächsten geplanten Fahrten hatte. *…I did not have enough range for the next trips I had planned.*	☐	☐	☐	☐	☐	☐
h3	4	… ich eine bestimmte Reservereichweite unterschritten hatte, die ich immer in der Batterie haben wollte. *…I was below a specific buffer range that I always wanted to have in the battery.*	☐	☐	☐	☐	☐	☐
l2	5	… ich in der Nähe einer meiner gewohnten Lademöglichkeit war. *…I was close to my usual charging site.*	☐	☐	☐	☐	☐	☐
l3	6	… eine bestimmte Zeitspanne überschritten wurde, nach der es sich eingebürgert hatte, einfach bei der nächsten Gelegenheit zu laden. *…a particular timeframe had elapsed, after which I had become accustomed to simply charging at the next opportunity.*	☐	☐	☐	☐	☐	☐
h4	7	… der Ladezustand auf ein bestimmtes Niveau abgesunken war. *…the state of charge fell to a certain level.*	☐	☐	☐	☐	☐	☐
l4	8	… ich eine bestimmte Fahrt in meinem Tagesablauf abgeschlossen hatte, nach der es für mich üblich war zu laden. *… I finished a particular trip in my daily routine, after which it was normal for me to charge.*	☐	☐	☐	☐	☐	☐

Note. The leftmost column shows the item IDs and was not displayed in the original questionnaire.

The UBIS 1 item.

Ich lade mein Efzg regelmäßig, ohne weiter auf den Ladezustand zu achten. *I charge my EV regularly without particular attention to the charge level.*	☐	☐	☐	☐	☐	☐	Ich lade mein EFzg immer wenn der Ladezustand unter ein bestimmtes Level fällt. *I charge my EV when the charge drops below a certain level.*

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Appendix B

Intercorrelations and descriptive statistics for scores included in the confirmatory analysis and for the UBIS-1 score.

Measures	*1*		*2*		*3*		*4*		*5*		*6*		*7*		*8*		*9*		*10*		*11*		*12*		*N*	*M*	*SD*
1. UBIS-8 (T2)	-																								75	4.08	0.85
2. UBIS-l4 (T2)	.73*	(75)	-																						75	3.71	1.12
3. UBIS-h4 (T2)	.76*	(75)	.11	(75)	-																				75	4.44	1.16
4. UBIS-1 (T2)	.61*	(74)	.43*	(74)	.48*	(74)	-																		76	4.04	1.64
5. UBIS-1 (T1 in S2)	.57*	(38)	.37*	(38)	.46*	(38)	.65*	(39)	-																40	3.23	1.62
6. CLstartSD	-.25	(56)	-.36*	(56)	-.03	(56)	.02	(56)	.20	(34)	-														57	0.00	1.00
7. CLstartKS	-.38*	(56)	-.32*	(56)	-.26	(56)	-.33*	(56)	-.22	(34)	.27*	(57)	-												57	0.00	1.00
8. CLstartM_CD	-.49*	(68)	-.38*	(68)	-.37*	(68)	-.52*	(68)	-.48*	(33)	.16	(53)	.41*	(53)	-										69	0.00	1.00
9. CLstartM_DL	-.52*	(56)	-.39*	(56)	-.41*	(56)	-.60*	(56)	-.46*	(34)	.13	(57)	.34*	(57)	.74*	(53)	-								57	0.00	1.00
10. ComfRange	.03	(72)	.02	(72)	.03	(72)	.28*	(72)	.09	(39)	.16	(55)	-.21	(55)	-.28*	(65)	-.36*	(55)	-						73	0.00	0.79
11. Mental model	.47*	(38)	.39*	(38)	.30	(38)	.22	(38)	.22	(39)	-.20	(33)	-.38*	(33)	-.10	(33)	-.32	(33)	.05	(38)	-				39	65.5	14.4
12. Range utilization	.28*	(75)	.06	(75)	.35*	(75)	.29*	(76)	.62*	(39)	.13	(57)	-.16	(57)	-.16	(69)	-.39*	(57)	.41*	(73)	.13	(38)	-		77	129	27.7
13. W2V efficiency	-.21	(71)	-.03	(71)	-.27*	(71)	-.14	(72)	-.09	(38)	.04	(53)	.11	(53)	.15	(65)	.19	(53)	-.05	(69)	-.19	(37)	-.15	(73)	74	0.00	1.00

Note. Sample sizes for intercorrelations are given in parentheses. Variables 6.-9. are factor scores and variable 13. is z-standardized, therefore M = 0.00. Abbreviated score labels: 1.-5. UBIS = user-battery interaction style; 6. CLstartSD = standard deviation of users CLstart values; 7. CLstartKS = the approximation of CLstart values to an equal minus to a normal distribution; 8. CLstartM_CD = mean charge level at start of charge as assessed by charging diary ; 9. CLstartM_DL = mean charge level at start of charge as assessed by data logger; 11. Mental model = users' confidence in their mental model of range dynamic; 13. W2V efficiency = wind-to-vehicle efficiency.
*p <.05.

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