How Can Mobile Applications Reduce Energy Consumption? An Experimental Investigation of Electric Vehicles

Kenan Degirmenci
Leibniz Universität Hannover, kenan.degirmenci@qut.edu.au

Torben M. Katolla
Leibniz Universität Hannover, katolla@iwi.uni-hannover.de

Michael H. Breitner
Leibniz Universität Hannover, breitner@iwi.uni-hannover.de

Follow this and additional works at: http://aisel.aisnet.org/ecis2015_cr

Recommended Citation
ISBN 978-3-00-050284-2
http://aisel.aisnet.org/ecis2015_cr/36
HOW CAN MOBILE APPLICATIONS REDUCE ENERGY CONSUMPTION? AN EXPERIMENTAL INVESTIGATION OF ELECTRIC VEHICLES

Degirmenci, Kenan, Leibniz Universität Hannover, Königsworther Platz 1, 30167 Hannover, Germany, degirmenci@iwi.uni-hannover.de
Katolla, Torben M., Leibniz Universität Hannover, Königsworther Platz 1, 30167 Hannover, Germany, katolla@iwi.uni-hannover.de
Breitner, Michael H., Leibniz Universität Hannover, Königsworther Platz 1, 30167 Hannover, Germany, breitner@iwi.uni-hannover.de

Abstract
The role of information systems for environmental sustainability has received considerable attention over the last several years. In view of global warming and climate change, a transition from combustion to electric vehicles (EVs) can help reduce greenhouse gas (GHG) emissions. Since sustainable behavior often lacks relevant information about its environmental effects, the role of information systems in influencing energy consumption is being explored in this paper. The main focus is to investigate the impact of driver assistance systems in the form of mobile applications on the energy consumption of EVs. To test such an impact, a field experiment is conducted by defining a control group and an experimental group. Test drives are performed with an all-electric, lithium-ion battery powered, small passenger city car. As the treatment of the study, a mobile application is chosen that monitors excessive acceleration and hard braking. The results reveal significant differences among the groups, which indicate that using smartphone-based driver assistance systems significantly reduces the energy consumption of EVs. This can entail several benefits, including an increase in range of EVs, electricity cost savings, decrease of vehicle wear, and reduction of GHG emissions. The findings are discussed and implications for research and practice are given.

Keywords: Environmental Sustainability, Energy Consumption, Electric Vehicles, Driver Assistance Systems, Mobile Applications, Field Experiment.

1 Introduction
In the past few years, research on information systems (IS) for environmental sustainability has received considerable attention in the IS community (Elliot, 2011; Hilpert et al., 2013; Ijab et al., 2012; Malhotra et al., 2013; Melville, 2010; Watson et al., 2010). The overall challenge is to mitigate global warming and thus climate change (Aoun et al., 2011; vom Brocke et al., 2013; Watson et al., 2010), which is mainly caused by greenhouse gas (GHG) emissions (Intergovernmental Panel on Climate Change, 2008, p. 39; National Academy of Sciences, 2005). Approximately 25% of worldwide carbon dioxide (CO2) emissions, which are an important ingredient of GHGs and contribute to global warming, are attributable to transport and nearly three-quarters of these are generated by road transport (International Energy Agency, 2009, p. 3). In this context, electric vehicles (EVs) are considered to have
the potential to reduce CO₂ emissions substantially, given that electricity is produced from renewable energy sources (see Figure 1).

![Diagram](image)

**Figure 1. Greenhouse gas emissions of various fuels and propulsion systems (Hohenberger and Mühlennhoff, 2014)**

From an economic perspective, compared to combustion vehicles, the main factors which impede the acceptance of EVs are high acquisition costs and short driving ranges due to insufficient battery technologies (Flath et al., 2012; Busse et al., 2013; Wagner et al., 2013b). Hence, reducing the energy consumption of EVs implies both ecological and economic benefits: it contributes to lowering CO₂ emissions, and it increases range. Moreover, electricity costs can be saved and vehicle wear can be reduced. Regarding McKinsey’s EV index that assesses a nation’s readiness to support an EV industry based on supply and demand, as of January 2012, the leading countries in the field of electric mobility in descending order are Japan, the United States, France, Germany, and China (Krieger et al., 2012). Among automotive manufacturers, there is a competition to lower operating costs and lower CO₂ emissions. The global market for EVs is expected to grow from 137,950 vehicles in 2012 to 1.75 million in 2020 (Hurst and Gartner, 2012).

According to Watson et al. (2012), sustainable behavior often lacks relevant information about its environmental effects, which is why there is a need to “develop information systems that provide individuals with accurate, meaningful, and actionable information about the environmental impact of personal decisions” (p. 30). One such information system is the driver assistance system that provides relevant information to improve driver behavior, e.g., by means of adaptive cruise control, forward collision warning, driver drowsiness detection, traffic sign recognition, parking assistance, night vision, etc. (Akhlaq et al., 2012). As a reaction to increasing CO₂ emissions, automotive manufacturer Toyota released a mobile application called “A Glass of Water,” which claims to lower energy consumption by 10% (Vandist, 2011). The application creates a digital glass of water on the smartphone that helps the driver to drive more carefully by not spilling water. This kind of driver assistance system in form of a mobile application has the task of warning the driver of excessive acceleration and braking (Guan and Frey, 2012). Another smartphone-based driver assistance system called “Smooth Driver” from Jettysoft, an Australian software development company, claims that it monitors hard braking
and acceleration (Apple, 2014a). The claims of Toyota and Jettysoft promise energy reduction through mobile applications, which can in turn help lower CO₂ emissions and increase range.

This paper investigates the impact of smartphone-based driver assistance systems on the energy consumption of EVs. Watson et al. (2010) called for research to analyze which information consumers need to increase their energy efficiency and to reduce CO₂ emissions in order to contribute to the new IS subfield of energy informatics. In this study, the focus is on smartphone-based driver assistance systems as a source of information, helping to improve driver behavior and reduce energy consumption. This approach attempts to offer recommendations for automotive manufacturers to better address the challenge of reducing energy consumption and thus CO₂ emissions. Several studies reported a strong influence of the driver behavior on the energy consumption, with the result that aggressive driving increases energy consumption by about 40% in city traffic (see, e.g., De Vlieger, 1997; Fonseca et al., 2010). In these studies, cars with a combustion engine were tested, and aggressive driving is defined by sudden acceleration and heavy braking.

In this regard, the article places emphasis on the following:

1. A smartphone-based driver assistance system is chosen that could influence the energy consumption of EVs.
2. An experimental design is developed by defining a control group and a treatment group, with the smartphone-based driver assistance system being determined as the treatment in order to measure the influence on the energy consumption.
3. A null hypothesis and an alternative hypothesis is generated to test the experimental design regarding differences in the energy consumption of the groups.

This paper makes a theoretical contribution by conceptualizing that the energy consumption of EVs is significantly influenced by smartphone-based driver assistance systems. An increasing number of studies within IS research examine information systems for environmental sustainability with a focus on EVs. However, a review of the literature suggests that the impact of smartphone-based driver assistance systems on the energy consumption of EVs has not yet been addressed. To fill this research gap, the following research question is being explored in this study:

**RQ:** What impact do smartphone-based driver assistance systems have on the energy consumption of electric vehicles?

This paper is structured as follows: First, a literature review on information systems for environmental sustainability with a focus on EVs is given. Then, the experimental design of the study is described and the null hypothesis and alternative hypothesis are generated. After analyzing data from test drives with an EV, the results of the field experiment are presented. Following the discussion of the findings, implications for research and practice are given. Finally, limitations and conclusions are provided.

## 2 Literature Review

To give an overview of the current research on information systems for environmental sustainability, a literature review was conducted on the six major IS research databases: ACM, AISel, IEEE, Science Direct, EBSCOHost, and SpringerLink. As search keywords, “environmental”, “sustainability”, “Green IS”, and “Green Information Systems” were used. The literature was analyzed intensively for relevance. Due to a comprehensive number of articles in various journals and conference proceedings, we focused on the eight journals listed by the Association for Information Systems (AIS) as top journals in the IS field: *European Journal of Information Systems*, *Information Systems Journal*, *Information Systems Research*, *Journal of the Association for Information Systems*, *Journal of Information Technology*, *Journal of Management Information Systems*, *Journal of Strategic Information Systems*, and *MIS Quarterly*. Hence, ten articles were identified in the *Journal of the Association for Information Systems*, in a Special Issue of the *Journal of Strategic Information Systems* ("The Greening of..."
IT”), in the Issues and Opinions as well as the Theory and Review section of the MIS Quarterly, and in a Special Issue of the MIS Quarterly (“IS & Environmental Sustainability”). The other journals showed no results for literature on information systems for environmental sustainability. The identified articles cover topics in the area of conceptual frameworks for IS and environmental sustainability, sustainable behavior research, organizational IS, mobile IS, and IS for transportation systems.

With regard to conceptual frameworks, Melville (2010) developed a research agenda on information systems for environmental sustainability by conducting a literature review of sustainability articles in five leading IS and operations research journals for the eight-year period from 2000-2007, yielding 35 articles. At that time, 34 articles had been published in operations research journals and only one article in an IS journal. Furthermore, a set of ten research questions were developed, associated with philosophical perspectives and theory, research methodology and data sources, and sustainability phenomena. Watson et al. (2010) designed a conceptual framework and discussed nine research questions related to interactions between relevant stakeholders (suppliers, consumers, and governments) and the energy system’s elements (sensor network, flow network, information system, and sensitized objects). They proposed that there is a need for a new subfield of IS, energy informatics, which recognizes the role of IS in reducing energy consumption and thus CO2 emissions. The core idea is expressed with a concise formula: Energy + Information < Energy (Watson et al., 2010, p. 24). Another conceptual framework developed by Elliot (2011) addresses issues of uncertainty about environmental sustainability on the basis of a holistic, transdisciplinary literature review. Holistic hypotheses are generated seeking to explore relationships between humans, human behavior, the environment, and technology. The conceptual framework analyzes characteristics of organizational sustainability transformations and the role of IS within such transformations, similar to the study by Seidel et al. (2013). They conducted semi-structured, open-ended interviews with selected key personnel involved in an organization’s sustainability initiative, and with software developers and consultants that are not directly involved in the organization’s sustainability initiative, but in the core processes of the organization. The study aims to uncover the perspectives of those driving the transformation process, and those being affected. Implications are derived from the study relating to the contribution, design, management, and further development of IS to create environmentally sustainable organizations. In the organizational context, Butler (2011) conducted semi-structured interviews, as well, for an explanatory case study design in order to explore the enabling effects of IS to help manage environmental compliance and related organizational risks. Further studies comprise the investigation of sustainable behavior through IS (Corbett, 2013; Loock et al., 2013; Marett et al., 2013), the implementation of IS into transportation systems to increase energy efficiency (Watson et al., 2011), and the integration of mobile IS such as smartphones into sustainable strategies for organizations (Pitt et al., 2011).

Very little research in IS focuses on EVs. In the process of our literature review, we found articles in this field in the following AIS conferences: Americas Conference on Information Systems, European Conference on Information Systems, and International Conference on Information Systems. The main focus of the identified articles is on EV charging. Wagner et al. (2013b) presented a point-of-interest-based business intelligence system for city planners to determine the optimal locations for EV charging stations by analyzing more than 32,000 charging sessions and validating data by means of a case study for Amsterdam and Brussels. Schmidt and Busse (2013) investigated the effects of EV charging on existing power plant capacities in Germany, while Flath et al. (2012) developed solution concepts on decision support systems for EV charging by using simulations based on empirical driving data and electricity price data. Further studies relate to synergy effects of IS on residential photovoltaic panels and EV charging to decrease energy costs (Brandt et al., 2013), an IS-based business model to use EVs as distributed storage devices to balance the grid (Kahlen et al., 2014; Wagner et al., 2013a), and EV adoption behavior in Germany and China (Busse et al., 2013).
3 Experimental Design and Hypothesis Generation

The main focus of this paper is to investigate the impact of smartphone-based driver assistance systems on the energy consumption of EVs. For this reason, a field experiment was conducted, in which the presence and absence of a mobile application was manipulated that served as a smartphone-based driver assistance system. In order to measure the energy consumption, test drives were arranged with an all-electric, lithium-ion battery powered, small passenger city car. The test drives were performed from June 26, 2014 to August 12, 2014 with 39 participants (see Appendix Table A1 for demographics). In order to increase external validity (Bordens and Abbott, 2002), the participants were randomly assigned to the control and experimental group. To minimize confounding effects, and hence increase internal validity (Shadish et al., 2002), extraneous conditions were controlled by using the same car and the same predetermined route for each test drive. For reasons of regional proximity, the test drives were performed in the city of Hanover, Lower Saxony, Germany. The test route was determined as follows: the starting point was the campus of the Department of Economics and Management of the University of Hanover, Königsworther Platz 1, continuing to Herrenhausen and Stöcken, turning left onto Westschnellweg (Bundesstraße 6), and finally turning left back to Königsworther Platz 1 (see Figure 2).

![Figure 2. Predetermined route for the test drives with an electric vehicle](map_data_2014_geobasis-de_bkg_2009_google)

The route is a mix of city traffic (50 km/h in Herrenhausen and Stöcken) and high-speed traffic (100 km/h and 70 km/h on Westschnellweg), which allows real-life conditions for the test vehicle in the city car class. Endogenous conditions concerning driving mode and auxiliary equipment parameters, such as the in-vehicle infotainment and the air conditioning system, were equally set in order to ensure similar conditions for the test drives. Exogenous conditions regarding traffic, weather, etc. were controlled by conducting all test drives on the same predetermined route to ensure similar traffic condi-
tions, and in a time period of about seven weeks to provide similar weather conditions. Minor variances of exogenous conditions regarding traffic and weather cannot completely be ruled out, which is implicated by real-life conditions in field experiments. The length of the route was approximately 13.8 km, and the duration was around 30 minutes. The blue lines in Figure 2 are the direction routes, orange means a medium amount of traffic, and red indicates traffic delays and slower speed (Google Maps, 2014). During the test drives, speed and height profiles were tracked with the mobile application GPSSpeed HD (Apple, 2014b) in order to monitor the controlled conditions. The speed and height profiles had a similar pattern, confirming similar conditions of the experimental setting. Figures 3(a) and 3(b) show screenshots of the speed and height profiles of test drives of the control and experimental group.

For the treatment of the experiment in order to monitor excessive acceleration and hard braking, several mobile applications were tested prior to the conduction of the test drives, i.e., “A Glass of Water”, “Acceleration gyroscope magnetometer sensor logger”, “AccelMeter – 3D Vector Accelerometer”, and “Smooth Driver”, all available at Apple’s app store. The deployment of “A Glass of Water” as the treatment for the experiment was discarded due to a technical problem involved with this application. The technical problem concerned a warning message, which could not be closed. For this reason, it was impossible to use the application, because the warning message covered the visualization of the glass of water, which was required to see in order for the application to work properly. The warning message referred to an instruction for safety reasons that the application should be started before starting to drive and that the driver should always keep the eyes on the road while driving. Regarding the application “Acceleration gyroscope magnetometer sensor logger”, only raw data in several graphs were displayed, though giving information to the driver, but not providing a particular task while driving and thereby not encouraging the driver to drive energy-efficiently. “AccelMeter – 3D Vector Accelerometer” visualized the direction and strength of gravity in the form of a big red arrow. Here, too,
the aspect of energy-efficient driving was missing. Ultimately, “Smooth Driver” was chosen as the treatment due to its accurate, practical, and relevant usability as well as the motivational aspect to drive more energy-efficiently by giving the task to drive without dropping a ball out of a visualized bowl. This task-oriented aspect with the goal to drive energy-efficiently was missing in other applications, which is why “Smooth Driver” was found to be more appropriate than other applications for the experiment.

With regard to the test drives, the participants were briefly introduced to the test vehicle and were told to drive as they normally would. They did not know that the energy consumption of the test drives were in focus of the study and they were not informed whether they were assigned to the control group or the experimental group. In the case of the experimental group, the mobile application was deployed during the test drives using an iPhone 5 with iOS 7.1.1 attached to a mount in the car. The application displayed a digital red ball, which rested in the middle of a grey bowl in its idle position. An abrupt change in velocity or direction moved the ball out of the bowl, sending a sound signal to the driver and resulting in an increase of the fail-counter at the bottom of the application. The goal was to drive without dropping the ball out of the bowl, encouraging the participants to drive more gently and thus more energy-efficiently. While there were three levels of difficulty to choose from, the application was set to normal mode (see Figure 4).

Prior to the test drives, seven rehearsal drives were performed in order to pretest the applicability of the EV, the predetermined route, and the mobile application. As part of the pretest, the beginner, normal, and master mode of the mobile application was also tested in order to find the accurate level of difficulty. The beginner mode extends the size of the bowl, whereas the master mode reduces the size making the task more difficult to perform. The choice of the mode implicates a balance between driving comfort and energy efficiency. For the experiment, the normal mode was chosen in order to ensure driving comfort and also to encourage energy-efficient driving.
On the basis of the experimental design, the following null hypothesis and according alternative hypothesis is being proposed:

\[ H_0: \text{Using smartphone-based driver assistance systems does not significantly reduce the energy consumption of electric vehicles.} \]

\[ H_1: \text{Using smartphone-based driver assistance systems significantly reduces the energy consumption of electric vehicles.} \]

4 Data Analysis and Results

Experimental data from the test drives were analyzed by means of statistical methods to test the null hypothesis. Following Baroudi and Orlikowski (1989), the statistical test of the null hypothesis was evaluated by examining the significance criterion \( \alpha \), the precision of sample estimates, and the effect size. For the significance criterion, a t-test was conducted (Dennis and Valacich, 2001; Hair et al., 2006) and the statistical approach was formulated as follows:

\[
t = \frac{\overline{x}_A - \overline{x}_B}{\hat{\sigma}_{\overline{x}_A-\overline{x}_B}}
\]

\[
\hat{\sigma}_{\overline{x}_A-\overline{x}_B} = \sqrt{\frac{(n_A - 1) \cdot \hat{\sigma}_A^2 + (n_B - 1) \cdot \hat{\sigma}_B^2}{(n_A - 1) + (n_B - 1)}} \left( \frac{1}{n_A} + \frac{1}{n_B} \right)
\]

\[
\hat{\sigma}^2 = \frac{\sum_{i=1}^{n} (x_i - \overline{x})^2}{n - 1}
\]

\[
df = n_A - 1 + n_B - 1
\]

\[ H_0 : \mu_A = \mu_B \]

where \( \overline{x} \) is the mean value of the energy consumption in kWh/100 km, \( A \) is the control group and \( B \) is the experimental group, \( \hat{\sigma} \) is the standard deviation of the mean, \( \hat{\sigma}^2 \) is the estimated variance, \( df \) is the number of degrees of freedom, and \( \mu \) is the expected value.

Six of the 39 test drives were identified as outliers (noise), which were excluded from the calculations due to a possible bias induced by the experiment and a significant impact on the statistics (Cousineau and Chartier, 2010). The t-test with 31 degrees of freedom produced a t-value of 3.25 at a significance level of \( p < 0.01 \) (two-tailed). The t-test was computed on the basis of the observed values of the energy consumption in kWh/100 km of the control group and the experimental group (see Appendix Table A2 for a full list of the observed values of each participant, as well as the mean values, estimated variances, and standard deviations of the groups).
Measuring the effect size of empirical observations is considered a supplement to the null hypothesis significance test, and it also determines the practical significance of results (Kirk, 1996). To measure the effect size, the following is posited:

$$d = \frac{\bar{x}_A - \bar{x}_B}{\hat{\sigma}_{AB}}$$  \hspace{1cm} (6)

$$\hat{\sigma}_{AB} = \sqrt{(n_A - 1) \cdot \hat{\sigma}_A^2 + (n_B - 1) \cdot \hat{\sigma}_B^2} \over (n_A - 1) + (n_B - 1)$$  \hspace{1cm} (7)

where $d$ is the effect size according to Cohen’s $d$ (Cohen, 1988), and $\hat{\sigma}_{AB}$ is the pooled standard deviation estimate (Hedges, 1981). The examination of the effect size returned a result of $d = 1.15$. Referring to Cohen (1988), $d = 0.2$ is a small effect, $d = 0.5$ is a medium effect, and $d = 0.8$ is a large effect. For $d = 1.15$, $n = 33$, and $\alpha = 0.01$, the power was 0.97 ($1 - \beta$), exceeding the recommended value of 0.80 for power (Cohen, 1992).

Regarding Gaskin (2013), variables such as age, gender, education, etc. must be controlled for in order to account for potential confounding effects. Particularly in experimental design research, confounding effects can bias the analysis of the causal relationship of the independent variable on the dependent variable (Campbell and Stanley, 1963). Thus, correlations of the variables were analyzed by using IBM SPSS Statistics version 21 (IBM, 2012). The variables relate to the participants’ demographics, the treatment of the study (the presence and absence of the smartphone-based driver assistance system), which is the independent variable, and the energy consumption of the participants’ test drives with the EV in kWh/100 km, which is the dependent variable. The results of the correlation analysis can be found in the correlation matrix in Table 1.

<table>
<thead>
<tr>
<th></th>
<th>TRT</th>
<th>KWH</th>
<th>SEX</th>
<th>AGE</th>
<th>PRO</th>
<th>EDU</th>
<th>INC</th>
</tr>
</thead>
<tbody>
<tr>
<td>TRT</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>KWH</td>
<td>0.50**</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SEX</td>
<td>0.11</td>
<td>0.22</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AGE</td>
<td>-0.16</td>
<td>-0.07</td>
<td>0.08</td>
<td>0.76**</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PRO</td>
<td>-0.18</td>
<td>-0.08</td>
<td>-0.09</td>
<td>-0.07</td>
<td>0.12</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>EDU</td>
<td>-0.31</td>
<td>-0.05</td>
<td>0.10</td>
<td>0.33</td>
<td>0.76**</td>
<td>0.22</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Notes: TRT = treatment, KWH = kilowatt hour, SEX = gender, AGE = age, PRO = profession, EDU = education, INC = income.
* Denotes significance level of $p < 0.05$ (two-tailed). ** Denotes significance level of $p < 0.01$ (two-tailed).

Table 1. Correlation matrix

The correlation between the treatment and the energy consumption in kWh ($r = 0.50$, $p < 0.01$) supports the significance criterion and effect size tests. Some demographic variables correlate with each other. For example, the correlation coefficient between age and profession is highly significant ($r = 0.76$, $p < 0.01$), since student participants of the sample are younger than employed participants (22 out of 24 student participants are younger than 30, and 8 out of 9 employed participants are 30 or older). The results indicate no confounding effects of the demographics on the independent or dependent variable, which is why such a bias can be excluded.
The results of the test drives are summarized in a boxplot in Figure 5. The boxplot shows the minimum, first quartile (Q₁), median, third quartile (Q₃), and the maximum of the energy consumption for the control group and the experimental group. ● represents the mean, and ○ represents outliers, which are 1.5-times of the interquartile range (Q₃ − Q₁) away from the box (Bordens and Abbott, 2002; Hair et al., 2006). The average energy consumption decreases from 12.6 kWh/100 km to 11.4 kWh/100 km, which implies an energy reduction by 9.5%.

![Boxplot for the results of the experiment](image)

**Figure 5.** Boxplot for the results of the experiment

## 5 Discussion and Recommendations

### 5.1 Discussion of findings

This study explores the impact of smartphone-based driver assistance systems on the energy consumption of EVs. The primary contribution is to generate insights into the context of energy reduction through mobile applications, which can help to lower CO₂ emissions and increase range specifically with regard to EV driving. We theorized that such an impact is depicted through relevant information about environmental effects, e.g., information on excessive acceleration and hard braking in order to improve driver behavior and eventually reduce energy consumption. The experimental design of the study aimed to produce data in order to analyze the null hypothesis by examining the significance criterion, the precision of sample estimates, and the effect size. The results of the statistical tests show that differences in the energy consumption of the control group and experimental group are statistically significant ($t = 3.25, p < 0.01$) and exhibit a large effect size ($d = 1.15, power = 0.97$). Thus, there is evidence supporting the hypothesis that using smartphone-based driver assistance systems significantly reduces the energy consumption of EVs. The null hypothesis is rejected. The findings show that 9.5% energy could be reduced by deploying a smartphone-based driver assistance system.
Besides energy consumption, during the test drives, average speed, maximum speed, acceleration, deceleration, and driving time were also tracked. In Figure 6, the mean values of the experimental group are compared to the control group, where the scale of the control group is set to 100%.

This comparison shows that energy-efficient driving does not necessarily involve a delay in the time of arrival. Energy consumption, average speed, maximum speed, acceleration, and deceleration are lower in the experimental group. However, a view on the bars in the line “driving time” illustrates that there is no major difference between the control group and the experimental group. With regard to the defined parameters of the test drives, this implies that both groups required a similar average time for the test route, although the experimental group consumed less energy.

5.2 Implications for research and practice

Due to the statistical and practical significance of the hypothesis testing of the influence of mobile applications on energy reduction, this phenomenon should be deeper examined. First, in the experimental investigation, a mobile application was employed that gives information on excessive acceleration and hard braking to the driver. Further research is recommended to explore for advanced conditions to influence acceleration and braking for energy-efficient driving, and moreover to consider additional functions that have the potential to improve driver behavior and consequently reduce energy consumption. In the context of EV driving, besides acceleration and braking, additional functions could refer to the energy recuperation system of a vehicle and to the auxiliary equipments such as the in-vehicle infotainment system and the air conditioning system of a vehicle. As a result, additional energy might be saved through efficient utilization of these systems, influenced by relevant information provided by mobile applications to support sustainable behavior. Further research should conduct appropriate experiments in order to investigate these hypothesized relationships. In this regard, an integration of smartphones in the car, e.g., phone-centric car connectivity solutions like Apple’s CarPlay, Android Auto and MirrorLink, could be examined. Second, the main focus of this study was on the energy consumption of electric vehicles. Further research could investigate interdependencies of velocity, acceleration, and energy consumption considering an influence of mobile applications on the driving behavior. Third, the adoption of driver assistance systems for EVs should be analyzed. An adoption is crucial for a successful implementation. In order to analyze the adoption, automotive manufacturers could be interviewed and potential users could be surveyed. Thus, influencing factors of the adoption would be identified and new insights would be provided to the field. In this context, further research could also investigate the day-to-day practicability of smartphone-based driver assistance systems for ener-
gy-efficient driving. Mobile applications such as “Smooth Driver” could be appropriate for training individuals to drive more energy-efficiently and therefore could have a long-term effect on the driving behavior. For this reason, further experiments could be conducted to test this causal relationship.

The results of this study provide practical implications for automotive manufacturers to better address the challenge of reducing energy consumption and thus CO₂ emissions. Hence, providing EV drivers with accurate, meaningful, and actionable information about the environmental impact of the driving behavior can lead to a reduction of the energy consumption. The findings show that smartphone-based driver assistance systems can offer such information. Automotive manufacturers compete to lower operating costs and lower CO₂ emissions, and a transition from combustion to EVs can help automotive manufacturers to achieve these goals. Nevertheless, there exists a critical perspective on a transition. For example, in the United States a transition from combustion to EVs could increase CO₂ emissions, because half of the electricity is produced from coal (Hasan and Dwyer, 2010). Against this backdrop, for a substantial reduction of CO₂ emissions, electricity needs to be produced from renewable energy sources. Automotive manufacturers should take this aspect into consideration in order not to establish a false front of low-emission EVs, which are operated with electricity from coal. As the global market for EVs is expected to grow, automotive manufacturers need to keep in mind that high acquisition costs and short driving ranges are the main factors that hamper the acceptance of EVs. By reducing energy consumption, range is being enhanced, which in turn can help to increase the acceptance of EVs. The findings of this paper suggest that mobile applications can help to reduce energy consumption and as a result contribute to lower CO₂ emissions and to increase the range of EVs.

6 Limitations and Conclusion

This study is subject to the following limitations, which present useful opportunities for further research. First, considering the precision of sample estimates, which is mainly affected by the sample size (Baroudi and Orlikowski, 1989), one limitation of this research relates to a small sample size (n = 33). This is due to the high amount of effort and time required to conduct the test drives under controlled conditions. Extraneous conditions must be controlled in order to reduce error variance caused by nuisance variables affecting the dependent variable (Kirk, 2013; Whitley and Kite, 2013). Taken together, the participants drove a total of approximately 540 km with a total driving time of around 20 hours. Cohen (1992) argues that “the investigator needs to know the n necessary to attain the desired power for the specified α and hypothesized effect size,” and hereby refers to the balance between statistical power and the investigator’s resources (p. 156). The results of the statistical tests show that the statistical significance, the large effect size, and the statistical power of the results indicate a strong relationship among the variables. Nevertheless, further studies should explore a bigger sample size to further examine the results. Second, further factors could be considered such as proficiency in driving and behavior of the person. Differences in these factors could lead to further findings, for example, a smartphone-based driver assistance system could influence the energy-efficiency behavior of inexperienced drivers different from experienced drivers. Behavior of the person could also have an effect since individuals who have a defensive style of driving might react differently to the mobile application compared to individuals who usually drive aggressively. Further factors such as type of car, choice of route, time of day, and season of year could also be tested in order to investigate variances of results. Type of car can be important in terms of different types of car models, particularly in relation to the weight, engine, battery, tires, brakes, etc. The route can have an effect, because different routes implicate various speed restrictions and diverse traffic conditions. Furthermore, the road surface and height profile of the route can affect energy consumption. Referring to time of day, e.g., peak traffic times can have an impact. In this study, test drives were conducted during the day outside peak traffic times. Further studies could compare test drives at different times and various traffic situations. Season of year can also be relevant for energy consumption due to the influence of temperature on the battery of EVs and thus energy consumption and range (Qin et al., 2015). Third, in terms of generalizability, another limitation relates to the demographic characteristics of the sample.
Most of the participants were male and under 30 years old (see Appendix Table A1). While the participants may fall into the category of target users for mobile applications, care must be taken when choosing an approach to generalize the findings beyond the confines of the sample. Further research is recommended to repeat this study with a more diverse sample for enhanced generalizability. Fourth, since cultural differences are not part of this study, a further limitation is that the test drives were conducted in Germany due to regional proximity. Therefore, measures in other countries may lead to different results. Further research should be conducted in other countries to generate insights into the context of cultural differences regarding the impact of smartphone-based driver assistance systems on the energy consumption of EVs.

The domain of information systems for environmental sustainability and green information systems has grown in the last years. To respond to the call for research investigating the role of information in influencing energy consumption, the main focus in this paper was on analyzing the impact of smartphone-based driver assistance systems on the energy consumption of electric vehicles. A field experiment was conducted to test such an impact by performing test drives with an electric vehicle. In order to examine differences between the control group and the experimental group, a driver assistance system in form of a mobile application was used as the treatment of the study. The results reveal significant differences of the groups, which indicate that using smartphone-based driver assistance systems significantly reduces the energy consumption of electric vehicles. This can entail several benefits, including an increase of range of electric vehicles, electricity cost savings, decrease of vehicle wear through energy-efficient driving, and reduction of greenhouse gas emissions. Considering the importance of global warming and climate change, the transportation sector has the potential to substantially reduce greenhouse gas emissions. In this context, electric vehicles are regarded as a promising transportation alternative, given that electricity is produced from renewable energy sources.

Acknowledgments
The authors gratefully acknowledge the German Federal Ministry for Economic Affairs and Energy for supporting this research under grant no. 16SNI011B.

References


**Appendix**

<table>
<thead>
<tr>
<th>Gender</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>24</td>
<td>72.7%</td>
</tr>
<tr>
<td>Female</td>
<td>9</td>
<td>27.3%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Age</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>18–29</td>
<td>23</td>
<td>69.7%</td>
</tr>
<tr>
<td>30–39</td>
<td>6</td>
<td>18.2%</td>
</tr>
<tr>
<td>40–49</td>
<td>2</td>
<td>6.1%</td>
</tr>
<tr>
<td>&gt;49</td>
<td>2</td>
<td>6.1%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Profession</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Student</td>
<td>24</td>
<td>72.7%</td>
</tr>
<tr>
<td>Employed</td>
<td>9</td>
<td>27.3%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Education</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>High school degree</td>
<td>9</td>
<td>27.3%</td>
</tr>
<tr>
<td>College degree</td>
<td>6</td>
<td>18.2%</td>
</tr>
<tr>
<td>Bachelor’s degree</td>
<td>15</td>
<td>45.5%</td>
</tr>
<tr>
<td>Master’s degree</td>
<td>3</td>
<td>9.1%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Income per month</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>≤ €1,000</td>
<td>18</td>
<td>54.5%</td>
</tr>
<tr>
<td>€1,001 – €2,000</td>
<td>6</td>
<td>18.2%</td>
</tr>
<tr>
<td>€2,001 – €3,000</td>
<td>3</td>
<td>9.1%</td>
</tr>
<tr>
<td>€3,001 – €4,000</td>
<td>2</td>
<td>6.1%</td>
</tr>
<tr>
<td>&gt;€4,000</td>
<td>2</td>
<td>6.1%</td>
</tr>
<tr>
<td>Not specified</td>
<td>2</td>
<td>6.1%</td>
</tr>
</tbody>
</table>

*Table A1. Demographics*
<table>
<thead>
<tr>
<th>Control group (n = 19)</th>
<th>kWh/100 km</th>
<th>Experimental group (n = 14)</th>
<th>kWh/100 km</th>
</tr>
</thead>
<tbody>
<tr>
<td>removed</td>
<td>16.5 (outlier)</td>
<td>removed</td>
<td>14.4 (outlier)</td>
</tr>
<tr>
<td>1</td>
<td>12.6</td>
<td>1</td>
<td>11.9</td>
</tr>
<tr>
<td>2</td>
<td>13.9</td>
<td>2</td>
<td>12.0</td>
</tr>
<tr>
<td>3</td>
<td>11.1</td>
<td>3</td>
<td>11.7</td>
</tr>
<tr>
<td>removed</td>
<td>16.4 (outlier)</td>
<td>4</td>
<td>12.1</td>
</tr>
<tr>
<td>4</td>
<td>13.9</td>
<td>removed</td>
<td>14.2 (outlier)</td>
</tr>
<tr>
<td>5</td>
<td>13.3</td>
<td>5</td>
<td>11.3</td>
</tr>
<tr>
<td>6</td>
<td>13.6</td>
<td>6</td>
<td>12.2</td>
</tr>
<tr>
<td>7</td>
<td>12.8</td>
<td>removed</td>
<td>14.2 (outlier)</td>
</tr>
<tr>
<td>8</td>
<td>13.0</td>
<td>7</td>
<td>9.8</td>
</tr>
<tr>
<td>9</td>
<td>11.0</td>
<td>8</td>
<td>12.9</td>
</tr>
<tr>
<td>10</td>
<td>13.0</td>
<td>removed</td>
<td>8.8 (outlier)</td>
</tr>
<tr>
<td>11</td>
<td>12.0</td>
<td>9</td>
<td>11.9</td>
</tr>
<tr>
<td>12</td>
<td>11.4</td>
<td>10</td>
<td>10.1</td>
</tr>
<tr>
<td>13</td>
<td>11.7</td>
<td>11</td>
<td>11.1</td>
</tr>
<tr>
<td>14</td>
<td>12.4</td>
<td>12</td>
<td>9.8</td>
</tr>
<tr>
<td>15</td>
<td>11.8</td>
<td>13</td>
<td>11.6</td>
</tr>
<tr>
<td>16</td>
<td>14.8</td>
<td>14</td>
<td>11.0</td>
</tr>
<tr>
<td>17</td>
<td>13.3</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>18</td>
<td>11.5</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>19</td>
<td>11.5</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$\bar{X}_A$</td>
<td>12.6</td>
<td>$\bar{X}_B$</td>
<td>11.4</td>
</tr>
<tr>
<td>$\hat{\sigma}^2_A$</td>
<td>1.17</td>
<td>$\hat{\sigma}^2_B$</td>
<td>0.88</td>
</tr>
<tr>
<td>$\hat{\sigma}_A$</td>
<td>1.08</td>
<td>$\hat{\sigma}_B$</td>
<td>0.94</td>
</tr>
</tbody>
</table>

$X$: mean value, $\hat{\sigma}^2$: estimated variance, $\hat{\sigma}$: standard deviation

Table A2. Data for the energy consumption of the participants in the control group and the experimental group