Bachelor Thesis

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SOLAR POWERED E-BIKES:

Analysis of a sustainable mobility system by performing statistical analyses on end-user studies and solar bike use variables

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Preface

This thesis is the result of my research being the final phase of my Bachelor Degree in Civil Engineering at the University of Twente. Within the Smart Living Campus project at the UT I have been focusing on the solar powered e-bike (solar bike). I have analyzed the data gathered by these bike together with the data from the surveys conducted under the participants of the solar bike project and tried to draw conclusions on the influences on the performance of the solar bike.

During the research, I had contact with Eindhoven University of Technology about the solar bike that is developed in Eindhoven by amongst others, Abby, TU/e Innovation Lab, and Segula. A similar project is running there using the same solar bikes. Solar bike and survey data were exchanged to create a larger data source.

I would like to thank all staff of the Center for Transport Studies of the University of Twente, the place where I performed this study, for the nice time I spend with you. In particular I would like to thank my supervisor Karst Geurs for the guidance and feedback you gave me. Also, I want to thank the people at Eindhoven University of Technology for the collaboration in this project.

I hope to provide the reader of this thesis an insight into the performance of a new, sustainable transportation mode.

Floris Nijland
Enschede, 5th of July, 2017

Image front page: Geurs (2017)

Table of contents

List of Tables

List of Figures

1. Summary

The research presented in this thesis analyzed the influences on the performance of the solar bike. The focus is on the energy production of the solar bike, the user experiences of the solar bike, and the consideration to use the solar bike for commuting.

A conceptual model is setup with expected relations between different factors and performance variables. The influences they have on each other are evaluated to confirm or modify the model. For the different evaluations, three data sources needed to be combined. The method to combine these sources had to be created to do so. The evaluations carried out were mainly comparing data and performing correlation and regression analyses.

Not all expected relationships were significant. On the energy production of the solar bike, solar radiation and bike parking strategies are the influencing factors. The user satisfaction is mainly influenced by crosswind hindrance, the suitability of the solar bike for commuting, and two attitudes towards to solar bike (that it creates flexibility and contributes to sustainability). The consideration to use a solar bike for commuting (the likelihood to buy a solar bike) is influenced by the user satisfaction.

1.1. Thesis structure

To lead the reader trough this thesis, the structure of it is briefly given below.

In Chapter 2 a general introduction is given with a short description of the problem context, the research aim, and the research questions. It will conclude with a paragraph on the used data.

The conceptual model of this research is presented in Chapter 3, where also a review of the studied literature can be found.

In Chapters 4, 5, 6 and 7, the results of the research questions are given. In Chapter 4, differences between e-bike commuters and regular cycling commuters are given, OViN data (CBS, 2014; CBS, 2015; CBS 2016) is analyzed to find these differences. In Chapter 5, the effects of different factors on the energy production of the solar bike are given. In Chapter 6, the user experiences of the solar bike are presented, including the analyses of correlations among different factors. In Chapter 7, the relationship between the user satisfaction, energy production and the consideration to use a solar bike as commuting mode is given.

The main content ends with a general conclusion and some recommendations given in Chapter 8, followed by the bibliography and appendices.

2. Introduction

Nowadays, air pollution is a big issue and the transport sector plays a big role in that. Air pollutants from the transport sector have considerably been reduced since 2000, but the emissions of nitrogen oxides, where the transport sector contributes for 46% of total EU-28 emissions in 2014, are not reduced enough to meet air-quality standards in urban areas (European Environment Agency, 2016). Electric bicycles (e-bikes) are considered one of the most promising sustainable alternatives to automobile transportation today. If the goal is to reduce car use, stimulating the adoption of the e-bike is effective (Kroesen, 2017). Furthermore, the e-bike solves many of the reasons people give for not cycling (distance, hills, physically strenuous) and offers many of the same benefits as the car (range, flexibility, rush-hour speed) (Fyhri & Fearnley, 2015). In the Netherlands, e-bikes are gaining in popularity, especially among elderly and commuters. The share of e-bikes in bike sales has rapidly grown from 12% in 2009 to over 28% in 2015 (BOVAG & RAI Vereniging, 2016). At the moment, there are over 1.4 million e-bikes in the Netherlands (SWOV, 2016). Recent innovations are the high-speed e-bike (speed pedelec) and the development of the solar bike. Solar bikes are e-bikes with integrated solar cells, which can charge battery when parked and during trips.

The solar bike research at the University of Twente (UT) is part of a bigger transdisciplinary Living Smart Campus project at the university that collects and analyzes data to understand the use patterns of e-bikes and their potential benefits as part of a sustainable mobility system (Reinders, 2017). A consortium of Abby, TU/e Innovation Lab, Segula and others developed an e-bike with CIGS solar panels in the front wheel. Due to these solar panels, the bike produces 100% sustainable energy. This so called solar bike is also equipped with a diversity of sensors to capture the details of usage. A couple of these solar bikes are being tested by UT-employees in Enschede and TU/e-employees in Enschede to generate data.

This chapter will continue with a short description of the problem context, followed by the research aim and questions, and will conclude with a paragraph on the data sources used in this research.

2.1. Problem context

Present-day, little is known about the use of different types of e-bikes, their health effects, and the effect they are having on motorized and regular bicycle travel (Reinders, 2017). A lot of information is opinionated and not supported by scientific evidence. Particularly on the effects of using solar bikes as transport mode, very little is known. Also, the influences on and of the solar bike, a new type of e-bike charging, are unknown. Usually, the batteries of e-bikes are only charged by electricity from the grid at home or at a charging spot at the workplace, if available. In the Living Smart Campus project, one goal is to compare different modes of charging. By using solar PV power, the solar bike can be charged during a trip.

The research presented in this thesis analyzed the influences on the energy production of the solar bike, the user experiences of the solar bike, and the influence of the solar bike on transport mode choice preferences, a brand-new transportation mode where lots of people are unfamiliar with.

2.2. Research aim

The main aim of this research is to evaluate the influence of different characteristics on user satisfaction of the solar bike, on energy production of the solar bike, and transport mode choices of participants. To achieve this aim, there is one main research question stated and several sub questions. These questions are discussed in the following paragraphs.

2.2.1. Main question

This research will examine the energy production of the solar bike, user satisfaction on the use of the solar bike, and transportation mode choices of commuters. The aim of this research is translated into a main research question:

What is the influence of different factors on the performance of the solar bike?

2.3. Methods

To answer the main question, several sub questions are stated. In this paragraph, these questions are described together with the methods used to give answer to these research questions.

2.3.1. Research question 1

Transportation mode choices of commuters play role in the research. Assumed is that the solar bike is equivalent to a regular e-bike. To get more insight in the differences between regular cyclists and e-bike users and their transportation mode choice reasons, the following question (1) is stated:

1. *What are differences between e-bike commuters and regular bicycle commuters?*

To answer this question (1), OViN data from 2013 (CBS, 2014), 2014 (CBS, 2015), and 2015 (CBS, 2016) is used to search for differences between e-bike and regular bicycle usage. The following tasks were set up:

- Analyzing OViN data on differences between e-bike cyclists and regular cyclists;
    - Focus on commuters.

The software used for the comparisons in the OViN is IBM SPSS Statistics (IBM Corp., Released 2016).

2.3.2. Research question 2

To gain insight in the influences on the energy production of the solar bike and the effect of different parking strategies of the bike on the energy production, but also the influence of commuting distance, the following question (2) is stated:

2. *What is the effect of different factors on the energy production of the solar bike?*

Firstly, there is checked whether there is a correlation between the energy production of the solar bike and the user satisfaction to see whether the energy production can be related to the user satisfaction. Secondly, the relation between solar radiation, parking strategies, and commuting distance and the energy production is analyzed. Posttest survey data is used to collect data related to parking strategies. Weather information of KNMI is used to obtain data on solar radiation (KNMI, 2017). Because the energy production is related to the solar radiation, the output variable of energy production is also translated to a factor that can be seen as energy production efficiency towards the available solar radiation. The following tasks were set up for this question (2):

- Converting the available solar bike energy production variable to an efficiency variable;
    - Aggregating the available solar bike data;
    - Combining weather data with the output variables of the solar bike;
- Performing a correlation analysis between the energy production and solar bike grading;
    - Combining the energy production data with survey data;
- Performing regression analyses between solar radiation and energy production;
    - Combining the energy production data with KNMI weather data, and survey data;
    - Two analyses: parking situation, traveling situation.

Aggregation of the solar bike data and the combining with weather data is done by using a Matlab (The MathWorks, Inc., 2016) script. For the correlation analysis between energy production and solar bike grading, Pearson's correlation coefficient is determined using IBM SPSS Statistics (IBM Corp., Released 2016). The regression analyses are also performed in IBM SPSS Statistics. For these regressions, survey data is added to the data set in Excel.

2.3.3. Research question 3

Since the participants are testing a new product, it is useful to gain insight in the user satisfactions of solar bike. Therefore, the following question (3) is stated:

3. *What is the user experience of the solar bike?*

To gather user experiences a posttest survey is conducted under test-users. Participants gave a general grading on the solar bike, gave insight in the purposes of their usage of the solar bike, commented on hindrance of crosswind on the front wheel (which is covered due to the solar panels), and gave their opinion on solar bike statements by means of a Likert scale. The grading of participants for the solar bike is analyzed in combination with user experience factors. By means of a multiple regression analysis grades are tried to forecast. The relation between crosswind hindrance and daily wind speed measurements is also interesting, due to the covered front wheel, and is evaluated with a correlation analysis.

- The inventory of user experiences factors at T1;
  - Reviewing of posttest survey results;
- Performing a correlation analysis between wind speeds and crosswind hindrance;
  - Combining survey data with KNMI weather data;
- Performing a multiple regression analysis between user experience factors and solar bike grading.

The multiple regression analysis is performed in IBM SPSS Statistics (IBM Corp., Released 2016), making use of a backward method to eliminate the variables that have a small contribution. The correlation analysis between wind speeds and crosswind hindrance is also performed in IBM SPSS Statistics.

2.3.4. Research question 4

To check whether the solar bike is a considered option as transportation mode for commuting, the following question (4) is stated:

4. *What is the relation between user satisfaction, energy production and the consideration to use a solar bike for commuting?*

Pre- and posttest survey data is used to answer this question. The experience of using a solar bike and its effect on transportation mode choice preferences is compared. The relation between grades on the solar bike, and the energy production of a participant and the consideration to use a solar bike for commuting is analyzed by means of correlation analyses. Furthermore, the likelihood to buy a solar bike is analyzed to check for differences before and after testing. The pretest survey is conducted before the test week of a participant and a posttest survey afterwards.

- Evaluation of the transportation mode preferences of participants before and after testing;
  - Combining pre- and posttest survey data;
- Evaluating the likelihood to buy a solar bike before and after testing;
  - Combining pre- and posttest survey data;
- Performing a correlation analyses between solar bike grading and energy production, and the consideration to use a solar bike as commuting mode;

- Combining energy production data with posttest survey data.

Evaluations and correlation analyses are performed IBM SPSS Statistics (IBM Corp., Released 2016).

2.4. Data

Solar bike data that is used is produced by test users that work at the UT or at TU/e. Employees could sign in on the project to get the possibility to use a solar bike for a week. In Table 1 the different solar bike use variables that are collected can be found, provided with the interval they are measured in.

Table 1 Solar bike variables

	Variable	[unit] explanation	Freq.
1	Seconds	[S] time stamp; seconds since start of data file	
3	Latitude	[-] latitude (GPS data)	1 Hz
4	Longitude	[-] longitude (GPS data)	1 Hz
5	Altitude	[-] altitude (GPS data)	1 Hz
6	Heading	[°] angle with respect to magnetic North	1 Hz
7	Voltage	[V] when voltage drops, the motor uses power	1 Hz
8	Watt	[W]	1 Hz

Weather data of the KNMI (KNMI, 2017) consists of two data sets. One with hourly data, the other with daily data. Only data on solar radiation and wind speeds is used. The weather data is measured at weather station Twenthe and weather station Eindhoven.

The OViN data that is used (CBS, 2014; CBS, 2015; CBS, 2016) is trip data of respondents collected by a national survey held in the Netherlands in 2013, 2014 and 2015.

In the pretest survey, conducted before testing, consist of four parts and is made by Vinken (2016). The first part contains questions about socio demographic characteristics of the respondent, such as age, gender, income, but also questions about transport mode usage and preferences. In the second part, several choice situations are presented to obtain information about purchase intentions. The third part also contains several choice situations, but this time to obtain information about transport mode choices. The fourth part evaluates perceptions on e-bikes, solar bikes, cars, mobility, sustainability, and innovation trough providing statements on these subjects. Data of the first and third pared are used.

The posttest survey, conducted after testing, only consists of two parts. The first one collects experiences with the solar bike, opinions on the solar bike, and some other questions on the usage of the bike. The second part is the same as the same as the third part of the pretest survey, transportation mode choice preferences.

3. Conceptual model

Before the analyses of the data are discussed, a conceptual model of the research is presented. To create this conceptual model, literature is studied. Since the solar bike is like a normal e-bike, but with an extra battery charging option, literature regarding e-bikes and bicycle commuting is reviewed.

3.1. A review of the literature

Literature on transportation mode choices of people and factors that influence their choices is found. First, an overview of factors that play role in the choice to cycle are given, secondly aspects related to commuting.

3.1.1. The choice to cycle

In the Netherlands, almost one million bikes were sold in 2015, of which more than a quarter where e-bikes (CBS, 2016). In 2014, 28% of the trips made in the Netherlands were made by bicycle (CBS, 2016). An individual's choice for a certain transportation mode for a trip is based on direct benefits for the individual in terms of time, comfort, and flexibility (Heinen et al., 2011). Besides direct benefits, the beliefs of effects of choosing a specific transportation mode are also important, because transport mode preferences of individuals are mainly driven by the beliefs on what the effects on one are (Collins & Chambers, 2005). Other benefits offered to the individual by cycling are improving health, being a cheap form of transportation, and even being faster than other transport modes, especially in urban areas to avoid traffic jams (Heinen, 2011). However, there is a negative perception of traffic lights by cyclists, as that slows them down (Heinen et al., 2010). A Danish case study of Haustein and Møller (2016) confirms that people use e-bikes because it is cheaper than other modes, or because of environmental reasons. Also, people use e-bikes because they like cycling and want to exercise (Haustein & Møller, 2016).

Bicycle mode choices of individuals can be explained by weather conditions and climate, socio-economic factors, trip distance and attitudes towards cycling (Heinen et al., 2013). The more positive attitude one has towards cycling, the higher the probability that person will cycle (Heinen et al., 2010). In terms of weather conditions there is a negative influence on the cycling probability when there are bad conditions, rain, low temperatures, and darkness. Also, hilliness has a negative effect on cycling. These natural environmental factors have a large influence on the choice to cycle or not, and the frequency of cycling (Heinen et al., 2010). A small case study on Dutch students shows that weather conditions are most important in transport mode choice decision making (Aarts et al., 1997). More recently a case study by Vinken (2016) shows that important factors for choosing an e-bike or solar bike as transportation mode are weather, time of day, and car parking (Vinken, 2016). Car parking is important, because when another transport mode than cycling, for example transport by car becomes more expensive due to payed car parking and thus becomes less attractive, cycling becomes more attractive (Heinen et al., 2010). This supports utility theory, which assume that each individual will act in such way that one maximizes one's utility (Heinen et al., 2010). Cost, time, and effort are the important factors in utility theory, where an increase in these for a certain transportation mode will result in a decrease in the probability that mode will be chosen. Other transportation modes have to be taken into account as well. If a certain mode becomes more expensive, the choice probability of others increase. Just like the beliefs of effects, here the perceived values for cost, time, effort, and also safety are more important that the real values (Heinen et al., 2010). For someone who cycles often, safety can be rated higher than of someone who cycles only occasionally. However, it seems that safety and also travel time are more important for cycling than for other transport modes (Heinen et al., 2010).

3.1.2. Commuting by bicycle

Commuting concentrates itself in terms of time and place, which may lead to various problems such as congestion, and environmental problems (Heinen, 2011). In the period 2013-2014, 17% of all the trips made were commuting trips (CBS, 2016). Daily that accounted for almost ten million trips. 25% of commuting trips is made by bicycle, but that only accounts for 6% of the total commuting distance travelled. These percentages indicate that bicycles are mostly used for short distance commuting trips. That is unfortunate, because cycling commuting is environmentally more sustainable than car commuting, and the infrastructure needed is relatively inexpensive (Heinen, 2011). Transport mode choice for commuting is one of the most environmentally significant decision made by an individual (Collins & Chambers, 2005).

The awareness of the effect one's behavior has on the environment and one's health, stimulates an individual to cycle over a larger distance to work (Heinen et al., 2011). The more importance attached to benefits, that were earlier mentioned, in terms of time saving, comfort, and flexibility by an individual, the more often this individual commute by bicycle. (Heinen et al., 2011). Personal factors also influence one's transportation mode choice. Having access to other transport modes than a bicycle decreases the likeliness that individual will cycle to work (Heinen et al., 2013), where people that only have access to a car on a non-regular basis are more likely to cycle to work. Also bicycle ownership positively influences the probability to cycle (Heinen et al., 2010). The positive attitude towards cycling increases over longer distances cycled to work by individuals (Heinen et al., 2011). The perception of the possibility to cycle to work also affects the choice to commute by bicycle, where over every distance class people are more likely to cycle if they perceive that cycling is possible, but this only influences decisions in commuting mode over short distances (Heinen et al., 2011). The expectations of colleagues can influence the commuting mode choice of individuals. If an individual is expected to commute to work by another mode than bicycle, that individual is less likely to commute to work than individuals who are expected to cycle to work (Heinen et al., 2013). Workers that have to commute over longer distances are not affected by the expectations of colleagues on travel mode choice, which indicates that cycling over longer commuting distances is largely a decision based on individual considerations without taking other opinions into account (Heinen et al., 2011).

Other factors that positively influences the choice to cycle to work are financial incentives, cycle facilities for around half the journey to work, and good parking and shower facilities at work will result in more cycling commuters and a decrease in car share (Wardman et al., 2007). Financial incentives, related to a particular transport mode, offered to employee will have a significant influence on the employee's commuting mode choice (Heinen et al., 2013). When offered free public transport or given access to a free car, that employee will less likely cycle to work. However, when the employer starts contributing to the cost of cycling, bicycle use will increase under employees (Heinen et al., 2013). Wardman et al. (2007) is supported by Heinen et al. (2013) that having access to certain facilities at work, such as bicycle storage inside, and clothes changing facilities increase the likeliness of an employee to cycle to work. If one needs to carry goods as part of one's work, or needs a car during working hours, that has a negative effect on the probability to cycling to work (Heinen et al., 2013). When a bicycle is needed during working hours, that probability is doubled. The earlier mentioned safety perception also plays a role in commuting by bicycle. People who do not care about either traffic safety or social safety, and people who do not consider cycling as being dangerous, are more likely to cycle to work (Heinen et al., 2011).

Heinen et al. (2011) conclude that the direct benefits offered by cycling influence the choice to cycle at every travel distance. Commuting distance itself has a negative influence on being a full-time cyclist, where women are more distance sensitive than men (Heinen et al., 2013). Full-time cyclists are those who cycle to work every day. Day-to-day decisions on cycling as commuting mode are largely influenced by short-term conditions such as weather conditions, trip characteristics and work characteristics (Heinen et al., 2011). Also, the direct benefits strongly influence the decision on cycling on daily basis (Heinen et al., 2011). The choice for an alternative commuting mode of frequent cyclists (66.6% of all commuting trips are made by bicycle) is affected by factors, as strong wind, and working at multiple locations where occasional cyclists (less than 33.3% of commuting trips made by bicycle) are affected by pleasant factors, as nice weather (Heinen et al., 2011). A positive attitude towards bicycle commuting increases the probability to cycle to work on daily basis, where free car parking at the workplace reduces it (Heinen et al., 2013). Other negative influences found by Heinen et al. (2013) are working hours that result in having to commute in the dark, and having to wear suits as clothing during work. In comparison to people who work 28 hours up to forty hours a week, people who work less than 28 hours a week are more likely to cycle to work full-time (Heinen et al., 2013).

Habit can affect the transportation mode choices of people. Therefore, some people will not take cycling into consideration when travelling to work (Heinen et al., 2010). The habit of cycling of an individual positively influences the likeliness one cycles to work full-time, they regard distance if they also cycle for other purposes (Heinen et al., 2011). Aarts et al. (1997) conclude that strong habit persons use fewer information of the circumstances for their transport mode decision making.

Differences in cycling culture, attitudes, norms, built environment, and facilities at work could cause the differences in commuting mode share of cycling between countries (Heinen et al., 2011). Here may lay one of the reasons that Dutch commuters cycle more than commuters in other countries.

3.1.3. Conclusion

Actual differences between e-commuters and regular commuters cannot be found in literature, nonetheless, important factors playing role in transportation mode choices are found. Utility theory explains that people base their transport mode decisions on cost, time, and effort (Heinen et al., 2010). The negative influence of hilliness (Heinen et al., 2010), which affects the effort of cycling, is less for e-commuting than for regular commuting, since e-commuting costs less effort due to the electric support. In terms of time, e-commuting should have a higher probability, since the mean travel speed of e-commuters is higher. The influence of weather conditions (Aarts et al., 1997; Heinen et al., 2010; Heinen et al., 2011; Heinen et al., 2013; Vinken, 2016) probably differs between e-commuting and regular commuting, since the electrical support can compensate the effort needed to cycle with strong winds. The negative influence of commuting distance on being a full-time cyclist (Heinen et al., 2013) could be lesser for e-commuting than for regular commuting. When looking at facilities at the workplace (Heinen et al., 2013; Wardman et al., 2007), charging facilities for e-bikes could increase the amount of e-commuters. Shower facilities are less important for commuters who chose the e-bike so they transpire less. However, secured bike parking could be more important, due to the value of e-bike compared with the value of regular bicycles. The accessibility to a transport mode is also important (Heinen et al., 2010). A commuter that does not have access to an e-bike, cannot e-commute.

3.2. Conceptual model

This research analyzes the performance of the solar bike which can be divided into three categories: energy production of the solar bike, user satisfaction of the solar bike, and consideration to use a solar bike for commuting (likelihood to buy, willingness to pay). The influences on these categories that are considered in the research can be divided into five categories: user characteristics, user attitudes, commuting distance, parking strategy and weather conditions. In Figure 1 the expected relationships between these categories are drawn. From the literature follows that user characteristics, attitudes, and commuting distance have influence on transportation mode choices of people. Therefore, it is likely that these factors influence the user satisfaction. Furthermore, it is assumed that the user satisfaction has its influence on the consideration to use a solar bike for commuting. No literature is known on this relationship. There is also no literature on the influences on the energy production of a solar bike. It is assumed that commuting distance, bike parking, and weather conditions have influence on the energy production. Besides, it is expected that the energy production has its influence on the user satisfaction.

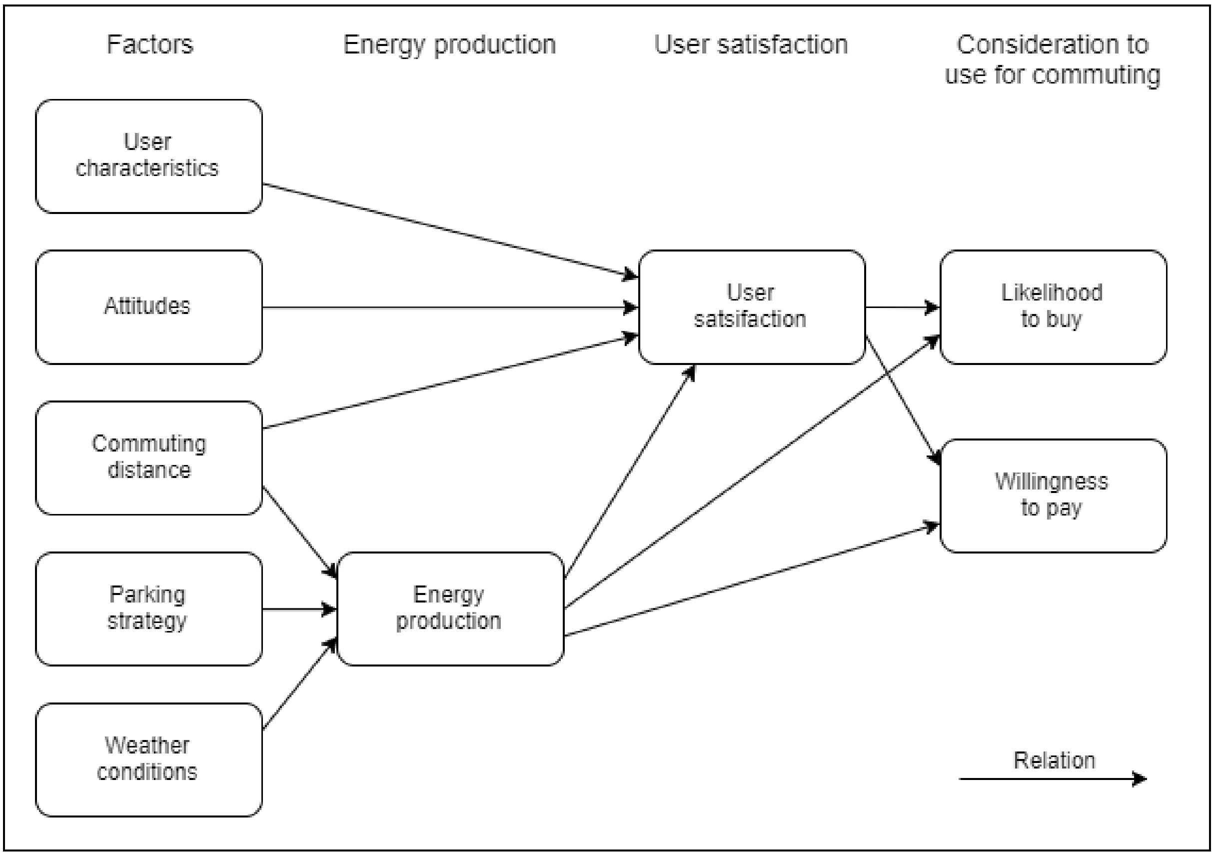

Figure 1 Conceptual model

4. Differences between e-commuters and regular commuters

It is interesting to consider the differences between commuters who use e-bikes (e-commuters) and commuters who use regular bicycles (regular commuters), since the solar bike a type of e-bike. To answer the first research question (1), data from a national survey conducted in the Netherlands is analyzed. The results of the analyzed OViN data (CBS, 2014, 2015, 2016) are presented in this chapter followed by a description of the group of participants, participating in the solar bike project.

1. What are the differences between e-commuters and regular commuters?

4.1. OViN data analyses

A national survey of CBS gathers data on the mobility of Dutchmen every year. Respondents give information on their travel behavior on a given day, and on certain personal characteristics. Data of 2013 (CBS, 2014), 2014 (CBS, 2015), and 2015 (CBS, 2016) is analyzed to find differences between e-commuters (who use electric bicycles) and regular commuters (who use non-electric bicycles). The OViN data is filtered on trip purpose (work-related) and travel mode (bicycle) to reduce the amount of input data for the analyses.

With the available data, it is possible to look into differences in gender, age, travelled distance, household disposable income, travel speed, and vehicle ownership between the two groups of commuters.

In Table 2 some characteristics of the two different groups are shown. From 2013 until 2015, in total there are 14 380 commuting trips made by bicycle, from whom are 1 092 trips made with an electric bicycle and 13 288 trips with a non-electric bicycle. Of the e-commuters, 38.0% are male and 62.0% are female. These percentages for regular commuters are for both male and female 50.0%.

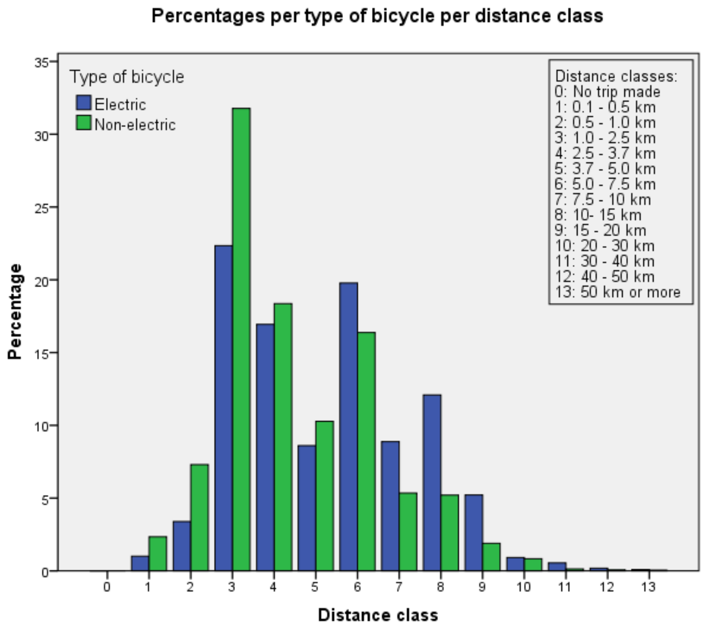

Figure 2 Percentages per type of bicycle per distance class

When looking at distances traveled, there is some difference between e-commuters and regular commuters. In Figure 2 can be seen that most of the regular commuters travel over distances between 1.0 and 2.5 km. For e-commuters, this distance class is also largest, but the percentage of e-commuters that travel more than 5.0 km per trip is larger than regular commuters. The mean travel distance of e-commuters is 6.0 km where the mean travel distance of regular commuters is only 4.1 km (see Table 2). This corresponds with CBS (2016) who says that trips made with an electric bicycle are 1.5 times longer in terms of distance than trips made with regular bicycles. An independent sample test shows that there is a significant difference between these two means (see Appendix 1.1). The mean distance traveled by e-commuters is larger than the mean distance travel by regular commuters.

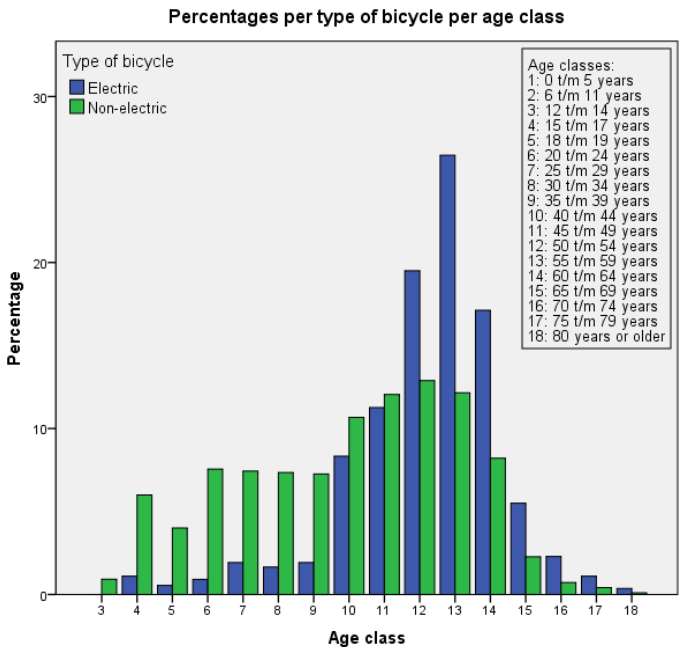

Figure 4 Percentages per type of bicycle per age class

In terms of age, a difference is expected because approximately half of the total e-bike distance covered (not only work-related), is cycled by people of 65 years and older (Kennisinstituut voor Mobiliteit (KiM), 2016). Figure 4 shows that most of the e-commuters are aged between 50 and 65 years and that the percentages for e-commuters for the higher age classes are slightly larger. Most commuters under the age of 40-year commute using non-electrical bicycles. The mean age of e-commuters is 56 and for regular commuters 42 (see Table 2). An independent sample test shows that there is a significant difference between these two means (see Appendix 1.1), where the mean age of e-commuters is higher than the mean age of regular commuters.

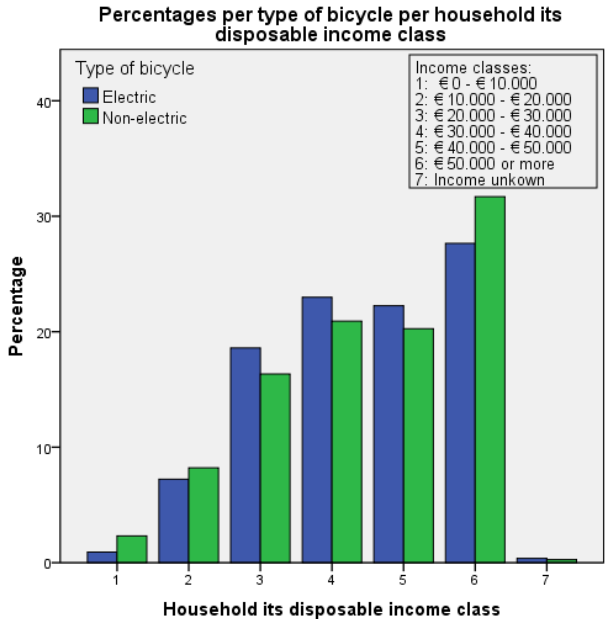

Figure 3 Percentages per type of bicycle per income class

You could expect that workers from higher income classes would e-commute more than workers out of lower income classes. However, as can be seen in Figure 3, there is not much difference in the deviation in household's disposable income among electrical compared with non-electrical bicycle commuters. An independent sample test also shows that there is no significant difference between the mean household its disposable income of e-commuters and regular commuters (see Appendix 1.1). A possible explanation for this, is that workers from lower income lasses cycle to work, because they have limited access to a car to commute with. An e-bike is better affordable than a car, and a more comfortable commuting mode than a regular bicycle. To check this, a cross table of the OViN data is made up to split the mean amount of transportation vehicles per type commuter household per household its disposable income class, (see Appendix 1.2). Out of the means can be concluded that it is true that households of lower income classes, have a lower mean amount of cars. But this relation is the same for the mean amount of other transportation vehicles. No clear explanation can be found for the difference between the mean disposable income of households of e-commuters and regular commuters.

Table 2 Differences between e-commuters and regular commuters

	Type of bicycle	Electric bicycle	Non-electric bicycle
Group size [-]		1 092	13 288
Gender [-]	Male	415 (38.0%)	6 642 (50.0%)
	Female	677 (62.0%)	6 646 (50.0%)
Age [years]			
Mean		56.38	41.83
St. deviation		10.752	15.138
95% Confidence Interval for mean	Lower bound	52.74	41.58
	Upper bound	54.02	42.09
Travel distance [km]			
Mean		5.959340659	4.128424142
St. deviation		5.818393881	4.291949142
95% Confidence Interval for mean	Lower bound	5.613861417	4.055442705
	Upper bound	6.304819901	4.201405579
Average travel speed [km/h]			
Mean		17.30995621	15.13260615
St. deviation		8.498555071	14.96295089
95% Confidence Interval for mean	Lower bound	16.80533682	14.87815303
	Upper bound	17.81457560	15.38705927
Amount of cars in household [-]			
Mean		1.28	1.17
St. deviation		0.807	0.781
95% Confidence Interval for mean	Lower bound	1.23	1.16
	Upper bound	1.33	1.18
Amount of E-bikes in household [-]			
Mean		1.38	0.12
St. deviation		0.648	0.449
95% Confidence Interval for mean	Lower bound	1.34	0.12
	Upper bound	1.42	0.13
Amount of regular bikes in household [-]			
Mean		2.30	3.79
St. deviation		1.918	1.985
95% Confidence Interval for mean	Lower bound	2.18	3.76
	Upper bound	2.41	3.82

The average travel speeds of every trip are calculated with the distance covered and the trip duration. It should be noted that respondents often rounded their trip distance and duration to multiples of 5 km and 5 minutes. The travel speeds are thus approximation, since the rounding has a strong influence on the calculations of travel speeds over short distances. The mean average travel speed of e-commuters is only 14.4% higher than the mean travel speed of regular commuters, respectively 17.3 km/h and 15.1 km/h (see Table 2). Figure 5 shows that over almost all age classes, e-commuters have a higher mean average travel speed than regular commuters. It is rather strange that e-commuters

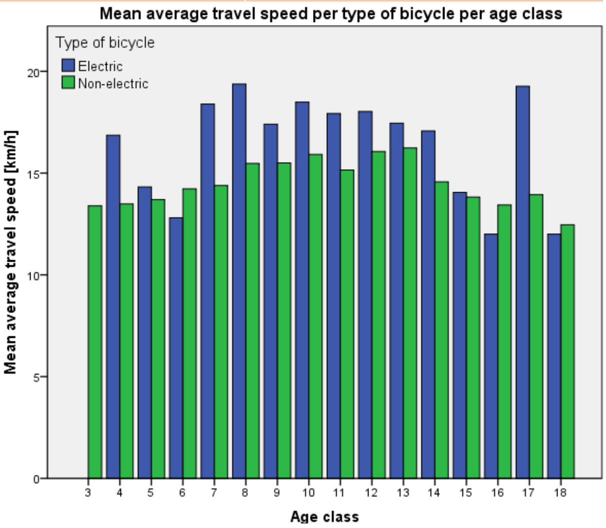

Figure 5 Mean travel speed per type of bicycle per age class

between 75 and 79 years old have the highest mean average travel speed. An independent sample test shows that there is a significant difference between the mean average speed of e-commuters and regular commuters (see Appendix 1.1).

The mean amount of cars in households of e-commuters and regular commuters are respectively 1.28 and 1.17, see Table 2. E-commuters have a mean amount of 1.38 E-bikes in their households, regular commuters only 0.12, see Table 2. The mean amount of regular bicycles in households of e-commuters is smaller than that mean amount in regular commuter households, respectively 2.30 and 3.79, see Table 2). Independent sample tests show that there are significant differences between the means of all three; mean amount of cars, mean amount of e-bikes, and mean amount of regular bicycles in the households of e-commuters and regular commuters (see Appendix 1.1).

4.2. Participants group

The group of participants that tested the solar bike consists of 79 employees, 37 working at the University of Twente and 42 working at Eindhoven University of Technology. The age of the participants ranges from 20 to 72, with a mean of 44.5. The amount of males and females are 61%, respectively 39%. The commuting distance of the participants lies between 1 km and 56 km, with a mean distance of 10.32 km.

These 79 participants all filled in the pre- and posttest survey. From 59 participants, data gathered by a solar bike was available for the evaluations. Therefore, the group sizes of the evaluations differ throughout the thesis.

4.3. Survey data compared to OViN

The survey data is compared to the OViN data (CBS, 2014,2015, 2016) in Table 3 to see whether participant's population is like the respondent's population of OViN. The descriptive statistics of the survey variables can be found in Appendix 1.3. The OViN data of e-commuters is used for the comparison. The mean age, gender, and commuting distance of the two data sources all differ significantly (see Appendix 1.4) for independent sample test results). Gross income of the data sources has different categories. Therefore, it is not possible to compare this variable statistically. When looking at the mean income ranges, it indicates that the OViN respondents have a slightly higher income than the solar bike users. It may be concluded that the participant's population does not equals the OViN population.

Table 3 Comparison survey and OViN data

	Survey data *(n=79)*		OViN data *(n=1092)*	
Variable	Mean	Std. deviation	Mean	Std. deviation
Age	44.48	10.586	53.38	10.752
Gender (1 = male, 2 = female)	1.39	.491	1.62	.486
Commuting distance	10.32	9.367	5.96	5.818
Gross income (different categories between sources)	3.89 (~ €2.500 - ~ €3.000)	1.038	4.43 (~ €2.900 - ~ €3.750)	1.318

4.4. Conclusion

Out of the OViN data analyses, differences between e-commuters and regular commuters are derived. The mean commuting distance of e-commuters is 6.0 km and for regular commuters 4.1 km. The mean amount of e-bikes owned by e-commuter households is 1.38 and that from regular commuters only 0.12. The mean age of e-commuters and regular commuters are 56, respectively 42. The mean travel speed of e-commuters is 17.3 km/h and of regular commuters 15.1 km/h. These all differ significantly. The differences between the solar bike project participants and OViN respondents in terms of age, gender, and commuting distance are also significant.

5. Influences on energy production

To get the most energy out of the sun with PV panels, they should be placed in direct sunlight, having the most optimal angle and facing the right direction. The energy production of fixed PV panels is mainly influenced by the weather. In the case of movable panels that is different. Not all users of a solar bike will park their bike in the most optimal way in terms of energy production. Out of the posttest survey it becomes clear that many users parked the bike at secured locations, which are often roofed. The influence of the different possible bike parking strategies on the energy production of the solar bike is unknown. Also, the influence of the trip distance of commuters is unknown. Analyzing the solar bike data in combination with weather data and the parking strategy and commuting distance of participants will give answer on the second research question (2):

2. What is the effect of different factors on the energy production of the solar bike?

The hypothesis is that weather conditions like solar radiation, have a great influence on the energy production. Furthermore, it is expected that different bike parking strategies result in different intensities of the relationship between solar radiation and the energy production of the solar bike when parking the bike. It is also expected that besides solar radiation, commuting distance has influence on the energy production during the trip. This chapter evaluates the relations of the conceptual model depicted in Figure 6.

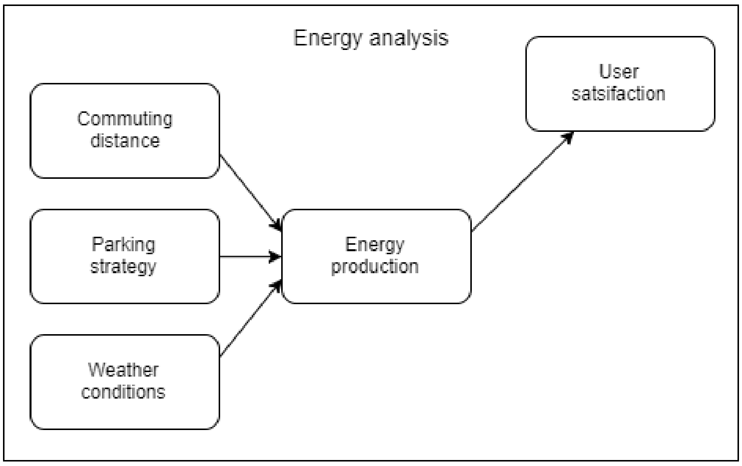

Figure 6 Energy part of conceptual model

5.1. Combining method

For the energy production analysis, but also for the user experience analysis and for the consideration to use a solar bike for commuting analysis, it is necessary to combine the different data sources. The data sources have some variables that correspond with each other. These corresponding variables are used to combine data from different sources. In Figure 7 the method used to combine the different data sources is sketched.

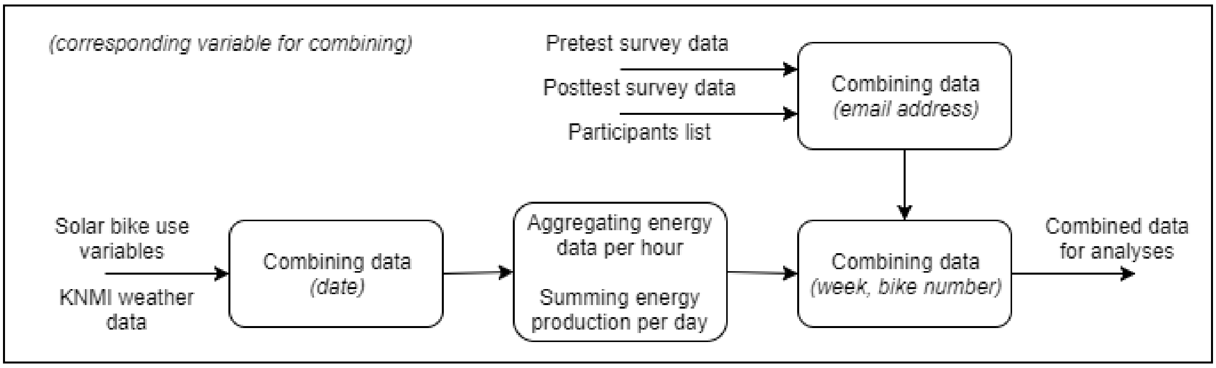

Figure 7 Method to combine different data sources

The solar use variables are aggregated per hour, due to lack of continuity in the data. Besides an aggregated data set, there is also a data set created consisting daily data on the total energy production per day in combination with corresponding daily weather information.

The combining of solar bike data and weather data is done using a MATLAB script (The MathWorks, Inc., 2016), which also aggregated the data. The survey data and participants list are combined using Microsoft Excel (2013), where also the aggregated data is added. In total, data of 59 participants is used for the analyses regarding energy production.

5.2. Correlation between energy production and user satisfaction

The relationship between the energy production and user satisfaction is checked by running a correlation analysis in IBM SPSS Statistics (IBM Corp., Released 2016). A bivariate correlation analysis shows that there was no significant relationship between the total energy produced by a participant and the general grading on the bike (see Appendix 2.1). However, the scatterplot (see Appendix 2.1) shows a slightly positive relationship. The absence of a significant relationship can be explained by the fact that participants do not get any respond on the energy production of the bike whilst they were using, or parking it.

5.3. Influences of bike parking and weather conditions on energy production

The influences on the energy production by weather conditions, bike parking strategies, and commuting distance are analyzed by performing regression analyses. The weather variable that is used to predict the energy production is solar radiation. The maximum mean energy production during a timeslot of an hour (9 – 10 AM) was 5.9 Wh, produced with a solar radiation of 478 W/m^2 (factor 0.021). The highest energy factor was 0.492, produced with parking strategy 3 (18 – 19 PM). Descriptive statistics of these variables can be found in Appendix 2.2. The energy factor is calculated with Formula 1:

$$energy\ factor = \frac{energy\ production\ [{}^{W}/_{0.6m^2}]}{solar\ radiation\ [{}^{W}/_{m^2}]} \quad (1)$$

A solar wheel is covered for approximately 0.6 m^2 of PV cells. A Flash Test on one side of the solar wheel measured a maximum power production between 11 W and 12 W. Obviously, in daily practice this power production is never measured.

5.3.1. Assumption

Unfortunately, there is no GPS data available to locate the solar bikes, therefore it cannot be determined whether a bike is parked at the university or not. The assumption is made that participants parked their bike at the university between a start time in the morning and an ending time in the afternoon (9 AM and 17 PM). For the energy analysis of commuting trips, hourly data between 7 AM and 9 AM, and 17 PM and 19 PM is used. Furthermore, all data with an energy production per hour of less than 1.0 joule is removed from the data set, because these points are not realistic and have negative influence on the analyses. This results in 978 hours of data for the parking analysis, and 327 hours of data for the trip analysis.

5.3.2. Bike parking strategies

The multiple regression analysis for the parked energy production is performed with solar radiation as prediction variable together with a parking strategy variable. In Table 4 the possible strategies are listed, no participant made use of strategy 4 or 5. Therefore, the strategy variable is changed to a variable ranging from 1 to 4.

Table 4 Possible bike parking strategies at the workplace

Bike parking strategies	Roof and amount of daylight that could reach the solar bike	Count *(n=978 hours)*	Percentage
1	Roofed, no daylight	297	30.37%
2	Roofed, limited daylight	517	52.86%
3	Roofed, much daylight	67	6.85%
4	Not roofed, no daylight	0	0.0%
5	Not roofed, limited daylight	0	0.0%
6	Not roofed, much daylight	97	9.92 %
Parking strategy variable values for regression			
1	Roofed, no daylight		
2	Roofed, limited daylight		
3	Roofed, much daylight		
4	Not roofed, much daylight		

5.3.3. Trip distances

The multiple regression analysis for the trip energy production is performed with solar radiation as prediction variable together with the commuting distance. The spread in distance in the dataset can be seen in Figure 8. Distances between 4 km and 11 km are well present. There is a gap between 20 km and 55 km.

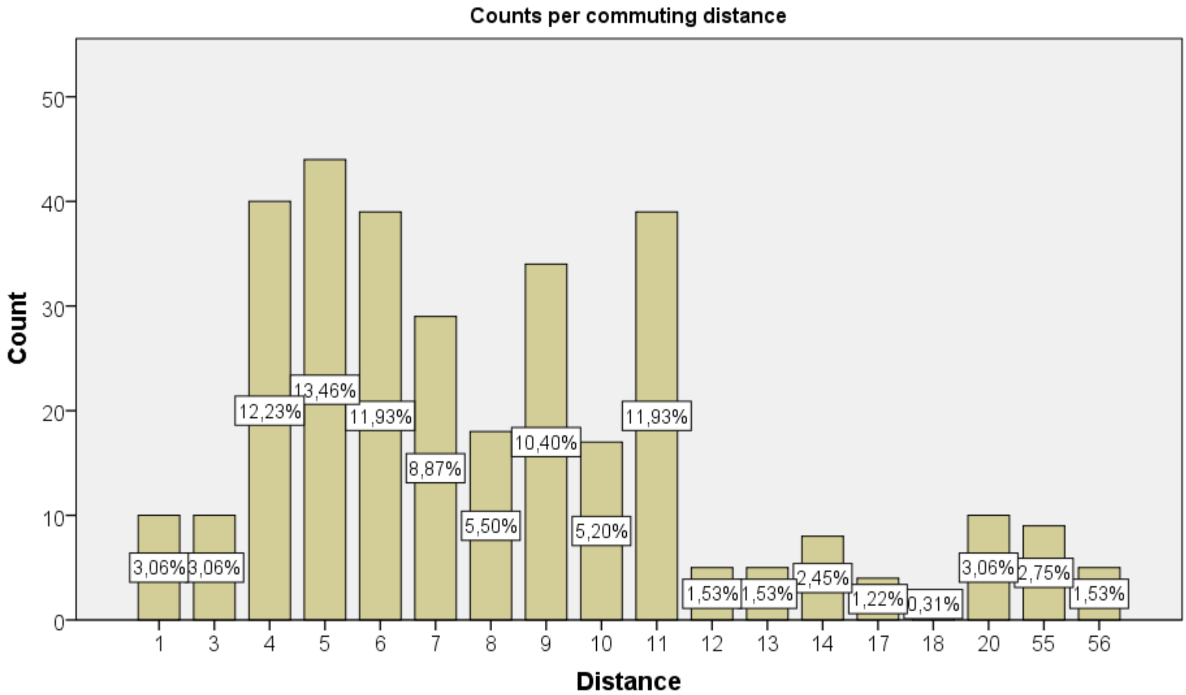

Figure 8 Histogram of distances (n=327 hours)

5.3.4. Method

Before the regression is ran in IBM SPSS Statistics (IBM Corp., Released 2016), there are some assumptions that needed to be checked (Lund Research LtD, 2017):

1. The dependent variable should be measured on a continuous scale (either interval or ratio);
2. There are two or more independent variables, which can be either continuous (interval or ratio) or categorical (ordinal or nominal);
3. There needs to be a linear relationship between the dependent variable and each of the independent variables;
4. There should be no significant outliers, high leverage points or highly influential points;
5. There is independence of observations;

6. The data needs to show homoscedasticity;
7. The data must not show multicollinearity;
8. The residuals (errors) should be approximately normally distributed.

The dependent variable is in this case the variable energy production, this variable has a continuous scale (assumption 1). The independent variables solar radiation and commuting distance are continuous, the parking strategy is ordinal (assumption 2). The linear relationship between the dependent variable and the independent variables is checked with scatterplots and correlation analyses (assumption 3). For the correlation analyses between continuous variables and energy production, Pearson's correlation coefficient is used and for the correlation analysis between the ordinal variable and energy production Kendall's tau. The reason for the use of Kendall's tau is, the high number of scores for certain ranks (Field, 2013). The scatterplots to check assumption 3, are also used to check for significant outliers (assumption 4). The independence of observations is checked using the Durbin-Watson statistic (assumption 5). The check for homoscedasticity is done by plotting the regression standardized residual with the dependent variable, drawing a fit line, and checking the consistency of the amount of error along the line (assumption 6). Multicollinearity is checked by looking at the collinearity statistics of the regression. Tolerance should be > 0.1 or VIF < 10 (assumption 7). The check for approximately normally distributed residuals is done by looking at a normal P-P plot of regression standardized residual (assumption 8).

5.3.5. Correlations

The correlations between energy production per hour, solar radiation, commuting distance, and parking strategy are evaluated. The results of these bivariate correlation analyses are in Table 5, which is split up in results for the parking analysis and the trip analysis. A scatterplot of the energy production and solar radiation can be found in Appendix 2.2. The relationship between the energy production during trips and commuting distance is not significant. This can be caused by the high amount of short trips in the data set.

Table 5 Results bivariate correlation analyses energy variables

Correlation between energy production per hour and:	Pearson's *r* Kendall's *τ*	BCa 95% CI	*p*-value	Significant relationship
Parking analysis				
Solar radiation	*r = .139*	*[.090, .187]*	*.000*	*Yes*
Parking strategy	*τ = .092*	*[.043, .139]*	*.000*	*Yes*
Trip analysis				
Solar radiation	*r = .243*	*[.153, .323]*	*.000*	*Yes*
Commuting distance	*r* = -.023	[-.073, .041]	.681	No

5.3.6. Regressions

The regression model for the parking analysis has the input variables solar radiation and parking strategy to predict the energy production. The regression model for the trip analysis only has solar radiation as input variable, because the correlation with commuting distance is not significant (assumption 2). In Table 6 the R^2s, betas included with their confidence intervals, and standard errors of the two models can be found. The confidence intervals and standard errors are based on 1000 bootstrap samples. All results of the regression are in Appendix 2.3, split up in parking analysis and trip analysis.

Table 6 Results regression models of energy production

	R^2	b		Std. Error B	Standardized ß	p
Parking analysis						
Constant	.139	245.83	[14.31, 479.45]	112.62		.030
Solar radiation		2.78	[1.63, 4.05]	.61	.14	.001
Parking strategy		35.92	[-95.89, 142.26]	55.13	.02	.510
Trip analysis						
Constant	.243	31.96	[-300.35, 300.00]	127.45		.822
Solar radiation		8.03	[4.38, 12.33]	2.35	.24	.007

The Durbin-Watson statistics are for the parking and trip analyses 1.936 respectively 1.598 (see Appendix 2.3) which are between the critical values of 1.5 and 2.5. This indicates that there is independence of observations (assumption 5). The scatterplot plots of energy production and regression standardized residual for both the models (see Appendix 2.3) show that there is homoscedasticity in the data (assumption 6). The tolerance statistic of all predictors is greater than 0.1 and the VIF smaller than 10 (see Appendix 2.3). For the parking analysis, the tolerance statistics are .984 and the VIFs are 1.107 which indicates that there is no multicollinearity (assumption 7). For the trip analyses, there is only one predictor, therefore this assumption can be ignored. The Normal P-P plots of regression standardized residuals (see Appendix 2.3) show a normal distribution of errors (assumption 8).

With the *b*-values known, for both the energy production while parked and during the commute, equations (2, 3) can be set up that tells us what the relationships between the predictors and the outcomes are. It also tells us to what degree each predictor affects the outcome if the effects of all other predictors are held constant.

$$Energy\ production\ (parked)_i = 245.83 + 2.78\ solar\ radiation_i + 35.92\ parking\ strategy_i \tag{2}$$

$$Energy\ production\ (travel)_i = 31.96 + 8.03\ solar\ radiation_i \tag{3}$$

In practice, these formulas cannot be right. The formulas indicate that there will always be energy production, even when there is no solar radiation. Of course, this can never be true. In the analyses, solar radiation measurements come from KNMI weather stations. It is almost certain that the measured solar radiation at the weather stations do not have the same values as the radiation the solar bikes were exposed to, because solar radiation is very sensitive towards clouds. If it would be possible to measure the exact radiation a solar bike is exposed to, there would be no constant in the formulas above.

5.4. Conclusion

The hypothesis concerning the energy production of the solar bike was that solar radiation would have great influence on the energy production, that the different parking strategies result in different intensities of the relationship between energy production and solar radiation when the bike is parked, and that the commuting distance would have influence on the energy production during trips. The correlation analyses show that there are significant relationships between the solar radiation and the energy production during parking and travelling, and between parking strategies and the energy production during parking. The relationship with commuting distance seems not to be significant, reason for this can be the small amount of longer distances in the dataset. Out of the descriptive statistics can be concluded that the highest energy efficiency (energy factor) was measured by a bike parked with strategy 3. The regression models only account for 13.9% and 24.3% of the variance in energy production. The discontinuity of the data before aggregation can be the cause for the poor correlations, because this discontinuity results in many cases in little energy production per hour.

6. User experience analysis

When testing a new product, user experiences and user characteristics are important. User experiences can be collected in various ways. In this case, surveys are used. Survey results from 79 participants are used for the user experience analyses. As earlier mentioned in earlier, participants filled in two surveys: a pre- and posttest survey. In the posttest survey participants gave a general grading on the solar bike. Other questions asked are on wind hindrance, statements about the solar bike (7 point Likert scale), and the suitability of the solar bike for commuting and recreational usage (5 point Likert scale). In the pre-test, user characteristics are gathered. Particularly there is an interest in the relationship between wind speeds and the complains of users about the covered front wheel, and the relationship of user experience factors and the general grading. These evaluations will give answer on the third research question (3).

3. What is the user experience of the solar bike?

The hypothesis that follows from the literature review is that user experience and characteristic variables age, commuting distance, and attitudes will have their effect on the general grading of the solar bike. This chapter evaluates the relations of the conceptual model depicted in Figure 9.

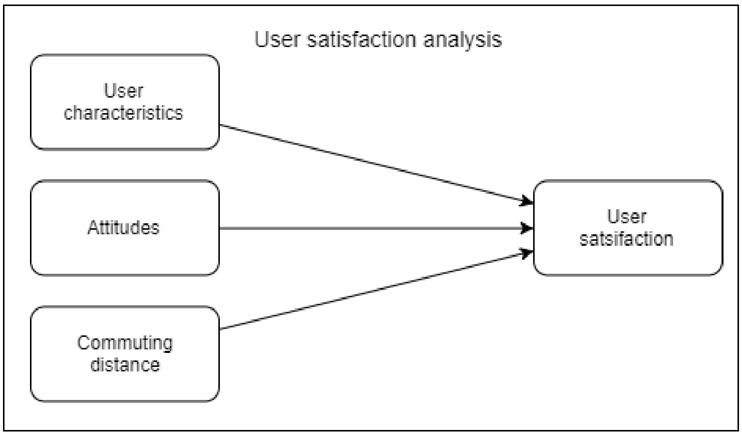

Figure 9 User satisfaction part of conceptual model

6.1. Correlation of wind speeds and crosswind hindrance

The solar panels of the solar bike are integrated in the front wheel of the bike, which results in an almost fully covert wheel that catches a lot of wind (see image front page). A covert wheel is something people are not used to when cycling. By comparing mean wind speeds during the test days of a participant with their indication of crosswind hindrance (see Table 7), there is tried to find a correlation between wind speeds and experiences or complaints of crosswind hindrance.

Table 7 Crosswind hindrance classes

Class	To what extent did you experience hindrance from crosswind on the front wheel?	Count *(n=79)*	Percentage
1	No / hardly any hindrance	9	11.4%
2	On some trips	25	31.6%
3	Regularly / often	31	39.2%
4	On all trips	14	17.7%

Table 8 Wind speed ranges

Wind speed [Beaufort]	Wind speed [km/h]	Count *(n=59)*		Percentage	
2 Light breeze	8 – 10	8	26	13.55%	44.1%
	10 – 12	18		30.5%	
3 Gentle breeze	12 – 14	19	33	32.2%	55.9%
	14 – 16	10		16.95%	
	16 – 18	3		5.1%	
	18 – 20	1		1.7%	

Following Table 7, it can be concluded that most participants experienced troubles with crosswind. Daily weather data of weather station Twenthe (KNMI, 2017) is used to calculate the mean wind speed during the test days of a participant. The range of mean wind speeds lies between 8 km/h and 20 km/h, with most mean wind speeds from 12 km/h to 19 km/h (see Appendix 3.1 for descriptive statistics). From 59 participants, it is known on which days they used a solar bike. When analyzing the scatterplot (see Appendix 3.1) of crosswind hindrance and mean wind speeds, a linear correlation can be found. A correlation analysis is performed in IBM SPSS Statistics (IBM Corp., Released 2016). Crosswind hindrance is an ordinal variable with only four categories which results in many scores having the same rank, therefore Kendall's tau is used (Field, 2013). The bivariate correlation analysis shows that there was a positive significant relationship between crosswind hindrance and mean wind speeds, $\tau = .239$ 95% BCa CI [.073, .389], $p = .017$. Given that crosswind hindrance is an ordinal variable, regression analysis is not possible. From Table 9 could be concluded that an increase of wind speed, results in an increase in crosswind hindrance complaints.

Table 9 Cross table wind speed - crosswind hindrance

(n=59)	Crosswind hindrance									
Wind speed [Beaufort]	**1**		**2**		**3**		**4**		**Total**	
2	6	23%	10	38%	9	35%	1	4%	26	100%
3	2	6%	12	36%	12	36%	7	21%	33	100%

In the open question of the survey, participants could give their opinion on negative aspects. A lot of participants complained about the crosswind hindrance, even at low wind speeds. Some said they experienced hindrance due to air pressure differenced, not in particularly due to wind. A passing lorry can already cause imbalance of the solar bike, and therefore hindrance. Furthermore, a larger correlation could probably be found if the exact wind speeds participants were exposed to are known.

6.2. Multiple regression analysis of user experience variables on general grading

In the posttest survey, participants gave a general grading for the solar bike. To find influential factors playing role in the grading of participants, a multiple regression analysis is performed on the different variables of the survey data.

The general grading of the participants lies between 3 and 9 with a mean of 6.84 (see Appendix 3.2 for descriptive statistics). More than 10% of the participants gave an insufficient grade, where most participants gave a 7 (see Table 10). When looking at the difference between e-bike users and non-e-bike users within the group of participants, you can expect that e-bike users will be more critical about the solar bike, since they already have experience with a normal e-bike. The mean general grading of e-bike users is 6.43, which is lower than the mean general grading of non-e-bike users (6.92). However, this difference in means is not significant (see Appendix 3.2).

Table 10 Counts and percentages per solar bike grade

Grade	Count *(n=79)*	Percentage	Grade	Count *(n=79)*	Percentage
1	0	0%	**6**	15	18.99%
2	0	0%	**7**	33	41.77%
3	1	1.27%	**8**	20	25.32%
4	2	2.53%	**9**	2	2.53%
5	6	7.59%	**10**	0	0%

6.2.1. Method

Before the regression is ran in IBM SPSS Statistics (IBM Corp., Released 2016), there are some assumptions the data should satisfy (Lund Research LtD, 2017):

1. The dependent variable should be measured on a continuous scale (either interval or ratio);
2. There are two or more independent variables, which can be either continuous (interval or ratio) or categorical (ordinal or nominal);
3. There needs to be a linear relationship between the dependent variable and each of the independent variables;
4. There should be no significant outliers, high leverage points or highly influential points;
5. There is independence of observations;
6. The data needs to show homoscedasticity;
7. The data must not show multicollinearity;
8. The residuals (errors) should be approximately normally distributed.

The dependent variable is in this case the variable general grading, this variable has a continuous scale (assumption 1). Most of the independent variables are categorical, some are continuous (assumption 2). The linear relationship between the dependent variable and the independent variables is checked with scatterplots and correlation analyses (assumption 3). For the correlation analyses between continuous variables and general grading, Pearson's correlation coefficient is used and for the correlation analyses between ordinal variables and general grading Kendall's tau. The reason for the use of Kendall's tau is, the high number of scores for certain ranks (Field, 2013). The scatterplots to check assumption 3, are also used to check for significant outliers (assumption 4). The independence of observations is checked using the Durbin-Watson statistic (assumption 5). The check for homoscedasticity is done by plotting the regression standardized residual with the dependent variable, drawing a fit line, and checking the consistency of the amount of error along the line (assumption 6). Multicollinearity is checked by looking at the collinearity statistics of the regression. Tolerance should be > 0.1 or VIF < 10 (assumption 7). The check for approximately normally distributed residuals is done by looking at a normal P-P plot of regression standardized residual (assumption 8).

Firstly, the correlations of the user experience variables with the general grading are checked. The results of these correlation analyses can be found in Table 11. Secondly, the variables that do correlate with general grading are put in to a backward regression model to eliminate the variables that do not contribute enough. The variables that are left over are entered in a new regression model.

6.2.2. Crosswind hindrance

In the open question for negative experiences of the posttest survey, a lot of participants (60%) complained about the covert front wheel or about crosswind. Therefore, a negative influence of crosswind hindrance on general grading is expected. A bivariate correlation analysis shows that crosswind hindrance was negatively significantly related to the general grading of the solar bike.

6.2.3. User characteristics

Age, gender, weight, length, commuting distance, amount of exercise per day, educational level, gross income, and the amount of testing days are variables that are all user characteristics. From the user characteristic variables only the amount of testing days is significantly related to general grading, in a positive way.

6.2.4. Attitudes

Participants gave scores on seven different solar bike statements, based on a 7 point Likert scale. The questions are:

1. A solar bike would give me a high amount of flexibility and freedom of movement, because it needs to be charged less often;
2. Solar bikes are for elderly;
3. Solar bikes are for non-sportive people;
4. A solar bike is a trendy and innovative product;

5. The fact that e-bikes are often stolen, makes buying a solar bike less attractive;
6. A solar bike contributes to a healthier lifestyle and daily exercise;
7. A solar bike contributes to a more sustainable and greener world.

From these statements, statements 1, 4, and 7 are positively significantly related to the general grading of the solar bike. Statement 5 is negatively significantly related to the general grading of the solar bike.

6.2.5. Other factors

Other user experience variables that can be derived from the posttest survey are the suitability of the solar bike for commuting, the suitability for recreation, and e-bike user. These variables all have are positively significantly related to the general grading of the solar bike. The variable e-bike user (participants that normally use an e-bike to commute) is not significantly related to the general grading.

6.2.6. Results correlation analyses

In Table 11, the results of all the bivariate correlation analyses are presented. The variables that have a significant relationship with general grading are highlighted. The 95% BCa confidence intervals are based on 1000 bootstrap samples.

Table 11 Results of bivariate correlation analyses between general grading and user experience variables (n=79)

Correlation between general grading and:	Kendall's τ Pearson's r	BCa 95% CI	p-value	Significant relationship
Crosswind hindrance	*τ = -.275*	*[-.435, -.106]*	*.004*	*Yes*
Age	r = .167	[-.037, .391]	.141	No
Gender	τ = .077	[-.156, .307]	.460	No
Weight	r = .067	[-.099, .262]	.558	No
Length	r = -.085	[-.278, .101]	.454	No
Commuting distance	r = -.006	[-.246, .178]	.959	No
Amount of exercise per day	τ = -.024	[-.228, .163]	.803	No
Educational level	τ = .053	[-.143, .250]	.568	No
Gross income	τ = .037	[-.158, .241]	.702	No
Amount of testing days	*r = .239*	*[-.064, .484]*	*.034*	*Yes*
1. SBike flexibility	*τ = .380*	*[.216, .532]*	*.000*	*Yes*
2. SBike elderly image	τ = -.061	[-.260, .155]	.532	No
3. SBike sportive image	τ = -.017	[-.188, .152]	.856	No
4. SBike trendy and innovative image	*τ = .264*	*[.101, .423]*	*.007*	*Yes*
5. SBike attractiveness due to theft	*τ = -.284*	*[-.449, -.111]*	*.003*	*Yes*
6. SBike healthy life style contribution	τ = .157	[-.055, .372]	.107	No
7. SBike sustainable contribution	*τ = .272*	*[.043, .476]*	*.006*	*Yes*
Suitability for commuting	*τ = .502*	*[.351, .648]*	*.000*	*Yes*
Suitability for recreation	*τ = .406*	*[.216, .576]*	*.000*	*Yes*
E-bike user	τ = -.123	[-.330, .123]	.237	No

The bivariate correlation analyses are also performed splitting up the data into two groups. A group of participants in Enschede working at the UT and a group of participants in Eindhoven working at the TU/e. The variables that have a significant relationship with general grading either for participants from Enschede or from Eindhoven are in Table 12. The results for all variables can be found in Appendix 3.3. The significant variables from these two groups match with the significant variables of the total population. Only three of these variables are significant for the TU/e group, where nine are significant for the UT group. This difference indicates that groups from different regions have different variations in variables.

Table 12 Results of bivariate correlation analyses between general grading and user experience variables for UT and TU/e

Location:	UT (Enschede) n = 37		TU/e (Eindhoven) n = 42	
Correlation between general grading and:	Kendall's τ Pearson's *r*	*p*-value	Kendall's τ Pearson's *r*	*p*-value
Crosswind hindrance	*τ = -.495*	*.000*	τ = -.084	.534
Amount of testing days	*r = .408*	*.012*	*r* = .000	1.000
1. SBike flexibility	*τ = .466*	*.001*	*τ = .309*	*.022*
4. SBike trendy and innovative image	*τ = .303*	*.035*	τ = .242	.072
5. SBike attractiveness due to theft	τ = -.135	.332	*τ = -.431*	*.001*
6. SBike healty life style contribution	*τ = .294*	*.041*	τ = .024	.860
7. SBike sustainable contribution	*τ = .313*	*.030*	τ = .231	.095
Suitability for commuting	*τ = .541*	*.000*	*τ = .481*	*.000*
Suitablility for recreation	*τ = .513*	*.000*	*τ = .323*	*.015*

6.2.7. Regression

With the results of the correlation analyses, the input variables for the multiple regression analysis could be chosen. To meet assumption 3, only the variables that have a linear relationship with general grading may be used, which are: crosswind hindrance, amount of testing days, solar bike statements 1, 4, 5 and 7, suitability for commuting, and suitability for recreation. The regression is performed on data of all 79 participants.

The chosen variables are put in to a multiple regression analysis with a backward method in IBM SPSS Statistics (IBM Corp., Released 2016). The backward method removed the variables, amount of testing days, solar statements 4 and 5, and suitability for recreation from the model (for results see Appendix 3.4, Backward method). A new multiple regression analysis is performed with the variables left over (crosswind hindrance, solar bike statements 1 and 7, and suitability for commuting), with a forced entry method to make bootstrapping possible (for all results see Appendix 3.4, Enter method). This new model results in a R^2 of .460. In Table 13 the beta's can be found, included with their 95% BCa confidence intervals and standard errors which are based on 1000 bootstrap samples.

Table 13 Results regression model of general grading

	b		Std. Error B	*Standardized ß*	*p*
Constant	3.72	[2.21, 5.03]	0.77		0.001
Crosswind hindrance	-0.32	[-0.31, -0.03]	0.13	-.26	0.028
1. SBike fexibility	0.32	[0.14, 0.49]	0.09	.24	0.002
7. SBike sustainable contribution	0.32	[-0.42, 0.72]	0.20	.19	0.124
Suitability for commuting	0.45	[0.21, 0.69]	0.11	.38	0.001

The Durbin-Watson statistic is 2.062 (see Appendix 3.4) which is between the critical values of 1.5 and 2.5. This indicates that there is independence of observations (assumption 5). The scatterplot plot of general grading and regression standardized residual (see Appendix 3.4) shows that there is homoscedasticity in the data (assumption 6). The tolerance statistic of all predictors is greater than 0.1 and the VIF smaller than 10 (see Appendix 3.4). The average tolerance statistic is .891 and the average VIF is 1.124 which indicates that there is no multicollinearity (assumption 7). The Normal P-P plot of regression standardized residual (see Appendix 3.4) shows a normal distribution of errors (assumption 8).

With the *b*-values known, an equation (4) can be set up that tells us what the relationships between the predictors and the outcome are. It also tells us to what degree each predictor affects the outcome if the effects of all other predictors are held constant.

$$\begin{aligned} General\ grading_i &= 3.72 - 0.32\ crosswind\ hindrance_i + 0.32\ SBike\ flexibility_i \\ &\quad + 0.32\ Sbike\ sustainable\ contribution_i + 0.45\ Suitability\ for\ commuting_i \end{aligned} \tag{4}$$

This formula may only be used with variable values that lie within the ranges of the variables in the data set (see Appendix 1.3).

6.3. Conclusion

From the user experience analyses can be concluded that the general experience of the solar bike is quite positive. The mean general grade is 6.84. The most influential factors that follow from the multiple regression analysis do not completely correspond with the hypothesis, which claimed that user characteristics age, commuting distance and attitudes would influence the general grading most. Two attitudes however do: solar bike flexibility and solar bike sustainability. Together with crosswind hindrance, and the suitability for commuting they account for 46.0% of the variability of general grading. Commuting distance only has a small variation within the group of participants, with only a couple of users that travel over 20 km. This may be the cause that this variable does not correlate well with general grading. Age however does have a nice spread over all ages between 26 and 64. It may be concluded that for employees of universities, age does not have influence on the general experience of the solar bike.

The covert front wheel causing crosswind hindrance was one of the main complaints of users. A positive significant correlation is found between the complaints about crosswind hindrance and wind speeds. If wind speeds increase, the amount of complaints also increases.

7. Consideration of a solar bike as commuting transportation mode

Since the solar bike is being tested by employees of the universities, it is interesting to know whether the participants consider the solar bike for commuting or not. Following Fyhri and Fearnly (2015), the intervention in the transportation mode behavior of the employees can have effects, which can transform into a behavioral shift. It is established that experience of a transport mode following incentives or marketing initiatives is associated with positive attitudes (Donaghy, 2011), increased use (Taniguchi & Fujii, 2007) and long-term adoption (Jones & Sloman, 2010). Learning from consumption means that experience of a transport mode increases the propensity for its use over time. (Fyhri & Fearnley, 2015). By letting the employees of the universities experience a solar bike as transportation mode, they may be considering it more as an option for commuting. The evaluation of the relationships between the consideration to use a solar bike for commuting, and user satisfaction and energy production will give answer on the fourth research question (4):

4. *What is the relation between user satisfaction, energy production and the consideration to use a solar bike for commuting?*

The influence of testing a solar bike on the transportation mode choice preferences of participants bike is also evaluated. The likelihood to buy a solar bike and the willingness to pay for a solar wheel (both questions in the survey) are variables that represent the consideration to use a solar bike for commuting. Here, the difference between two groups: e-bike users, and non-e-bike users, is also reviewed to see whether there is a difference between participants that are familiar with an equivalent transportation mode of the solar bike and participants that are not. This chapter evaluates the relations of the conceptual model depicted in Figure 10.

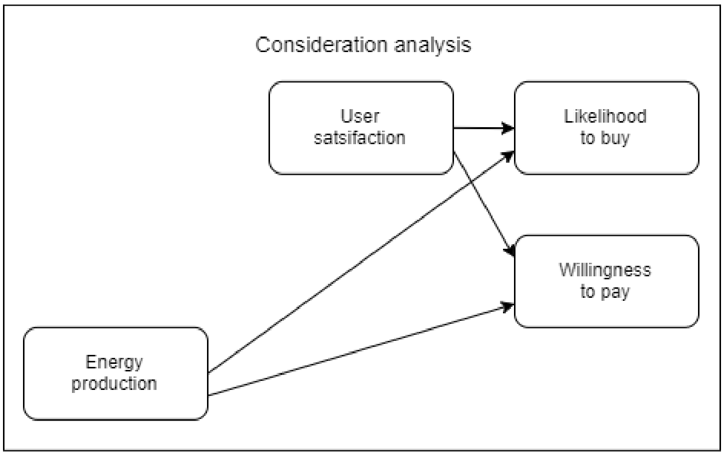

Figure 10 Consideration part conceptual model

7.1. Transportation mode choice preferences

In the pre- and posttest surveys, participants gave their transportation mode preferences in nine different situations. The amount of solar bike choices is counted in both pre- and posttest surveys. The mean amount of solar bike choices before testing was 2.25. After testing the solar bike, participants had a mean amount of solar bike choices of 2.67 of nine situations. It could be concluded that using a new transportation mode for a while, has influence on the transportation mode choice preferences of people. The groups e-bike users and non-e-bike users do not differ much. The difference in solar bike choices between the means of these groups is only 0.05 (see Appendix 4.1). When comparing the amount of solar bike choices after testing with the general grading of the solar bike, a positively significantly relation was found between the amount of solar bike choice preferences and the general grading of the solar bike, $r = 0.462$ 95% BCa CI [.317, .588] $p = .000$ (see Appendix 4.1), for a scatterplot and descriptive statistics).

7.2. Likelihood to buy

The participants answered a question about the likelihood to buy a solar bike, in both pre- and posttest surveys. The difference between the likelihood to buy a solar bike before and after testing is compared. In Table 14 the amounts and percentages of participants per category are given. In Figure 11 the cumulative percentages are presented. From this figure, we can conclude that more than 60% of the participants are unlikely to buy a solar bike in their current situation after testing a solar bike. Before testing, this group was only 40%. A paired-samples t-test shows that on average, participants are less likely to buy a solar bike after testing a solar bike than before testing a solar bike. This difference, was significant (see Appendix 4.2).

Table 14 Amount and percentage of users per Likert scale score of likelihood to buy before and after testing a solar bike

Likelihood to buy (Likert scale)	Pre-test	Post-test	Pre-test	Post-test
1 Almost certainly not	10	18	13%	23%
2 Very unlikely	13	13	16%	16%
3 Unlikely	9	21	11%	27%
4 Neither likely or unlikely	30	16	38%	20%
5 Likely	14	8	18%	10%
6 Very likely	2	2	3%	3%
7 Almost certain	1	1	1%	1%
Total	79	79	100%	100%
Mean	3.4	2.9		

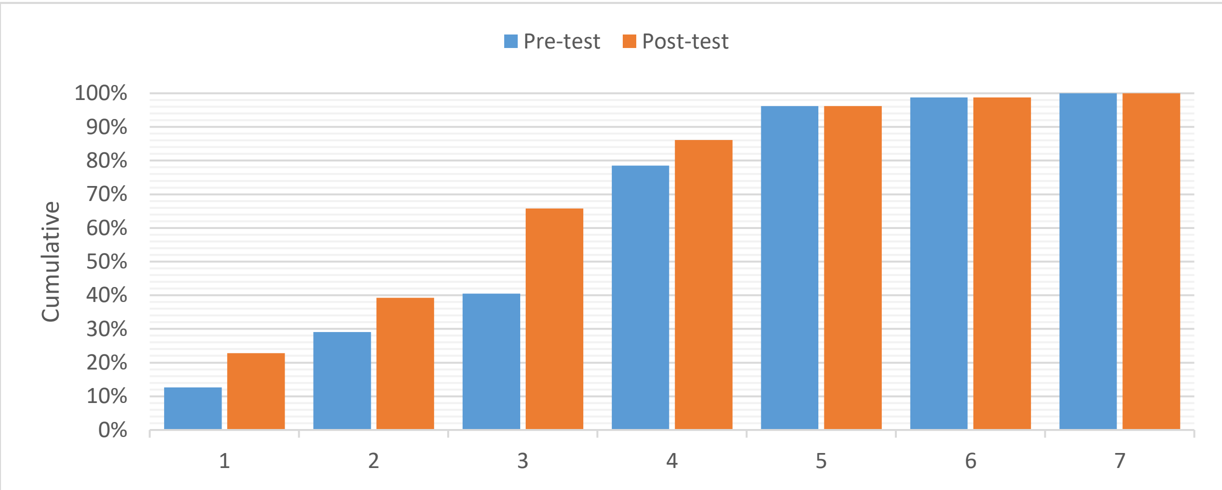

Figure 11 Cumulative percentages of Likert scale scorings of likelihood to buy before and after testing a solar bike (n = 79)

With respect to the two groups (e-bike users and non-e-bike users), an independent sample test shows that the difference in likelihood to buy after testing between the groups is not significant (see Appendix 4.2).

7.3. The consideration to use a solar bike for commuting

The relationship between user satisfaction, energy production and the consideration to use a solar bike for commuting is analyzed to find the interrelationships. The likelihood to buy after testing and the willingness to pay are the consideration variables evaluated. The range of the willingness to pay is between €50 and €2500 with a mean price of €722,59 (Std. deviation 702.061). The question were the willingness to pay follows from was “A great buy for the money”. Participants also had to give prices for “so low that you would feel the quality could not be very good”, “not too expensive, you have to think about it”, and “so expensive you would not consider buying it”.

7.3.1. User satisfaction

The general grading participants gave, is a grade that represents their satisfaction with the solar bike. The relationship between the general grading and the likelihood to buy and willingness to pay are evaluated by bivariate correlation analyses. These show that general grading is positively significantly related to the likelihood to buy a solar bike, τ = .286 95% BCa CI [.097, .462], p = .002, but that general grading is not significantly related to the willingness to pay, r = .149 95% BCa CI [-.049, .323], p = . 190. Correlations between the other given prices (too low, expensive, too expensive) and general grading are also checked, but were not significant (see Appendix 4.3).

7.3.2. Energy production

The relations between the total energy production of a participant and the two consideration variables are also evaluated with bivariate correlation analyses. The results show that there was no significant relationship between the total produced energy of a user and the likelihood to buy a solar bike, τ = -.071 95% BCa CI [-.265, .146], p = .462, and neither between the total produced energy and the willingness to pay for a solar wheel, r =-.020 95% BCa CI [-.199, .212], p = .880. Correlations between the other given prices (too low, expensive, too expensive) and energy production are also checked, but were also not significant (see Appendix 4.3). It could be that if participants had a longer testing period, they would start noticing the energy production of the solar wheel. Then it is possible that participants start seeing financial benefits in terms of cost savings on their energy bill, however charging a 300 Wh battery only costs around €0,10. Buying a solar wheel of €700,- will not provide financial profits for the first 19 years, when charging every day.

7.3.3. Ordinal regression

Since a significant relationship only is found between general grading and likelihood to buy, only an ordinal regression analysis is performed for the likelihood to buy a solar bike, with general grading as predicting variable. Before the regression is ran in IBM SPSS Statistics (IBM Corp., Released 2016), there are some assumptions the data should satisfy (Lund Research LtD, 2017):

1. The dependent variable should be measured at the ordinal level;
2. There are two or more independent variables, which can be either continuous, or categorical;
3. The data must not show multicollinearity;
4. There have to be proportional odds.

In this case, likelihood to buy is the dependent variable, being ordinal (assumption 1). The independent variable is general grading, being continuous (assumption 2). There is only one independent variable, so multicollinearity is not possible (assumption 3). A test of parallel lines is used to check whether there are proportional odds (assumption 4).

The results of the regression (see Appendix 4.3) show that an increase in general grading was associated with an increase in the odds of the likelihood to buy a solar bike, with an odds ratio of 1.730 (95% CI, 1.86 to 2.523), Wald $\chi^2(1)$ = 8.112, p = 0.004. The proportional odds assumption (4) holds, since the significance of Chi-Square statistic of the parallel lines test is 0.493 (> 0.05).

7.4. Conclusion

The claim of Fyhri & Fearnley (2015) appears to apply in this situation considering transportation mode choice preferences. The intervention on the transportation mode behavior of the employees had effect on their transportation mode preferences, concerning the solar bike. However, testing the solar bike did decrease the likelihood to buy a solar bike of users. After testing, only 14% of the participants had a positive stand in the likelihood to buy a solar bike. With respect to the conceptual model, the relationship between energy production and the consideration to use the solar bike for commuting is not significant, yet for the user satisfaction there is a positive significant relationship, though this is only present for likelihood to buy as consideration variable.

8. Conclusion and recommendations

In this chapter, the main conclusion of the research is given together with some recommendations.

8.1. Conclusion

The aim of this research was to evaluate the influence of different characteristic on user satisfaction of the solar bike, on energy production of the solar bike, and transportation mode choices of participants. The research questions were:

What is the influence of different factors on the performance of the solar bike?

To get more insight in factors playing role in the user satisfaction and transportation mode choices of people, literature and OViN data is evaluated to answer the first research question:

1. *What are differences between e-bike commuters and regular bicycle commuters?*

Important factors playing role in the transportation mode choices of commuters that were derived from literature are basically cost, time, and effort. E-commuting costs less effort than regular commuting and saves time. Furthermore, the accessibility to a transportation mode is important. From the OViN evaluation it can be concluded that the mean travel speed and age of e-commuters is higher than for regular commuters. Also, the commuting distance of e-commuters is larger than for regular commuters, and e-commuter's households own substantially more e-bikes than regular commuter's households.

To evaluate the influences on energy production of the solar bike, the solar bike data on energy production is analyzed to answer the second research question:

2. *What is the effect of different factors on the energy production of the solar bike?*

The hypothesis was that solar radiation would have a great influence on the energy production, and that different parking strategies result in different intensities of the relationship between energy production and solar radiation. Furthermore, it was expected that commuting distance would have influence on the energy production during a commute. However, the analyses show that this last relationship is not significant. The relationship between solar radiation and energy production is significant, but not large given that the measurements of solar radiation were not done at the exact locations of the solar bikes. From the descriptive statistics follows that a parking strategy that allows much daylight reaching the bike, results in the highest energy production efficiency. Nevertheless, the maximum measured power production is much lower than the maximum power production possible, tested in a lab.

To evaluate the user satisfaction on the solar bike, the survey data is analyzed to answer the third research question:

3. *What is the user experience of the solar bike?*

From the evaluation of the survey data, it may be concluded that the general experience of the solar bike is quite positive. The most influential factors on the general grading are crosswind hindrance, the suitability of the solar bike for commuting, the likelihood to buy a solar bike and two attitudes: solar bike flexibility and solar bike sustainability. The hypothesis stated was that user characteristics age and commuting distance also would have influence, tough this appears not to be true. With respect to crosswind hindrance, a positive significant correlation is found between the complaints about crosswind hindrance and mean wind speeds during the test days of participants.

To evaluate the transportation mode choices of participants and their consideration to use a solar bike for commuting the transportation mode preferences and likelihood to buy a solar bike are analyzed to answer the fourth research question:

4. *What is the relation between user satisfaction, energy production and the consideration to use a solar bike for commuting?*

The hypothesis that experiencing a new transportation mode would have influence on the transportation mode choice preferences is met. There is a slight increase in solar bike choices in transportation mode choice situation after testing. However, the likelihood to buy a solar bike decreased. Correlation analyses showed that energy production is not significant related to either the likelihood to buy, or the willingness to pay. Tough, general grading is significantly related to the likelihood to buy. An increase in general grading is associated with an increase of the likelihood to buy a solar bike.

In Figure 12 the conceptual model is revised with the findings that follow from the evaluations.

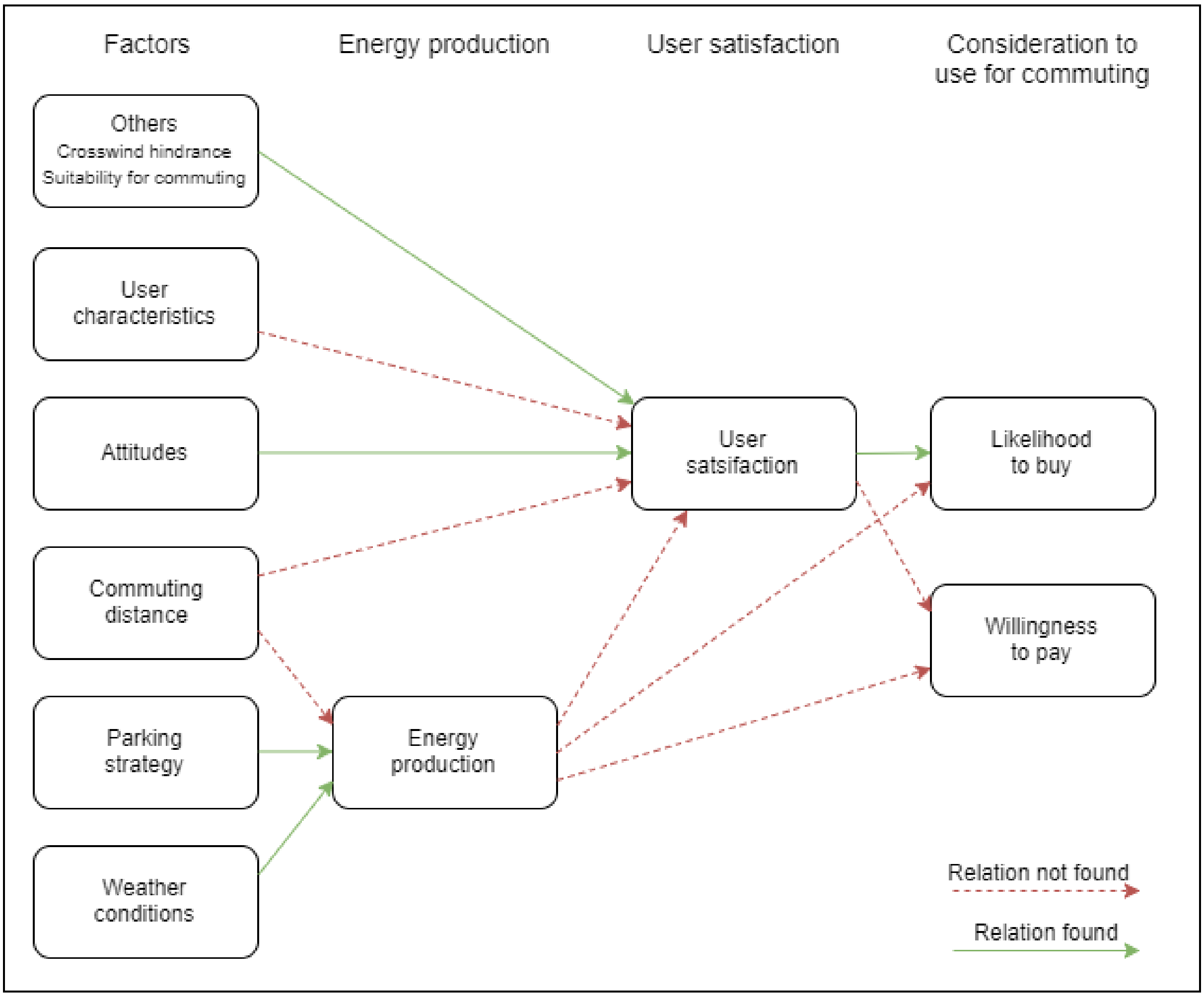

Figure 12 Conclusion of conceptual model

Overall can be concluded that many factors influence the performance of the solar bike. The influences on the three performance categories that were expected and sketched in the conceptual model are not all found. The evaluations show that solar radiation and bike parking strategies only have small relationship with the energy production of the solar bike, and that commuting distance has no

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significant relationship. Most important factors influencing the user satisfaction are the suitability of the solar bike for commuting, two attitudes: solar bike flexibility and solar bike sustainability, and crosswind hindrance. This last factor is also significantly related wind speeds. The user characteristics, and also commuting distance do not have a significant relationship with the user satisfaction. Furthermore, there is no significant relationship between energy production and user satisfaction, and also not with the consideration to use a solar bike for commuting. Tough, user satisfaction is significantly related to the likelihood to buy a solar bike, one of the consideration variables.

8.2. Recommendations

For further research regarding solar bike energy analyses, it is recommended to make use of GPS data to determine the location of a bike. It than becomes easier to determine whether a participant was travelling with a bike or had it parked. Also, more accurate locations for the weather measurements probably will lead to better correlations. Furthermore, applying another method for aggregation to handle the discontinuity of the data, could result in better outcomes.

For research related to user experience evaluation, it may be recommended to set up a survey for the research itself, so that all aspects relevant for the research are included in the data. Now, it was not possible to evaluate all factors that are importing in transportation mode choices of people, e.g. from utility theory the factors time and effort.

Furthermore, I would like to recommend for any research related to transportation of people to analyze some OViN data. This can be a valuable starting point for research.

9. Bibliography

Aarts, H., Verplanken, B., & van Knippenberg, A. (1997). Habit and information use in trave mode choices. *Acta Psychologica, 96*, 1-14.

BOVAG & RAI Vereniging. (2016). Kerncijfers . *Tweewielers 2016*. Amsterdam: Stichting BOVAG RAI Mobiliteit.

CBS. (2014). Onderzoek Verplaatsingen in Nederland 2013. Den Haag: Centraal Bureau voor de Statistiek.

CBS. (2015). Onderzoek Verplaatsingen in Nederland 2014. Den Haag: Centraal Bureau voor de Statistiek.

CBS. (2016). Onderzoek Verplaatsingen in Nederland 2015. Den Haag: Centraal Bureau voor de Statistiek.

CBS. (2016). *Transport en mobiliteit 2016.* Den Haag: Centraal Bureau voor de Statistiek.

Collins, C. M., & Chambers, S. M. (2005). Psychological and situational influences on commutertransport-mode choice. *Environment and behavior, 37:5*, 640-661.

Donaghy, K. (2011). Models of travel demand with endogenous preference change and heterogeneous agents. *J. Geogr. Syst. 13*, 17-30.

European Environment Agency. (2016). *Air quality in Europe - 2016 report.* Luxemburg: Publication Office of the European Union.

Field, A. (2013). *Discovering Statistics Using IBM SPSS Statistics.* London: SAGE Publications.

Fyhri, A., & Fearnley, N. (2015). Effects of e-bikes on bicycle use and mode share. *Transportation Research Part D: Transport and Environment 36*, 45-52.

Haustein, S., & Møller, M. (2016). Age and attitude: Changes in cycling patterns of different e-bike user segments. *International Journal of Sustainable Transportation, 10:9*, 836-846.

Heinen, E. (2011). *Bicycle commuting; Proefschrift.* Delft: Delft University Press.

Heinen, E., Maat, K., & van Wee, B. (2011). Day-to-Day Choice to Commute or Not to Bicycle. *Transportation Research Record: Journal of the Transportation Research Board, 2230*, 9-18.

Heinen, E., Maat, K., & van Wee, B. (2011). The role of attitudes toward characteristics of bicycle commuting on the choice to cycle to work over various distances. *Transportation Research Part D, 16*, 102-109.

Heinen, E., Maat, K., & van Wee, B. (2013). The effect of work-related factors on the bicycle commute mode choice in the Netherlands. *Transporation, 40*, 23-43.

Heinen, E., van Wee, B., & Maat, K. (2010). Commuting by Bicycle: An Overview of the Literature. *Transport Reviews, 30:1*, 59-96.

IBM Corp. (Released 2016). IBM SPSS Statistics for Windows, Version 24.0. Armonk, NY: IBM Corp.

Jones, P., & Sloman, L. (2010). Encouraging behavioural change through marketing and management: what can be achieved? *10th International Conference on Travel Behaviour Research.* Lucerne.

Kennisinstituut voor Mobiliteit (KiM). (2016). *Mobiliteitsbeeld 2016.* Den Haag: Ministerie van Infrastructuur en Milieu.

KNMI. (2017, April). *Dag gegevens van het weer in Nederland.* Retrieved from Koninklijk Nederlands Meteorologisch Instituut: https://www.knmi.nl/nederland-nu/klimatologie/daggegevens

Kroesen, M. (2017). To what extent do e-bikes substitute travel by other modes? Evidence from the Netherlands. *Transport Research Part D, 53*, 377-387.

Lund Research LtD. (2017, May). *How to perform a Multiple Regression Analysis in SPSS Statistics | Laerd Statistics*. Retrieved from SPSS Statistics Tutorials and Statistical Guides | Laerd Statistics: https://statistics.laerd.com/spss-tutorials/multiple-regression-using-spss-statistics.php

Lund Research LtD. (2017, July). *How to perform an Ordinal Regression in SPSS | Laerd Statistics*. Retrieved from SPSS Statistics Tutorials and Statistical Guides | Laerd Statistics: https://statistics.laerd.com/spss-tutorials/ordinal-regression-using-spss-statistics.php

Reinders, A. (2017, April). *Solar powered E-bikes: Monitoring and analysis of a sustainable mobility system*. Retrieved from AriseTogether: http://arisetogether.nl/portfolio/solar-powered-ebikes-monitoring-and-analysis-of-a-sustainable-mobility-system/

SWOV. (2016, December). SWOV-factsheet. *Electrische fietsen en speed-pedelecs*. Den Haag.

Taniguchi, A., & Fujii, s. (2007). Promoting public transport using marketing techniques in mobility management and verifying their quantitative effects. *Transportation 34:1*, 37-49.

The MathWorks, Inc. (2016). MATLAB R2016b. Natick, MA.

Vinken, S. (2016). *Understanding the product acceptance of Solar Bikes.* Eindhoven.

Wardman, W., Tight, M., & Page, M. (2007). Factors influencing the propensity to cycle to work. *Transportation Research Part A, 41*, 339-350.

10. Appendices

1. Appendices differences between commuters

1.1. Results independent sample tests OViN

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Distance	Equal variances assumed	111,528	,000	13,140	14378	,000	18,309	1,393	15,578	21,040
	Equal variances not assumed			10,174	1190,557	,000	18,309	1,800	14,778	21,840
Household's disposable income class	Equal variances assumed	12,777	,000	-,420	14378	,674	-,019	,044	-,105	,068
	Equal variances not assumed			-,446	1305,615	,656	-,019	,042	-,100	,063
Average travel speed [km/h]	Equal variances assumed	1,043	,307	4,746	14376	,000	2,177350059	,4587727691	1,278096243	3,076603875
	Equal variances not assumed			7,558	1708,653	,000	2,177350059	,2880834545	1,612316614	2,742383504
Age	Equal variances assumed	406,656	,000	24,696	14378	,000	11,546	,468	10,630	12,463
	Equal variances not assumed			32,906	1472,215	,000	11,546	,351	10,858	12,235
Amount of cars in household	Equal variances assumed	3,928	,047	4,344	14378	,000	,107	,025	,059	,155
	Equal variances not assumed			4,222	1264,478	,000	,107	,025	,057	,157
Amount of E-bikes in household	Equal variances assumed	583,284	,000	85,776	14378	,000	1,260	,015	1,231	1,289
	Equal variances not assumed			63,036	1178,467	,000	1,260	,020	1,221	1,299
Amount of regular bikes in household	Equal variances assumed	6,203	,013	-23,922	14378	,000	-1,491	,062	-1,614	-1,369
	Equal variances not assumed			-24,630	1290,710	,000	-1,491	,061	-1,610	-1,373

1.2. Cross table of amount of vehicles in household per disposable income class

Mean amounts of per commuter its household				Cars	Motorcycles	Mopeds	Light mopeds	Regular bicycles	Electric-bicycles
Household's disposable income class	1	Type of commuter	Electric	1.000	0.000	0.000	0.000	0.800	1.000
			Regular	0.523	0.045	0.032	0.026	2.695	0.065
		Mean		0.538	0.044	0.031	0.025	2.635	0.094
	2	Type of commuter	Electric	0.532	0.000	0.051	0.025	0.924	1.114
			Regular	0.454	0.070	0.049	0.032	2.087	0.030
		Mean		0.459	0.065	0.049	0.032	2.009	0.103
	3	Type of commuter	Electric	0.852	0.074	0.049	0.089	1.305	1.320
			Regular	0.819	0.064	0.054	0.036	2.784	0.093
		Mean		0.821	0.065	0.054	0.041	2.658	0.198
	4	Type of commuter	Electric	1.112	0.120	0.060	0.068	2.151	1.382
			Regular	1.106	0.114	0.067	0.048	3.674	0.127
		Mean		1.107	0.114	0.066	0.050	3.548	0.231
	5	Type of commuter	Electric	1.465	0.119	0.095	0.086	2.523	1.514
			Regular	1.269	0.148	0.081	0.060	4.174	0.141
		Mean		1.286	0.145	0.082	0.062	4.037	0.255
	6	Type of commuter	Electric	1.758	0.172	0.060	0.079	3.334	1.407
			Regular	1.568	0.167	0.091	0.047	4.674	0.152
		Mean		1.581	0.167	0.089	0.049	4.585	0.236
	7	Type of commuter	Electric	1.000	0.000	0.000	0.000	1.000	1.000
			Regular	0.686	0.286	0.000	0.000	2.114	0.114
		Mean		0.718	0.256	0.000	0.000	2.000	0.205
	All classes	Type of commuter	Electric	1.277	0.000	0.064	0.075	2.299	1.383
			Regular	1.170	0.000	0.073	0.046	3.790	0.123
		Mean		1.179	0.124	0.072	0.049	3.677	0.218

1.3. Descriptive statistics survey data

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
General grading	79	3	9	6,84	1,126
Crosswind hindrance	79	1	4	2,63	,908
Age	79	20	72	44,48	10,586
Gender	79	1	2	1,39	,491
Weight	79	0	108	76,47	14,663
Length	79	160	200	177,54	9,322
Commuting distance	79	1	56	10,32	9,367
Amount of exercise per day	79	1	5	4,25	1,138
Level of education	79	2	9	6,29	1,360
Gross income	79	1	5	3,89	1,038
Amount of testing days	79	1	8	4,94	1,580
E-bike user	79	0	1	,18	,384
Flexibility	79	1	5	3,06	,837
Elderly image	79	1	4	1,89	,862
Sportive image	79	1	4	2,27	,902
Trendy and innovative image	79	1	5	3,73	,916
Attractiveness due to theft	79	1	5	3,19	,988
Healthy life style contribution	79	1	5	3,66	,815
Sustainable contribution	79	2	5	4,04	,669
Suitable for commuting	79	1	5	3,76	,964
Suitable for recreation	79	1	5	3,51	,972
Amount of solar bike choice preferences (pre)	79	0	9	2,25	2,514
Amount of solar bike choice preferences (post)	79	0	9	2,67	2,654

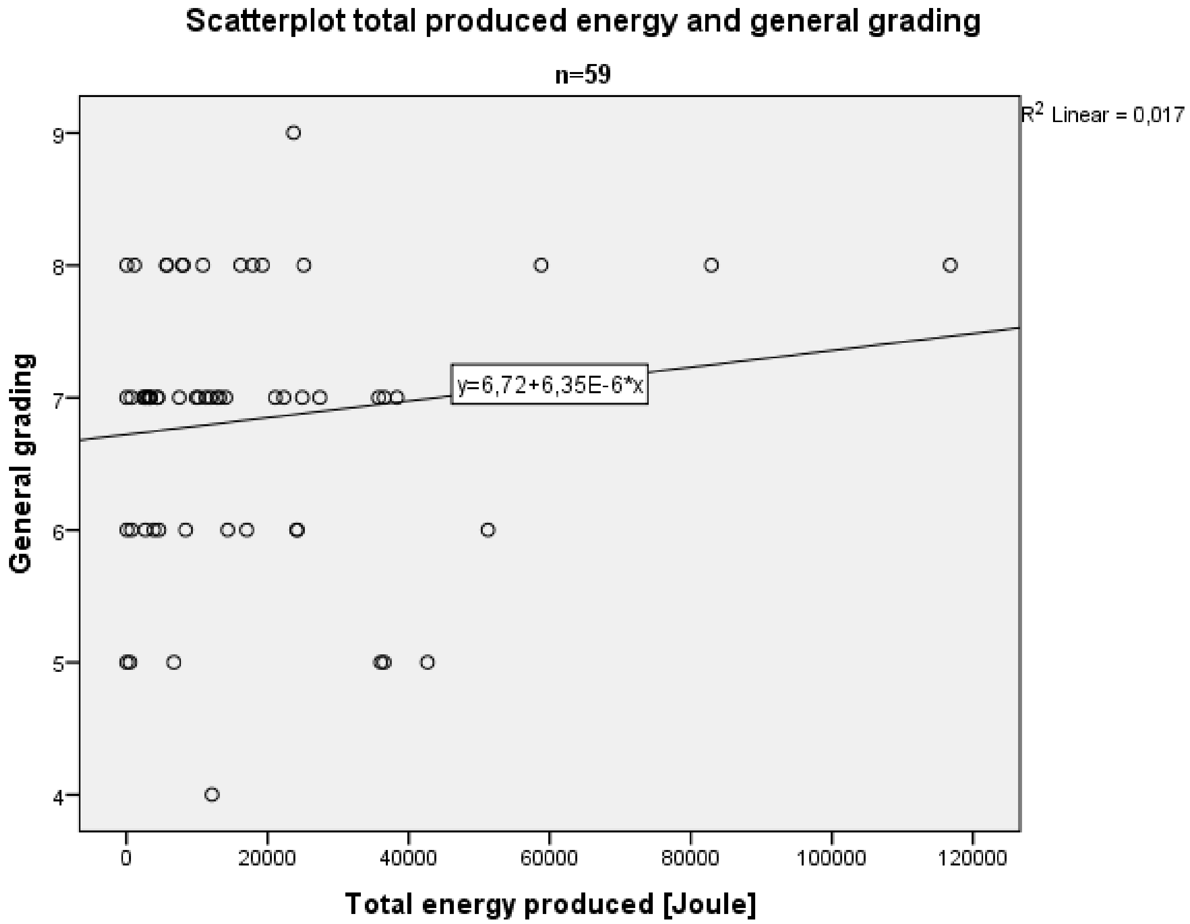
1.4. Comparison survey data – OviN data

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Age	Equal variances assumed	,656	,418	-7,109	1169	,000	-8,896	1,251	-11,352	-6,441
	Equal variances not assumed			-7,205	90,041	,000	-8,896	1,235	-11,349	-6,443
Gender	Equal variances assumed	,174	,677	-4,019	1169	,000	-,22756	,05662	-,33865	-,11646
	Equal variances not assumed			-3,978	89,379	,000	-,22756	,05721	-,34122	-,11390
Commuting distance	Equal variances assumed	10,874	,001	6,111	1169	,000	4,35712	,71297	2,95827	5,75596
	Equal variances not assumed			4,078	82,411	,000	4,35712	1,06843	2,23184	6,48239

2. Appendices energy production analyses

2.1. Correlation between energy production and general grading



Correlations

				Total energy produced	General grading
Total energy produced	Pearson Correlation			1	,131
	Sig. (2-tailed)				,323
	N			59	59
	Bootstrap[c]	Bias		0	-,016
		Std. Error		0	,136
		BCa 95% Confidence Interval	Lower	.	-,167
			Upper	.	,322
General grading	Pearson Correlation			,131	1
	Sig. (2-tailed)			,323	
	N			59	59
	Bootstrap[c]	Bias		-,016	0
		Std. Error		,136	0
		BCa 95% Confidence Interval	Lower	-,167	.
			Upper	,322	.

c. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

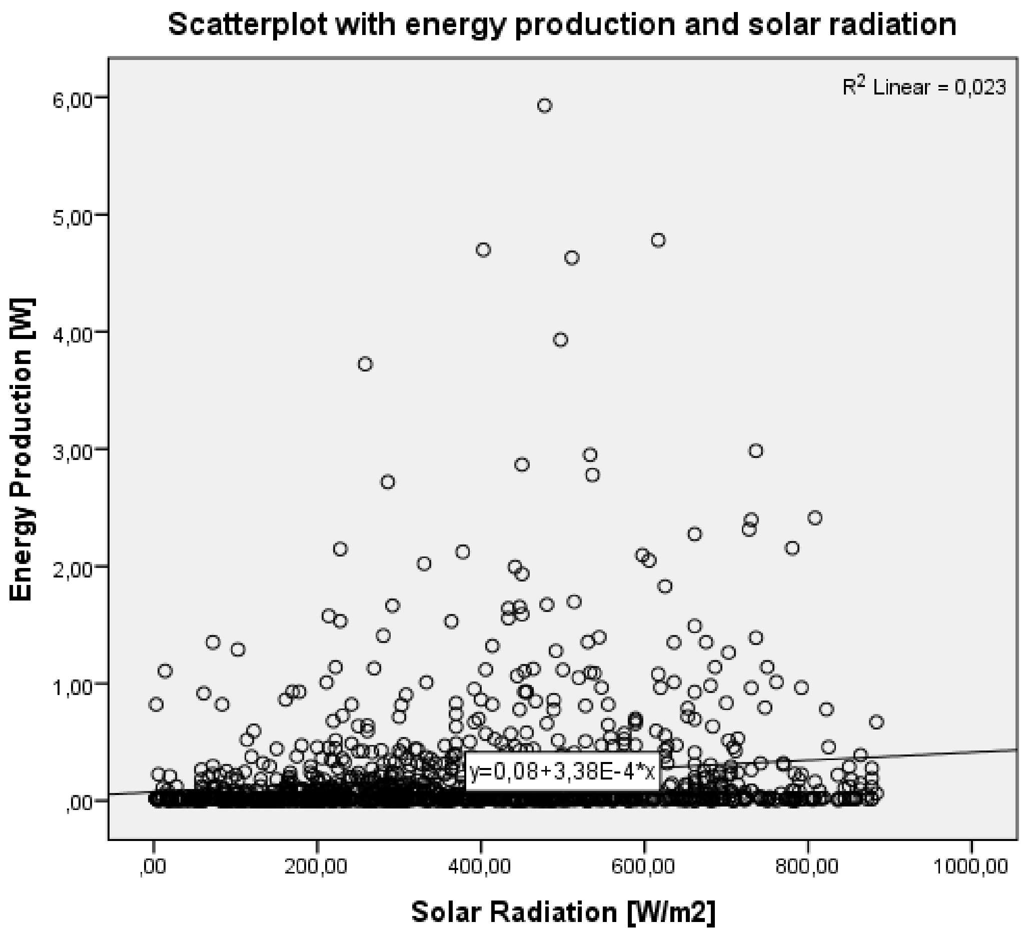
2.2. Descriptive statistics energy variables

Descriptive Statistics

All hours 9 AM – 7 PM	N	Minimum	Maximum	Mean	Std. Deviation
Energy Production	1315	,00	5,93	,2010	,48334
Solar Radiation	1315	2,78	883,33	371,8864	218,73143
Factor	1315	,00	,49	,0016	,01438
Valid N (listwise)	1315				

Descriptive Statistics

Strategy variable		N	Minimum	Maximum	Mean	Std. Deviation
1	Energy Production	296	,00	2,31	,1822	,38352
	Solar Radiation	296	36,11	883,33	409,5533	213,22395
	Factor	296	,00	,02	,0008	,00205
	Valid N (listwise)	296				
2	Energy Production	517	,00	5,93	,2053	,47781
	Solar Radiation	517	44,44	877,78	403,6106	205,29425
	Factor	517	,00	,02	,0009	,00179
	Valid N (listwise)	517				
3	Energy Production	67	,00	1,65	,2365	,39508
	Solar Radiation	67	19,44	750,00	323,5904	192,79869
	Factor	67	,00	,03	,0022	,00479
	Valid N (listwise)	67				
4	Energy Production	97	,00	2,28	,2324	,41380
	Solar Radiation	97	166,67	883,33	556,9874	206,96973
	Factor	97	,00	,02	,0009	,00187
	Valid N (listwise)	97				



2.3. Results regression energy production

2.3.1. Parking analysis

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Strategy variable, Solar radiation per hour[b]	.	Enter

a. Dependent Variable: Energy per hour
b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,139[a]	,019	,017	1566,39983000	1,936

a. Predictors: (Constant), Strategy variable, Solar radiation per hour
b. Dependent Variable: Energy per hour

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	47264286,520	2	23632143,260	9,632	,000[b]
	Residual	2392268217,000	975	2453608,428		
	Total	2439532504,000	977			

a. Dependent Variable: Energy per hour
b. Predictors: (Constant), Strategy variable, Global radiation per hour

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	245,831	148,696		1,653	,099		
	Global radiation per hour	2,782	,658	,135	4,229	,000	,984	1,017
	Strategy variable	35,922	57,647	,020	,623	,533	,984	1,017

a. Dependent Variable: Energy per hour

Bootstrap for Coefficients

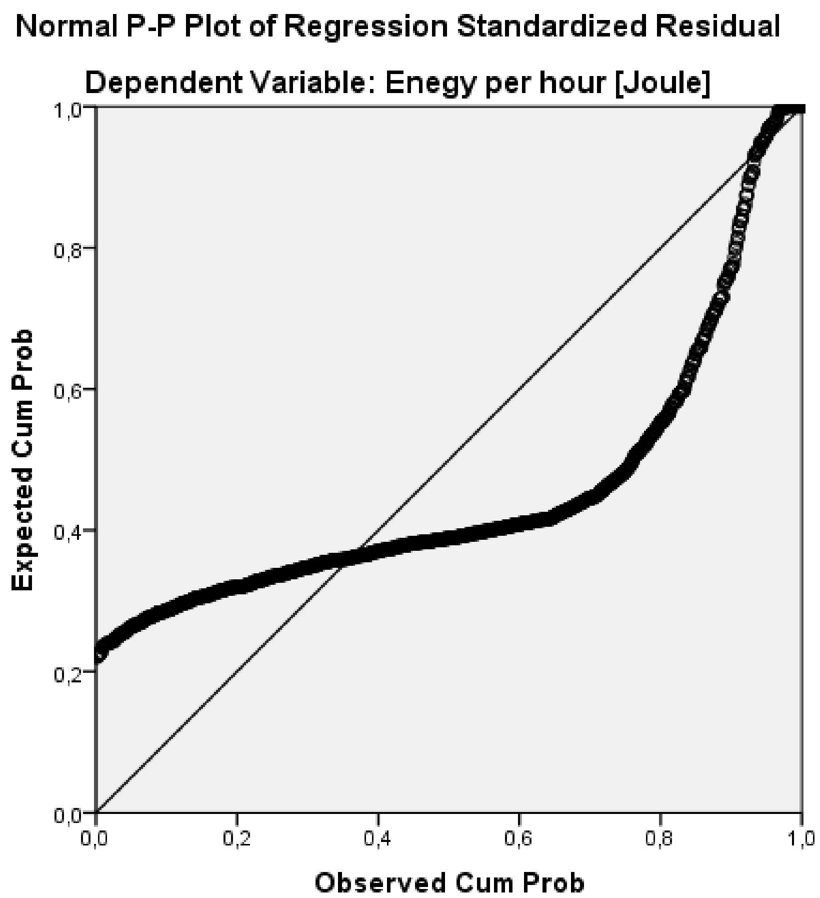
Model		B	Bootstrap[a]				
			Bias	Std. Error	Sig. (2-tailed)	BCa 95% Confidence Interval	
						Lower	Upper
1	(Constant)	245,831	-3,246	104,245	,022	48,083	444,121
	Global radiation per hour	2,782	-,013	,629	,001	1,645	3,978
	Strategy variable	35,922	2,207	54,419	,516	-69,560	150,991

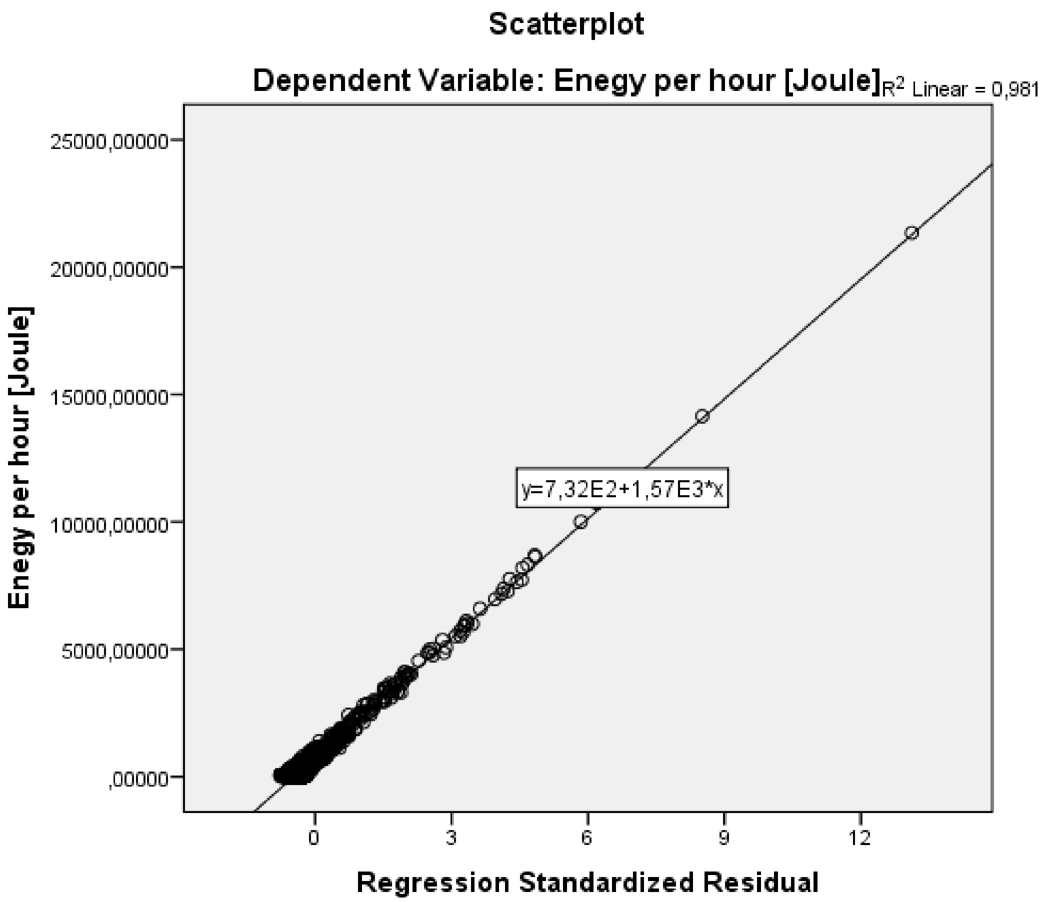
a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	281,7529602	1274,0555420	731,6441795	219,94762220	978
Residual	-1209,74865700	20549,14844000	,00000000	1564,79573400	978
Std. Predicted Value	-2,045	2,466	,000	1,000	978
Std. Residual	-,772	13,119	,000	,999	978

a. Dependent Variable: Energy per hour





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2.3.2. Trip analysis

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Global radiation per hour[b]	.	Enter

a. Dependent Variable: Energy per hour
b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,243[a]	,059	,056	2108,64326600	1,598

a. Predictors: (Constant), Global radiation per hour
b. Dependent Variable: Energy per hour

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	90993681,120	1	90993681,120	20,465	,000[b]
	Residual	1445072338,000	325	4446376,425		
	Total	1536066019,000	326			

a. Dependent Variable: Energy per hour
b. Predictors: (Constant), Global radiation per hour

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	31,925	190,268		,168	,867		
	Global radiation per hour	8,034	1,776	,243	4,524	,000	1,000	1,000

a. Dependent Variable: Energy per hour

Bootstrap for Coefficients

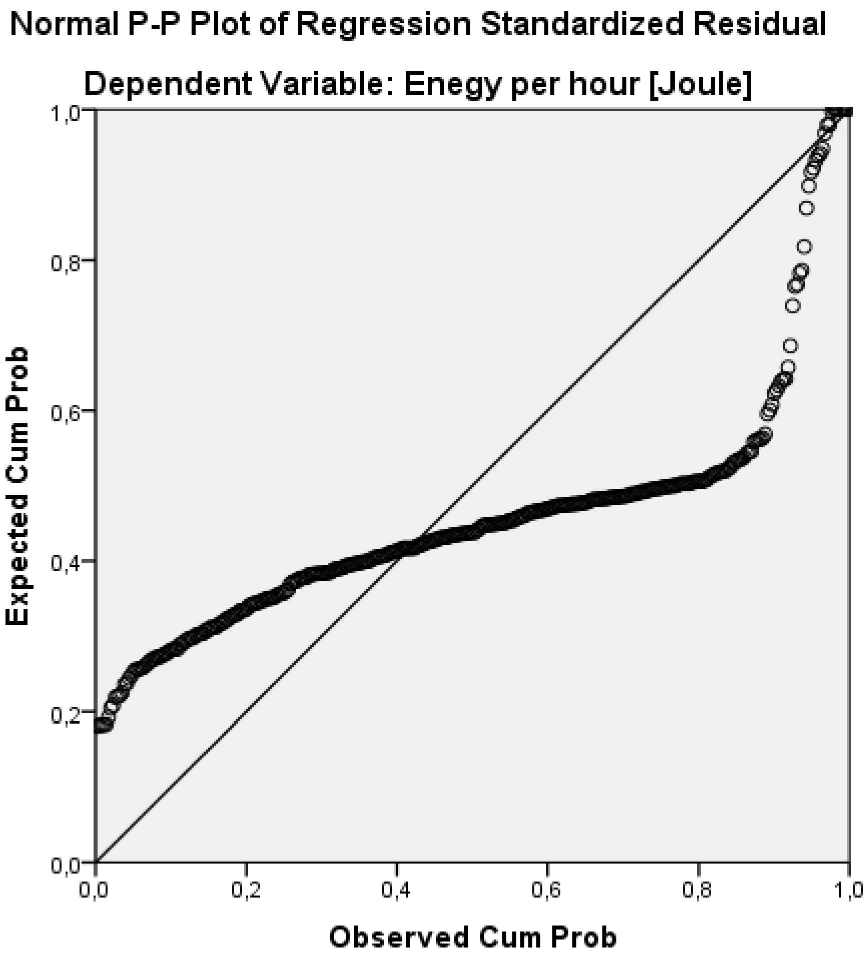
Model		B	Bootstrap[a]				
			Bias	Std. Error	Sig. (2-tailed)	BCa 95% Confidence Interval	
						Lower	Upper
1	(Constant)	31,925	10,597	127,448	,822	-300,347	301,001
	Global radiation per hour	8,034	-,131	2,349	,007	4,378	12,331

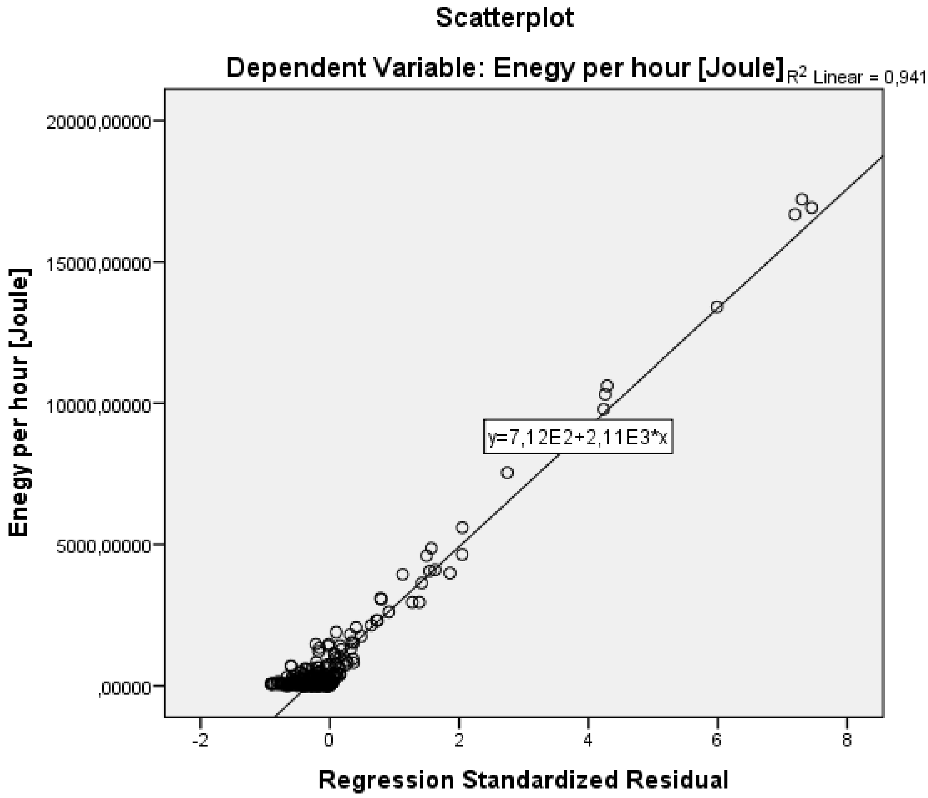
a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	31,9250031	1992,2960210	712,0647380	528,31971500	327
Residual	-1924,23486300	15711,90332000	,00000000	2105,40666700	327
Std. Predicted Value	-1,287	2,423	,000	1,000	327
Std. Residual	-,913	7,451	,000	,998	327

a. Dependent Variable: Energy per hour


Normal P-P Plot of Regression Standardized Residual
Dependent Variable: Enegy per hour [Joule]
Expected Cum Prob
Observed Cum Prob
1,0
0,8
0,6
0,4
0,2
0,0
0,0
0,2
0,4
0,6
0,8
1,0

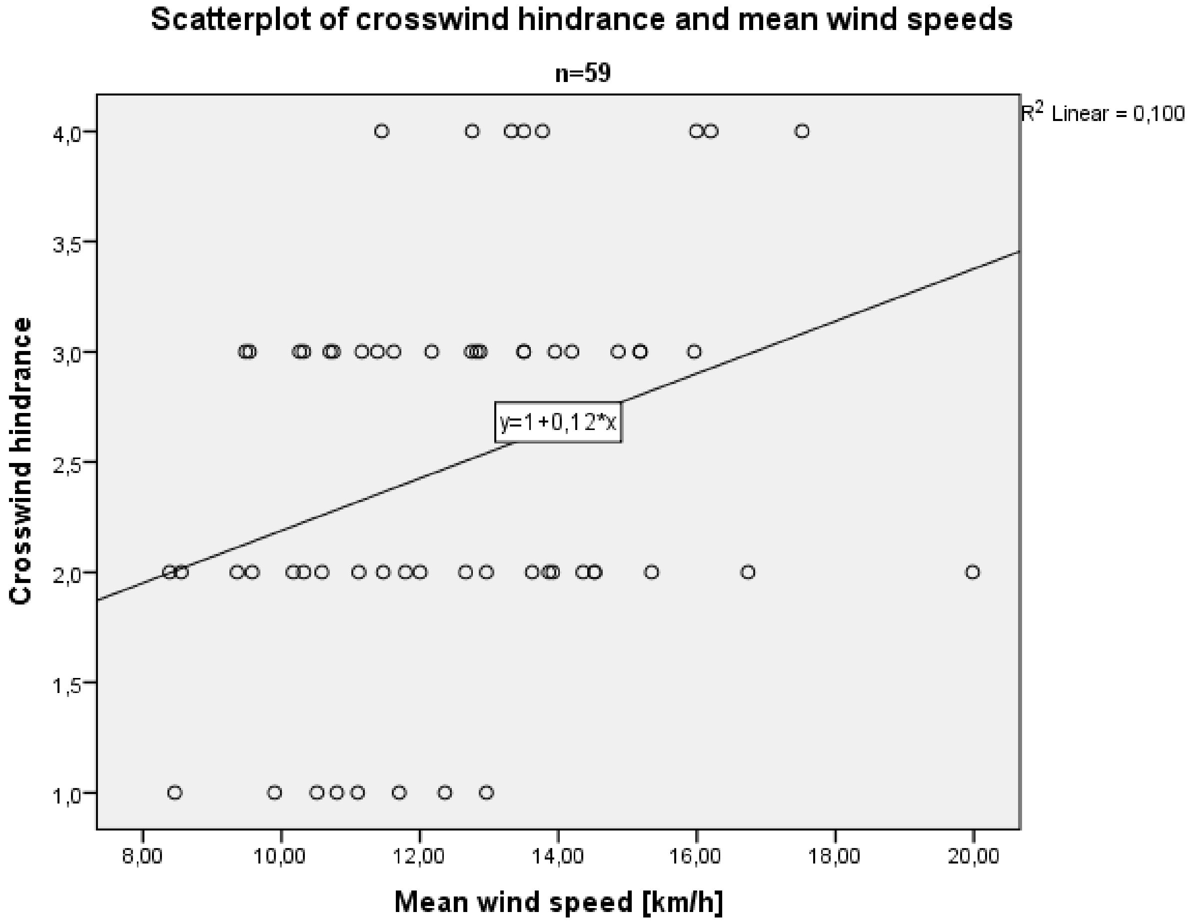

Scatterplot
Dependent Variable: Enegy per hour [Joule]
R2 Linear = 0,941
y=7,12E2+2,11E3*x
Enegy per hour [Joule]
20000,00000
15000,00000
10000,00000
5000,00000
,00000
-2
0
2
4
6
8
Regression Standardized Residual

3. Appendices user satisfaction analyses

3.1. Correlation between crosswind hindrance and mean wind speeds

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Mean wind speed [km/h]	59	8,38	19,98	12,5463	2,39538
Valid N (listwise)	59				



3.2. General grading

3.2.1. Descriptive statistics general grading

Descriptive Statistics

		Statistic	Bootstrap[a] Bias	Bootstrap[a] Std. Error	BCa 95% Confidence Interval Lower	BCa 95% Confidence Interval Upper
General grading	N	79	0	0	.	.
	Minimum	3				
	Maximum	9				
	Mean	6,84	,00	,13	6,59	7,06
	Std. Deviation	1,126	-,013	,106	,930	1,294
Valid N (listwise)	N	79	0	0	.	.

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

3.2.2. Comparison e-bike users and non-e-bike users

Group Statistics

	E-bike user	N	Mean	Std. Deviation	Std. Error Mean
General grading	1	14	6,43	1,399	,374
	0	65	6,92	1,050	,130

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
General grading	Equal variances assumed	2,200	,142	-1,503	77	,137	-,495	,329	-1,150	,161
	Equal variances not assumed			-1,249	16,302	,229	-,495	,396	-1,332	,343

3.3. Correlations between user experience factors and general grading UT – TU/e

Location:	***UT (Enschede) n = 37***		***TU/e (Eindhoven) n = 42***	
Correlation between general grading and:	Kendall's τ Pearson's *r*	*p*-value	Kendall's τ Pearson's *r*	*p*-value
Crosswind hindrance	***τ = -.495***	***.000***	τ = -.084	.534
Age	*r* = -.103	.543	*r* = .441	.003
Gender	τ = .288	.130	τ = -.063	.665
Weight	τ = -.144	.395	τ = .229	.145
Length	*r* = -.224	.183	*r* = .079	.621
Commuting distance	*r* = .209	.215	*r* = .126	.428
Amount of exercise per day	τ = -.085	.554	τ = .026	.845
Educational level	τ = -.008	.954	τ = .101	.439
Gross income	τ = -.037	.792	τ = .127	.339
Amount of testing days	***r = .408***	***.012***	*r* = .000	1.000
Good price for solar wheel	*r* = .196	.244	*r* = .079	.619
1. SBike flexibility	***τ = .466***	***.001***	***τ = .309***	***.022***
2. SBike elderly image	τ = -.142	.317	τ = .036	.792
3. SBike sportive image	τ = .031	.827	τ = -.067	.619
4. SBike trendy and innovative image	***τ = .303***	***.035***	τ = .242	.072
5. SBike attractiveness due to theft	τ = -.135	.332	***τ = -.431***	***.001***
6. SBike healty life style contribution	***τ = .294***	***.041***	τ = .024	.860
7. SBike sustainable contribution	***τ = .313***	***.030***	τ = .231	.095
Suitable for commuting	***τ = .541***	***.000***	***τ = .481***	***.000***
Suitable for recreation	***τ = .513***	***.000***	***τ = .323***	***.015***
Likelihood to buy	***τ = .344***	***.010***	τ = .200	.126

3.4. Results regression analysis of general grading

3.4.1. Backward method

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Suitable for recreation, Flexibility, Crosswind hindrance, Trendy and innovative image, Amount of testing days, Attractiveness due to theft, Sustainable contribution, Suitable for commuting[b]	.	Enter
2	.	Trendy and innovative image	Backward (criterion: Probability of F-to-remove >= ,100).
3	.	Suitable for recreation	Backward (criterion: Probability of F-to-remove >= ,100).
4	.	Attractiveness due to theft	Backward (criterion: Probability of F-to-remove >= ,100).
5	.	Amount of testing days	Backward (criterion: Probability of F-to-remove >= ,100).

a. Dependent Variable: General grading
b. All requested variables entered.

Model Summary[a]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,705[b]	,497	,440	,843	
2	,703[c]	,494	,444	,839	
3	,699[d]	,488	,445	,838	
4	,691[e]	,477	,441	,841	
5	,679[f]	,460	,431	,849	2,062

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	49,152	8	6,144	8,652	,000[b]
	Residual	49,709	70	,710		
	Total	98,861	78			
2	Regression	48,853	7	6,979	9,909	,000[c]
	Residual	50,007	71	,704		
	Total	98,861	78			
3	Regression	48,242	6	8,040	11,436	,000[d]
	Residual	50,619	72	,703		
	Total	98,861	78			
4	Regression	47,178	5	9,436	13,328	,000[e]
	Residual	51,682	73	,708		
	Total	98,861	78			
5	Regression	45,517	4	11,379	15,785	,000[f]
	Residual	53,344	74	,721		
	Total	98,861	78			

a. Dependent Variable: General grading
b. Predictors: (Constant), Suitable for recreation, Flexibility, Crosswind hindrance, Trendy and innovative image, Amount of testing days, Attractiveness due to theft, Sustainable contribution, Suitable for commuting
c. Predictors: (Constant), Suitable for recreation, Flexibility, Crosswind hindrance, Amount of testing days, Attractiveness due to theft, Sustainable contribution, Suitable for commuting
d. Predictors: (Constant), Flexibility, Crosswind hindrance, Amount of testing days, Attractiveness due to theft, Sustainable contribution, Suitable for commuting
e. Predictors: (Constant), Flexibility, Crosswind hindrance, Amount of testing days, Sustainable contribution, Suitable for commuting
f. Predictors: (Constant), Flexibility, Crosswind hindrance, Sustainable contribution, Suitable for commuting

3.4.2. Enter method

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Crosswind hindrance, Flexibility, Sustainable contribution, Suitable for commuting[b]	.	Enter

a. Dependent Variable: General grading
b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,679[a]	,460	,431	,849	2,062

a. Predictors: (Constant), Crosswind hindrance, Flexibility, Sustainable contribution, Suitable for commuting
b. Dependent Variable: General grading

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	45,517	4	11,379	15,785	,000[b]
	Residual	53,344	74	,721		
	Total	98,861	78			

a. Dependent Variable: General grading
b. Predictors: (Constant), Crosswind hindrance, Flexibility, Sustainable contribution, Suitable for commuting

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	3,721	,737		5,050	,000		
	Crosswind hindrance	-,320	,110	-,258	-2,906	,005	,924	1,082
	Flexibility	,318	,121	,236	2,628	,010	,903	1,108
	Sustainable contribution	,322	,154	,191	2,095	,040	,877	1,141
	Suitable for commuting	,448	,108	,384	4,164	,000	,858	1,165

a. Dependent Variable: General grading

Bootstrap for Coefficients

Model		B	Bootstrap[a] Bias	Bootstrap[a] Std. Error	Bootstrap[a] Sig. (2-tailed)	BCa 95% Confidence Interval Lower	BCa 95% Confidence Interval Upper
1	(Constant)	3,721	-,056	,765	,001	2,211	5,033
	Crosswind hindrance	-,320	,015	,130	,028	-,608	-,031
	Flexibility	,318	,003	,087	,002	,143	,488
	Sustainable contribution	,322	,000	,198	,124	-,042	,715
	Suitable for commuting	,448	,005	,112	,001	,208	,668

Collinearity Diagnostics[a]

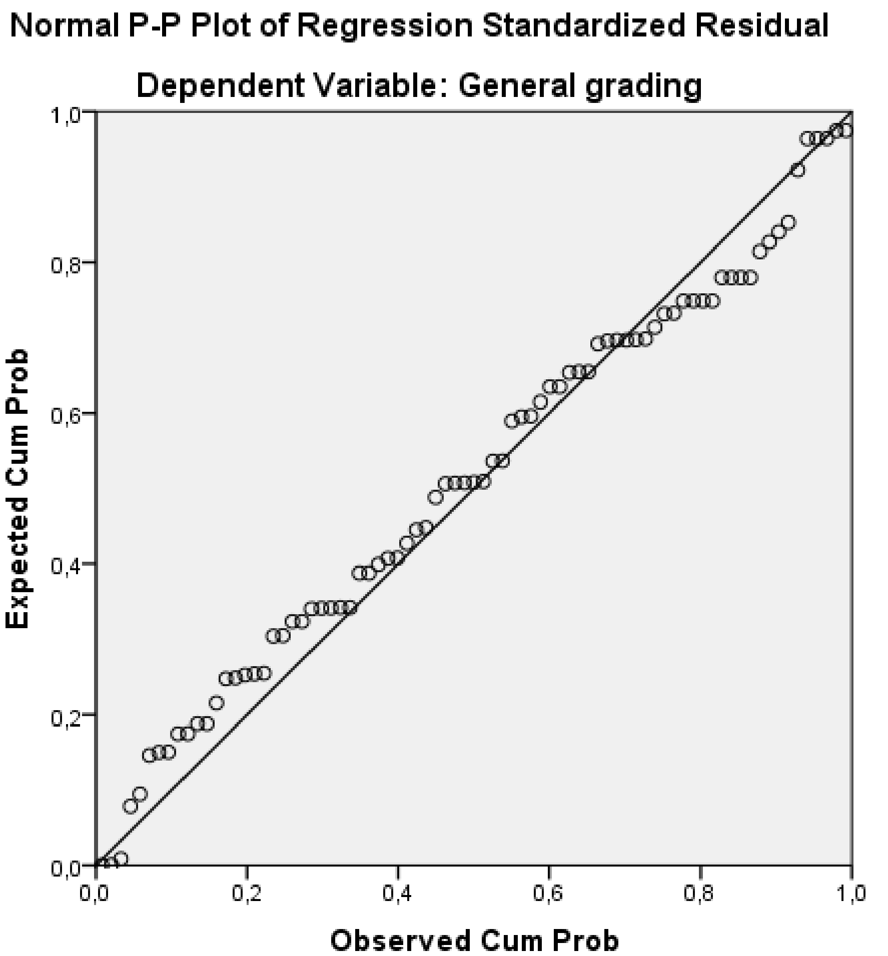
Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	Crosswind hindrance	Flexibility	Sustainable contribution	Suitable for commuting
1	1	4,794	1,000	,00	,00	,00	,00	,00
	2	,117	6,404	,00	,59	,08	,00	,06
	3	,051	9,721	,00	,00	,70	,00	,43
	4	,026	13,514	,08	,31	,19	,42	,48
	5	,012	19,794	,92	,09	,03	,57	,03

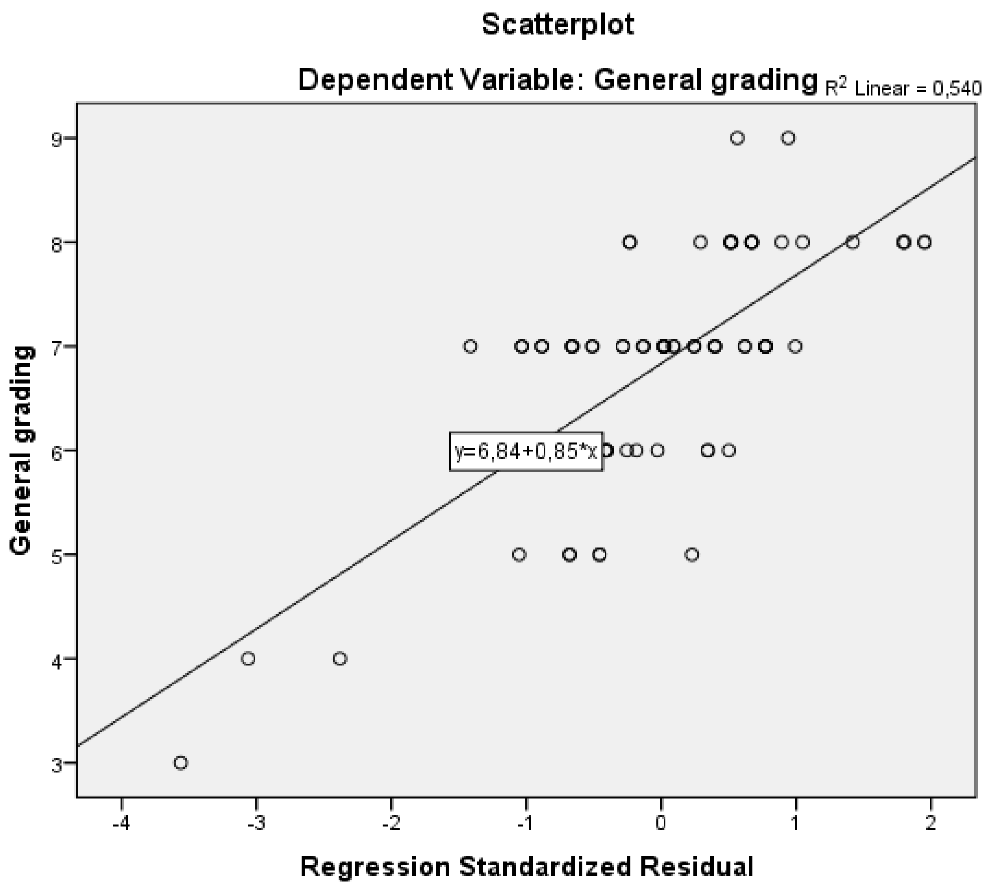
a. Dependent Variable: General grading

Residuals Statistics[a]

		Statistic	Bootstrap[b] Bias	Bootstrap[b] Std. Error	BCa 95% Confidence Interval Lower	BCa 95% Confidence Interval Upper
Predicted Value	Minimum	4,81				
	Maximum	8,52				
	Mean	6,84	,00	,12	6,59	7,08
	Std. Deviation	,764	,014	,097	,552	,992
	N	79	0	0	.	.
Residual	Minimum	-3,028				
	Maximum	1,658				
	Mean	,000	,000	,000	,000	,000
	Std. Deviation	,827	-,038	,096	,663	,908
	N	79	0	0	.	.
Std. Predicted Value	Minimum	-2,655				
	Maximum	2,207				
	Mean	,000	,000	,000	.	.
	Std. Deviation	1,000	,000	,000	1,000	1,000
	N	79	0	0	.	.
Std. Residual	Minimum	-3,563				
	Maximum	1,953				
	Mean	,000	,000	,000	,000	,000
	Std. Deviation	,974	,000	,000	.	.
	N	79	0	0	.	.

a. Dependent Variable: General grading
b. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples


Normal P-P Plot of Regression Standardized Residual
Dependent Variable: General grading
Expected Cum Prob
1,0
0,8
0,6
0,4
0,2
0,0
0,0
0,2
0,4
0,6
0,8
1,0
Observed Cum Prob


Scatterplot
Dependent Variable: General grading
R2 Linear = 0,540
y=6,84+0,85*x
General grading
9
8
7
6
5
4
3
-4
-3
-2
-1
0
1
2
Regression Standardized Residual

4. Appendices consideration of the solar bike

4.1. Solar bike choice preferences

Amount of solar bike choice preferences (pre) * Altebike Crosstabulation

Count

		Altebike 0	Altebike 1	Total
Amount of solar bike choice preferences (pre)	0	27	4	31
	1	5	3	8
	2	6	1	7
	3	7	3	10
	4	9	2	11
	5	3	0	3
	6	4	0	4
	7	1	0	1
	8	0	0	0
	9	3	1	4
Total		65	14	79
Mean		2.26	2.21	2.25

Amount of solar bike choice preferences (post) * Altebike Crosstabulation

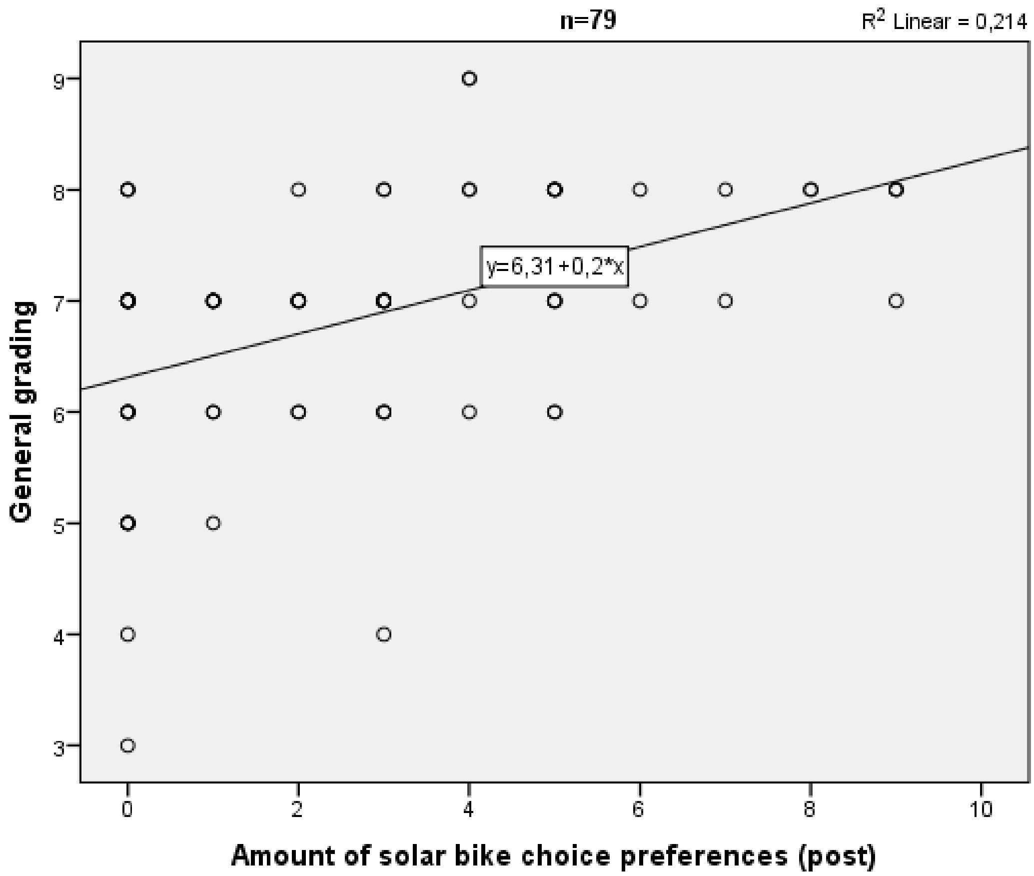
Count

		Altebike 0	Altebike 1	Total
Amount of solar bike choice preferences (post)	0	19	6	25
	1	7		9
	2	7	0	7
	3	11	1	12
	4	5	1	6
	5	9	1	10
	6	2	0	2
	7	1	1	2
	8	1	1	2
	9	3	1	4
Total		65	14	79
Mean		2.66	2.71	2.67

Descriptive Statistics

	N	Range	Sum	Mean	Std. Deviation
Amount of solar bike choice preferences (pre)	79	9	178	2,25	2,514
Amount of solar bike choice preferences (post)	79	9	211	2,67	2,654
Valid N (listwise)	79				

Scatterplot solar bike transport mode preference (post) and general grading



4.2. Differences in likelihood to buy

4.2.1. Paired sample t-test

Paired Samples Statistics

			Statistic	Bootstrap[a] Bias	Std. Error	BCa 95% Confidence Interval Lower	Upper
Pair 1	Likelihood to buy (pre)	Mean	3,44	,00	,16	3,13	3,75
		N	79				
		Std. Deviation	1,421	-,015	,094	1,259	1,554
		Std. Error Mean	,160				
	Likelihood to buy (post)	Mean	2,91	,01	,16	2,61	3,25
		N	79				
		Std. Deviation	1,461	-,016	,101	1,286	1,600
		Std. Error Mean	,164				

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

Paired Samples Correlations

		N	Correlation	Sig.	Bootstrap for Correlation[a] Bias	Std. Error	BCa 95% Confidence Interval Lower	Upper
Pair 1	Likelihood to buy (pre) & Likelihood to buy (post)	79	,476	,000	-,009	,106	,260	,654

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

Paired Samples Test

	Paired Differences Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference Lower	Upper	t	df	Sig. (2-tailed)
Likelihood to buy (pre) - Likelihood to buy (post)	,532	1,475	,166	,201	,862	3,204	78	,002

Bootstrap for Paired Samples Test

		Mean	Bootstrap[a] Bias	Std. Error	Sig. (2-tailed)	BCa 95% Confidence Interval Lower	Upper
Pair 1	Likelihood to buy (pre) - Likelihood to buy (post)	,532	-,007	,163	,004	,241	,810

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

4.2.2. Difference between the two groups

1 = e-bike user, 0 = non-e-bike user

Group Statistics

	E-bike user		Statistic	Bootstrap[a] Bias	Std. Error	BCa 95% Confidence Interval Lower	Upper
Likelihood to buy (post)	0	N	65				
		Mean	2,88	,00	,19	2,52	3,23
		Std. Deviation	1,463	-,015	,124	1,235	1,656
		Std. Error Mean	,181				
	1	N	14				
		Mean	3,07	-,01	,39	2,31	3,80
		Std. Deviation	1,492	-,064	,180	1,183	1,662
		Std. Error Mean	,399				

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference Lower	Upper
Likelihood to buy (post)	Equal variances assumed	,059	,809	-,450	77	,654	-,195	,433	-1,056	,667
	Equal variances not assumed			-,444	18,782	,662	-,195	,438	-1,112	,723

Bootstrap for Independent Samples Test

		Mean Difference	Bootstrap[a] Bias	Std. Error	BCa 95% Confidence Interval Lower	Upper
Likelihood to buy (post)	Equal variances assumed	-,195	,004	,440	-1,038	,675
	Equal variances not assumed	-,195	,004	,440	-1,038	,675

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

4.3. Ordinal regression likelihood to buy

Bivariate correlation analyses

Correlation between general grading and:	Pearson's r	BCa 95% CI	p-value
Solar wheel price too low	r = .102	[-.098, .290]	.372
Solar wheel price expensive	r = .151	[-.036, .317]	.185
Solar wheel price too expensive	r = .154	[-.069, .339]	.175

Correlation between total energy production and:	Pearson's r	BCa 95% CI	p-value
Solar wheel price too low	r = -.049	[-.185, .137]	.712
Solar wheel price expensive	r = .005	[-.199, .246]	.968
Solar wheel price too expensive	r = -.026	[-.211, .225]	.846

Case Processing Summary

		N	Marginal Percentage
Likelihood to buy (post)	1	18	22,8%
	2	13	16,5%
	3	21	26,6%
	4	16	20,3%
	5	8	10,1%
	6	2	2,5%
	7	1	1,3%
Valid		79	100,0%
Missing		0	
Total		79	

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	85,933			
Final	77,844	8,089	1	,004

Link function: Logit.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	55,570	35	,015
Deviance	37,616	35	,350

Link function: Logit.

Pseudo R-Square

Cox and Snell	,097
Nagelkerke	,101
McFadden	,030

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound	Odds ratios Estimate	Odds ratios 95% Confidence Interval Lower Bound	Odds ratios 95% Confidence Interval Upper Bound
Thres -hold	[buy = 1]	2,409	1,305	3,405	1	,065	-,150	4,967	11,118	,861	143,561
	[buy = 2]	3,246	1,326	5,991	1	,014	,647	5,845	25,683	1,909	345,459
	[buy = 3]	4,420	1,366	10,467	1	,001	1,742	7,097	83,081	5,710	1208,739
	[buy = 4]	5,658	1,411	16,090	1	,000	2,893	8,423	286,607	18,056	4549,403
	[buy = 5]	7,119	1,506	22,350	1	,000	4,167	10,070	1234,995	64,553	23627,385
	[buy = 6]	8,260	1,716	23,166	1	,000	4,896	11,623	3865,665	133,804	111680,778
Location	algoordeel	,548	,193	8,112	1	,004	,171	,926	1,730	1,186	2,523

Link function: Logit.

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	77,844			
General	73,440	4,404	5	,493

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.
a. Link function: Logit.