MASTER

User acceptance of solar vehicles for passenger mobility

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USER ACCEPTANCE OF SOLAR VEHICLES FOR PASSENGER MOBILITY

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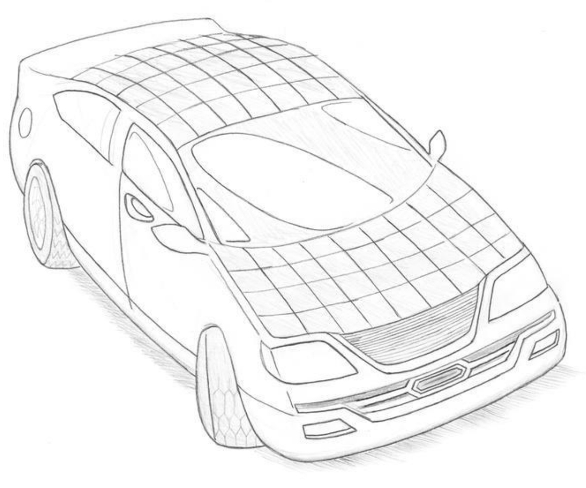

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This thesis is publicly available.
This thesis has been carried out in accordance with the rules of the TU/e Code of Scientific Integrity.

Preface

This thesis is the culmination of my graduation project at Eindhoven University of Technology (TU/e) and concludes my master's degree in Architecture, Building and Planning: Urban Systems and Real Estate.

A special thanks to my supervisors, Feixiong Liao and Aloys Borgers, for their ongoing supervision, support, and guidance throughout my graduation project, and to Theo Arentze for joining as the third supervisor and providing feedback during the final stages.

Additionally, my sincere thanks to each individual that filled out my questionnaire, as well as those who helped distribute it. Finally, I am grateful for the continuous support from my family and friends during my studies, as well as all the students, lecturers, and professors at the TU/e with whom I had the pleasure of sharing classes during my master's program.

Without everyone mentioned above, the result you see before you would not have been possible.

Once again, many thanks, and I hope you enjoy reading this paper.

Stijn van den Hurk,
Eindhoven, July 2024

Summary

The climate is changing and people's concerns about the climate have rapidly grown recent years. Despite the growing concerns, global CO2 emissions keep increasing and hit an all-time high last year. The transportation sector is responsible of 21% of these emissions and vehicles and vans account for almost half of this. In order to reduce the amount of CO2 emissions, the transportation industry has to adept. Recent years, many studies have focused on the adoption intention of electric vehicles. Electric vehicles are seen a sustainable way of transportation, and thus an alternative way of transportation to reduce the industry's emissions. However, a transition to a full-electrical fleet encompasses significant challenges. In the Netherlands, the majority of electricity is still being produced by burning fossil fuels, the amount of charging stations is not near enough, and the electricity grid is already at full capacity. This causes the need for solutions, solutions that are able to alleviate these challenges.

One possible solution is solar vehicles. These vehicles rely less on the electricity grid as they are able to obtain their energy directly from the sun. This reduces the demand for charging stations and reduces the amount of electricity needed. In turn, this lowers the demand for fossil fuel power plants which ultimately causes greener mobility. Moreover, people's concerns about the infrastructure and range of electric vehicles make people hesitant to adopt them. These are hurdles which solar vehicles can overcome.

Despite the possibilities of solar vehicles, scientists have till today only studied the efficiency of solar vehicles and possible ways to increase their efficiency, however, the behavioral side remains unstudied. The behavioral side encompasses the user's adoption, which includes people's preferences and expectations. These preferences and expectations towards solar vehicles are important to understand, as the degree to which solar vehicles are acknowledged and adopted by consumers will eventually determine its success. Therefore, this study fills this knowledge gap. This study focusses on the adoption intention of solar vehicles, more specifically, the user acceptance of solar vehicles for passenger mobility. The main question of this study is as follows: *What psychological factors and user characteristics influence the adoption intention of solar vehicles?* This paper presents recommendations and interventions for both policymakers and manufacturers, to increase the awareness and adoption of solar vehicles.

This paper is the first to study the user acceptance of solar vehicles and does so by making use of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework. This framework is commonly used in user acceptance studies and includes variables such as Behavioral Intention and Use Behavior. In this study, Use Behavior is defined as the adoption of solar vehicles. A literature study has been conducted to extend this framework. From the literature follows that there are several psychological constructs that influence individuals' decision-making, two of those constructs are Technophilia, one's attraction and enthusiasm towards new technology, and Attitude, one's overall positive and negative feelings regarding a behavior.

In this paper, two frameworks are analyzed, a standard framework that contains the more commonly studied UTAUT2 variables (Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, Price Value, Facilitating Conditions, and Environmental Beliefs) and an extended framework that contains more complex relationships, the constructs Technophilia and Attitude, as well as the more commonly studied UTAUT2 variable, Habit. To get a better understanding of which type of individuals are more attracted towards the adoption of solar vehicles, the sociodemographics gender, age, income, education, and experience with electric and hybrid vehicles are also included. The standard framework is analyzed using data collected in December 2022 (N = 523) and the extended framework is analyzed using data collected between March and May 2024 (N = 250).

Results show that Attitude is the most crucial factor that predicts the adoption intention of individuals regarding solar vehicles. Attitude is shaped by individuals Price Value and Environmental Beliefs, which together enhance its positivity. Individuals who perceive solar vehicles as a good value for their money, are more likely to have a positive attitude and are more likely to adopt them. This

implies the importance of a good price range, and therefore manufacturers should market their solar vehicles at a reasonable price to enhance its adoption. Price Value is partially explained by Technophilia, which does not directly result in a more positive Attitude towards solar vehicles, but indirectly through a more positive Price Value. It implies that Individuals with a strong enthusiasm for new technology assume solar vehicles to be a good value for their money and are likely to pay more for a solar vehicle. The importance of Environmental Beliefs can be explained by the growing concerns about climate change and global warming. In order to stimulate the adoption of solar vehicles, the eco-friendliness of these vehicles should be clearly emphasized. Both the government and manufacturers can do so via commercials or campaigns.

Besides Attitude, Price Value, Environmental Beliefs, and Technophilia, Performance Expectancy is identified to be a significant factor explaining the adoption intention of solar vehicles. The perceived efficiency and effectiveness of these vehicles are found to play an important role predicting the Use Behavior of individuals. For manufacturers, this again implies that disseminating the right type of information, in this case the performance and efficiency of solar vehicles, is important for the promotion of these vehicles.

Habit shows similar positive effects. Habits are developed through repeated behavior and strengthen with increased familiarity with a technology. This effect becomes increasingly apparent when studying the effect of experience with electric and hybrid vehicles, which shows a significant positive effect on, amongst others, Habit. This emphasizes the role of familiarity and experience with a technology, which can be increased by offering test drives and by explaining the marginally changes in habit needed in order to utilize solar vehicles.

Effort Expectancy and Facilitating Conditions are not identified as important determinants of the adoption intention of solar vehicles. These results can be explained by the increasing knowledge, awareness, and infrastructure of electric vehicles, which makes other psychological factors more important. Hedonic Motivation plays an important role only in the standard framework. In the extended framework, their effects are possibly captured elsewhere. A similar finding is found for Social Influence. This might be explained by the fact that solar vehicles are a new type of technology, not yet available on the market, and therefore not a subject of discussion amongst friends and family.

In terms of sociodemographics, marginal results are uncovered. In the standard framework, a direct effect is observed for gender and age. Females and older individuals experience a lower intention to adopt solar vehicles. In the extended framework, gender and age only affect the adoption intention through a more positive Price Value, implying that females and older individuals are willing to pay more for a solar vehicle or perceive a higher value for their money, contradicting the expectations. Additionally, income and education have no direct effects on the adoption intention but tend to indirectly affect the adoption intention through a more negative Habit and Performance Expectancy. Individuals with a higher income and a higher education level might have higher expectations towards solar vehicles and more critically reflect on the possible drawbacks of these vehicles, resulting in a lower adoption intention.

To conclude, an individual's attitude towards solar vehicles is positively influenced by their perceived effectiveness and efficiency, environmental beliefs, and enthusiasm for new mobility solutions. Together with electric vehicle and hybrid vehicle experience, along with the perception that solar vehicles are a good value for money, play an important role in shaping more positive feelings regarding solar vehicles, thereby promoting their adoption. The effects of age, gender, education, and income on the adoption intention of solar vehicles was found minimal.

This study is the first of its kind to study the adoption intention of solar vehicles, and like any study, it comes with its limitations. Nonetheless, these limitations provide opportunities for future work. In this study, results between both frameworks are compared, however, these comparisons should be interpreted with caution, as there are differences in time of data collection and sample size. Moreover, this study is conducted in one single country, the Netherlands, which makes generalizing the results internationally not possible. Furthermore, potential larger effects might not have been captured in the extended framework due to the limited sample size and the use of two-indicator constructs. For future work, both frameworks can serve as a basis for follow-up studies in the Netherlands and other countries to create a better understanding of individuals' attitudes regarding new, more environmentally friendly mobility solutions, such as solar vehicles. This can increase its adoption, which ultimately causes greener mobility that results in a reduction of the transportation sector's CO2 emissions.

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1. Introduction

Climate change is seen as one of the single most serious problems in today's world (European Union, 2019). Public concerns about climate change and global warming have seen an increase during the last decade (United Nations, 2007; European Union, 2019; World Health Organization, 2023). However, global CO2 emissions have seen an increase too. The global CO2 emissions hit an all-time high last year and the transportation sector is responsible for 21% of the global emissions (Statista, 2023a). CO2 is one of the primary gases that are emitted by burning fossil fuels, such as in combustion engines of gasoline vehicles. Vehicles and vans alone account for 48% of the total transport CO2 emissions (Statista, 2023b). The global transportation sector, amongst others, has to adapt in order to reduce the amount of greenhouse gas emissions and air pollution. In this context, electric vehicles are seen as an alternative mode of transportation to gasoline vehicles.

The first electric vehicle saw its appearance in 1834 (Kley et al., 2011) but was overtaken by the competition of fossil-fuel vehicles (Vaitheeswaran & Vehicleson, 2007). In 2011 electric vehicles reappeared in larger numbers than previously seen (IEA, 2012), facilitated by, amongst others, battery advancements and global warming (Motavalli, 2012). Electric vehicles do not rely on fossil fuels for their operation, but they use electricity instead. In this study, electric vehicles are defined as vehicles that obtain all or part of their energy from the electrical grid (Larson et al., 2014).

Electric vehicles are seen as a sustainable way of transportation (Shahid & Agelin-Chaab, 2023; Office of Energy Efficiency & Renewable Energy, 2024). This is also acknowledged by the Dutch authorities, as the Dutch National Government presented several tax incentives and purchase aids to incentivize the purchase of electric vehicles over gasoline vehicles in recent years. Motavalli (2012) projected in 2012 that in a few years "one out of every two vehicles on the road could be a hybrid or electric vehicle" (Motavalli, 2012). This level has not been reached, but a significant growth over the last years has happened as the total sales increased sixfold over the last five years (IEA, 2024). In 2023, almost 14 million new electric or hybrid vehicles were registered (IEA, 2024). Despite this significant increase, a recent study of S&P Global Mobility (2023) shows that consumers' consideration of purchasing an electric vehicle has fallen from 81% (2021) to 52%. Furthermore, nearly half of electric vehicle households would still buy a gasoline vehicle next time. Infrastructure, range, and price are the top three reasons amongst consumers to not purchase an electric vehicle next time (S&P Global Mobility, 2023).

The Netherlands aims to reduce CO2 emissions by 55% by 2030 and aims to be fully climate-neutral by 2050 (Ministerie van Economische Zaken en Klimaat et al., 2023). To accomplish this goal, all mobility must be climate-neutral by 2050. While electric vehicles have several benefits, e.g., economic benefits (reduced fuel costs) and environmental benefits (reduced emissions), problems for a transition away from gasoline vehicles towards an all-electrical fleet arise. Electric vehicles drive on electricity which can be produced from renewable energy sources, yet the majority of electricity in the Netherlands is being produced by burning fossil fuels (Compendium voor de Leefomgeving, 2023). The energy industry therefore has to adapt in order to make electric vehicles drive on green- and renewable energy. The second issue is the current infrastructure. The infrastructure in the Netherlands is currently not fit to accommodate this transition (Ministerie van Economische Zaken en Klimaat, 2019). At the moment there are 137.000 charging stations, 100.000 private charging stations and 37.000 public charging stations. Projected is that in 2030, 1.8 million charging stations will be needed to accommodate the needs of drivers (Ministerie van Economische Zaken en Klimaat, 2019). Moreover, these charging stations need to be connected to the electricity grid. However, the electricity grid is already at full capacity across most of the Netherlands (Ministerie van Economische Zaken en Klimaat, 2023). This presents a significant challenge for both the current infrastructure and policymakers.

A new type of technology that may be able to alleviate this challenge is solar vehicles. Solar vehicles are electric vehicles equipped with solar panels on the roof and/or hood of the vehicle (Paterson et al., 2016). This enables the collection of energy while the vehicle is on the move and while being stationary. Less charging is required as these solar panels generate energy required by the vehicle, using truly green- and renewable energy. This reduces the energy required from fossil fuel power plants and reduces the demand for charging stations. Solar panels can reduce the charging needs for 33% of the cars in urban areas and even more for cars in rural areas (Brito et al., 2021). Moreover, solar vehicles are a potential means that can help overcome obstacles present when purchasing electric vehicles, such as charging and range limitations, and may therefore be an alternative to ordinary electric vehicles, simultaneously reducing the demand for charging stations. As an extension of the definition of electric vehicles by Larson et al. (2014), solar vehicles are in this study defined as vehicles that obtain all of their energy from electricity from the electrical grid or directly from the sun.

The first solar vehicle saw its appearance decades ago in 1955 (History.com Editors, 2020) and in recent years, several manufacturers announced vehicle concepts capable of collecting solar energy (Lightyear (Lightyear, 2019), (Tesla (Tesla, 2019), Hyundai (Hyundai, 2019), Fisker (Fisker Inc., 2024)). For a handful of companies, developing solar vehicles is their primary business (Squad (Hoevers, 2019), Aptera (Aptera, 2020)). Scientists focus on the technology and efficiency of solar panels and solar vehicles (e.g., Coraggio et al., 2010; Brito et al., 2021; Ota et al., 2022; Gallagher & Clarke, 2023), yet no prior research can be found that aims to study the user behavior in relation to solar vehicles. However, it is important to know people's preferences and expectations regarding solar vehicles to increase the rate of adoption, as the degree to which solar vehicles are acknowledged and adopted by consumers will eventually determine the success of solar vehicles. Therefore, the purpose of this study is to explore the degree to which users are willing to accept solar vehicles, the user acceptance, by answering the following research question: ***What psychological factors and user characteristics influence the adoption intention of solar vehicles?***

To answer this question, the current research is conducted using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework, designed by Venkatesh et al. (2012) to understand human behavior towards new technology. This framework is widely accepted and commonly used to study behavioral intentions and user acceptance towards new technology. Two UTAUT2 frameworks (a standard framework and an extended framework) will independently be studied. The standard framework will be analyzed using an existing data set, the extended framework will be analyzed using newly collected data.

This study aims to present recommendations and interventions to improve the awareness and adoption of solar vehicles. The aim is to propose recommendations and interventions for both policymakers and manufacturers to encourage the use behavior and adoption intention of solar vehicles in order to stimulate climate-neutral mobility, emphasizing the societal relevance of this study. Moreover, this research will be the first to study the user acceptance of solar vehicles, make a theoretical contribution by presenting an extended version of the UTAUT2 framework, and add to the scarce literature available regarding solar vehicles, emphasizing the academic relevance.

The remainder of this thesis is structured as follows: Chapter 2 presents a review of the literature and hypothesis development. Chapter 3 describes the research methodology. In Chapter 4 a standard UTAUT2 framework is analyzed, and the findings of this analysis are discussed. Chapter 5 discusses the data collection by which an extended framework with new constructs is analyzed and presents the analysis results. Chapter 6 discusses the results of both frameworks, provides policy and managerial implications, and concludes this paper with limitations and scope for future work.

2. State of practice and model development

This study is based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework, which is commonly used in user acceptance studies. This chapter first discusses this framework, followed by the hypotheses development that results in the conceptual model.

2.1 Unified Theory of Acceptance and Use of Technology 2

Commonly used theories to study human behavior are the Theory of Planned Behavior (TPB) (Ajzen, 1991) and the Technology Acceptance Model (TAM) (Davis, 1989). The TPB is widely used in many fields and suggests that human actions are influenced by attitudes toward the behavior, subjective norms, and perceived behavioral control. In other words, the evaluation of certain behavior, social influence, and ease of use are important determinants to predict and understand human behavior (Ajzen, 1991). The TAM is based on the TPB and widely used in the field of technology acceptance. TAM aims to understand users' acceptance and adoption of new information technologies and systems by means of five components: perceived usefulness, perceived ease of use, attitude towards use, behavioral intention to use, and actual system use. A higher perceived usefulness and ease of use leads to a stronger positive attitude and behavioral intention to use the technology, which in turn results in actual system use (Davis, 1989). Venkatesh et al. (2003) combined the TPB and TAM together with the Theory of Reasoned Action (TRA), Social Cognitive Theory (SCT), Innovation Diffusion Theory (IDT), Motivational Model (MM), Model of PC Utilization (MPCU), and combined TAM and TPB (C-TAM-TPB) to design the Unified Theory of Acceptance and Use of Technology (UTAUT) framework.

The UTAUT framework aims to understand and predict how individuals accept and use a new technology. This theoretical framework suggests that Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) impact use behavior via behavioral intention. Furthermore, Facilitating Conditions (FC) directly influence use behavior. This framework also includes gender, age, experience, and voluntariness of use as moderating variables of these constructs (Venkatesh et al., 2003). In 2012 the framework was enhanced and is now broadly known as the UTAUT2 framework (Venkatesh et al., 2012), shown in Figure 1, adapted from Venkatesh et al. (2012). The constructs Hedonic Motivation (HM), Price Value, (PV), and Habit Behavior (HB) were added to better predict use behavior via behavior intention. Additionally, Facilitating Conditions (FC) now also indirectly affect use behavior via behavioral intention. This improves the framework's exploratory power for both behavioral intention and technology use, namely 74% and 52%, respectively, compared to the 56% and 40% of its previous version (Venkatesh et al., 2012).

Both the UTAUT framework and the UTAUT2 framework have been used in the transportation field to study topics such as demand-responsive transportation (Pak et al., 2023), mobility as a service (Ye et al., 2020), bicycle- and vehicle sharing systems (Jahanshahi et al., 2020; Curtale et al., 2021), and electric vehicles (e.g., Abbasi et al., 2021; Zhou et al., 2021). Furthermore, both frameworks are also applied in other fields such as mobile banking (Baptista & Oliveira, 2015), mobile application usage (Medeiros et al., 2022), and artificial intelligence (Gansser & Reich, 2021).

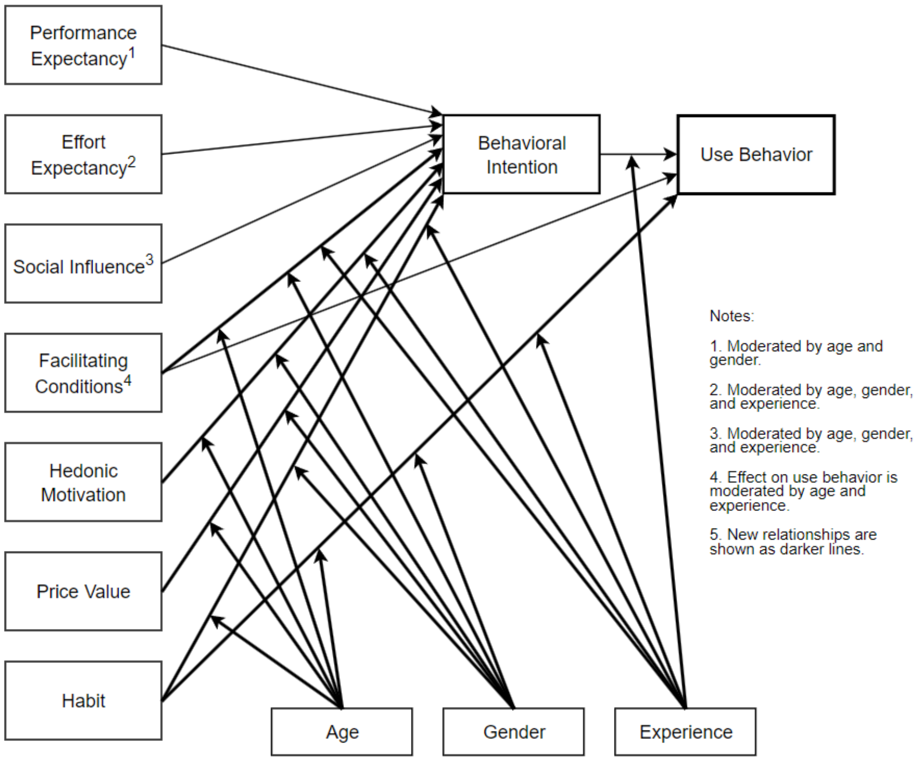

Figure 1. Conceptual framework UTAUT2.
Note: adapted from Venkatesh, V., Thong, J. Y., & Xu, X. (2012).

2.2 Conceptual model and hypothesis development

In this study, the UTAUT2 framework serves as a basis to explain the user acceptance of solar vehicles. Based on the literature, the framework is extended by adding Technophilia and Attitude to better predict use behavior in this study. Moreover, next to the three moderating variables age, gender, and experience, two additional moderating variables are added: income and education.

2.2.1 Performance expectancy (PE)

PE relates to the degree of advantages and benefits consumers anticipate to gain from the use of a technology (Venkatesh et al., 2012). In the automotive context, PE refers to how much a consumer believes that using a vehicle will contribute to the efficient and effective completion of a car trip (Osswald et al., 2012). Thus, in the context of this study, PE is defined as the level to which a consumer believes that using a solar vehicle will contribute to the efficient and effective completion of a car trip. PE embodies the perspective that solar vehicles could be time-effective, cost-effective, and environmentally friendly (Singh et al., 2023). Gunawan et al. (2022) observed PE to be the strongest predictor of Attitude (AT) towards use, and Zhou et al. (2021) found PE to be the strongest predictor of BI to adopt electric vehicles. Similar findings are uncovered in the study by Curtale et al. (2021) regarding the intention to adopt electric car-sharing services, and in the study by Pak et al. (2023) regarding the adoption of demand-responsive transportation. Moreover, recent studies (Bhat et al., 2021; Singh et al., 2023) show that PE is a strong component in predicting the adoption intention of electric vehicles. As a result, there is a reason to believe that this also holds for solar vehicles, that is to say, PE influences AT and BI. Hence, the following hypotheses:

Hypothesis 1a (H1a): PE positively affects attitude towards solar vehicles.
Hypothesis 1b (H1b): PE positively affects behavioral intention of using solar vehicles.

2.2.2 Effort Expectancy (EE)

EE represents the degree of ease consumers associate with the use of a technology (Venkatesh et al., 2012). The components of EE defined in the study of Singh et al. (2023) are adopted in this study, including easy learning, ease of use, clear interaction, and skillfulness in using solar vehicles. It is assumed that the perceived ease of using solar vehicles and the user-friendly features of solar vehicles positively affect BI. This is confirmed in the study by Zhou et al. (2021) which shows a significant positive relationship between EE and BI of electric vehicles. EE is also found to play a crucial role in the adoption of transportation systems such as Mobility as a Service (MaaS) (Ye et al., 2020). Moreover, Abbasi et al. (2021) and Jain et al. (2022) observed that EE influences the adoption intention to adopt electric vehicles and Gunawan et al. (2022) found AT towards use to be influenced by EE. It is assumed that the consumers' BI is influenced by the perceived ease of use of this technology. Moreover, EE is a key construct in TAM influencing AT (Davis, 1986). Therefore, the following hypotheses:

Hypothesis 2a (H2a): EE positively affects attitude towards solar vehicles.
Hypothesis 2b (H2b): EE positively affects behavioral intention of using solar vehicles.

2.2.3 Social Influence (SI)

SI refers to the extent to which consumers believe that others support the use of a technology (Venkatesh et al., 2012). The greater the social pressure, the higher the possibility that certain behavior is performed (Fishbein & Ajzen, 2009). Positive opinions from the general public are found to influence the adoption of electric vehicles, although the results vary among different types of social networks (i.e., friends, family, colleagues) and the market share of electric vehicles within these social networks (Kim et al., 2014). Furthermore, Gunawan et al. (2022) also observed a positive relationship between SI and electric vehicle adoption, and Curtale et al. (2021) found similar findings regarding the intention to adopt electric car-sharing services. In the context of this study, SI consists of other people's perceptions of the use of solar vehicles. Therefore, it is assumed that a favorable perception of solar vehicles by friends, family, and (social) media positively influences consumers' BI.

Moreover, SI was observed to influence AT. The effect of SI on AT is studied by Sumak et al. (2010) and Dwivedi et al. (2017), which studied the UB of a new information technology. Both observed SI to positively influence AT. One possible reason may be that individuals refine their attitudes based on information and stories of others (Dwivedi et al., 2017). Therefore, there is a reason to believe that SI influences AT and BI towards solar vehicles. Hence, the following hypotheses:

Hypothesis 3a (H3a): SI positively affects attitude towards solar vehicles.
Hypothesis 3b (H3b): SI positively affects behavioral intention of using solar vehicles.

2.2.4 Hedonic Motivation (HM)

HM represents the extent of enjoyment, pleasure, and happiness derived from the use of a technology (Venkatesh et al., 2012). Satisfaction, emotions, pride, and other subjective feelings are psychological factors that contribute to the fueling of HM (Lestari & Tiarawati, 2020). These psychological factors can arise by beliefs that solar vehicles are an exciting new technology, produce lower noise levels, and have better acceleration capabilities compared to combustion engine vehicles, as emphasized by Khazaei and Tareq (2021) and Zhou et al. (2021). The literature shows that HM has a positive effect on the BI to adopt electric vehicles (Zhou et al., 2021; Gunawan et al., 2022; Singh et al., 2023). This implies that a greater HM results in increased BI towards electric vehicles.

Moreover, Rosenberg (1956) created an expectancy-value model in the attitude area and argues that this attitude is "accompanied by a cognitive structure made up of beliefs about the potentialities of that object for attaining or blocking the realization of valued states" (Rosenberg, 1956). The more a given "object" contributes to obtaining positive feelings and blocks negative feelings, the more favorable the attitude towards that "object." Thus, enjoyment, pleasure, and happiness derived from a product or service can contribute to a favorable attitude towards that product or service (i.e., solar vehicles). Therefore, the following hypotheses:

Hypothesis 4a (H4a): HM positively affects attitude towards solar vehicles.
Hypothesis 4b (H4b): HM positively affects behavioral intention of using solar vehicles.

2.2.5 Price Value (PV)

PV is defined as consumers' cognitive trade-off between the perceived benefits and the monetary value of a product or service (Venkatesh et al., 2012). PV has a positive influence on BI if the benefits of a technology are perceived to be greater than the costs (Venkatesh et al., 2012). Costs are defined as the total cost of ownership, which includes the initial vehicle price and operating costs such as maintenance costs, insurance costs, and vehicle tax (Palmer et al., 2018). Multiple studies show the importance of PV on the BI of electric vehicles (e.g., Egbue and Long, 2012; Noel & Sovacool, 2016; Singh et al., 2023). Moreover, Degirmenci and Breitner (2017) also showed PV to positively affect AT towards electric vehicles. Hence, the following hypotheses:

Hypothesis 5a (H5a): PV positively affects attitude towards solar vehicles.
Hypothesis 5b (H5b): PV positively affects behavioral intention of using solar vehicles.

2.2.6 Technophilia (TP)

TP is defined as the attraction and enthusiasm of individuals towards a new technology (Osiceanu, (2015). People with technophilia are characterized by their enthusiasm and positive emotions towards new technology. Technological enthusiasts tend to be eager to adopt new technological developments, especially in the early adopter stage (Rogers, 2003; Egbue and Long, 2012). This is in line with Wappelhorst et al. (2014) and Ye et al. (2020), who found that individuals affiliated with technology and innovation are more interested in adopting new mobility innovations. Egbue and Long (2012) also emphasize the fact that these individuals are more concerned about technical problems rather than financial problems in terms of electric vehicles. TP is not only about emotions but also a motivation towards adopting new technologies (Abbasi et al., 2021). Moreover, Osiceanu (2015) also highlights the fact that TP can evoke strong positive futuristic feelings. Therefore, there is a reason to believe that TP influences the decision-making of individuals in relation to solar vehicles. Individuals who experience TP may develop positive attitudes towards solar vehicles, highlighting the advantages of solar vehicles. On the opposite, these individuals may overlook or downplay shortcomings. Therefore, the following hypotheses:

Hypothesis 6a (H6a): TP positively affects attitude towards solar vehicles.
Hypothesis 6b (H6b): TP positively affects an individual's PE.
Hypothesis 6c (H6c): TP positively affects an individual's EE.
Hypothesis 6d (H6d): TP positively affects an individual's SI.
Hypothesis 6e (H6e): TP positively affects an individual's HM.
Hypothesis 6f (H6f): TP positively affects an individual's PV.
Hypothesis 6g (H6g): TP positively affects an individual's FC.
Hypothesis 6h (H6h): TP positively affects an individual's HB.

2.2.7 Facilitating Conditions (FC)

FC relates to the degree of support and resources consumers perceive to be available to perform a behavior (Venkatesh et al., 2012). Charging infrastructure is considered as an important external resource (Wolbertus et al., 2018) and vehicle range as an important internal resource (Skippon & Garwood, 2011). Other internal resources may include seat adjustments, Bluetooth connectivity, and reader manuals (Jain et al., 2022). FC is often found to positively influence the behavioral intention to adopt electric vehicles (Bhat et al., 2021; Zhou et al., 2021; Singh et al., 2023), bicycle sharing systems (Jahanshahi et al., 2020), and Mobility as a Service (MaaS) (Ye et al., 2020). Moreover, lack of charging stations and limited vehicle range are commonly seen to be important barriers to adopt electric vehicles (Egbue & Long, 2012; Axsen & Kurani, 2013). In the context of solar vehicles, FC refers to the availability of facilities, such as charging stations, range extenders, interior features, user manuals, and maintenance facilities. It is assumed that the presence and recognition of these facilities positively affect the intention to use and adoption of solar vehicles. Hence, the following hypotheses:

Hypothesis 7a (H7a): FC positively affects behavioral intention of using solar vehicles.
Hypothesis 7b (H7b): FC positively affects adoption of solar vehicles.

2.2.8 Habit (HB)

HB represents the degree to which people tend to perform a behavior automatically, influenced by prior learning (Venkatesh et al., 2012). HB is viewed as prior behavior and measured as the extent to which individuals believe that their behavior is automatic (Venkatesh et al., 2012). HB is formed over time and depends on the interaction and familiarity with the technology. Drivers have to change their fueling/charging habits and mileage estimation, similar to electric vehicles (Zhou et al., 2021). The research of Zhou et al. (2021) has shown a positive impact on the BI to adopt electric vehicles. Therefore, the following hypotheses:

Hypothesis 8a (H8a): HB positively affects behavioral intention of using solar vehicles.
Hypothesis 8b (H8b): HB positively affects adoption of solar vehicles.

2.2.9 Environmental Beliefs (EB)

EB relates to an individual's attitude, perception, and values regarding the environment and environmental issues (Balundė et al., 2020). Schuitema et al. (2013) argue that "people who believe that a pro-environmental self-identity fits with their self-image are more likely to have positive perceptions of EV attributes" (Schuitema et al., 2013), implying that individuals with pro-environmental beliefs are more likely to view attributes of electric vehicles positively and evoke more positive attitudes. Moreover, early adopters of electric vehicles are more "environmentally sensitive" than non-adopters (Deloitte Consulting LLP, 2010). Considering the early stage of solar vehicles, it may be that a positive AT and BI toward solar vehicles is influenced by individuals' environmental beliefs. Hence, the following hypotheses:

Hypothesis 9a (H9a): EB positively affects attitude towards solar vehicles.
Hypothesis 9b (H9b): EB positively affects behavioral intention of using solar vehicles.

2.2.10 Attitude (AT)

AT is defined as the individual's overall evaluation, including positive and negative feelings, about performing a behavior, influenced by their beliefs about the outcomes of that behavior (Fishbein & Ajzen, 1975). The role of AT in BI is complex. Fishbein and Ajzen (1975) argue that behavior is only influenced by beliefs through their impact on AT, while Davis (1986) and Davis et al. (1989) argue that AT does not fully mediate the impact of all beliefs on UB. As the UTAUT2 framework is based on, amongst others, the TRA, TAM, and TPB, we can argue that AT is to some extent already included in the UTAUT2 framework. However, Dwivedi et al. (2017) critically reviewed the UTAUT framework and showed by means of an empirical study that AT is central to predicting BI and UB. AT was found to mediate the effect of exogenous constructs on BI, although not fully, which is in line with Davis (1986) and Davis et al. (1989). Moreover, by explicitly adding AT as a construct, the framework's explanatory power increased from 38% to 45% in explaining the variability of BI and from 21% to 27% in explaining the variability of UB. AT is therefore included as a distinct construct in this research, both influencing BI and UB, to aim for a better explanatory power of the model. Therefore, the following hypotheses:

Hypothesis 10a (H10a): AT positively affects behavioral intention of using solar vehicles.
Hypothesis 10b (H10b): AT positively affects the adoption of solar vehicles.

2.2.11 Behavioral Intention (BI)

BI is defined as the degree of someone's intention to perform a behavior (Fishbein & Ajzen, 1975) and is confirmed to play a crucial role in the acceptance and use of new technology (Venkatesh et al., 2003; Venkatesh et al., 2012). Individuals who have positive intentions to use the system are more likely to engage in actual system use. In this study, individuals who have positive perceptions about solar vehicles, lead to positive intentions, and these positive intentions, in turn, contribute to the acceptance of solar vehicles. Hence, the following hypothesis:

Hypothesis 11 (H11): BI positively affects the adoption of solar vehicles.

2.2.12 Demographic variables - gender, age, income, education

Venkatesh et al. (2012) proposed several moderating variables in the UTAUT2 framework and found the demographic variables age and gender to influence several constructs. Venkatesh et al. (2012) emphasizes that in the early stage of new technology older women rely more on external resources and are more price-sensitive, while younger men are more motivated to use new technology because of the hedonic benefits.

Other scientists have also studied the role of demographic variables (Zhou et al., 2021; Singh et al., 2023). Zhou et al. (2021) studied the adoption of electric vehicles among taxi drivers in China by means of the UTAUT2 framework. All constructs, except SI, are found to be influenced by at least one demographic variable. Moreover, Singh et al. (2023) observed age to have a moderating effect on several constructs of the UTAUT2 framework by studying electric vehicle adoption. Additionally, middle-aged, and older groups were observed to be more influenced by the opinions of friends, family, and society, emphasizing the moderation effect of age on SI. Egbue and Long (2012) observed differences in attitudes, knowledge, and perceptions towards electric vehicles across age, gender, and education groups. Moreover, Kim et al. (2014) observed differences in perceptions towards electric vehicles between income groups. Therefore, there are reasons to believe that demographic variables gender, age, income, and education have a direct influence on UB and a moderating effect on relationships between constructs. Therefore, the following hypotheses:

Hypothesis 12a (H12a): Males have higher UB.
Hypothesis 12b (H12b): Younger people have higher UB.
Hypothesis 12c (H12c): People with a higher income have higher UB.
Hypothesis 12d (H12d): People with a higher education have higher UB.
Hypothesis 12e (H12e): Demographic variables moderate relationships on AT and BI.

2.2.13 Experience

As solar vehicles are not widely available, it is expected that knowledge and experience with solar vehicles is limited. According to practitioners, hybrid vehicles have served as a springboard for electric vehicles (Brescia et al., 2023), suggesting that experience with hybrid vehicles contributes to the adoption of electric vehicles. Consequently, experience with electric vehicles may contribute to the adoption of solar vehicles. Schmalfuß et al. (2017) investigated the effect of electric vehicle experience and found experience to positively influence its acceptance. Additionally, several studies emphasize that experience is important to overcome prejudices, raise awareness, and challenge misconceptions regarding electric vehicles (Ozaki & Sevastyanova, 2011; Egbue & Long, 2012; Bakker & Trip, 2013; Burgess et al., 2013). Therefore, in this study, experience (i.e., hybrid, electric, and solar vehicle experience) possibly has a direct effect on UB and a moderating effect on relationships between constructs. Hence, the following hypothesis:

Hypothesis 13a (H13a): Experience positively affects UB.
Hypothesis 13a (H13b): Experience moderates relationships on AT and BI.

2.3 Conclusion

Figure 2 illustrates the conceptual model of this study based on the UTAUT2 framework. In this study, UB is defined as the adoption of solar vehicles. Use Behavior (UB), Behavioral Intention (BI), and Attitude (AT) are the primary constructs, which are driven by eight UTAUT2 factors (Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Hedonic Motivation (HM), Price Value (PV), Facilitating Conditions (FC), Habit (HB), and Environmental Beliefs (EB)) and one newly introduced exogenous factor (Technophilia (TP)). Seven of these endogenous factors are believed to be influenced by the exogenous factor Technophilia (TP). Moreover, four demographic variables and experience (i.e., hybrid, electric, and solar vehicle experience) are believed to directly influence Use Behavior (UB) and moderate relationships between constructs.

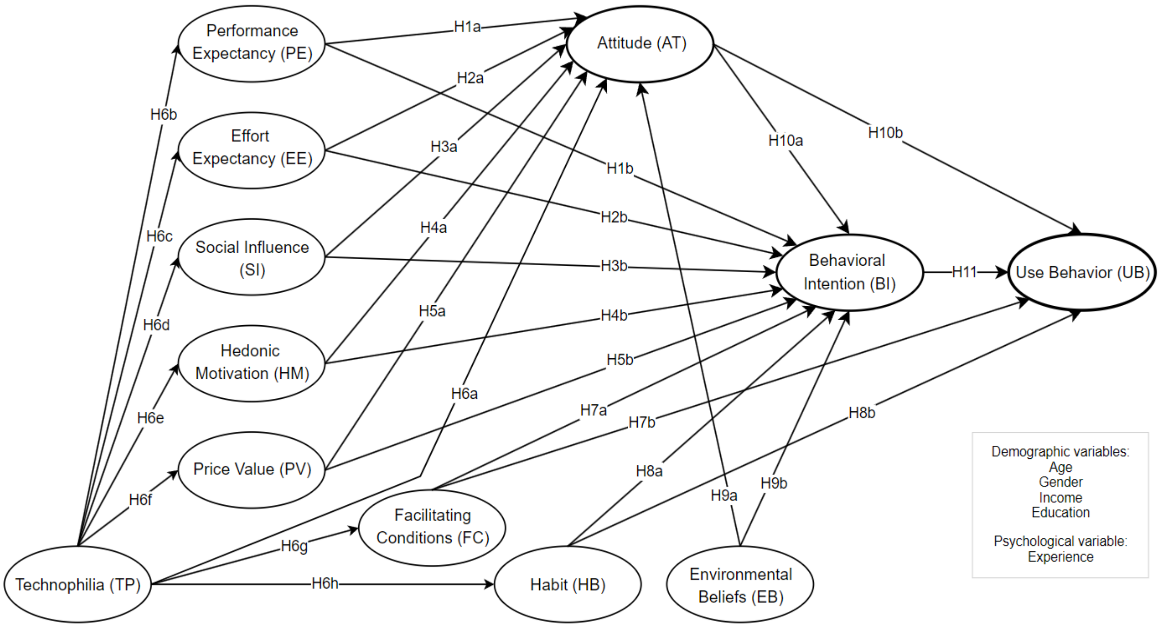

Figure 2. Hypothesized conceptual model - extended framework.

3. Methodology

Structural equation modeling (SEM) is a method frequently used to study the relationships between latent variables. This chapter discusses this method, its assumptions, requirements, and the performance assessment.

3.1 Structural Equation Modeling (SEM)

The conceptual model depicted in Figure 2 consists of multiple relationships between constructs that cannot be directly observed; these contructs are called latent variables. A commonly used method to study latent variables is SEM. SEM is a framework that combines a measurement model and a structural model (Kline, 2016; Wang & Wang, 2019). This framework allows for studying complex causal relationships between constructs that are observed and constructs that are latent (Wang & Wang, 2019). Moreover, it aims to validate or invalidate the proposed hypotheses by analyzing the effects of direct and indirect effects of mediators on the relationship between dependent and independent constructs (Kumar & Upadhaya, 2017). In this study, AT and BI are mediators and we are interested in the effects of nine constructs (i.e., PE, EE, SI, HM, PV, TP, FC, HB, and EB) on UB. All the 12 constructs in the model are latent: constructs that cannot be directly measured but are derived from observable indicators. The term observable indicators can interchangeably be used with the terms observable variables, measurement items, measured variables, measured indicators, manifest indicators, and manifest variables (Kline, 2016; Wang & Wang, 2019). However, for ease of understanding, the term observable indicators and measurement items will be further used in this study. Given this terminology, it is important to note that SEM includes six iterative steps, as outlined by Kline (2016):

1. Specification of the model: design of the conceptual model.
2. Identification of the model: translation of the conceptual model to a statistical model and check whether the parameters in the model can be estimated.
3. a) Measure selection: defining the measurement model, i.e., specify the relationship between observable indicators and latent variables.
   b) Data collection: collecting and preparing the data.
4. Estimation of the model: estimation of the parameters and evaluate the model fit. Maximum Likelihood Estimation (MLE) and Chi-square test are commonly used.
5. Respecification of the model: modification of the model if the model fit is not sufficient.
6. Reporting the results: describing the results of the analysis.

3.1.1 Measurement Model

SEM consists of two models based on theories from the domain knowledge, namely a measurement model that relates the latent variables to observable indicators, and a structural model, an extension of the measurement model, that studies the relationship between latent variables (Kumar & Upadhaya, 2017). These models together allow for a simultaneous study of structural paths (i.e., relationships between latent variables) and measurement paths (i.e., relationship between latent variables and observable indictors). A simplified version of both models is depicted in Figure 3.

A measurement model consists of measurement paths and provides empirical evidence about the quality of the measurements, showing whether the observed indicators accurately represent the latent constructs (Kumar & Upadhaya, 2017). A measurement model consists of causal indicators or effect indicators (Smelser & Baltes, 2001). Causal indicators are observable indicators that determine the latent construct ($X \rightarrow \eta$), while effect indicators are observable indicators that are determined *by* the latent construct ($X \leftarrow \eta$) (Smelser & Baltes, 2001). Moreover, constructs and observable indicators can be both continuous and noncontinuous (Smelser & Baltes, 2001).

An observable indicator consists of two components, namely a factor loading (λ) (a regression coefficient) and a unique variance (ε) (Brown, 2015). The factor loading represents the strength and direction of the relationship between the latent variable (η) and observable indicator (X), while the unique variance represents the error variance, the part of the observable indicator that is not explained by the latent variable. Hence, the following equation:

$$X_i = \lambda_i \eta + \varepsilon_i \quad (1)$$

where X_i represents the i-th observable indicator, λ_i the i-th factor loading, η the latent variable, and ε_i the i-th unique variance, in which $\lambda_i\eta$ represents the "true score" and ε_i the error component.

A measurement model specifies whether there are single or multiple indicators, commonly referred to as single-indicator measurement and multiple-indicator measurement (Kline, 2016). In multiple-indicator measurement, the combined effect of all observable indicators can be expressed by a single equation (Brown, 2015; Kumar & Upadhaya, 2017; Wang and Wang, 2019):

$$X = \Lambda_X \eta + \varepsilon \quad (2)$$

where X represents the vector of observable indicators, Λ_X the matrix of factor loadings of latent variable X, η the vector of latent variables, and ε the vector of unique variances.

3.1.2 Structural model

As previously mentioned, the structural model is an extension of the measurement model. The structural model provides a theoretical framework to test the hypotheses between the latent variables (Kumar & Upadhaya, 2017). In this model, the paths between latent variables are called structural paths, these are path coefficients (γ) (Brown, 2015; Kumar & Upadhaya, 2017; Wang and Wang (2019). The structural path between two latent variables can be described as follows:

$$\eta_i = \gamma_{ij}\eta_j + \zeta_i\ \varepsilon \quad (3)$$

where η_i represents the i-th dependent latent variable, γ_{ij} the path coefficient between the i-th and j-th latent variables, η_j the j-th independent latent variable, and ζ_i the unique variance of the i-th latent variable.

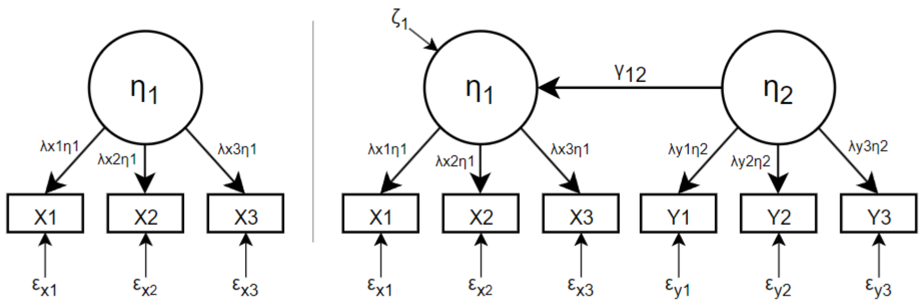

Figure 3. Measurement model (left) and Structural model (right).

3.1.3 Assumptions and requirements

There are two factor analysis techniques, namely Explanatory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). Unrestricted measurement models are analyzed in EFA, and restricted measurement model are analyzed in CFA (Kline, 2016). EFA is used to explore the underlaying structure of observable indicators in relation to latent variables, with its goal to analyze which observable indicators influence which latent variables (Kline, 2016; Orçan, 2018). In contrast, CFA is used to test hypotheses within a conceptual model, analyzing existing relationships between observable indicators and latent variables (Kline, 2016; Orçan, 2018). In this research, a conceptual model based on existing literature will be analyzed. Therefore, only CFA will be adopted in this research to test the measurement model.

In CFA, factor loadings represent the relationship between observable indicators and latent variables (Wang & Wang, 2019). Standard CFA models consist of observable indicators that are linked to only one latent variable. Therefore, the factor loadings between observable indicators and latent variables with no relationship are fixed to zero. Moreover, the measurement errors of these variables are not correlated with other measurement errors. In contrast, a non-standard CFA model consists of observable indicators which have cross-factor loadings, which are linked to more than one latent variable (Wang & Wang, 2019).

In CFA, measurement models need to be identified, that is because parameters in under identified models cannot be estimated (Wang & Wang, 2019). There are two general requirements measurement models in CFA must meet in order to be identified (Kline, 2016; Wang & Wang, 2019). First, every latent variable must be scaled (including error terms) to establish a measurement scale of a latent variable. This can be done by setting the variance of each latent variable to 1, which ensures a simplified interpretation of the model, or by setting the variance of one factor loading to 1. Second, the degrees of freedom in the model must be at least 0 ($df_m \geq 0$). The degree of freedom is calculated by subtracting the number of estimated parameters (i.e., factor loadings, variances, covariances, residual variances) from the number of observable indicators.

Next to the two general requirements, Kline (2016) notes that standard CFA models with a single latent variable need at least three observable indicators and that standard CFA models with two or more latent variables require two or more observable indicators. If the model meets these conditions, then the model is identified.

3.1.4 Performance assessment and interpretation of results

Kline (2016) emphasizes that both the individual parameters and the overall model fit need to be tested and reported. A model can have a good overall fit, while at the same time the model fits the data poorly on specific parts.

To test the performance of specific parts of the model, attention should be paid to the factor loadings (Wang & Wang, 2019). Factor loadings (λ) represent the strength and direction of the relationship between observable indicators and latent variables. These factor loadings can take values between -1 and 1. The sign of the factor loading indicates whether the relationship is positive or negative, whereas the magnitude indicates the strength of the relationship. For standardized factor loadings, a λ-value of .30-.40 is generally considered as the "cut-off point" (Ford et al., 1986; Brown, 2015). Kumar and Upadhaya (2017) and (Hair et al., 2011) point out that this value should be ≥.70, indicating that factor loadings with a lower absolute value indicate an insufficient relation between the observable indicator and latent variable. Moreover, Brown (2015) indicates that a specific guideline does not exist, emphasizing that the "cut-off point" depends on the research context. Therefore, to be conservative, this study aims for factor loadings > .60. Nonetheless, acceptable indicators should always be statistically significant (Wang & Wang, 2019). Therefore, a statistically significant factor loading with a high magnitude can be interpreted as a strong relationship, meaning that the observable indicator accurately predicts the latent construct.

Cronbach's Alpha (CA), Composite Reliability (CR), and Average Variance Extracted (AVE) will be used to assess the reliability and validity of the constructs. CA and CR measure the internal reliability of constructs, which is considered acceptable they exceed the threshold value of .70 (Hair et al., 2011; Hair et al., 2014). A threshold of .60 is acceptable for explanatory research, indicating a more modest reliability (Hair et al., 2011). AVE measures convergent validity and is considered acceptable above .50 (Hair et al., 2011; Hair et al., 2014).

The square root of AVE and the cross-loadings between constructs will be used to assess the discriminant validity of constructs. Discriminant validity is confirmed if the square root of AVE is greater than the cross-loadings with another construct (Henseler et al., 2009).

To evaluate the fit of the model, several goodness of fit indices will be documented. These are the Chi-square to degree of freedom ratio (CMIN/DF), the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), the Steiger–Lind Root Mean Square Error of Approximation (RMSEA), and the Standardized Root Mean Square Residual (SRMR). CFI and TLI range between 0 and 1, where a TLI and CFI value of 1 indicates a perfect fit. The opposite follows for CMIN/DF, RMSEA and SRMR, for which a low value implies a good model fit. Acceptable values for these tests are CMIN/DF ≤ 3, CFI and TLI ≥ .90, and RMSEA and SRMR ≤ .07 (Byrne, 2010; Hair et al., 2018; Cho et al., 2020). Additionally, to test how well the model performs, the R-squared will be reported. The R-squared value measures the variability explained by the model; it shows how well the model fits the data (Hair et al., 2018).

3.2 Conclusion

Structural equation modeling (SEM) is a method frequently used to study latent variables. It consists of a measurement model (to study relationships between observable indicators and constructs) and a structural model (to study relationships between constructs). Confirmatory Factor Analysis (CFA) will be used to develop the measurement model. This model is the basis of the SEM model.

To assess the performance of the CFA and SEM models, factor loadings, Cronbach's Alpha (CA), Composite Reliability (CR), Average Variance Extracted (AVE), goodness of fit indices, and R-squared will be reported.

4. Standard framework

Before analyzing the conceptual framework (Figure 2), first, a more standard framework will be analyzed based on previously collected data via an online questionnaire. This data set is referred to as Data set 1 and this questionnaire is referred to as questionnaire 1 (Q1). This chapter starts with a discussion of the data, followed by the sample description, the distribution of the items, the results of CFA, and the results of SEM of the standard framework.

4.1 Data

In December 2022, the data were collected amongst Dutch residents aged 22 years or older, non-students with a driving license. This data set includes observable indicators that allow the study of a large set of, not all, (latent) variables and relationships in Figure 2. This data was collected by co-workers from the Urban Planning and Transportation Group at Eindhoven University of Technology (TU/e) and the observable indicators are mainly based on Curtale et al. (2021).

The framework in this section is referred to as the Standard framework (Figure 4). The hypotheses in this framework are added subscript *-s* in order to differentiate them from the theorized hypothesis. Each hypothesis number in the standard framework correspondents to the proposed hypothesis in Section 2.2; however, due to the absence of BI, the proposed paths in H1 to H9 are instead modeled on UB. The standard framework will be analyzed independently, and results will be compared to the results of the extended framework (discussed in the following chapter) to gain deeper insights into the determinants of UB and to provide a more comprehensive analysis.

The questionnaire contained a cover letter, describing the relevance of the study, followed by two parts. The first part is used to gather demographic details (i.e., age gender, income, and education) and the second part is used to measure the (latent) variables. In Table 1, each construct from this framework with their respective measurement items (i.e., observable indicators) that are present in the questionnaire of Data Set 1 are depicted. For each construct, respondents were asked to score each item on a 5-point Likert scale, ranging from 1 (= *strongly disagree*) to 5 (= *strongly agree*).

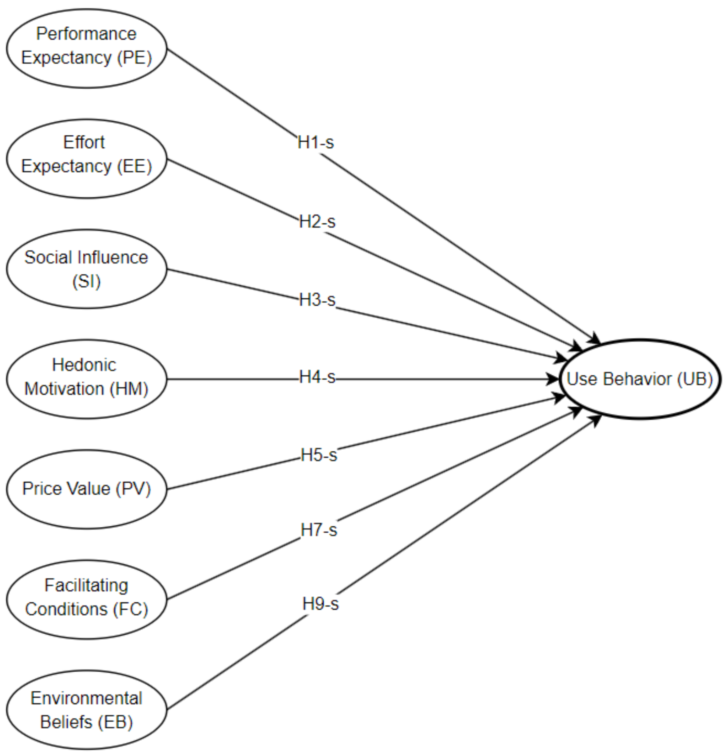

Figure 4. Standard framework - Questionnaire 1.

Table 1. Measurement items - Questionnaire 1.

Construct	Code	Item
Performance Expectancy (PE)	PE1 PE2 PE3 PE4	The solar vehicle will be as comfortable as a regular car. The solar vehicle will receive enough solar energy while parking and driving. The solar vehicle will enhance my travel convenience. The solar vehicle will be the most energy-efficient.
Effort Expectancy (EE)	EE1 EE2 EE3 EE4	I expect that it will be easy to learn how to drive the solar vehicle. I expect that it will be easy to charge the solar vehicle. I expect that it is clear and simple to operate the solar vehicle. I expect that you will quickly become adept at using the solar vehicle.
Social Influence (SI)	SI1 SI2 SI3 SI4	People who are important to me think that I should use a green energy car. People whose opinions I value think that I should use a green energy car. I would use a solar-powered car if my friends/colleagues recommend me to. I would use the solar vehicle sooner if my friends/colleagues also use one.
Hedonic Motivation (HM)	HM1 HM2 HM3	I think driving a solar vehicle is enjoyable. I think driving a solar vehicle is entertaining. I think driving in a solar vehicle is pleasurable.
Price Value (PV)	PV1 PV2 PV3 PV4	I expect that the solar vehicle is reasonably priced given its innovative nature. I expect that the solar vehicle will save money on fuel in the long term. I expect that the solar vehicle will save me travel time. I expect that the solar vehicle is of great value to our environment.
Technophilia (TP)	*Not included.*	
Facilitating Conditions (FC)	FC1 FC2 FC3	I expect that I would receive sufficient guidance to use the solar vehicle. I expect that the solar vehicle integrates perfectly with existing charging systems for electric cars. I expect that the maintenance of the solar vehicle will be simpler with advanced technologies.
Habit (HB)	*Not included.*	
Attitude (AT)	*Not included.*	
Use Behavior (UB)	BI1 BI2 BI3 BI4	I plan to purchase a solar vehicle in the future. I plan to purchase a solar vehicle if the opportunity arises. I would buy a solar vehicle if it is available at an affordable price. I would encourage friends/colleagues to purchase a solar vehicle.
Environmental Beliefs (EB)	EB1 EB2 EB3 EB4	I would pay attention to the energy label when purchasing a product. I would use sustainable products, even if they are sometimes more expensive. I would consider the solar vehicle an innovative solution to address traffic emissions. If necessary, I would avoid using gasoline or diesel to reduce emissions.

4.2 Sample description

The sample consists of a Dutch panel that represents the Dutch population. The questionnaire was divided into two parts. The first part contained questions regarding sociodemographics relevant to this study, as well as other questions irrelevant to this study. The second part contained the observable indicators. A total of 765 respondents completed part one of the questionnaire, and 555 respondents completed both parts of the questionnaire. Of these 555 respondents, 32 respondents provided invariant answers across all Likert scale questions ($SD \leq 0.25$) and were excluded from the analysis. This resulted in 523 respondents used for the analysis. The data contained no missing values.

The sociodemographic and car-related characteristics are binned to appropriate levels and the final results are depicted in Table 2. In the final sample, males are slightly overrepresented. All respondents are aged over 22 and 53.5% of the respondents are aged over 50. In terms of income, 43.2% have a net monthly income of less than €2.000, 39.4% have a net monthly income between €2.000 and €3.000, and 17.4% have a net monthly income of more than €3.000. Regarding the net monthly income of respondents' partners, 59.3% earn less than €3.000, 7.6% earn more than €3.000, and 33.1% either have no partner or a partner with no income. Of the respondents, 38.6% is highly educated and 61.4% do not possess a higher-educations degree. All respondents are in possession of a driver's license and 96.4% of the respondents are experienced drivers with more than 4 years of driving experience.

In addition, 64.6% are in possession of one private vehicle, 29.8% are in possession of two or more private vehicles, and 5.6% do not possess a private vehicle. Of these private vehicles, 7.1% is an electric vehicle and slightly more respondents drive an electric vehicle (8.2%) (e.g., private vehicle or company vehicle). Of the respondents, 44.4% indicate that they were familiar with the concept ‘solar vehicle’ prior to reading the introduction text in the questionnaire.

Table 2. Sociodemographic and car-related characteristics - Q1 (N = 523).

Variable	Levels	Percentage
Gender	male *(ref.)*	54.3
	female	45.7
Age	under or 30 *(ref.)***	8.6
	30-50**	37.9
	over 50	53.5
Income	low (< €2.000) *(ref.)***	43.2
	medium (€2.000 - €3.000)**	39.4
	high (> €3.000)	17.4
Income partner	no partner or no income *(ref.)*	33.1
	low and medium (≤ €3.000)**	59.3
	high (> €3.000)**	7.6
Education level	non-higher education *(ref.)*	61.4
	higher education	38.6
Years of driving experience	0-4 years *(ref.)*	3.6
	> 4 years	96.4
Number of vehicles in household	0 *(ref.)***	5.6
	1**	64.6
	2 or more	29.8
Electric vehicle in household	no *(ref.)*	92.9
	yes	7.1
Drives electric vehicle	no *(ref.)*	91.8
	yes	8.2
Familiar with solar vehicles*	no	55.6
	yes	44.4

(ref.) = reference group
** = variable not included in analysis*
*** = combined into one level for analysis*

4.3 Consistency, heterogeneity, and distribution of items

For each item, the mean, standard deviation, skewness, and kurtosis are determined by descriptive statistics. The mean shows an average score of 3.3, which is around the middle level of the five-point Likert scale. Most standard deviations are around one, showing a degree of heterogeneous responses. For almost all items, except SI, the skewness is negative with a mean of -0.37 and a mean absolute value of 0.46. This implies that the data is slightly asymmetric and slightly favors scores above the mean. Most items have a positive kurtosis with a mean of 0.28 and a mean absolute value of 0.63, indicating heavier tails. To conclude, the data have sufficient heterogeneity and lean to slightly asymmetric distribution with a high frequency of extreme answers. All skewness and kurtosis values are within the boundaries suggested by Kline (2016). All mean, standard deviation, skewness, and kurtosis values of Q1 can be accessed in Appendix A, Table A1.

4.4 CFA results

IBM SPSS AMOS version 28 was used to conduct CFA. First, all items were loaded into the model. Five factor loadings (<0.6), two CA-values (<0.7), one CR-value (<0.7), and four AVE-values (<0.5) were observed below the recommended values (Hair et al., 2011; Hair et al., 2014) (Table 3). Moreover, four of five goodness of fit indices (CMIN/DF = 3.600, CFI = 0.893, TLI = 0.877, RMSE = 0.071) violate the rules of a good measurement model (Byrne, 2010; Hair et al., 2018; Cho et al., 2020). Only SRMR (0.061) was found acceptable (Hair et al., 2018; Cho et al., 2020).

Second, to increase the model’s performance, a data elimination process was conducted. A total of 21 CFA models were tested and compared. The elimination process was conducted using a CA analysis in SPSS and modification indices analysis in AMOS. The final model resulted in the elimination of eight items (PE1, EE2, SI4, PV1, PV3, FC3, EB3, and UB3). These items are dropped to ensure better overall CR scores, AVE scores, and model fit. Moreover, three covariances are added between error terms of items with the same underlaying latent variable, namely PE2-PE4, PE3-PE4, and BI2-BI4. These covariances were added by making use of the modification indices provided by AMOS to ensure a better model fit.

In the final model, all factor loadings, except PE2, report a value above the aimed value of 0.6 (Table 3). Moreover, all factor loadings, except PE2, EB1, and EB2, report a value above the stricter guideline of 0.7, suggested by (Hair et al., 2011). All items are statistically significant (p-value <0.001). The CR values of all items are above 0.7 and AVE values of all items are above 0.5, validating the validity and reliability (Hair et al., 2011; Hair et al., 2014). The CA values are also above the recommended value, except for PE2, which reports a CA of 0.677. This value is close to the recommended value, but not ideal, and is in this case considered to have a moderate reliability. The constructs PE2, EB1, and EB2 (factor loadings of 0.593, 0.627, and 0.692, respectively) are not considered for removal, as their removal results in a significant drop in CA, CR, and AVE of the respective construct (Henseler et al., 2009).

Table 3. Reliability, validity, and goodness of fit - Q1 (N = 523).

Construct	Item	Initial Model Q1				Final Model Q1			
		Factor loading (λ)	Cronbach's Alpha	CR	AVE	Factor loading (λ)	Cronbach's Alpha	CR	AVE
Performance Expectancy	PE1	0.582	0.712	0.709	0.380	dropped	0.677	0.775	0.539
	PE2	0.544				0.593			
	PE3	0.672				0.769			
	PE4	0.658				0.821			
Effort Expectancy	EE1	0.732	0.862	0.866	0.620	0.741	0.853	0.852	0.658
	EE2	0.730				dropped			
	EE3	0.825				0.811			
	EE4	0.854				0.876			
Social Influence	SI1	0.906	0.887	0.886	0.664	0.919	0.885	0.894	0.739
	SI2	0.903				0.915			
	SI3	0.770				0.732			
	SI4	0.654				dropped			
Hedonic Motivation	HM1	0.876	0.875	0.877	0.704	0.871	0.875	0.877	0.704
	HM2	0.764				0.765			
	HM3	0.882				0.877			
Price Value	PV1	0.333	0.627	0.663	0.346	dropped	0.709	0.710	0.550
	PV2	0.717				0.753			
	PV3	0.512				dropped			
	PV4	0.706				0.730			
Facilitating Conditions	FC1	0.701	0.667	0.707	0.450	0.759	0.733	0.740	0.588
	FC2	0.754				0.774			
	FC3	0.539				dropped			
Environmental Beliefs	EB1	0.616	0.794	0.793	0.491	0.627	0.752	0.751	0.505
	EB2	0.648				0.692			
	EB3	0.742				dropped			
	EB4	0.783				0.801			
Use Behavior	UB1	0.856	0.902	0.905	0.704	0.840	0.878	0.895	0.740
	UB2	0.884				0.901			
	UB3	0.818				dropped			
	UB4	0.795				0.839			

Goodness of fit	Initial Model	Final Model
CMIN/DF	3.600	2.217
CFI	0.893	0.967
TLI	0.877	0.957
RMSEA	0.071	0.048
SRMR	0.061	0.040

CR = Composite Reliability, AVE = Average Variance Extracted, CMIN/DF = Chi-square to degree of freedom ratio, CFI = Comparative Fit Index, TLI = Tucker-Lewis Index, RMSEA = Steiger–Lind Root Mean Square Error of Approximation, SRMR = Standardized Root Mean Square Residual

Discriminant validity is assessed by the square root of AVE, which ranges from 0.734 to 0.860, and the cross-loadings. Some cross-loadings on other constructs report a higher value than the square root of AVE. Therefore, discriminant validity of the model is not satisfied.

Lastly, the goodness of fit indices of the model increased (CMIN/DF = 3.600→2.217, CFI = 0.893→0.967, TLI = 0.877→0.957, RMSEA = 0.07→0.048, SRMR = 0.061→0.040), resulting in an adequate fit values (Byrne, 2010; Hair et al., 2018; Cho et al., 2020) (Table 3).

4.5 SEM results

In this section, the direct effects on UB and mediating effects are discussed, followed by the moderating effects.

4.5.1 Direct and mediating effects

The final CFA model was used for the structural model to analyze the structural paths between the latent variables. The variables in the first model (Model 1) explain 59.2% of the variability in UB (CMIN/DF = 2.217, CFI = 0.967, TLI = 0.957, RMSEA = 0.048, SRMR = 0.040). The strongest predictor of UB in this model is EB, which shows a significant path coefficient (β) of 0.292 (p-value = 0.006), followed by HM (β = 0.284, p-value = <0.001), PE (β = 0.164, p-value = 0.055), and SI (β = 0.148, p-value = 0.013) (Table 4). EE, PV, and FC show no statistical significance on their impact on UB. In the second model (Model 2) mediating effects are tested. An iterative process is carried out to test whether the constructs that show insignificant direct impact on UB possibly have indirect effects via mediating variables. The constructs PV and FC were found to have significant effects on PE and HM. In Model 2, PV and FC are variables that have an indirect effect on UB via the mediating variables PE and HM. PE and HM are in this model endogenous. The path from PV to PE (β = 0.677, p-value = <0.001) and PV to HM (β = 0.496, p-value = <0.001) are positive and significant. The same follows for FC to PE (β = 0.156, p-value = 0.028) and FC to HM (β = 0.350, p-value = <0.001). EE does not seem to have its effect on UB mediated via other constructs. The direct effects on UB are shown in Table 4. Again, the direct effect of EB is strongest (β = 0.283, p-value = 0.002), followed by HM, SI, and PE. In Model 2, the explained variability of UB slightly decreased to 58.8% (CMIN/DF = 2.395, CFI = 0.961, TLI = 0.951, RMSEA = 0.052, SRMR = 0.046).

The third model (Model 3) includes sociodemographic and car-related characteristics. Covariances between the variables that deemed logical and with a modification index score of > 10 were added to ensure a better model fit. By adding the sociodemographic and car-related characteristics, the explained variability of UB increased to 61.0% (CMIN/DF = 2.243, CFI = 0.932, TLI = 0.922, RMSEA = 0.049, SRMR = 0.064). EB remained the strongest predictor of UB (β = 0.325, p-value = <0.001), followed by HM (β = 0.269, p-value = <0.001), PE (β = 0.141, p-value = 0.054), and SI (β = 0.140, p-value = 0.004) (Table 4). This supports hypotheses H1-s, H3-s, H4-s, H9-s and rejects H2-s. For the sociodemographic characteristics, both gender (β = -0.067, p-value = 0.035) and age (β = -0.059, p-value = 0.065) have a negative impact on UB as hypothesized, supporting H12a-s ad H12b-s. This implies that females and older individuals exhibit lower levels of adoption. Other sociodemographic and car-related variables are not significant, rejecting H12c-s, H12d-s, and H13a-s.

To test whether the significant impact of PV and FC on PE and HM results in a significant indirect effect on UB. Bootstrapping, using 5000 repeated samples (N = 5000), was used at a significance level of 0.05. Bootstrapping results show that PE and HM both have significant mediation effects. The total effect of PV on UB is significant at the 0.10 level (β = 0.287, p-value = 0.065), the direct effect is insignificant (β = 0.011, p-value = 0.931), and the indirect effect is significant and positive at the 0.01 level (β = 0.276, p-value = 0.009). This suggests a full mediation and confirms H5-s due to its indirect effect on UB. While the total effect and direct effect of FC on UB are insignificant (β = 0.054, p-value = 0.682; β = -0.066, p-value = 0.716), the indirect effect on UB is significant and positive (β = 0.120, p-value = 0.071). This again suggests a full mediation, thus confirming H7-s.

Additionally, to test whether PE and HM have mediating effects for both PV and FC, user estimands were defined. User estimands are custom functions in AMOS that allow for more comprehensive analysis. This allows for the study of indirect effects through multiple constructs separately, rather than only testing the total indirect effect. Both indirect effects via PE and HM are significant for PV. Only HM is significant for FC. Hence, the results show that PE has a mediation effect on PV, and HM has a mediation effect on both PE and FC. For all bootstrapping results of Q1, see Appendix B, Table 1.

Finally, a supplementary model was tested including the indirect effects of sociodemographic and car-related characteristics on UB. While significant effects are found between sociodemographic characteristics, car-related characteristics, and other constructs, suggesting that sociodemographic and car-related characteristics with insignificant direct impact on UB have indirect effect on UB through mediating constructs, the model fit, and explanatory power of the model severely decreased. Therefore, the more parsimonious model, Model 3, is chosen as the final model. In Figure 5, the direct and indirect effects of this model are schematically shown.

Table 4. Path coefficients direct impact on UB - Q1 (N = 523).

Dependent variable → UB	**Model 1**		**Model 2**		**Model 3**	
	β	***p*-value**	***β***	***p*-value**	***β***	***p*-value**
Performance Expectancy	0.164*	0.055	0.138*	0.064	0.141*	0.054
Effort Expectancy	0.052	0.636	0.049	0.650	0.069	0.519
Social Influence	0.148**	0.013	0.160***	0.001	0.140***	0.004
Hedonic Motivation	0.284***	<0.001	0.277***	<0.001	0.269***	<0.001
Price Value	0.040	0.782	0.067	0.650	0.050	0.731
Facilitating Conditions	-0.054	0.701	-0.046	0.733	0.059	0.656
Environmental Beliefs	0.292***	0.006	0.283***	0.002	0.325***	<0.001
Gender					-0.067**	0.035
Age					-0.059*	0.065
Income					0.025	0.440
Income partner					0.009	0.795
Education level					-0.044	0.170
Driving experience					-0.009	0.771
Vehicles in household					0.033	0.334
Electric vehicle in household					0.010	0.822
Drives electric vehicle					-0.035	0.448
R-square	0.592		0.588		0.610	

β = standardized regression weight
**** = p-value <0.01, ** = p-value <0.05, * = p-value <0.10*

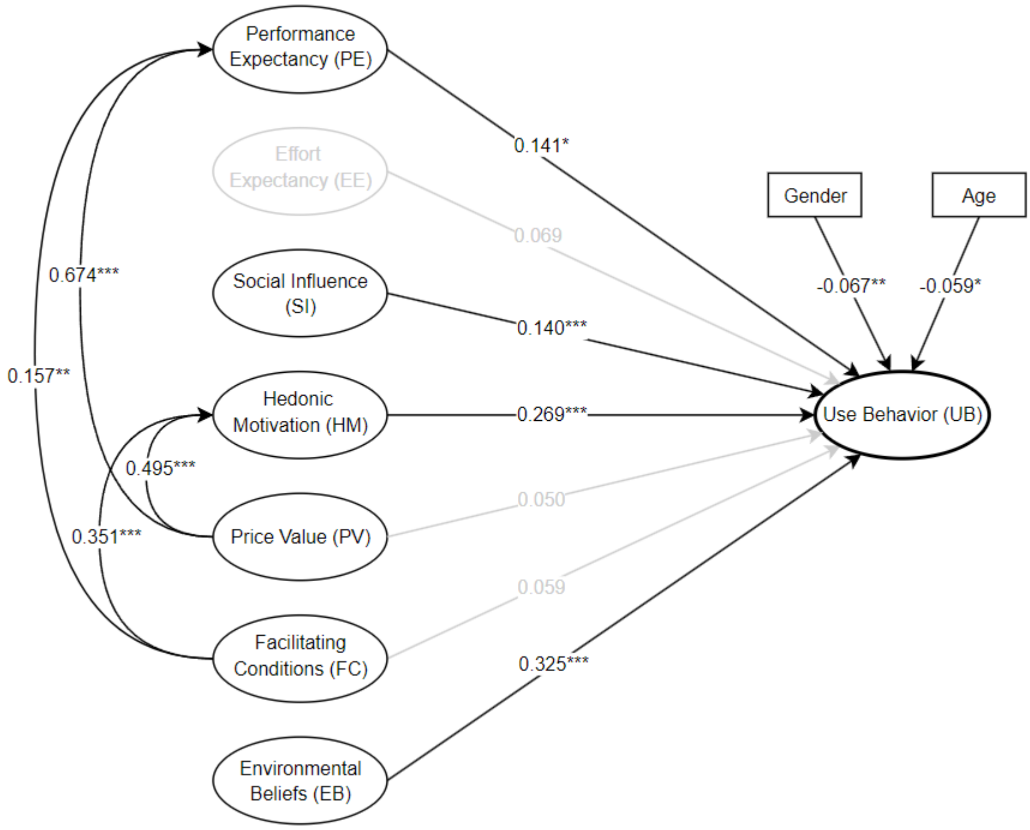

Figure 5. Schematic results of the standard framework - Q1 (N = 523).
**** = p-value <0.01, ** = p-value <0.05, * = p-value <0.10*

4.5.2 Moderating effects

The moderating effects of gender, age, income, education level, and electric vehicle experience on the direct paths on UB are tested by making use of multi-group analysis in AMOS. To find which of these variables significantly influences one or more paths on UB, an unconstrained model is compared to several constrained models. For each variable, the difference between two groups was tested. For gender: males and females, for age: under or 50 and over 50, for income: low and medium (≤ €3.000) and high (> €3.000), for education: non-higher and higher education, and for EV experience: yes/no EV experience.

First, a constrained model, in which all structural weights are constrained, was compared to the unconstrained model for each of the five variables independently. The invariance test between groups was conducted through a Chi-square difference test. If the Chi-square difference test was determined significant, meaning that the overall models between groups are inequivalent, constrains between paths were one by one lifted to find the relationships that significantly differ between groups. The paths EE and FC on UB were found to significantly differ between males and females: females exhibit a negative moderating effect on the path of EE on UB and exhibit a positive moderating effect on the path FC on UB. The paths PE and SI on UB were found to significantly differ between age levels: individuals with a higher age exhibit a negative moderating effect on these paths. The paths EE and SI on UB were found to significantly differ between income groups: individuals with a higher income exhibit a negative moderating effect on these paths. The paths PE, HM, and EB on UB were found to significantly differ between education levels: individuals with a higher education exhibit a negative moderating effect on these paths (Table 5). This partially supports H12e-s. Electric vehicle experience does not seem to have moderating effects on the direct relationships between latent constructs on UB, hence rejecting H13b-s. A list of all hypotheses is depicted in Table 6.

Table 5. Summary of multi-group analysis - Q1 (N = 523).

Path	Moderated by				
	Gender	**Age**	**Income**	**Education**	**EV experience**
PE → UB	no	yes (-)	no	yes (-)	no
EE → UB	yes (-)	no	yes (-)	no	no
SI → UB	no	yes (-)	yes (-)	no	no
HM → UB	no	no	no	yes (-)	no
PV → UB	no	no	no	no	no
FC → UB	yes (+)	no	no	no	no
EB → UB	no	no	no	yes (-)	no

+ = positive impact, - = negative impact
EV = electric vehicle

Table 6. Hypotheses testing - Q1 (N = 523).

Hypothesis	Supposed path and impact	Supported by		Mediating variable
		Direct effect	**Indirect effect**	
H1-s	PE → UB (+)	yes	-	-
H2-s	EE → UB (+)	no	no	-
H3-s	SI → UB (+)	yes	-	-
H4-s	HM → UB (+)	yes	-	-
H5-s	PV → UB (+)	no	yes	PE, HM
H7-s	FC → UB (+)	no	yes	HM
H9-s	EB → UB (+)	yes	-	-
H12a-s	Gender → UB (-)	yes	-	-
H12b-s	Age → UB (-)	yes	-	-
H12c-s	Income → UB (+)	no	n.t.	-
H12d-s	Education → UB (+)	no	n.t.	-
H13a-s	EV experience → UB (+)	no	n.t.	-
Hypothesis		**Supported**		**Moderating variable**
H12e-s	Moderation effect of sociodemographics	yes, partially		gender, age, income, education
H13b-s	Moderation effect of EV experience	no		-

+ = positive impact, - = negative impact
EV = electric vehicle
n.t. = not tested

4.6 Conclusion

Data collected in 2022 allowed for a partial study of the conceptual model theorized in Section 2.2. The model for this data set is referred to as the standard framework. The standard framework supports four hypotheses of psychological constructs on UB (PE; H1-s, SI; H3-s, HM; H4-s, and EB; H9-s) and rejects three hypotheses (EE; H2-s, PV; H5-s, FC; H7-s), although H5-s and H7-s are partially supported through their indirect effect via PE and HM. Gender and age are found to directly affect UB, supporting H12a-s and H12b-s. The other sociodemographic and car-related characteristics do not directly affect UB, thus H12c-s, H12d-s, H13a-s are rejected.

For some sociodemographic and car-related variables, their moderating effects are tested on the relationship between psychological constructs and UB. Gender, age, income, and education have moderating effects on these relationships, partially supporting H12e-s. Electric vehicle experience has no moderating effect, rejecting H13a-s.

5. Extended framework

This chapter discusses the conceptual framework depicted in Figure 2. As previously discussed, Data set 1 does not contain all the information necessary to analyze all variables and relationships presented in this conceptual model. Therefore, this chapter starts with a discussion of the (additional) data needed and the minimum sample size in order to analyze this model, followed by the sample description, the distribution of the items, the results of CFA, and the results of SEM of the extended framework.

5.1 Data

This section discusses the design of questionnaire 2 (Q2) and the minimum sample size.

5.1.1 Questionnaire design

To test the complete theoretical model (Figure 2), additional questions are needed to collect all psychological variables. Therefore, questionnaire 1 was adapted. The new questionnaire, referred to as questionnaire 2, was designed by using questionnaire 1 as a basis. The measurement items of some items are slightly adapted, and some items are replaced by other items. This is done to enhance clarity and consistency throughout the new questionnaire. The adaptation and removal of items is done by making use of previous literature (Venkatesh et al., 2003; Venkatesh et al., 2012; Abbasi et al., 2021; Bhat et al., 2021; Zhou et al., 2021; Gunawan et al., 2022) (Table 7).

Questionnaire 2 contained the following information, also present in questionnaire 1:

- Sociodemographics (age, gender, income, education);
- Experience with electric vehicles;
- Individuals' environmental beliefs;
- Individuals' beliefs regarding the time-effectiveness, cost-effectiveness, and environmental friendliness of a solar vehicle;
- Individuals' beliefs regarding the difficulty of using a solar vehicle;
- Influence of friends, family, and society on individuals' actions;
- Individuals' beliefs regarding the feelings when using a solar vehicle;
- Individuals' beliefs regarding the costs of a solar vehicle;
- Individuals' beliefs regarding the resources and knowledge available of a solar vehicle;
- Individuals' intention to adopt a solar vehicle.

And the following information is not present in questionnaire 1:

- Individuals' affinity with technology;
- Individuals' beliefs regarding (adjusting) the habits to align with the use of a solar vehicle;
- Individuals' overall attitude towards a solar vehicle;
- Individuals' intention to use a solar vehicle.

Consistent with questionnaire 1, this questionnaire contains a cover letter describing the relevance of the study and the same 5-point Likert scale, ranging from 1 (= *strongly disagree*) to 5 (= *strongly agree*).

5.1.2 Sample size

For SEM, the minimum sample size is not fixed. Wolf et al. (2013) determined that the sample size depends on several factors, such as the complexity of the study, the number of latent variables, the number of observable indicators, and the chosen significance level. Through Monte Carlo simulations, Wolf et al. (2013) explored the minimum sample size for SEM and identified a complex relationship between the minimum sample size and the number of latent variables, the number of observable indicators, and the magnitude of factor loadings. They observed that the number of latent variables significantly increases the minimum sample size, while the number of observable indicators and a higher magnitude of the factor loadings significantly decreases the minimum sample size. However, in many models the need for a larger sample size is not driven by the statistical power, but rather due to bias and errors in the study (Wolf et al., 2013). Therefore, it is difficult to determine the minimum sample size. For this reason, the minimum sample size will be based on several rules of thumb. These range from 100-200 observations (Boomsma, 1983), to 10 observations per variable (Nunnally, 1967), and 5 or 10 observations per parameter (Bentler & Chou, 1987; Hair et al., 2016). Considering 45 observable indicators, this puts the minimum sample size at 225.

Table 7. Measurement items - Questionnaire 2.

Construct	Coding	Items
Performance Expectancy (PE)	PE1	Using a solar vehicle will be cost-effective.*
	PE2	Using a solar vehicle will enhance my travel convenience.*
	PE3	Using a solar vehicle will be the most energy-efficient.*
	PE4	Using a solar vehicle will increase my overall productivity.*
Effort Expectancy (EE)	EE1	It will be easy for me to learn how to drive the solar vehicle.*
	EE2	It will be easy for me to charge the solar vehicle.*
	EE3	It will be easy for me to operate the solar vehicle.*
	EE4	I will quickly become adept at using the solar vehicle.*
Social Influence (SI)	SI1	People who are important to me think that I should use an emission-free car.*
	SI2	People whose opinions I value think that I should use an emission-free car.*
	SI3	I would use a solar vehicle if my friends/colleagues recommend me to.
	SI4	I would use a solar vehicle sooner if my friends/colleagues also use one.
Hedonic Motivation (HM)	HM1	I think driving a solar vehicle is enjoyable.
	HM2	I think driving a solar vehicle is entertaining.
	HM3	I think driving in a solar vehicle is pleasurable.
	HM4	Using a solar vehicle will make me more proud.**
Price Value (PV)	PV1	I expect that the solar vehicle will be reasonably priced.*
	PV2	Using a solar vehicle will save money on fuel in the long term.*
	PV3	By using a solar vehicle I will get good value for my money.**
	PV4	The solar vehicle seems of great value to our environment.*
Technophilia (TP)**	TP1	I get excited about a new product in the market.**
	TP2	I like to buy new products early after their launch.**
	TP3	Innovative mobility technologies make me enthusiastic to adopt a solar vehicle.**
Facilitating Conditions (FC)	FC1	I expect that I would receive sufficient support to use the solar vehicle.*
	FC2	I expect that I would receive sufficient information to use the solar vehicle.**
	FC3	I expect that the solar vehicle integrates perfectly with existing charging systems for electric cars.
	FC4	I expect that the solar vehicle will be compatible with other technologies I use.**
Habit (HB)**	HB1	Using a solar vehicle will become a habit for me.**
	HB2	Using a solar vehicle will become natural for me.**
	HB3	I will be used to using a solar vehicle.**
	HB4	My habit of using a combustion engine vehicle makes it impossible for me to use a solar vehicle. (negatively coded)**
Attitude (AT)**	AT1	Using a solar vehicle is an important thing.**
	AT2	Using a solar vehicle is a good idea.**
	AT3	I think it is necessary to use a solar vehicle in the near future**
Behavioral Intention (BI)**	BI1	I intend to use a solar vehicle in the near future.**
	BI2	I intend to use a solar vehicle whenever I have the possibility.**
	BI3	I predict I will use a solar vehicle in the near future.**
Use Behavior (UB)	UB1	I plan to purchase a solar vehicle in the future.
	UB2	I plan to purchase a solar vehicle if the opportunity arises.
	UB3	I would purchase a solar vehicle if it is available at an affordable price.
	UB4	I would recommend others to buy a solar vehicle whenever they plan to buy a vehicle.
Environmental Beliefs (EB)	EB1	I pay attention to the energy label when purchasing a product.*
	EB2	I use sustainable products, even if they are sometimes more expensive.*
	EB3	I consider the solar vehicle an innovative solution to address traffic emissions.
	EB4	I avoid using gasoline or diesel to reduce emissions.*

** = adapted/rephrased item, ** = new item/construct*

5.2 Sample description

The online questionnaire was administered in the Netherlands between March and May 2024 using a combination of social media advertisements (Facebook and Instagram), LinkedIn, and outreach through students, colleagues, friends, and relatives. In total, 254 respondents completed the questionnaire, three respondents did not agree with the consent form, and one respondent provided invariant answers across all Likert scale questions (SD ≤ 0.25). These observations were excluded from the analysis, which resulted in 250 observations used for the analysis. This sample size is sufficient according to Nunnally (1967), Boomsma (1983), Bentler & Chou (1987), and Hair et al. (2016). The data contained no missing values.

The sociodemographic and car-related characteristics are again binned to appropriate levels (Table 8). Some variables contain different levels compared to the previous questionnaire. This is due to variations in the levels of measurement, making binning into the same levels impossible or resulting in too few responses for certain levels. For comparison, the sample of questionnaire 1 and questionnaire 2 are combined and accessible in Appendix C.

Among the respondents of questionnaire 2, 62.8% are males and 37.2% are females. The three age levels are relatively well balanced with 28.8%, 37.6%, and 33.6% for the age categories under or 30, 30-50, and over 50, respectively. Regarding income, 55.2% have a net monthly income of a maximum of €3.000 and 44.8% have a net monthly income of more than €3.000. Regarding the net monthly income of respondents' partners, 43.2% earn less than €3.000, 26.4% earn more than €3.000, and 30.4% either have no partner or a partner with no income. The majority (65.2%) are highly educated and 34.8% do not possess a higher-education degree. In terms of employment, 68.4% have a full-time job of at least 32 hours per week, 22.0% are unemployed or have a part-time job of less than 32 hours per week, and 9.6% are students. All but three respondents are in possession of a driver's license and the vast majority, 72.8%, have more than 10 years of driving experience, in comparison to 7.6% with less than 4 years of driving experience and 19.6% who have between 4 and 10 years of driving experience. Combined, 26.4% drives an electric or hybrid vehicle, of which 17.2% electric and 9.2% hybrid. This contains either their personal vehicles and/or other vehicles (i.e., company vehicle) that they regularly use. Contradictory to questionnaire 1, the majority (76.0%) indicate that they were familiar with the concept of 'solar vehicle' prior to reading the introduction text in the questionnaire.

Table 8. Sociodemographic and car-related characteristics - Q2 (N = 250).

Variable	Levels	Percentage
Gender	male *(ref.)*	62.8
	female	37.2
Age	under or 30 *(ref.)***	28.8
	30-50**	37.6
	over 50	33.6
Income	low and medium (≤ €3.000) *(ref.)*	55.2
	high (> €3.000)	44.8
Income partner	no partner or no income *(ref.)*	30.4
	low and medium (≤ €3.000)**	43.2
	high (> €3.000)**	26.4
Education level	non-higher education *(ref.)*	34.8
	higher education	65.2
Employment type*	full time (32 hours/week or more)	68.4
	part time (<32 hours/week) or no employment	22.0
	student	9.6
Years of driving experience	< 4 years *(ref.)***	7.6
	4-10 years**	19.6
	> 10 years	72.8
Drives electric/hybrid vehicle	no *(ref.)*	73.6
	yes, hybrid**	9.2
	yes, electric**	17.2
Familiar with solar vehicles*	no	24.0
	yes	76.0

(ref.) = reference group
** = variable not included in analysis*
*** = combined into one level for analysis*

5.3 Consistency, heterogeneity, and distribution of items

Again, for each item the mean, standard deviation, skewness, and kurtosis are determined by descriptive statistics. The mean shows an average score of 3.22, which is around the middle level of the five-point Likert scale (same as Data set 1). Most standard deviations range from 0.82 to 1.00, although there are a few outliers. The highest standard deviation reported is 1.416 for PV1, indicating heavy variant answers between respondents on this construct. For most constructs, the skewness is negative, except for SI (same as Data set 1). The skewness has a mean of -0.26 and an absolute mean of 0.44. This indicates a mild asymmetry in the data that slightly favors scores above the mean (same as Data set 1). The kurtosis has a mean of 0.21, a mean absolute value of 0.54, and around two-thirds of the items have a positive kurtosis, indicating heavier tails and thus a high frequency of extreme answers (same as Data set 1). Overall, the mean, standard deviation, skewness, and kurtosis are comparable with Data set 1 and all skewness and kurtosis values of Data set 2 are acceptable (Kline, 2016). All the mean, standard deviation, skewness, and kurtosis values of questionnaire 2 can be accessed in Appendix A, Table A2.

5.4 CFA results

The same steps have been completed for the CFA process as for the standard framework. All items were loaded into the model and a data elimination process was carried out (CA analysis and modification indices analysis) to increase the model performance. In the final model, BI was removed. BI had a cross-loading of 0.95 on UB, indicating a high correlation. By dropping items and making small changes in the model, preliminary SEM models were used to assess whether this would cause issues going forward. It became evident that including both BI and UB resulted in an overfitted model, as an explanatory power of 0.90 is extremely rare in this line of behavioral studies. Hence, it was decided to remove BI and keep UB in the model. Additionally, one standardized factor loading of above 1 was identified in the final model, commonly referred to as a Heywood case. A small sample size and less than three items per construct often result in a Heywood case (Farooq, 2022). The Heywood Case was solved by constraining the unobserved constructs variance to 1 and constraining the paths of TP1 and TP2 to be equal. This forces the unstandardized results to be similar and the standardized results to differ between the items, resulting in standardized factor loading below 1.

Overall, the data elimination process resulted in a significant increase in reliability, validity, and model fit. All factor loadings are above 0.6 (except PE2) and all CA and CR values are above 0.7, except for PE, indicating reliability and validity issues for this construct. The final model contains the two indicators that resulted in the highest reliability and internal validity for this construct. The reliability and validity for this construct are not ideal, but replacing these two indicators of this construct results in an even lower score. All items are statistically significant (p-value <0.001), and all but three items load on their construct with a factor loading > 0.7.

Convergent validity is not met for PE and PV (AVE of 0.392 and 0.456, respectively) per Hair et al. (2011) and Hair et al. (2014). The square root of AVE ranges from 0.626 to 0.874 and is lower than the cross-loadings of PE and PV, which means that discriminant validity is not satisfied (Henseler et al., 2009). This is explained by the rather low AVE values for PE and PV. By assessing discriminant validity without these two constructs, discriminant validity is validated.

Finally, the goodness of fit of the model increased, resulting in an adequate fit (CMIN/DF = 2.168→1.635, CFI = 0.834→0.952, TLI = 0.813→0.934, RMSEA = 0.068→0.050, SRMR = 0.084→0.045 (Byrne, 2010; Hair et al., 2018; Cho et al., 2020) (Table 9).

Table 9. Reliability, validity, and goodness of fit - Q2 (N = 250).

Construct	Item	Initial Model Q2				Final Model Q2			
		Factor loading (λ)	Cronbach's Alpha	CR	AVE	Factor loading (λ)	Cronbach's Alpha	CR	AVE
Performance Expectancy	PE1	0.513	0.610	0.619	0.289	dropped	0.559	0.563	0.392
	PE2	0.520				0.589			
	PE3	0.531				dropped			
	PE4	0.584				0.653			
Effort Expectancy	EE1	0.761	0.848	0.868	0.626	0.757	0.870	0.877	0.706
	EE2	0.627				dropped			
	EE3	0.907				0.924			
	EE4	0.842				0.831			
Social Influence	SI1	0.906	0.822	0.823	0.555	0.763	0.715	0.716	0.558
	SI2	0.905				dropped			
	SI3	0.618				0.730			
	SI4	0.444				dropped			
Hedonic Motivation	HM1	0.853	0.838	0.868	0.627	0.906	0.840	0.843	0.730
	HM2	0.819				dropped			
	HM3	0.867				0.799			
	HM4	0.599				dropped			
Price Value	PV1	0.211	0.566	0.658	0.354	dropped	0.711	0.714	0.456
	PV2	0.618				0.627			
	PV3	0.641				0.638			
	PV4	0.760				0.753			
Technophilia	TP1	0.561	0.738	0.691	0.441	0.803	0.746	0.751	0.601
	TP2	0.514				0.747			
	TP3	0.863				dropped			
Facilitating Conditions	FC1	0.773	0.759	0.759	0.447	dropped	0.756	0.762	0.617
	FC2	0.767				dropped			
	FC3	0.520				0.723			
	FC4	0.576				0.843			
Habit	HB1	0.902	0.595	0.804	0.641	0.817	0.860	0.865	0.763
	HB2	0.962				dropped			
	HB3	0.859				0.927			
	HB4	-0.296				dropped			
Environmental Beliefs	EB1	0.756	0.703	0.737	0.418	0.861	0.790	0.794	0.659
	EB2	0.702				0.759			
	EB3	0.493				dropped			
	EB4	0.603				dropped			
Attitude	AT1	0.844	0.802	0.814	0.595	0.846	0.766	0.775	0.663
	AT2	0.714				dropped			
	AT3	0.750				0.742			
Behavioral Intention	BI1	0.715	0.807	0.799	0.572	*dropped*			
	BI2	0.840							
	BI3	0.706							
Use Behavior	UB1	0.789	0.845	0.850	0.587	0.838	0.815	0.825	0.702
	UB2	0.813				0.838			
	UB3	0.718				dropped			
	UB4	0.741				dropped			

Goodness of fit	**Initial model**	**Final model**
CMIN/DF	2.168	1.635
CFI	0.834	0.952
TLI	0.813	0.934
RMSEA	0.068	0.050
SRMR	0.084	0.045

CR = Composite Reliability, AVE = Average Variance Extracted, CMIN/DF = Chi-square to degree of freedom ratio, CFI = Comparative Fit Index, TLI = Tucker-Lewis Index, RMSEA = Steiger–Lind Root Mean Square Error of Approximation, SRMR = Standardized Root Mean Square Residual

5.5 SEM results

In this section, the direct effects on UB and mediating effects are discussed, followed by the moderating effects.

5.5.1 Direct and mediating effects

The final CFA model is used for SEM. Repeatedly, several models were tested. Since BI was removed from the model, the paths from PE, EE, SI, HM, and PV on BI are replaced by a direct path on UB.

Model 1 includes all variables except AT and TP and explains 55.4% of the variability of UB (CMIN/DF = 1.578, CFI = 0.963, TLI = 0.948, RMSEA = 0.048, SRMR = 0.044). In this model, EB was modeled on UB due to AT being absent in the model. Three constructs directly influence UB, namely PE (β = 0.425, p-value = 0.097), HB (β = 0.379, p-value = <0.001), and EB (β = 0.131, p-value = 0.070) (Table 10). Other constructs show no significant impact. By adding AT and TP in Model 2, the model explanatory power increases to 62.6% (CMIN/DF = 2.114, CFI = 0.903, TLI = 0.884, RMSEA = 0.067, SRMR = 0.069). In this model, the path between EB on UB was dropped and replaced by the path of EB on AT. The effect of TP on AT is insignificant, but TP shows a significant impact on other constructs as a possible mediator. TP has the strongest significant effect on PE (β = 0.785, p-value = <0.001) and the weakest significant effect on EE (β = 0.409, p-value = <0.001). However, PV (β = 0.685, p-value = <0.001) and EB (β = 0.197, p-value = 0.002) are the only two significant predictors of AT, indirectly affecting UB (Table 10). All direct loadings of TP in Model 2 are accessible in Appendix D, Table D1.

Model 3 includes the sociodemographic and car-related variables. These variables were modeled to study the direct impact on UB and the indirect impact through the more standard UTAUT2 constructs (PE, EE, SI, HM, PV, HB, EB). It is interesting to note that the addition of these variables reduces the variability explained from 62.6% to 61.0% and reduces the model fit (CMIN/DF = 1.944, CFI = 0.887, TLI = 0.850, RMSEA = 0.062, SRMR = 0.077). This likely is a combination of the significant increase in complexity of the model and limited sample size. To avoid even more overfitting and allow for a more parsimonious model that fits the data better, TP and AT are excluded as mediating variables for the sociodemographic and car-related variables since this would reduce the model fit and explanatory power of the model even more. In Model 3, PV (β = 0.692, p-value < 0.001) and EB (β = 0.217, p-value < 0.001) are significant predictors of AT, and in turn, AT is the strongest predictor of UB (β = 0.659, p-value = 0.005) (Table 10). This is as expected and therefore confirms hypotheses H5a, H9a, and H10b. Other psychological constructs have no direct impact on AT, rejecting H1a, H2a, H3a, and H4a. The psychological construct PE is the second strongest predictor of UB (β = 0.315, p-value = 0.066), followed by HB (β = 0.313, p-value = 0.002). This confirms H1b and H8b. Other constructs have no direct impact on UB, thus the hypotheses H2b, H3b, H4b, H5b, and H7b are rejected. In contrast to the expectations, TP does not directly affect AT and therefore H6a is rejected (β = 0.187, p-value = 0.264). However, TP does have a significant effect on PE, EE, SI, HM, PV, FC, and HB (Appendix D, Table D2). Therefore, H6b to H6h are supported. Only PV is significant on AT, and only PE and HB are significant on UB. Thus, the indirect effect of TP on UB, if there is any, is explained by only these three constructs.

To test the significance of the indirect psychological constructs, the same method is used when testing the indirect effects in the standard framework (bootstrapping N = 5000, significance level 0.05). The bootstrapping results show that TP indeed has a strong indirect effect on UB (β = 0.618, p-value = <0.001). The defined estimands give insights into which constructs are responsible for this indirect effect of TP. PV is found a significant mediator of TP, while PE and HM are not significant. Moreover, AT is confirmed a significant mediator of PV (β = 0.456, p-value = 0.085) and EB (β = 0.143, p-value = 0.049), although the total effect of PV is insignificant. For all bootstrapping results of Q2, see Appendix B, Table B2.

All sociodemographic variables, except income partner, have no direct impact on UB, but have their effects mediated through other constructs. Gender and age do not directly affect UB, but indirectly through a more positive PV (β = 0.180, p-value = 0.010; β = 0.262, p-value = <0.001), suggesting that females and older individuals experience greater perceived benefits in terms of monetary value. Gender also has a direct effect on EE, SI, and FC, but due to their insignificance on AT and UB, the indirect effect of gender through these constructs is not captured. Income and income partner both have negative effects on UB. Income has an indirect effect through a more negative HB (β = -0.119, *p*-value = 0.070), and income partner has a negative direct effect (β = -0.102, *p*-value = 0.096). Moreover, education has an indirect effect through a more negative PE (β = -0.158, *p*-value = 0.045), implying that higher educated individuals perceive solar vehicles as less efficient and effective.

Car-related characteristics have no direct effect on UB; their effects are likewise mediated by other constructs. Driving experience has a significant and negative effect on SI (β = -0.196, *p*-value = 0.020), implying that more experienced drivers are less influenced by what others think, and a significant and positive effect on EB (β = 0.220, *p*-value = 0.009), implying that more experienced drivers are more environmentally conscious. Regardless, SI has no significant effect, thus this indirect effect is rejected. Moreover, electric and hybrid vehicle experience has its effect mediated by a more positive PE, HB, and EB, emphasizing the importance of experience as expected. Electric and hybrid vehicle experience also has a direct impact on EE, SI, HM, and FC, but its indirect effect on UB is rejected due to its insignificant impact on both AT and UB. Thus, H12a to H12d, and H13a are accepted due to the presence of indirect effects on UB. All direct and indirect effects of the sociodemographic and car-related characteristics are accessible in Appendix E.

Indirect effects of insignificant psychological constructs on AT and UB were explored in a subsequent model. Consequently, the model fit, and explanatory power decreased, hence the more parsimonious model, Model 3, is chosen as the final model. Direct and indirect effects of the final model are schematically shown in Figure 6.

Table 10. Path coefficients direct impact on UB and AT - Q2 (N = 250).

Dependent variable → UB	**Model 1**		**Model 2**		**Model 3**	
	β	***p*-value**	***β***	***p*-value**	***β***	***p*-value**
Performance Expectancy	0.425*	0.097	0.303**	0.039	0.315*	0.066
Effort Expectancy	-0.112	0.221	-0.042	0.525	-0.040	0.558
Social Influence	-0.078	0.569	-0.081	0.398	-0.050	0.613
Hedonic Motivation	0.032	0.749	-0.059	0.572	-0.048	0.650
Price Value	0.042	0.821	-0.320	0.167	-0.328	0.178
Facilitating Conditions	0.066	0.450	-0.016	0.813	-0.041	0.530
Habit	0.379***	<0.001	0.315***	<0.001	0.313***	0.002
Environmental Beliefs	0.131**	0.070	*Replaced by EB → AT*		*Replaced by EB → AT*	
Attitude	-		0.706***	0.006	0.659***	0.005
Gender					0.079	0.213
Age					0.002	0.977
Income					0.039	0.539
Income partner					-0.102*	0.096
Education level					-0.053	0.413
Driving experience					0.082	0.247
EV/hybrid vehicle experience					0.052	0.411
R-square	0.554		0.626		0.610	
Dependent variable → AT	**Model 1**		**Model 2**		**Model 3**	
	β	***p*-value**	***β***	***p*-value**	***β***	***p*-value**
Performance Expectancy			0.018	0.906	-0.101	0.411
Effort Expectancy			-0.033	0.561	-0.035	0.526
Social Influence			0.130	0.124	0.112	0.130
Hedonic Motivation			0.134	0.235	0.097	0.327
Price Value			0.685***	<0.001	0.692***	<0.001
Environmental Beliefs			0.197***	0.002	0.217***	<0.001
Technophilia			-0.003	0.991	0.187	0.264
R-square	0.554		0.626		0.610	

β = standardized regression weight
**** = p-value <0.01, ** = p-value <0.05, * = p-value <0.10*

5.5.2 Moderating effects

The same procedure was followed to test the moderating effects of gender, age, income, education level, and electric vehicle and hybrid vehicle experience on direct paths on UB. Models were constrained and the invariance test (Chi-square difference test) was used to check for differences between groups. For each variable, the difference between two groups was tested. For gender: males and females, for age: under or 50 and over 50, for income: low and medium (≤ €3.000) and high (> €3.000), for education: non-higher and higher education, and for EV experience: yes/no EV experience.

This test was significant only for income and education, meaning that the groups in other variables are equivalent. This indicates that gender, age, and electric/hybrid vehicle experience have no moderating effects on direct paths on UB. Therefore, the iterative process of lifting constraints was only done for the variables income and education to get a deeper understanding of which paths significantly differ between groups. The paths SI and FC on UB were found to significantly differ between income groups: individuals with a higher income exhibit a negative moderating effect on the path of SI on UB and exhibit a positive moderating effect on the path FC on UB. The paths PE and FC on UB were found to significantly differ between education levels: individuals with a higher education exhibit a positive moderating effect on the path PE on UB and exhibit a negative moderating effect on the path FC on UB (Table 11). However, since FC is insignificant on UB, income only moderates the effect of SI on UB, and education only moderates the effect of PE on UB. This concludes that income and education both have a moderating effect on one distinct direct path. Hence, H12e is marginally accepted and H13b is rejected. A list of all hypotheses is depicted in Table 12.

Table 11. Summary of multi-group analysis - Q2 (N = 250).

Path	**Moderated by**				
	Gender	**Age**	**Income**	**Education**	**EV experience**
AT → UB	no	no	no	no	no
PE → UB	no	no	no	yes (+)	no
EE → UB	no	no	no	no	no
SI → UB	no	no	yes (-)	no	no
HM → UB	no	no	no	no	no
PV → UB	no	no	no	no	no
FC → UB	no	no	yes (+)	yes (-)	no
HB → UB	no	no	no	no	no

+ = positive impact, - = negative impact

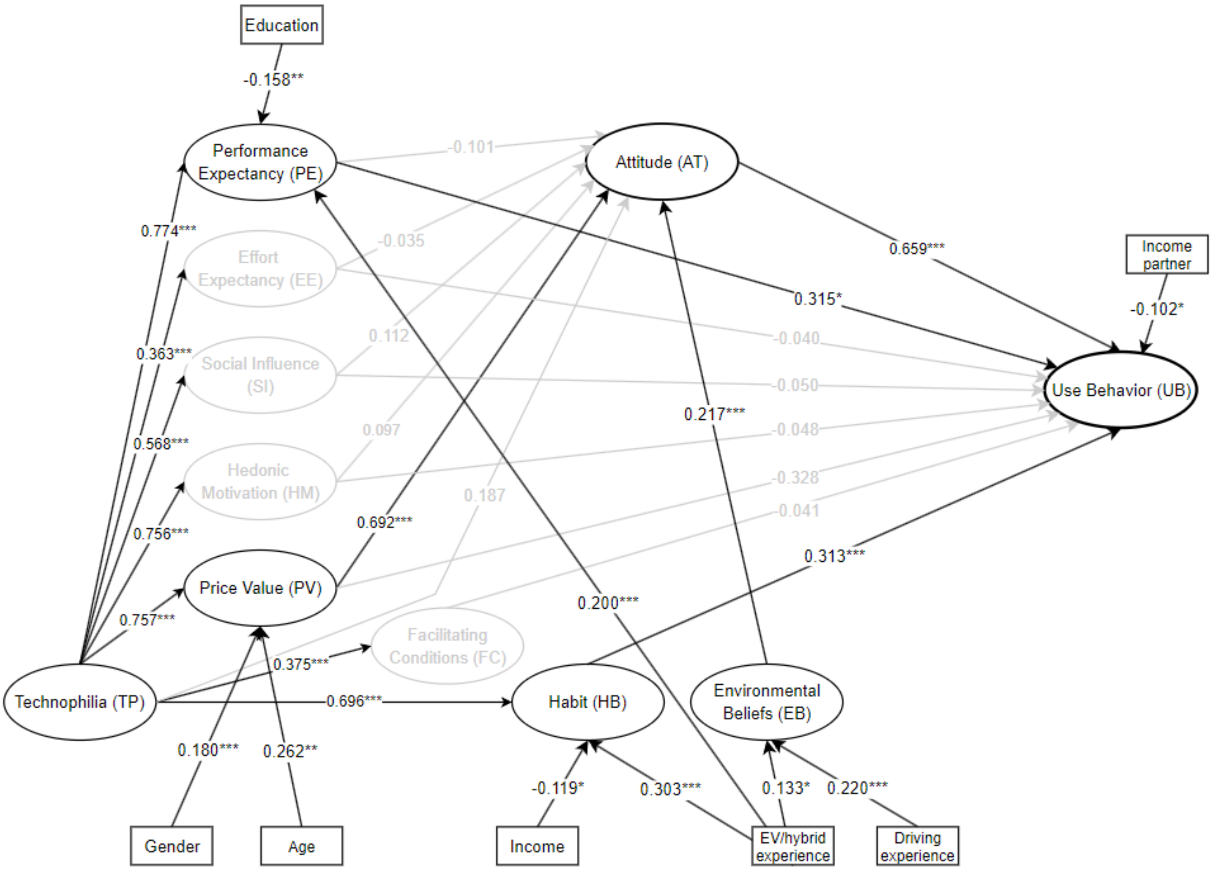

Figure 6. Schematic results of the extended framework - Q2 (N = 250).
**** = p-value <0.01, ** = p-value <0.05, * = p-value <0.10*

Table 12. Hypotheses testing - Q2 (N = 250).

Hypothesis	Supposed path and impact	Supported by		Mediating variable
		Direct effect	Indirect effect	
H1a	PE → AT (+)	no	n.t	-
H1b*	PE → ~~BI~~ UB (+)	yes	-	-
H2a	EE → AT (+)	no	n.t	-
H2b*	EE → ~~BI~~ UB (+)	no	n.t	-
H3a	SI → AT (+)	no	n.t	-
H3b*	SI → ~~BI~~ UB (+)	no	n.t	-
H4a	HM → AT (+)	no	n.t	-
H4b*	HM → ~~BI~~ UB (+)	no	n.t	-
H5a	PV → AT (+)	yes	-	-
H5b*	PV → ~~BI~~ UB (+)	no	n.t	-
H6a	TP → AT (+)	no	yes	PV
H6b	TP → PE (+)	yes	-	-
H6c	TP → EE (+)	yes	-	-
H6d	TP → SI (+)	yes	-	-
H6e	TP → HM (+)	yes	-	-
H6f	TP → PV (+)	yes	-	-
H6g	TP → FC (+)	yes	-	-
H6h	TP → HB (+)	yes	-	-
H7a	FC → BI (+)	n.t.	n.t.	-
H7b	FC → UB (+)	no	n.t	-
H8a	HB → BI (+)	n.t.	n.t.	-
H8b	HB → UB (+)	yes	-	-
H9a*	EB → ~~BI~~ AT (+)	yes	-	-
H9b	EB → UB (+)	n.t.	n.t.	-
H10a	AT → BI (+)	n.t.	n.t.	-
H10b	AT → UB (+)	yes	-	-
H11	BI → UB (+)	n.t.	n.t.	-
H12a	Gender → UB (-)	no	yes	EE (opposite), SI, PV (opposite)
H12b	Age → UB (-)	no	yes	PV (opposite)
H12c	Income → UB (+)	no	yes	HB (opposite)
H12d	Education → UB (+)	no	yes	PE (opposite), EE, SI
H13a	EV/hybrid experience → UB (+)	no	yes	PE, EE, SI, HM, FC, HB, EB

Hypothesis		Supported	Moderating variable
H12e	Moderation effect of sociodemographics	yes, partially	income, education
H13b	Moderation effect of EV/hybrid experience	no	-

** = BI is removed due to a high correlation, path to BI replaced by path to UB or AT*
+ = positive impact, - = negative impact
EV = electric vehicle
n.t. = not tested

5.6 Conclusion

By adaptation of questionnaire 1, new data were collected in 2024, with which the hypothesized model was tested. The model for this data set is referred to as the extended framework. Since a high correlation was observed between BI and UB, BI was removed to avoid overfitting the model. The paths that were initially modeled on BI were replaced by paths on UB or AT.

In this model, the variability of UB is explained up to 61.0% by adding TP, AT, and the sociodemographic and car-related characteristics. Three out of eight hypotheses of psychological constructs on the direct effect on UB are supported and show significant positive effects (PE; H1b, HB; H8b, and AT; H10b). Four are rejected (EE; H2b, SI; H3b, HM; H4b, FC; H7b) and one is partially supported due to its indirect effect (PV; H5b). Surprisingly, only PV and EB are found significant on AT, confirming H5a and H9a. TP has no significant direct effect on AT but has its effect fully mediated by PV. All socio-demographic and car-related variables, except income partner, show no direct impact on UB but have their effect fully mediated by at least one psychological construct, confirming H12b to H12d. Although several opposite effects are found. Some indirect effects of socio-demographic and car-related variables on UB are rejected, as their mediating construct is insignificant on both AT and UB. Electric/hybrid vehicle experience shows the strongest indirect effect, affecting the constructs PE, HB, and EB. This confirms H13a.

At last, moderating effects were tested. Only age and education were found to have a moderating effect and all other effects are statistically equivalent between groups, marginally supporting H12e and rejecting H13b. However, this was anticipated due to the complexity of the model together with the limited sample size.

6. Discussion, implications, and limitations

This study is the first to analyze the user acceptance of solar vehicles. It does so by analyzing two frameworks (a standard framework and an extended framework) based on the UTAUT2. This study uncovered both complementary and contradictory findings across the models and provides valuable insights into the psychological and sociodemographic characteristics behind the adoption intention of solar vehicles. This chapter discusses these findings, followed by managerial implications, and scope for future work. The hypothesis testing of both models is combined in one table in Appendix F.

6.1 Discussion

Two UTAUT2 frameworks are analyzed, a standard framework that contains more commonly studied UTAUT2 variables, and an extended framework that contains more complex relationships, as well as the constructs attitude, technophilia, and habit. The findings uncover that by including these constructs, the explained variability in the model increases.

In the extended framework, two less frequently studied concepts in UTAUT frameworks were included. Attitude emerges as the most important factor influencing the adoption of solar vehicles. A strong positive attitude is explained by individuals' perceived price value and environmental beliefs. While technophilia does not directly influence an individual's attitude, a greater level of technophilia leads to a more positive attitude due to a more positive price value. This implies that individuals with a strong enthusiasm for new technology are willing to pay more for solar vehicles or assume solar vehicles to be a good value for their money. The assumption that technophilia leads to an increased adoption of solar vehicles due to a more positive effort expectancy, social influence, hedonic motivation, and facilitating conditions cannot be fully supported, as these constructs have insignificant effects on the adoption. Even though the effect of technophilia is less than expected, only by means of a more positive performance expectancy, price value, and habit, this marginally implies that individuals experiencing technophilia seem more interested in solar vehicles. This is in line with the studies by Wappelhorst et al. (2014) and Ye et al. (2020) regarding the adoption of new mobility innovations.

In both the standard and extended frameworks, performance expectancy is an important factor affecting the adoption of solar vehicles. This is similar to the findings of Bhat et al. (2021) and Singh et al. (2023), which study the adoption intention of electric vehicles, and Curtale et al. (2021) regarding electric car-sharing services. The perceived efficiency and effectiveness of a solar vehicle play an important role among individuals. Interestingly, performance expectancy tends to decrease with education, while electric and hybrid vehicle experience increases perceived performance expectancy. The effect of education seems unusual, however, highly educated people might have higher expectations towards solar vehicles, or more critically evaluate the pros and cons associated with these vehicles. The fact that prior electric vehicle and hybrid vehicle experience positively affects performance expectancy can be explained by the increase in confidence regarding the performance and technology of electric vehicles (Ozaki & Sevastyanova, 2011), which can in turn increase the perceived performance of solar vehicles.

Both frameworks also emphasize the importance of environmental beliefs. Environmental belief is found to be an important factor in explaining the attitude towards solar vehicles and the adoption of solar vehicles. This is in line with other studies (e.g., Schuitema et al., 2013) and might be explained by the increasing public concerns about climate change and global warming (United Nations, 2007; European Union, 2019; World Health Organization, 2023). Individuals who are more concerned about the environment express a more positive attitude towards these solar vehicles, resulting in greater levels of solar vehicle adoption.

Hedonic motivation is a significant factor explaining the adoption intention of solar vehicles in the standard framework, however, insignificant in the extended framework. In the extended framework hedonic motivation does not significantly affect the adoption of solar vehicles. It does not support the claim that perceived enjoyment and happiness derived from the use of a solar vehicle positively affects its adoption. Their effects are possibly captured elsewhere, although this is contradictory to the studies of Zhou et al. (2021) and Gunawan et al. (2022) in which they showed hedonic motivation to be an important determinant of behavioral intention to electric vehicles. A similar contradictory finding is uncovered for the effect of social influence. Social influence is commonly observed to play an important role in shaping attitudes towards products and services (Dwivedi et al., 2017; Curtale et al., 2021; Gunawan et al., 2022). Bhat et al. (2021) and Singh et al. (2023) found similar results studying the adoption intention of electric vehicles. In their studies, similarly to the extended frame, social influence has no direct influence on the adoption intention. While Bhat et al. (2021) observed an indirect effect, the extended framework does not capture this indirect effect.

Habit is included in the extended framework and shows a significant positive effect on the adoption intention of solar vehicles, supporting the study of Zhou et al. (2021) and Gunawan et al. (2022) on the adoption of electric vehicles. Habits are formed through repeated behavior and tend to become stronger as familiarity with the technology increases (Venkatesh et al., 2012). This becomes evident when studying the effect of electric vehicle and hybrid vehicle experience on habit. A significant positive effect is observed between experience and habit. Individuals with greater levels of experience develop habits that are in line with electric and hybrid vehicles. For these individuals transitioning to a solar vehicle requires minimal behavioral adjustments which has a positive effect on the adoption of solar vehicles. Experience with electric and hybrid vehicles further results in a more positive effort expectancy, social influence, hedonic motivation, and facilitating conditions. This is in line with existing literature (e.g., Egbue & Long, 2012; Bakker & Trip, 2013). However, the model in this study does not capture the effects of those variables on the adoption intention, as these psychological factors are not found to significantly influence either attitude or the adoption intention.

Effort expectancy does not explain the adoption intention of solar vehicles, nor does it result in a more favorable attitude towards those vehicles. This is consistent with Singh et al. (2023) regarding the adoption of electric vehicles and Curtale et al. (2021) regarding electric car-sharing services. However, it is contradictory to the studies of Gunawan et al. (2022) which showed a positive relationship between effort expectancy and attitude.

A significant effect between price value and the adoption intention of solar vehicles was found in the standard framework. In the extended framework, attitude towards solar vehicles benefits from a meaningful positive effect from price value. Individuals who believe that a solar vehicle is a good value for their money, whether it is financially or environmentally, are more likely to have a positive attitude and are more likely to adopt a solar vehicle. This emphasizes the importance of a good price range necessary for these vehicles. These results confirm the findings of Egbue and Long (2012), Noel & Sovacool, (2016), and Degirmenci and Breitner (2017) which identified similar results towards the adoption of electric vehicles. Moreover, in the extended framework, price value increases with gender and age. This implies that females and older individuals are willing to pay more for a solar vehicle or perceive a higher value for their money, contradicting the expectations.

Facilitating conditions is not a significant factor on individuals' adoption of solar vehicles. This is contradictory to other studies on the adoption of electric vehicles (Zhou et al., 2021; Singh et al., 2023). Perceived resources such as support and charging stations are often found as important factors towards the adoption of electric vehicles. However, these results do not suggest the same for the adoption of solar vehicles. It is possible that users nowadays have higher levels of awareness and perceive similar levels of support and resources, resulting in homogeneity. In recent years, the facilitating conditions have greatly improved in the Netherlands and the Netherlands is the leading country in terms of charging stations (European Commission, 2024), therefore, facilitating conditions might not be their primary concern anymore which makes other psychological factors more important.

In terms of sociodemographic and car-related characteristics, gender significantly affects the adoption of solar vehicles in the standard framework, similar to age. Females and older individuals experience a lower intention to adopt a solar vehicle, in line with expectations. In the extended framework, their effects are mediated by other constructs. Similarly, the sociodemographic factors such as income and education have no direct impact, however, they indirectly influence the adoption intention through a lower performance expectancy and habit. The same applies to experience with electric and hybrid vehicles, which does not have a direct effect, but as discussed, has its effect mediated by several other psychological factors.

To conclude, an individual's attitude, which seems to be shaped by the individuals' perceived effectiveness and efficiency, environmental beliefs, and affinity and enthusiasm towards new mobility solutions, positively affects the adoption intention of solar vehicles. Experience with electric and hybrid vehicles and the feeling that a solar vehicle is a good value for their money plays an important role in shaping more positive feelings regarding solar vehicles. For solar vehicles, this implies that individuals with technological affinity and individuals with electric and hybrid vehicle experience are both more likely to be early adopters. Moreover, to increase its adoption, solar vehicles should be effective, efficient, and reasonably priced. The effects of sociodemographics such as age, gender, education, and income on the adoption intention of solar vehicles are found to be limited in this study.

6.2 Managerial implications

Some managerial implications follow from the analysis results. First, as performance expectancy is an important determinant of attitude and the adoption of solar vehicles, for manufacturers this entails the dissemination of the right type of information. When solar vehicles become more widely available and accessible, manufacturers should focus on emphasizing the performance and efficiency of these vehicles. Commercials, expo events, or social media can be used to convey this information. Moreover, policymakers should prioritize how beneficial solar vehicles are in daily life, educating citizens about the cost-effectiveness and time savings, increasing the expected performance.

Second, the significance of price value shows that having a product that is reasonably priced and provides a good value for their money, leads to greater levels of adoption. A great value for money can be achieved by selling solar vehicles for a reasonable price. Additionally, this can be achieved by showing the long-term cost savings in terms of fuel and maintenance costs. Manufacturers should emphasize the capabilities and energy efficiency of solar vehicles, highlighting their cost-saving benefits. If the Dutch government aims to promote a widespread adoption of solar vehicles, it can play a role by offering financial incentives, similar to those seen for electric vehicles in recent years.

Third, from the significant effect of environmental beliefs, it follows that it is important to emphasize the eco-friendliness of solar vehicles. Both manufacturers and the government can contribute to this effort through targeted commercials or campaigns that emphasize the environmental benefits of solar vehicles.

Fourth, the Netherlands' goal is to be climate-neutral by 2050. That means that the complete transport industry has to become CO2 neutral. Non-automated transport and public transport seem most appropriate to achieve these goals. However, it might be hard to cause this behavioral shift. Changing individuals' habits from using a personal vehicle to using public transport can be more challenging than changing individuals' habits from a combustion engine vehicle to a solar vehicle, as the former encompasses more sizeable changes. As habit and electric and hybrid vehicle experience are observed to play an important role in the adoption of solar vehicles, offering test drives can be highly beneficial. By offering test drives, the marginal behavioral change needed can be highlighted. Additionally, they increase individuals' familiarity with these vehicles, a crucial factor in promoting the adoption of solar vehicles.

6.3 Limitations and scope future work

Like any research, this paper comes with its limitations. First, the difference in framework, time of data collection, and sample size, does not allow for a one-on-one comparison between the two frameworks. Moreover, Data set 1 is more representative for the Dutch population. Data set 2 was collected with closer personal connections. Results cannot be generalized between the two samples and conclusions should be drawn cautiously. Therefore, to test the true difference between the frameworks, a follow-up study should be conducted testing both frameworks using the same data set.

Second, this study is conducted in one single country, the Netherlands. The results cannot be generalized internationally, however, this does provide an opportunity for future work. The Netherlands is a relatively wealthy and well-developed country in terms of infrastructure for electric vehicles, which may introduce bias. Future studies should investigate whether the same findings apply to countries with less developed electric vehicle infrastructure.

Third, the rather limited sample size, especially for the second framework, led to data binning into broader levels. Additionally, the model includes several two-indicator constructs, which may limit the capture of larger effects. Reducing the number of indicators per constructs was intended to improve the model fit. However, it would be interesting to check whether retaining more indicators per construct would lead to different findings. Therefore, future studies should focus on collecting larger sample sizes and include more than two indicators per construct when studying such comprehensive models.

Fourth, several relationships on use behavior were found to be insignificant. However, these relationships might have been significant if behavioral intention had been included. Future studies should consider less closely related observable indicators in the questionnaire to allow for both constructs, behavioral intention and use behavior, to be present in the model.

Fifth, the somewhat limited experience with AMOS did not allow the retrieval of standardized values for the moderating effects. Therefore, only general findings for the moderation effects are reported, without specifying their strength. Future studies should test the strength of the moderating effects of those variables.

To conclude, this study contributes to the scarce literature available on this topic and provides opportunities for future research. Both frameworks can serve as a basis for follow-up studies in the Netherlands or in other countries to enhance the understanding of individuals' attitudes regarding new, more environmentally friendly mobility solutions, such as solar vehicles.

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Appendix A

Table A1. Mean, standard deviation, skewness, and kurtosis Q1 (N = 523)

Code	Mean	Construct mean	Standard deviation	Skewness	Kurtosis
PE1	3.54	3.35	0.869	-0.591	0.425
PE2	3.15		0.825	-0.008	-0.410
PE3	3.08		0.830	0.115	0.079
PE4	3.63		0.864	-0.511	0.357
EE1	3.88	3.77	0.779	-0.889	1.731
EE2	3.64		0.858	-0.673	0.418
EE3	3.74		0.781	-0.799	1.153
EE4	3.82		0.776	-0.964	1.640
SI1	2.70	2.65	0.973	0.134	-0.145
SI2	2.71		0.994	0.120	-0.252
SI3	2.60		1.037	0.253	-0.491
SI4	2.57		1.045	0.244	-0.639
HM1	3.92	3.59	0.699	-0.942	2.392
HM2	3.67		0.827	-0.743	0.984
HM3	3.17		0.911	-0.122	-0.296
PV1	3.53	3.35	0.826	-0.424	0.429
PV2	3.30		0.891	-0.255	0.073
PV3	3.52		0.824	-0.303	0.311
PV4	3.05		1.242	0.044	-1.115
FC1	3.79	3.39	0.891	-0.943	1.212
FC2	2.54		0.945	0.368	-0.156
FC3	3.85		0.899	-0.739	0.504
EB1	2.64	2.90	0.955	-0.178	-0.113
EB2	2.85		1.050	-0.219	-0.561
EB3	3.34		1.102	-0.691	-0.130
EB4	2.78		1.046	-0.099	-0.537
UB1	3.60	3.49	0.888	-0.868	0.897
UB2	3.18		0.959	-0.161	-0.267
UB3	3.76		0.891	-0.926	1.221
UB4	3.41		1.001	-0.468	-0.189

Table A2. Mean, standard deviation, skewness, and kurtosis Q2 (N = 250)

Code	Mean	Construct mean	Standard deviation	Skewness	Kurtosis
PE1	3.25	3.00	0.829	-0.287	-0.062
PE2	2.84		0.880	0.061	-0.589
PE3	3.49		0.958	-0.698	0.204
PE4	2.42		0.789	0.129	0.380
EE1	4.16	4.07	0.782	-0.957	1.500
EE2	3.85		0.930	-0.726	0.187
EE3	4.12		0.699	-0.447	0.078
EE4	4.13		0.684	-0.477	0.276
SI1	2.40	2.55	0.948	0.547	0.025
SI2	2.51		0.954	0.526	0.127
SI3	2.58		0.950	0.221	-0.525
SI4	2.72		1.046	0.072	-0.833
HM1	3.64	3.37	0.821	-0.421	0.794
HM2	3.40		0.796	-0.064	0.478
HM3	3.46		0.792	-0.052	0.566
HM4	2.98		1.092	0.059	-0.612
PV1	3.21	3.46	1.416	-0.151	-1.378
PV2	3.89		0.833	-1.173	2.323
PV3	2.98		0.719	-0.427	1.286
PV4	3.76		0.956	-0.726	0.214
TP1	3.36	2.83	0.886	-0.238	-0.464
TP2	2.38		0.912	0.636	0.056
TP3	2.74		0.931	0.140	-0.433
FC1	3.48	3.63	0.861	-0.579	0.402
FC2	3.70		0.782	-1.055	1.383
FC3	3.72		0.918	-0.836	0.661
FC4	3.62		0.858	-0.673	0.427
HB1	3.27	3.09	0.926	-0.200	-0.157
HB2	3.35		0.907	-0.300	-0.040
HB3	3.66		0.860	-0.888	1.030
HB4	2.09		0.920	0.782	0.352
AT1	3.34	3.37	0.851	-0.173	0.119
AT2	3.82		0.751	-0.733	1.266
AT3	2.94		0.988	0.154	-0.360
EB1	3.66	3.39	0.931	-0.848	0.445
EB2	3.44		0.931	-0.653	0.282
EB3	3.82		0.835	-0.853	0.997
EB4	2.65		1.153	0.561	-0.627
BI1	2.51	2.72	0.870	0.031	-0.320
BI2	2.98		0.978	-0.098	-0.513
BI3	2.66		0.906	0.148	-0.090
UB1	2.73	3.01	0.800	-0.180	0.302
UB2	2.95		0.982	-0.075	-0.468
UB3	3.55		0.887	-0.755	0.717
UB4	2.82		0.909	0.178	-0.113

Appendix B

Table B1. Bootstrapping results - indirect effect of PV and FC - Q1 (N = 523)

Path	Effects	*β*	Bias-corrected 95% CI		*p*-value
			Lower	**Upper**	
PV → UB	Total effect	0.287*	-0.022	0.683	0.065
	Direct effect	0.011	-0.421	0.568	0.931
	Indirect effect	0.276***	0.098	0.659	0.009
FC → UB	Total effect	0.054	-0.276	0.615	0.682
	Direct effect	-0.066	-0.416	0.432	0.716
	Indirect effect	0.120*	-0.013	0.299	0.071

Path	Bias-corrected 95% CI		*p*-value
	Lower	**Upper**	
PV → PE → UB**	0.018	0.649	0.035
PV → HM → UB***	0.072	0.356	0.002
FC → PE → UB	-0.045	0.185	0.259
FC → HM → UB**	0.022	0.261	0.014

β = standardized regression weight
CI = Confidence Interval
**** = p-value <0.01, ** = p-value <0.05, * = p-value <0.10*

Table B2. Bootstrapping results - indirect effect of TP, PV, and EB - Q2 (N = 250)

Path	Effects	*β*	Bias-corrected 95% CI		*p*-value
			Lower	**Upper**	
TP → UB	Total effect	0.618***	0.489	0.796	<0.001
	Direct effect	-	-	-	-
	Indirect effect	0.618***	0.489	0.796	<0.001
PV → UB	Total effect	0.129	-0.571	0.574	0.625
	Direct effect	-0.328	-1.357	0.646	0.388
	Indirect effect	0.456*	-0.147	1.577	0.085
EB → UB	Total effect	0.143**	0.000	0.306	0.049
	Direct effect	-	-	-	-
	Indirect effect	0.143**	0.0040	0.306	0.049

Path	Bias-corrected 95% CI		*p*-value
	Lower	**Upper**	
TP → PE → UB	-0.071	0.974	0.123
TP → HB → UB	0.144	0.031	0.292
TP → PV → AT → UB**	0.031	0.292	0.023

β = standardized regression weight
CI = Confidence Interval
**** = p-value <0.01, ** = p-value <0.05, * = p-value <0.10*

Appendix C

Sociodemographic and car-related characteristics Q1 (N = 523) and Q2 (N = 250)

Variable	**Q1 N = 523**		**Q2 N = 250**	
	Levels	**Percentage**	**Levels**	**Percentage**
Gender	male	54.3	male	62.8
	female	45.7	female	37.2
Age	under or 30	8.6	under or 30	28.8
	30-50	37.9	30-50	37.6
	over 50	53.5	over 50	33.6
Income	low (< €2.000)	42.3	low and medium (≤ €3.000)	55.2
	medium (€2.000 - €3.000)	39.4		
	high (> €3.000)	17.4	high (> €3.000)	44.8
Income partner	no partner or no income	33.1	no partner or no income	30.4
	low and medium (≤ €3.000)	59.3	low and medium (≤ €3.000)	43.2
	high (> €3.000)	7.6	high (> €3.000)	26.4
Education level	non-higher education	61.4	non-higher education	34.8
	higher education	38.6	higher education	65.2
Years of driving experience	0-4 years	3.6	< 4 years	7.6
	> 4 years	96.4	4-10 years	19.6
			> 10 years	72.8
Number of vehicles in household	0	5.6		
	1	64.6		
	2 or more	29.8		
Electric vehicle in household	no	92.9		
	yes	7.1		
Drives electric/hybrid vehicle	no	91.8	no	73.7
			yes, hybrid	9.2
	yes, electric	8.2	yes, electric	17.2
Employment type			full time (32 hours/week or more)	68.4
			part time (<32 hours/week) or no employment	22.0
			student	9.6
Familiar with solar vehicles	no	55.6	no	24.0
	yes	44.4	yes	76.0

Appendix D

Table D1. Path coefficients direct impact of TP Model 2 - SEM Q2 (N = 250)

Dependent variable	**Independent variable**	***β***	***p*-value**
Technophilia	Attitude	-0.003	0.991
	Performance Expectancy	0.785***	<0.001
	Effort Expectancy	0.409***	<0.001
	Social Influence	0.616***	<0.001
	Hedonic Motivation	0.772***	<0.001
	Price Value	0.756***	<0.001
	Facilitating Conditions	0.445***	<0.001
	Habit	0.759***	<0.001

β = standardized regression weight
**** = p-value <0.01, ** = p-value <0.05, * = p-value <0.010*

Table D2. Path coefficients direct impact of TP Model 3 - SEM Q2 (N = 250)

Dependent variable	**Independent variable**	***β***	***p*-value**
Technophilia	Attitude	0.187	0.264
	Performance Expectancy	0.774***	<0.001
	Effort Expectancy	0.363***	<0.001
	Social Influence	0.568***	<0.001
	Hedonic Motivation	0.756***	<0.001
	Price Value	0.757***	<0.001
	Facilitating Conditions	0.375***	<0.001
	Habit	0.696***	<0.001

β = standardized regression weight
**** = p-value <0.01, ** = p-value <0.05, * = p-value <0.010*

Appendix E

Impact of sociodemographic and car-related characteristics on psychological constructs - Q2 (N = 250)

Independent variable	Dependent variable															
	PE		**EE**		**SI**		**HM**		**PV**		**FC**		**HB**		**EB**	
	β	***p*-value**	***β***	***p*-value**	***β***	***p*-value**	***β***	***p*-value**	***β***	***p*-value**	***β***	***p*-value**	***β***	***p*-value**	***β***	***p*-value**
Gender	0.052	0.528	-0.160**	0.016	0.161**	0.028	0.107	0.111	0.180**	0.010	-0.126*	0.072	0.046	0.468	0.090	0.206
Age	0.097	0.243	-0.064	0.327	0.091	0.208	0.008	0.906	0.262***	<0.001	-0.052	0.441	-0.004	0.945	0.080	0.262
Income	0.041	0.634	-0.064	0.345	0.029	0.694	0.027	0.693	-0.111	0.118	0.074	0.290	-0.119*	0.070	-0.029	0.693
Income partner	0.015	0.864	0.015	0.864	-0.038	0.619	0.018	0.796	-0.019	0.797	0.068	0.344	0.039	0.555	0.114	0.132
Education	-0.158**	0.045	0.133**	0.033	0.114*	0.099	0.022	0.734	-0.014	0.833	0.091	0.162	0.073	0.220	0.094	0.163
Driv. exp.	-0.148	0.117	0.038	0.610	-0.196**	0.020	-0.014	0.854	-0.015	0.852	-0.042	0.586	-0.051	0.480	0.220***	0.009
EV/hybrid exp.	0.200**	0.012	0.245***	<0.001	0.166**	0.017	0.109*	0.086	0.088	0.176	0.236***	0.002	0.303***	<0.001	0.133*	0.052

β = standardized regression weight
**** = p-value <0.01, ** = p-value <0.05, * = p-value <0.10*
Driv. Exp. = Driving experience, EV/hybrid exp. = Electric vehicle/hybrid vehicle experience, PE = Performance Expectancy, EE = Effort Expectancy, SI = Social Influence, HM = Hedonic Motivation, PV = Price Value, FC = Facilitating Conditions, HB = Habit, EB = Environmental Beliefs

Appendix F

Hypotheses testing Q1 (N = 523) and Q2 (N = 250)

Hypo-thesis	Supposed path and impact	Standard framework			Extended framework		
		Direct	**Indirect**	**Mediating variable**	**Direct**	**Indirect**	**Mediating variable**
H1a	PE → AT (+)				no	n.t	-
H1b*	PE → ~~BI~~ UB (+)	yes	-	-	yes	-	-
H2a	EE → AT (+)				no	n.t	-
H2b*	EE → ~~BI~~ UB (+)	no	no	-	no	n.t	-
H3a	SI → AT (+)				no	n.t	-
H3b*	SI → ~~BI~~ UB (+)	yes	-	-	no	n.t	-
H4a	HM → AT (+)				no	n.t	-
H4b*	HM → ~~BI~~ UB (+)	yes	-	-	no	n.t	-
H5a	PV → AT (+)				yes	-	-
H5b*	PV → ~~BI~~ UB (+)	no	yes	PE, HM	no	n.t	-
H6a	TP → AT (+)				no	yes	PV
H6b	TP → PE (+)				yes	-	-
H6c	TP → EE (+)				yes	-	-
H6d	TP → SI (+)				yes	-	-
H6e	TP → HM (+)				yes	-	-
H6f	TP → PV (+)				yes	-	-
H6g	TP → FC (+)				yes	-	-
H6h	TP → HB (+)				yes	-	-
H7a	FC → BI (+)				n.t.	n.t.	-
H7b	FC → UB (+)	no	yes	HM	no	n.t	-
H8a	HB → BI (+)				n.t.	n.t.	-
H8b	HB → UB (+)				yes	-	-
H9a*	EB → ~~BI~~ AT (+)				yes	-	-
H9b	EB → UB (+)				n.t.	n.t.	-
H10a	AT → BI (+)				n.t.	n.t.	-
H10b	AT → UB (+)				yes	-	-
H11	BI → UB (+)				n.t.	n.t.	-
H12a	Gender → UB (-)	yes	-	-	no	yes	EE (opposite), SI, PV (opposite)
H12b	Age → UB (-)	yes	-	-	no	yes	PV (opposite)
H12c	Income → UB (+)	no	n.t.	-	no	yes	HB (opposite)
H12d	Education → UB (+)	no	n.t.	-	no	yes	PE (opposite), EE, SI
H13a	EV/hybrid experience → UB (+)	no	n.t.	-	no	yes	PE, EE, SI, HM, FC, HB,EB

Hypothesis		Standard framework	Moderating variable	Extended Framework	Moderating variable
H12e	Moderation effect of sociodemographics	yes, partially	gender, age, income, education	yes, partially	income, education
H13b	Moderation effect of EV/hybrid experience	no	-	no	-

** = BI is removed due to a high correlation, path to BI replaced by path to UB or AT*
+ = positive impact, - = negative impact
EV = electric vehicle
n.t. = not tested