A Study of Factors Affecting Consumer Preferences for Innovative and Sustainable Technologies

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Table of Contents

List of Tables

List of Figures

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Declaration

I, Teresa Antonia Roth, confirm that the work presented in this thesis is my own and has not been submitted in whole or in part for consideration for any other degree or qualification in this or any other university. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

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Abstract

This thesis investigates the influence of changes in the context of technology use, evaluated through the technology acceptance model (TAM) and the affect heuristic, on the assessment and preference for sustainable technologies. The specific objective is to advance the exploration of how decision interfaces and contexts, varying in conveyed risks and benefits, influence technology judgment and preference with the aim of contributing to existing literature on behaviour change. The two studies, denoted as Study 1 and Study 2, focus on measuring individuals' judgments of battery electric vehicles (BEVs) for business trips and the choice between BEVs and internal combustion engine vehicles. By conducting both studies in Germany, this thesis specifically investigates BEVs as the sustainable alternative to conventional cars in a country that exhibits a slower adoption rate of BEVs compared to other nations. The outcomes of the TAM in Study 1 largely align with the findings of comparable TAM variants. Incorporating gamification into car booking software influenced several TAM relationships in predicting individuals' behavioural intentions to book a BEV. Furthermore, the results demonstrate an influence of gamification and differentially risky BEV usage contexts on the strength of the association between individuals' behavioural intentions and their choice of car type. However, the data reveal that gamification did not serve as a motivating factor for participants to prefer BEVs over conventional cars, regardless of the level of risk associated with the business trip. Additionally, making car choices for higher-risk business trips was linked to a higher attrition rate from the car booking experiment. In Study 2, the re-examination of the inverse correlation between risks and benefits of items was substantiated concerning BEVs. However, the findings indicate that the utilisation of information, including a gamified variant, aimed at modifying individuals' judgments of BEVs, did not significantly impact the assessment of risks or benefits. When gamification was absent (i.e. control group), the majority of participants booked a BEV, and car type choices did not exhibit statistically significant differences across the four experimental conditions. Conversely, when gamification was present (i.e. treatment group), the preference for the car type varied noticeably across the four conditions. Consequently, the results of this thesis illustrate how even seemingly minor alterations to a technology usage context can

influence individuals' judgment and choices of technologies. Particularly, the findings of Study 2 provide novel insights into the broader application of gamification, extending beyond its conventional role in enhancing performance or engagement.

Chapter 1: Introduction and Literature Review

Introduction

Prolonged or intensified droughts, heatwaves, floods, and impacts on biodiversity, such as species loss and extinction, along with ocean acidification and the rise in global sea levels, constitute a subset of observations that have occurred with increased frequency over recent decades (Intergovernmental Panel on Climate Change (IPCC), 2022). Furthermore, these ecological effects intricately intertwine with social risks, such as threats to health, food and water security as well as economic risks, including diminished crop yields (IPCC, 2022). The observed phenomena and their associated threats, as delineated by the United Nations Framework Convention on Climate Change (UNFCCC) (n.d.-a), are connected to the rise in global temperatures attributed to anthropogenically induced increments in greenhouse gases[1], aligning with the advent of industrialisation. The IPCC (2022) estimates that anthropogenic emissions since the onset of industrialisation have led to an approximate 1°C increase in temperature. The IPCC (2022) claims that a continuous increase in global temperature is projected to be accompanied by a heightened risk of encountering, for example, adverse weather events with higher frequency and intensity.

While sustainability is not a novel concept from the 20th century[2], the central goal of mitigating anthropogenic greenhouse gas emissions has led to the formulation of shared definitions, proposed policies, agendas, and blueprints through 28 conferences involving the United Nations and associated organisations (e.g. World Commission on Environment and Development). One notable instance is the Brundtland report of 1987, wherein the World Commission on Environment and Development, an organisation commissioned by the United Nations, introduced the concept of sustainable development as follows: „Humanity has the ability to make development sustainable to ensure that it meets the needs of the present without compromising the ability of future generations

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[1] Carbon dioxide, methane, nitrous oxide, and others (Ritchie et al., 2020a).

[2] Fundamentally, Hans Carl von Carlowitz addressed the core concept of sustainability in 1713 with his publication on sustainable forestry. He posited that only as much forest should be cleared as can regrow for future generations and their needs (Aachener Stiftung Kathy Beys, 2015).

to meet their own needs" (World Commission on Environment and Development, 1987, Sustainable Development section). This concept of sustainability gained further elaboration in the context of the Rio Conference in 1992 (i.e. the United Nations Conference for Environment and Development), where an agenda and blueprint were developed for sustainable development, which emphasised the integration and balancing of economic, social, and environmental concerns (Kleine & von Hauff, 2009; United Nations, n.d.). To give another example, the Kyoto Protocol in 1997 marked the United Nations' initial commitment to reducing greenhouse gases to defined targets against 1990 emission levels (UNFCCC, n.d.-b). While not the most recent conference, it is noteworthy that in 2015, within the context of the Paris Agreement, 196 countries agreed to implement measures to limit the increase in global temperature by the end of this century to below 2°C and ideally 1.5°C, aiming to mitigate the risks indicated above (UNFCCC, n.d.-a). According to the UNFCCC (n.d.-a), anthropogenic emissions must peak before 2025 and decline by 43% by 2030 to achieve the 1.5°C target. However, current emission trends do not indicate a sufficient change. If the present trend persists, global temperatures are projected to increase by 2.8°C by the end of this century (Bauer, 2023), indicating that current efforts fall short of reaching the stipulated targets.

Upon scrutinising diverse segments contributing to anthropogenic greenhouse gas emissions, spanning (1) electricity and heat generation, (2) transport, (3) manufacturing and construction, (4) agriculture, (5) buildings, and others, estimations reveal that the transport sector stands as the second-largest source of global emissions (Ritchie et al., 2020a). In relation to the transport sector, numerous national and international policies are in effect with the objective of mitigating emissions from various modes of transportation. While there are initiatives incentivising the use of public transport (e.g. the Deutschland-Ticket in Germany[3]), the following examples will primarily focus on individual motorised mobility.

[3] Obtaining the Deutschland-Ticket grants access for using public transport (excluding fast trains) across Germany, independent of the federal states, transport associations, etc. (Bundesregierung, 2023).

Measures aimed at mitigating emissions from individual motorised mobility range from small, local initiatives, such as the congestion charge in London[4] (Transport for London, n.d.) or the ban of older diesel cars in Munich[5] (Landeshauptstadt München, n.d.-a, n.d.-b), to national measures, such as the prohibition of sales of internal combustion engine vehicles (i.e. petrol and diesel) from 2030 in the UK (Climate Change Committee, 2023). These efforts extend to international measures. At the European Union level, procedural enhancements of emission standards for newly produced cars have been implemented. These standards aim to reduce carbon emissions from newly produced cars to 95 g carbon dioxide (CO_2)/km by 2024, with a further gradual reduction to 0 g CO_2/km beyond 2035 (European Commission, n.d.). Car manufacturers commonly achieve this target by transitioning from combustion-based propulsion to cars with an electric engine, which are carbon balanced with 0 g CO_2/km (Stegmeier & Harloff, 2021).

The examples above suggest that policies addressing individually motorised mobility predominantly centre around the phase-out of combustion engine vehicles in favour of electric cars, as further corroborated by the following example: according to the UK Climate Change Committee, which presented progress on reducing UK emissions to parliament in 2023, evidence has shown that carbon savings from plug-in hybrid electric vehicles[6] are three to five times lower in reality than previously assumed. Consequently, the committee proposed prioritising battery electric vehicles (BEVs) over plug-in hybrid electric vehicles (Climate Change Committee, 2023). In summary, as suggested by the above mentioned national and international initiatives, BEVs have been positioned as a sustainable alternative to combustion engine vehicles.

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[4] London has placed a daily charge of £15 for driving within the congestion charge zone (Transport for London, n.d.).

[5] For instance, the city of Munich has implemented a step-by-step plan for the introduction of a diesel driving ban in Munich's city centre with the aim of reducing local nitrogen dioxide emissions to comply with EU law (Landeshauptstadt München, n.d.-a, n.d.-b).

[6] Plug-in hybrid electric vehicles are equipped with two propulsion systems – a combustion engine and an electric engine – with the combustion engine serving as the primary system. In contrast, BEVs are characterised by having a single propulsion system – an electric engine – without any additional supporting systems.

With regard to the ecological dimension, sustainable product alternatives should distinguish themselves from their conventional alternatives by reducing emissions measured across the entire product lifecycle, as will be explained below. While the positive ecological impact is clearly evident in certain items and associated behaviours (e.g. using reusable items instead of single use items), there are also purported sustainable alternatives where the actual contribution to the environment is not always clear. For instance, there is ongoing debate in the media about whether products made from soy (e.g. Ogasa, 2022; Ritchie, 2021) or avocados (e.g. Eldridge, 2020; Lebreton, 2023) are genuinely more sustainable than the consumption of meat.[7] Similar uncertainties have been emphasised in the media regarding the ecological benefits of electric cars compared to their combustion engine counterparts (e.g. Clarke, 2017; Franklin-Cheung, 2022; Tabuchi & Plumer, 2021): are electric cars truly more sustainable than combustion engine vehicles? For example, findings from research conducted in Germany indicate a decrease in the proportion of individuals perceiving BEVs as environmentally friendly, dropping from 75% in 2013 to 58% in 2019 (Aral Aktiengesellschaft, n.d.-a, n.d.-b).

In the endeavour to determine whether presented sustainable product alternatives result in fewer carbon emissions than their conventional counterparts, various approaches exist to measure and ultimately compare products throughout their lifecycle. For instance, the carbon dioxide cradle-to-grave lifecycle assessment initiates with the measurement of emissions generated during the extraction of resources required for production. This assessment spans emissions generated during production, distribution, product use, and concludes with the energy used for disposal (Nickel, n.d.). When recycling is considered in the assessment after disposal to close the cycle, it is commonly

[7] The global soybean production has surged tenfold in the past 50 years, playing a significant role in deforestation in the Amazon and other forests. However, while 77% is utilised as animal feed, only about 7% of soybean production is directly used for human consumption (e.g. tofu) (Ritchie, 2021). Similarly, the sustainability of avocado production is questioned due to concerns about deforestation, water-intensive cultivation, and long transportation distances involved (Eldridge, 2020; Lebreton, 2023).

referred to as a cradle-to-cradle lifecycle assessment (Nickel, n.d.). As mentioned above, the European Commission evaluates electric cars at 0 g CO_2/km, utilising the scope of the so-called car-specific tank-to-wheel lifecycle assessment, which specifically measures emissions generated during vehicle use (Gustafsson et al., 2021). Since electric cars produce no emissions during direct use compared to internal combustion engine vehicles, the emissions of BEVs are thus set at 0 g CO_2/km. Returning to the example above, for the comparison of cars with different powertrains, the more comprehensive and also car-specific well-to-wheel scope considers the emissions generated from fuel or electricity generation, distribution, and usage (e.g. Gustafsson et al., 2021). However, this variant of the lifecycle assessment omits emissions generated during vehicle production, including battery production and recycling (nor do any of the variants address social concerns), which are argued to be among the key elements influencing the total emissions of BEVs throughout their lifecycle (e.g. Buchal et al., 2019; Crawford et al., 2022; Taub, 2022). Consequently, concerns about the genuine environmental advantage have been addressed by various national and international research efforts conducting lifecycle assessments of BEVs. Driven by the aim to determine whether BEVs are indeed more sustainable than their conventional alternatives, conclusions of such assessments vary with the scope of the assessment and contributing factors, such as the underlying electricity mix[8] (e.g. Abdul-Manan, 2015; Buberger et al., 2022; Buchal et al., 2019; European Environment Agency, n.d.; Helmers et al., 2020; Jochem et al., 2015).

In summary, the considerations above indicate that while there are product or behavioural alternatives that create less doubt when estimating their contribution to the environment, such as using a bicycle for journeys that would otherwise be completed using a car, there also exist presented sustainable product alternatives for which the actual environmental contribution may not come along with a straightforward answer, as may apply to BEVs. Furthermore, findings from

[8] The electricity mix refers to the primary energy sources used to generate electricity, including the burning of fossil fuels (e.g. coal, gas), nuclear power, renewable sources (e.g. wind power, solar, hydropower), and others (Ritchie et al., 2020b).

Johnstone and Tan (2015) on the green attitude-behaviour gap[9] indicated that experiences of corporate *greenwashing*[10] led some participants respond cynically towards green product alternatives and report a lack of trust in green marketing claims. Johnstone and Tan (2015) implied from their findings that greenwashing may have made it more difficult for consumers to identify legitimate green products. Nevertheless, sustainable ambitions are in vain if people do not start using such offered alternatives. While there are studies indicating that individuals tend to consume sustainable product alternatives, for example, when driven by conspicuous consumption[11] (e.g. Griskevicius et al., 2010; Johnson et al., 2018)[12], the considerations above suggest the need to identify further ways to motivate individuals to choose the presented sustainable alternative to status quo solutions when aiming to mitigate anthropogenic greenhouse gas emissions.

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[9] The green attitude-behaviour gap describes the phenomenon of consumers deviating from their intentions to consume green products in favour of their non-green alternatives (Johnstone & Tan, 2015).

[10] Within the trajectory of sustainable transformation, instances have emerged where companies professing a commitment to sustainability were found to be involved in what is commonly referred to as greenwashing. Upon closer examination of their actual contributions, it became evident that their stated sustainability achievements were either less significant than advertised or entirely false (Akepa, 2021).

[11] Veblen coined the term conspicuous consumption in 1899, which outlines humans' overt display of luxury products to demonstrate their abundance of available time, (pecuniary) strength, etc. to others with the aim of enhancing their image or status (Veblen, 1912).

[12] Griskevicius et al. (2010) demonstrated that a desire for status, particularly when coupled with the public visibility of one's actions, can lead to a preference for environmentally friendly yet less luxurious products over equally priced, more luxurious alternatives. Among other findings, Johnson et al. (2018) discovered that a higher fear of negative evaluation by others strengthened the positive association between conspicuous consumption of pro-social goods, such as reusable grocery bags or clothing supporting a cause, and individuals' need for status (i.e. respect, prestige, or similar recognition awarded by others).

Theories to Predict Technology Acceptance

This chapter provides a concise overview of various models designed to assess individuals' judgments of items and their intentions to perform a particular behaviour or accept specific technologies. Following this, motivational concepts, specifically, in the form schematic approaches to behavioural interventions will be introduced, which have been identified as effective means to encourage individuals to make specific choices or perform specific behaviours.

The Evolution of the Theory of Reasoned Action to the Technology Acceptance Model

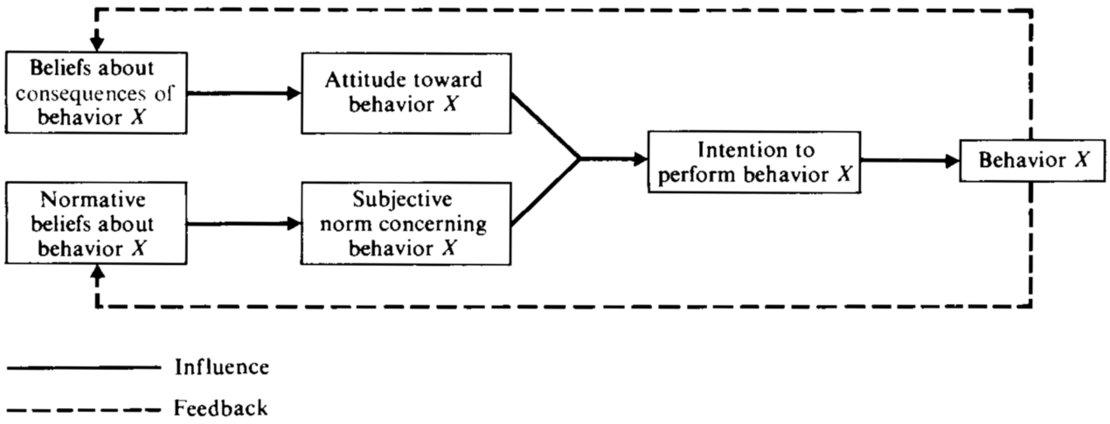
This section begins by introducing models designed to predict human behaviour, with a particular focus on individuals’ acceptance of technologies. First, the theory of reasoned action by Fishbein and Ajzen (1975) is discussed, serving as a foundational framework for subsequent theoretical developments and adaptations across various domains and application contexts. These include the theory of planned behaviour by Ajzen (1991) and the technology acceptance model (TAM) by Davis (1986). Given its pivotal role in Study 1 of this thesis, this introductory chapter primarily highlights the theoretical advancements within the TAM.

Theory of Reasoned Action and Theory of Planned Behaviour

In the context of introducing the theory of reasoned action, Fishbein and Ajzen (1975) emphasised the perspective that humans generally act rationally by systematically utilising available information to make reasoned decisions about their subsequent behaviour. Fishbein and Ajzen (1975) proposed their theory with the aim to predict individuals' subjective probability of performing a specific behaviour, commonly referred to as their behavioural intention. This intention is influenced by two key factors (see Figure 1): first, an individual’s attitude towards the behaviour, encompassing their personal evaluations and feelings about it; and second, the subjective norm, representing an individual’s perceived social pressure and influence related to the behaviour based on beliefs about what others think should be done (Fishbein & Ajzen, 1975). In their model, Fishbein and Ajzen (1975) posited that behavioural intention is the sole predictor of actual behaviour.

Figure 1

Theory of Reasoned Action

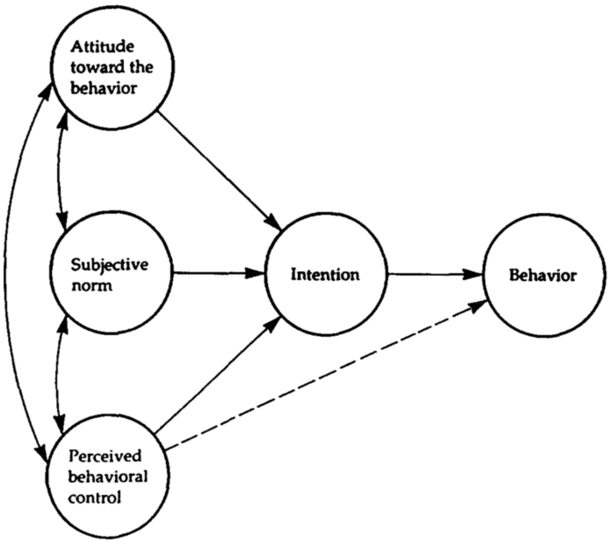


Note. Figure from Fishbein and Ajzen (1975, p. 16).

Expanding upon the theory of reasoned action, Ajzen (1991) introduced an extension known as the theory of planned behaviour. This theory was notably enhanced by the incorporation of the predictor variable, perceived behavioural control (see Figure 2). As elucidated by Ajzen (1991), perceived behavioural control refers to an individual's perception of the ease or difficulty associated with carrying out a specific behaviour. This concept encompasses the recognition of internal factors, such as one's abilities and skills as well as external factors including considerations related to time and financial resources. These factors can either facilitate or impede one's perceived ability to execute the desired behaviour. In particular, concerning the acknowledgment of internal factors, the notion of perceived behavioural control shares similarities with Bandura's (1982) notion of self-efficacy. Self-efficacy pertains to an individual's personal evaluation of their ability to perform a specific behaviour (Bandura, 1982).

Figure 2

Theory of Planned Behaviour



Note. Figure from Ajzen (1991, p. 182).

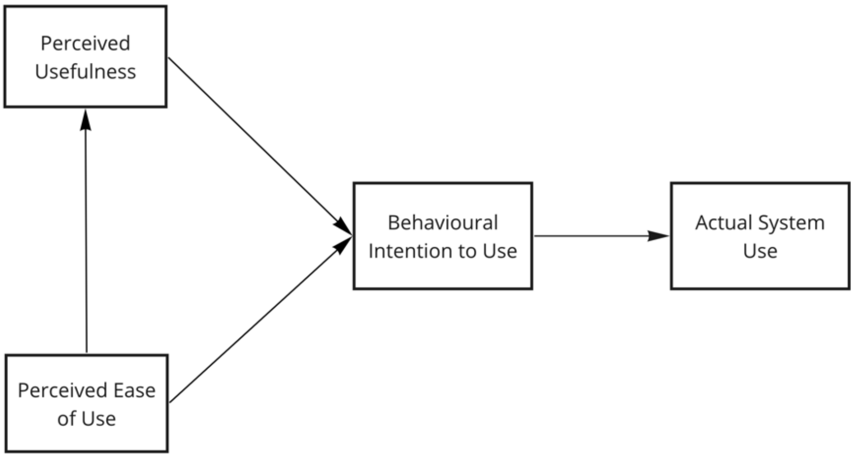
Variations of the Technology Acceptance Model and Related Theories

Fishbein and Ajzen's (1975) theory of reasoned action also laid the theoretical groundwork for the TAM, initially introduced by Davis in 1986. Aimed at predicting the acceptance of technologies, Davis's (1986) TAM posits that two key factors – the perceived usefulness of an information technology for the task at hand and the perceived ease of using the technology – influence an individual's attitude towards accepting the technology and, consequently, the decision to use it. In contrast to the theory of reasoned action, Davis (1986) did not incorporate measurements for subjective norms or behavioural intentions in the proposed model. According to Davis (1986), the TAM was developed for applied user acceptance testing of new technologies. Consequently, Davis (1986) justified the omission of the subjective norm due to the scope of measurement. Specifically, Davis (1986) argued that in situations where individuals would typically encounter a new system (e.g. a prototype) for the first time, they would lack cues or other normative indications from significant reference persons. Furthermore, Davis (1986) suggested that the exclusion of behavioural intentions from the TAM was warranted by the nature of their study. Davis (1986) assumed that individuals would require time for careful deliberation before arriving at a meaningful decision regarding whether to use the new system in the future. As a result, because the measurement would occur immediately after the system demonstration to the individual, Davis (1986) posited that individuals' intentions concerning whether or not to use the system, would not yet be fully formed. Therefore, Davis (1986) proposed that attitude would serve as a more stable predictor of individuals’ behaviours than intentions.

However, in a subsequent study, Davis et al. (1989) compared the TAM with the theory of reasoned action, including combined versions of the two models. Their findings indicated that attitudes did not fully mediate the effects of perceived usefulness and ease of use on behavioural intentions. Furthermore, Davis et al. (1989) did not find the subjective norm to significantly influence behavioural intentions. Consequently, Davis et al. (1989) introduced an updated variant of the TAM (see Figure 3). This revised so-called parsimonious TAM variant positioned behavioural intentions as the sole predictor of actual behaviour. Furthermore, Davis et al. (1989) proposed that perceived usefulness is the primary determinant of behavioural intentions, with perceived ease of use serving as the secondary determinant. After a testing period of 14 weeks, perceived ease of use was found to influence only perceived usefulness directly. Concludingly, their revision led to the exclusion of attitude and subjective norm from the model.

Figure 3

Parsimonious Technology Acceptance Model



Note. This variant of the technology acceptance model represents an updated version of Davis's (1986) initial model. The visualisation is based on the concluding findings from Davis et al. (1989).

In addition to the parsimonious TAM, the TAM has undergone further adaptations and extensions since its inception. Originally designed to predict the acceptance of information systems for business purposes, the TAM has evolved over the past three decades into various versions, differing in the kinds and numbers of predictors. Moreover, these adaptations may extend beyond the original context of business applications, such as by investigating individuals' acceptance of technologies for personal use. For instance, López-Nicolás et al. (2008) presented a TAM variant which was designed to assess the acceptance of advanced mobile services, considering the then-available evolution of internet speed and corresponding mobile devices. Abramson et al. (2015) adapted a TAM to gauge students' intentions to use mobile devices within the context of using a learning management system. Similarly, Koenig-Lewis et al. (2015) used an adapted TAM to investigate the acceptance of mobile payment solutions. All three examples pertain to usage contexts outside of a business environment.

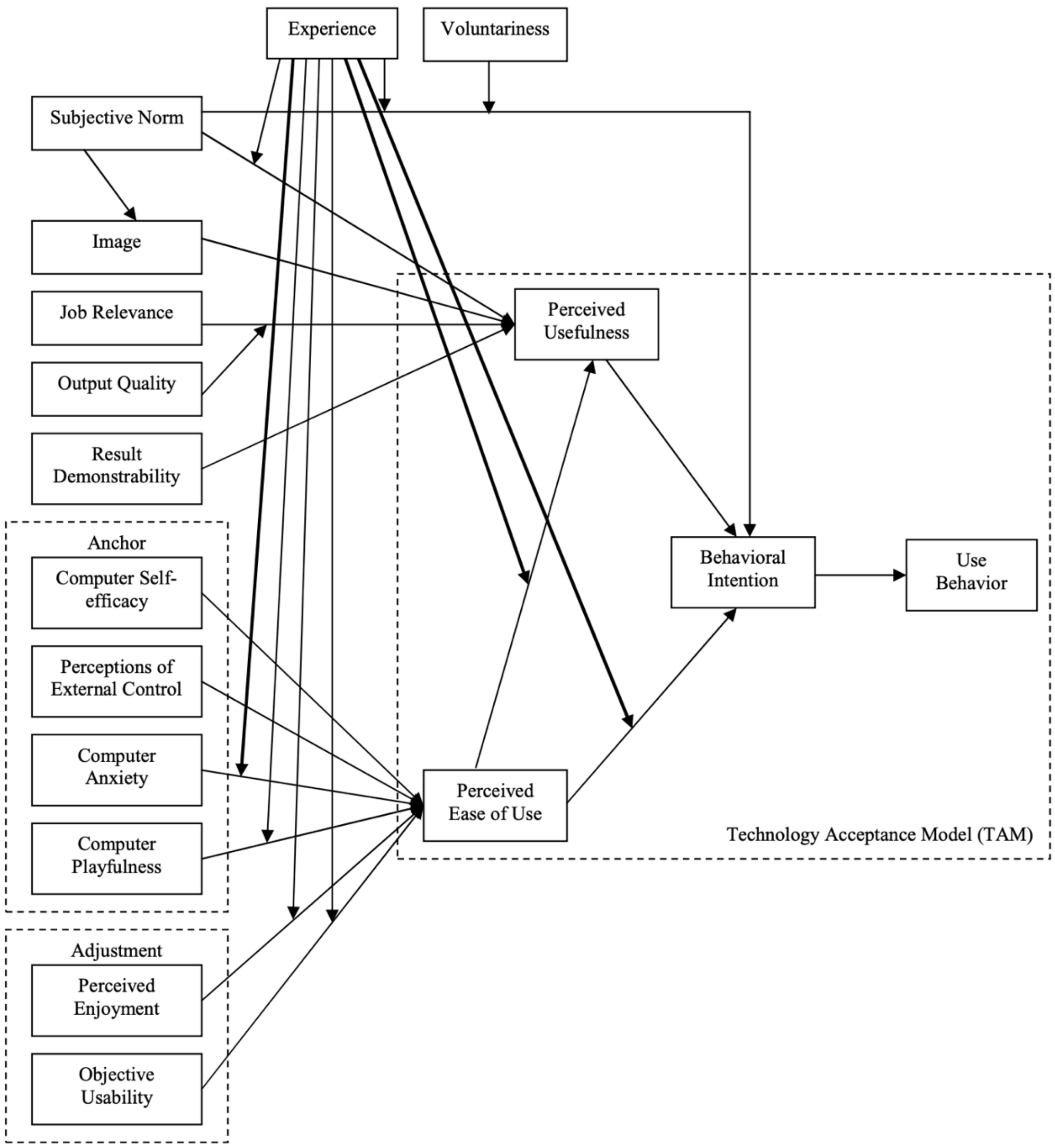
Among others, notable variants of the TAM include a variant by Venkatesh (2000), the so-called TAM 2 by Venkatesh and Davis (2000), TAM 3 by Venkatesh and Bala (2008) as well as the unified theory of acceptance and use of technology 1 by Venkatesh et al. (2003) and version 2 by

Venkatesh et al. (2012). Fundamentally, the aforementioned TAM variants differ from the parsimonious TAM proposed by Davis et al. (1989) in terms of the number and nature of their predictors. Nonetheless, these variants retain the core predictors of the TAM, perceived usefulness and perceived ease of use, as determinants of behavioural intentions to use a specific technology in the future. Venkatesh and Davis (2000) introduced additional predictors of perceived usefulness (e.g. job relevance, result demonstrability[13]) and Venkatesh (2000) of perceived ease of use (e.g. self-efficacy, perceived enjoyment of using the system). TAM 3, as proposed by Venkatesh and Bala (2008), integrates the previous model extensions by Venkatesh (2000) and Venkatesh and Davis (2000) into one unified model (see Figure 4).

[13] Job relevance denotes the extent to which the newly introduced system is applicable to the job (Venkatesh & Davis, 2000). Result demonstrability pertains to the degree to which the outcomes of using the system are observable and communicable (Moore & Benbasat, 1991).

Figure 4

Technology Acceptance Model 3 by Venkatesh and Bala (2008)



Note. Figure from Venkatesh and Bala (2008, p. 280).

Unified theory of acceptance and use of technology 1, developed by Venkatesh et al. (2003), and unified theory of acceptance and use of technology 2, introduced by Venkatesh et al. (2012), each present a framework integrating insights from eight theoretical models. They include the theory of reasoned action by Fishbein and Ajzen (1975), the theory of planned behaviour by Ajzen (1991), TAM variants (e.g. Venkatesh & Davis, 2000), the innovation diffusion theory by Rogers (1983), and other pertinent theories. It is noteworthy that both the unified theory of acceptance and use of technology 1 and 2 do not follow a hierarchical structure, as seen in TAM 3 (see Figure 4), which models the effects of relevant predictors as being mediated by perceived usefulness and ease of use on behavioural intentions. Instead, Venkatesh et al. (2003) and Venkatesh et al. (2012) posit that all proposed predictors directly influence behavioural intentions or even actual behaviour.

As noted above during the outline of the unified theory of acceptance and use of technology, a range of alternative TAM models and related concepts exists, such as Rogers' (1983) theory of diffusion of innovations. However, unlike unified theory of acceptance and use of technology versions 1 and 2 or the numerous variations of TAM, Rogers' (1983) model does not specifically address the acceptance of information systems for business purposes but is presented as more generic and broadly applicable beyond information systems. In his work, Rogers (1983) aims to explore critical aspects of the diffusion of innovations, including the concept of the *critical mass* of users required for an innovation to gain widespread acceptance. Within this context, Rogers (1983) introduced a typology comprising five distinct categories of adopters for innovations[14]. Rogers (1983) positioned these five types along a proposed illustration of an innovation's lifecycle, spanning from its introduction in the marketplace to the innovation’s eventual decline in popularity. Nonetheless, Rogers’ (1983) model shares similarities with the TAM in terms of the proposed predictors of individuals’ adoption of technologies. Rogers (1983) refers to these predictors as the perceived characteristics of an innovation, which he assigns to the persuasion phase – one of the stages in Rogers’ so-called innovation-decision process.[15] In this phase, individuals (or other decision-making

[14] Typology of adopters for innovations: innovators, early adopters, early majority, late majority, and laggards (Rogers, 1983).

[15] Rogers’ (1983) innovation-decision process refers to a five-step sequence. (1) Knowledge: the individual (or, similarly for the subsequent steps, another decision-making unit) gains awareness of an innovation. Persuasion: (2) the individual forms a favourable or unfavourable attitude towards the innovation based on predictors such as relative advantage and complexity. (3) Decision: the individual decides whether to adopt or reject the innovation.

units) form their attitude towards the innovation. To illustrate two of these predictors, Rogers' (1983, p. 213) concept of a technology's relative advantage, defined as "the degree to which an innovation is perceived as being better than the idea it supersedes" bears similarities with the concept of perceived usefulness in the TAM. Further, Rogers' (1983, p. 223) concept of complexity, defined as "the degree to which an innovation is perceived as relatively difficult to understand and use" shares similarities with the concept of the perceived ease of use in the TAM.

When further comparing the various theories introduced above – namely, the theory of reasoned action, the theory of planned behaviour, and the TAM – it becomes evident that they propose measuring the acceptance of technologies, understood as actual system use, typically by using individuals' attitudes or intentions as antecedents. However, the precise measurement of attitudes or intentions can vary depending on the context of application, as demonstrated by the following studies on the acceptance of electric cars. For instance, Dudenhöffer (2013) focused on assessing individuals' acceptance of electric cars for personal use by measuring their behavioural intention to use an electric car. Fazel (2014) explored the acceptance of fully battery electric vehicles in the context of public carsharing by evaluating a range of intentions, including (1) participants' general intentions to use a BEV (e.g. imagining spontaneous use for short trips in the city centre or regular use in addition to a household-owned car), (2) participants' intentions to buy a BEV, and (3) participants' intentions to drive BEVs when considering imagining the use of public carsharing. Furthermore, the inclusion of a measurement for actual system use within the scope of the TAM varies by study. For example, Davis (1986) or Venkatesh and Bala (2008) assessed actual behaviour by measuring employees' subjective ratings of system use, such as the average frequency and duration of usage per time period. In contrast, Dudenhöffer (2013) and Fazel (2014) did not include measurements of actual system use in their studies.

In summary, the various models have been developed with the aim of predicting individuals'

(4) Implementation: the individual begins using the innovation. (5) Confirmation: the final phase, where the decision is either reinforced or reversed.

behaviours. Specifically, when examining the theory of reasoned action, the theory of planned behaviour, and the diverse technology acceptance model variants, it becomes evident that, despite differences in the number and types of predictors of behavioural intentions or attitudes as well as variations in the precise specifications of their measurement models depending on the context of investigation, these models fundamentally exhibit significant resemblance in their overall modelling approach.

However, the proliferation of TAM variants has not gone without criticism. Notably, Benbasat and Barki (2007) raised concerns about the emergence of theoretical chaos resulting from numerous studies that merely adapted, extended, and introduced further TAM variants while investigating a changing IT environment. To provide a specific example, Benbasat and Barki (2007) specifically criticised researchers who repeatedly utilised the predictors of perceived usefulness and ease of use in their respective models, treating them as black boxes without delving into factors that would genuinely render a system useful.

Furthermore, as elucidated in the preceding section, Fishbein and Ajzen (1975, p. vi) initiate their introduction of the theory of reasoned action by asserting that their model fundamentally builds upon the premise that “humans are rational animals who systematically utilize or process the information available to them”. This viewpoint aligns with the broader category of expected utility theories as highlighted by Loewenstein et al. (2001), who describe such theories as taking a consequentialist perspective. According to Loewenstein et al. (2001), the term consequentialist denotes the concept that individuals make decisions by evaluating the potential consequences, specifically the outcomes, associated with different choice alternatives. Moreover, Loewenstein et al. (2001) assert that these models would also incorporate emotions, even in the context of risky decisions, in a manner consistent with the consequentialist and cognitive perspective. However, the affect heuristic (e.g. Slovic et al., 2004) and relatedly, Loewenstein et al.’s (2001) risk-as-feelings hypothesis, offer an alternative perspective to such consequentialist approaches, focusing on the primary role of emotions in judgment and decision-making, particularly in risky situations, as will be presented in the following section.

The Affect Heuristic

In the literature, the processing of information by humans is commonly categorised into two modes of thinking. For example, Kahneman (2012) subdivides these into the so-called *system 1* (i.e. thinking fast) and *system 2* (i.e. thinking slow), while Slovic et al. (2004) refer to the *experiential system* and the *analytic system*, respectively. According to Slovic et al. (2004), the analytic system utilises logic and reason, processes information more slowly and with a higher level of consciousness compared to the experiential system. Slovic et al. (2004) assert that the experiential system is driven by affective responses, incorporates past experiences and mental images, and operates with a faster processing speed compared to the analytic system. According to Slovic et al. (2004), both systems function in parallel, each depending on the other system for guidance. In the context of these two modes of thinking, the affect heuristic attributes emotions a central and determining role in individuals' judgments and decisions, especially in situations involving risk (Loewenstein et al., 2001; Slovic et al., 2004). According to Slovic et al. (2004), the affect heuristic posits that evaluations of risky situations are primarily shaped by individuals' affective responses, meaning their emotional reactions to stimuli. These responses are categorised as, for example, good or bad based on individuals' emotional evaluations, consciously or unconsciously (Slovic et al., 2004).

When considering whether to engage in a specific behaviour or when faced with a decision, insights from Slovic et al. (2004; see also somatic marker hypothesis by Damasio, 1994) suggest that imagining a particular situation or recalling past experiences can evoke positive or negative emotions related to that contemplation. Additionally, when evaluating risky decisions, Loewenstein et al. (2001) and Slovic et al. (2004) argue that emotions might diverge from cognitive judgments. Moreover, within the context of the risk-as-feelings hypothesis, a concept associated with the affect heuristic, Loewenstein et al. (2001) emphasise that emotional responses to risk may even drive behaviour to the extent that individuals might pursue a behaviour they would not have otherwise considered as their best course of action.

Consequently, unlike models following a consequentialist perspective, as elucidated by Loewenstein et al. (2001), the affect heuristic and related concepts, such as the risk-as-feelings hypothesis, assign emotions a central role in individuals' judgments and decisions. In the previous section, the TAM or related theories were introduced, presenting models designed to predict individuals' intentions to perform a specific behaviour or to use a technology in the future. While the affect heuristic is a general concept of judgement and decision-making, it has nevertheless also been used for the assessment of technologies (e.g. Alhakami & Slovic, 1994; Finucane et al., 2000; King & Slovic, 2014). Alhakami and Slovic (1994), for instance, had participants rate a range of activities and technologies (e.g. nuclear power, automobiles, vaccines) for their perceived risks and benefits. They observed an inverse relationship between individuals' judgments of the risks and benefits associated with these technologies: technologies rated as risky were linked to low benefits, and vice versa. Further, affect was found to be a reliable predictor of this relationship. For example, when individuals experience negative affect associated with performing a particular behaviour, they are likely to evaluate this behaviour negatively across all dimensions, such as judging the behaviour as low in benefits and high in risks. Conversely, when individuals experience positive affect, they are more likely to evaluate the behaviour as being high in benefits and low in risks (see Alhakami & Slovic, 1994).

Nevertheless, as indicated previously, because genuinely sustainable products may not be easily discernible from less sustainable products to individuals, additional methods need to be identified to motivate individuals to choose the presented sustainable alternative to status quo solutions when aiming to mitigate anthropogenic greenhouse gas emissions.

Utilising Nudges and Gamification to Induce Behavioural Change

In the literature, scholars (e.g. Dolan et al., 2012; Loewenstein et al., 2001; Thaler & Sunstein, 2014) discuss how humans may exhibit irrational behaviour in their choices, deviating from what they would typically perceive as their optimal course of action. For example, Tversky and Kahneman (1974) delve into how individuals might employ heuristics, such as the representativeness heuristic[16], the availability heuristic[17], or, as indicated above, the affect heuristic, to simplify complex tasks (e.g. assessing probabilities) into simpler judgmental operations. Tversky and Kahneman (1974) argue that while the use of heuristics may possess some validity, it can also lead to systematic errors. As a response to observed erratic behaviours and with the objective of guiding individuals towards specific behaviours or choices, such as the sustainable choice option in this thesis, scholars have introduced what can be termed as *motivational toolboxes* or a schematic approach to the design of behavioural interventions. Examples include *nudges* (Thaler & Sunstein, 2014), *mindspace*[18] (Dolan et al., 2012), and in a broader sense, *gamification* (e.g. Hamari, 2017; Landers et al., 2017).

The following section will offer a concise introduction to nudges from Thaler and Sunstein (2014), followed by an introduction to the concept of gamification in the subsequent section.

Utilising Nudges to Induce Behavioural Change

Within the nudges framework, Thaler and Sunstein (2014) presented the following six categories of behavioural interventions: (1) incentives, (2) understand mappings, (3) default, (4) give feedback, (5) expect error, and (6) structure complex choices. Thaler and Sunstein (2014) introduced nudges as a guide for what they term *choice architects*, essentially designers of decision environments. Specifically, they define choice architects as individuals who consciously modify the decision environment of others with the aim at assisting the user/consumer (referred to as the *nudgee*) by highlighting the choice option that individuals would have selected if they had paid

[16] According to Tversky and Kahneman (1974) and Kahneman (2012), individuals utilise the representativeness heuristic to make judgments about the probability of an individual or event belonging to a particular group based on perceived similarity to a stereotype which may involve neglecting relevant base rate frequencies or prior probabilities.

[17] According to Tversky and Kahneman (1974), individuals employ the availability heuristic to assess the frequency or probability of an event by recalling instances or events that easily come to mind.

[18] Essentially, the mindspace framework resembles nudges and refers to the following behavioural intervention categories: (1) messenger, (2) incentives, (3) norms, (4) defaults, (5) salience, (6) priming, (7) affect, (8) commitment, and (9) ego (Dolan et al., 2012).

attention, been fully informed, possessed sufficient self-control, and so forth. Furthermore, Thaler and Sunstein (2014) recommend applying nudges in situations involving rare and complex decisions, where prompt feedback is lacking, and when it is challenging to translate aspects of the situation into more transparent and understandable terms. Because the choice architect should not deliberately constrain the nudgee's freedom of choice, Thaler and Sunstein (2014) consider their understanding of intervention design in the context of nudges as what they term a *libertarian paternalistic* approach.

In the following, two examples for the above mentioned nudge categories will be outlined to give an impression of what Thaler and Sunstein (2014) understand a choice architect could do. For instance, in the context of the category *expect errors*, they describe that a choice architect should anticipate and avoid likely errors, such as those that may occur when using a product or a service. To illustrate, in older cars, the driver had to manually switch the lights on and off, occasionally leading to instances where individuals forgot to turn off the headlights. This oversight drained the car battery, preventing the vehicle from starting when attempting to drive again. To avoid that probable error, in newer cars, headlights automatically switch off when the driver turns off the car's ignition. With the *feedback* category, Thaler and Sunstein (2014) refer to warnings informing the individual that something might end in a consequence that is perhaps undesired. To revisit the headlight example, another intermediate variant existed between the two mentioned above. If the driver turned off the ignition before switching off the headlights, a warning sound would alert the driver to the lights still being on. (Of course, the driver could theoretically choose to ignore this warning sound, exit the car, and allow the battery to run down.)

Behavioural interventions of this kind have been found to influence behaviours or choices, as evidenced by specific observations. For example, the use of a fake fly in urinals at Schiphol airport in the Netherlands improved accuracy, as individuals tended to aim at the fly (Thaler & Sunstein, 2014). Political implementations, such as Sweden's use of defaults to enhance vaccine uptake (Bonander et al., 2022)[19], and other empirical findings (e.g. Chang et al., 2016; Ouvrard et al., 2020; Wensing et al., 2020) further illustrate the effectiveness of such behavioural interventions.

As mentioned above, gamification can also be regarded as a systematic approach to influence behaviour, typically to enhance performance and engagement, which will be introduced below.

Utilising Gamification to Enhance Performance and Engagement

There are some classics among New Year's resolutions, such as adopting a regular exercise routine, embracing healthier eating habits, quitting smoking, reducing alcohol consumption, and many other pursuits falling under the category of pleasures when consumed or practiced but not necessarily considered life-prolonging. Individuals evidently use the beginning of the year as a starting point to diligently implement these new resolutions. For instance, fitness centres report a significantly higher enrolment rate in January compared to other months (Dams et al., 2012). Simultaneously, fitness centres acknowledge that individuals may encounter difficulties in maintaining these desired routines. While gyms experience crowding in the first few months, they tend to empty out over the course of the year (Dams et al., 2012) and the exercise cycle begins anew in the next year.

However, for those intending to maintain their declared resolution, digital applications exist (e.g. on smartphones or smartwatches) that not only track one's sporting activities but also incorporate what is known as gamification: because of their recognised motivational power in conventional games, among other factors, created by immersive experiences (e.g. Weibel & Wissmath, 2012; Yee, 2006), gamification involves adding game design elements to existing, non-game applications (Deterding et al., 2011; Hamari & Koivisto, 2013). Gamification elements, such as points, badges, progress bars, or others (see Table 1), have been found to augment individuals'

[19] For example, during the COVID-19 pandemic, 16 and 17 year olds in Uppsala, Sweden, were sent letters with pre-booked but nevertheless voluntary vaccination appointments, which, in comparison to other control regions, showed a comparatively higher vaccination rate (Bonander et al., 2022).

enjoyment of using a gamified system (Codish & Ravid, 2015; Mitchell et al., 2020), individuals' engagement with incentivised behaviours, and improved task performance upon task completion as demonstrated in various studies (e.g. Boratto et al., 2017; Gutt et al., 2020; Hamari & Koivisto, 2013; Landers et al., 2017; Landers & Landers, 2014).

Table 1

A Sample of Common Gamification Elements

Gamification element	Aim of gamification element
Point system	Points are numerical values awarded upon the successful completion of designated actions, enhancing an individual's overall score. This quantified measure of progress can also be a fundamental component of other elements, such as badges or leaderboards (Basten, 2017; Sailer et al., 2017).
Badges	Badges function as visual affirmations of individuals' achievements, delineating their progress through levels or the attainment of goals. Badges commonly encompass three elements: the visual and textual components, the specified criteria for badge acquisition, and the corresponding reward – the earned badge (Hamari, 2017; Sailer et al., 2017).
Leaderboard	Leaderboards create competition through a display or list, ranking individuals according to their relative success by measuring their performance against specific criteria. Therefore, they present an ordered list that compares individuals' achievements to those of others (Basten, 2017; Sailer et al., 2017).
Levels	A level typically signifies a particular stage attainable by individuals, achieved, for instance, through the accumulation of points from accrued experience, task completion, or the attainment of specific milestones. Consequently, it functions as an indicator of an individual's progress over time (Basten, 2017).

Progress bar or performance graphs	A progress bar functions as a visual representation of an individual's performance over time relative to a specific reference standard, highlighting the remaining steps required to complete a task or challenge (Sailer et al., 2017).
Avatars	Avatars serve as a visual representation of an individual within the system, typically taking the form of an illustration or animation (Sailer et al., 2017).
Teammates	Individuals can interact with real or virtual others through competitions or collaborations, including the formation of teams working towards a shared goal (Sailer et al., 2017).
Meaningful story	The collection of points or related elements can be enhanced by a narrative context, such as a specific title or storylines commonly found in games (Sailer et al., 2017).

Stieglitz (2015) posits that gamification elements exert a motivational influence by satisfying basic human needs that encompass both intrinsic and extrinsic dimensions: concerning intrinsic need fulfilment, Stieglitz (2015) alludes to social interactions, the sense of group belonging, the pursuit of specific skills, the mastery of challenges, and the perception of engaging in something meaningful, self-determined, and relevant. Regarding extrinsic need satisfaction, Stieglitz (2015) points out that individuals may undertake a task with the desire for social recognition, rewards, or the acquisition of power or privileges.

To elucidate the observed effectiveness of gamification elements, Stieglitz (2015) references several theories, such as Maslow's pyramid of needs[20], self-determination theory[21] (Ryan & Deci,

[20] In the context of the theory of human motivation, Maslow (1943) introduced five sets of goals that he regarded as basic but hierarchical needs. These include physiological needs, the need for safety, love, self-esteem as well as self-actualisation.

[21] According to Ryan and Deci (2000), self-determination theory pertains to individuals' intrinsic or extrinsic motivation, encompassing a taxonomy of different types of extrinsic motivation to adopt values and associated behaviours.

2000), goal-setting theory[22] (e.g. Locke & Latham, 2002), and other theories, as further substantiated by a meta-analysis of gamification literature by Krath et al. (2021). In their meta-analysis, Krath et al. (2021) integrated 118 different theories with the aim of investigating the theoretical foundations that explain the aforementioned motivational effects (e.g. increased performance) linked to gamification. According to Krath et al. (2021), the self-determination theory by Ryan and Deci (2000) emerged as the most frequently cited theory, as investigated by researchers, such as Mitchell et al. (2020) or Sailer et al. (2017). For example, Sailer et al. (2017) examined the effects of various gamification elements (e.g. badges, teammates) and their associated mechanisms (e.g. teammates conveying a sense of relevance or badges providing cumulative feedback) on the fulfilment on Ryan and Deci's (2000) defined basic psychological needs (e.g. the need for competence). Amongst other findings, Sailer et al. (2017), observed that game design elements, such as teammates, avatars, or meaningful stories, influenced social relatedness and feelings of relevance through a shared goal.

In summary, the literature suggests that game design elements can motivate an individual to perform specific actions (Boratto et al., 2017; Gutt et al., 2020; Hamari & Koivisto, 2013; Landers et al., 2017; Landers & Landers, 2014), including fostering more sustainable behaviours (e.g. Günther et al., 2020)[23]. Hence, gamification exhibits conceptual similarities with Thaler and Sunstein's (2014)

Ryan and Deci (2000) elaborate on these motives in connection with satisfying what they describe as three fundamental psychological needs: autonomy, competence, and relatedness.

[22] Locke and Latham's (2002) goal-setting theory provides a comprehensive framework for structuring goals as meaningful and potent motivators to enhance performance. The theory examines various goal types, including distal and proximal goals, elucidating the mechanisms through which goals operate (e.g. eliciting arousal and a sense of discovery). Additionally, Locke and Latham (2002) discuss the role of goals as mediators of incentives and explore the influence of moderating factors (e.g. feedback, goal commitment, self-efficacy) on the relationship between goal difficulty and specificity, and performance.

[23] In a field study, Günther et al. (2020) studied participants who had access to a shared corporate vehicle pool consisting of BEVs and other modes of mobility. If participants chose a BEV, they were incentivised to eco-drive for their business trips by utilising (1) post-drive feedback regarding energy consumption, (2) feedback plus gamification, and (3) feedback, gamification, and financial rewards, which was implemented stepwise. Günther et al. (2020) found that

concept of nudges. However, Rackwitz (2018) argues that conceptually, nudges and gamification might pursue different aims. Concerning nudges, Rackwitz (2018) asserts that that the choice architect simplifies difficult decisions for individuals by modifying the presentation of choice options to highlight the path of least resistance for the target choice option. Conversely, the use of gamification aims to enhance individuals' motivation to engage more deeply with a topic and subsequently make a decision. Nevertheless, while acknowledging for the differences between both concepts, Schrape (2014) argues that both concepts share the overarching idea of presenting methods aimed at regulating individuals and societies.

Dark Patterns, Dark Nudges, Sludges, and Other 'Exploitations'

Recall that a guiding principle of libertarian paternalism asserts that nudges should assist and not harm the nudgee (Thaler & Sunstein, 2014). However, Sunstein (2022) acknowledged that nudges could also be employed to the disadvantage of those being nudged. When utilised for the latter, such interventions are associated with terms, such as *dark patterns* (commonly used in the field of user experience design), *sludges*, or *dark nudges* (e.g. Mills et al., 2023; Petticrew et al., 2020; Sunstein, 2022). While there are subtle differences between the three terms, they essentially revolve around the deliberate use of specific design patterns, including detours for the user, the use of social norms, obfuscation, and related methods by interface designers/choice architects with the aim of adversely influencing users (Mills et al., 2023; Petticrew et al., 2020; Sunstein, 2022). These patterns can make it particularly challenging for users to perform their intended behaviour or even induce users to make decisions they would not typically have made. Ultimately, the implementation of dark patterns, sludges, or dark nudges primarily favours the influencing party (e.g. a shop owner) over the consumer (Mills et al., 2023; Petticrew et al., 2020; Sunstein, 2022).

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gamification was most effective at reducing individuals' energy consumption, followed by financial incentives, whereas feedback alone had no determinable effect.

The deletion of a user account can serve as an illustrative example of such patterns: while the registration process, for example, on an online shopping platform, may have been quick and easy for the user, attempting to delete the user account might not be as straightforward. For instance, Schaffner et al. (2022) interviewed 200 individuals registered on several social media platforms. Their findings showed that most participants stated attempting to delete at least one of their social media accounts in the past. A portion of participants reported failure in their attempts, referring to difficulties, such as being unable to locate the delete button or perceiving the process as being too tedious or complicated (Schaffner et al., 2022). As indicated by the previous example, in commercial applications, patterns can be observed, which, from a user perspective, are unnecessarily protracted, confusing, and time-consuming. This may involve extensive searching for the right navigation path, unnecessary clicking, reading, and unnecessary confirming or rejecting at various steps of the process, including so-called *confirmshaming* (e.g. Veiga, 2023). Confirmshaming, as defined by Brignull et al. (2023), refers to the use of elements (e.g. sad emojis) with the aim of eliciting negative emotions, such as guilt or shame, to influence user behaviour for the benefit of the service provider.

In summary, the aforementioned considerations suggest that the design of choice architecture may not necessarily aim to assist the consumer in making better choices but rather to provide advantages to the influencing party.

By terming gamification as *exploitationware*, Bogost (2014, p. 65) issued a related critique, considering gamification to be “primarily a practice of marketers and consultants who seek to construct and then exploit an opportunity for benefit.” Among other reasons, Bogost (2011) fundamentally critiques proponents of gamification for suggesting a simplistic and automatic application of elements, such as points and levels, for any purpose. Bogost (2011) cautions against a one size fits all mentality in the context of gamification, emphasising the danger of reducing essential insights from the gaming industry solely for the purpose of enhancing customer loyalty. Instead, he highlights the more profound aspects of games, such as the sensations they evoke, including enlightenment, fascination, hope, or even terror. According to Bogost (2011), these deeper experiences are elemental to games, while points and levels are merely tools for measuring progress.

Aim of This Thesis

Previous research findings have substantiated the validity of the technology acceptance model and the affect heuristic for modelling individuals' perceptions and judgments concerning technologies, including their perceived benefits, risks, and other pertinent factors. Regarding the affect heuristic, extant literature suggests that evaluations of behaviours, activities, or technologies may be susceptible to the influence of an individual's affective responses, especially when involving risk. In this context, research results have indicated that providing information explicitly emphasising the risks or benefits of items or behaviours can influence individuals' judgments of those items or behaviours based on a change in evaluative affect. Relatedly, gamification can be considered a schematic approach to influencing target behaviour, typically through the use of virtual rewards, and occasionally, losses.

However, concerning the technology acceptance model and the affect heuristic, prior research has not extensively explored the extent to which a change in technology usage contexts, specifically through variations in risks or benefits associated with technology use (e.g. the incorporation of gamification elements) relates to individuals’ technology preferences for sustainable products or their incumbent alternatives. Addressing a recognised gap in the literature, this dissertation explores the specific example of individuals choosing between the sustainable BEVs and conventional cars with an internal combustion engine for business mobility purposes in Germany. The primary research question guiding this thesis is as follows:

To what extent do changes in the context of technology use, as evaluated through the technology acceptance model and the affect heuristic, influence the assessment and preference for sustainable technologies?

Contributions and Applications

Innovations can only prevail if they are also actively utilised. As evidenced by the extensive literature on technology acceptance and the application of behavioural interventions, the continual exploration of novel methods to incentivise individuals is crucial for ensuring a sustainable future.

This exploration aims to motivate individuals to overcome reservations and potential fears, thereby fostering their willingness to engage with new, innovative, and sustainable technologies. This thesis scrutinises a particular technology within a market where it has been promoted for several years, necessitating additional insights into how its acceptance can be strengthened. Specifically, this thesis explores the impact of risky or advantageously conveyed technology usage contexts on the judgment and technology preferences of potential users.

The results of this thesis advance discussions on the measurement of judgment and acceptance of sustainable technologies by demonstrating the value of both the TAM and the affect heuristic within this specific research context. The findings illustrate how variations in perceived risk associated with technology use in particular situations, or the incorporation of gamification elements in the decision-making process, influence individuals' choices between a sustainable technology and its conventional counterpart.

Additionally, this thesis provides novel insights into the affect heuristic literature by re-examining the inverted correlation between risks and benefits in this specific research context and testing this relationship through the integration of gamification. Despite critiques concerning the numerous adaptations of the TAM to specific research contexts since its introduction in the 1980s, the results underscore the importance of measuring emotional valence in assessing technology acceptance. Emotions were found to be a dominant predictor of individuals' behavioural intentions. Further, the data suggest that negative emotions notably influence individuals' responses to technology usage contexts perceived as high risk, as evidenced by a reduced willingness to participate in an online experiment involving hypothetical choices. Hence, this thesis underscores the importance of considering and measuring emotions not only for theoretical development and prediction of individuals' responses but also highlights the relevance of hedonic aspects of technologies, even within a business context.

By exploring variations of gamification in decision-making contexts, this thesis offers new perspectives on the gamification literature, suggesting that its application may extend beyond its traditional roles in performance enhancement and engagement to influence choices between sustainable technologies and their conventional alternatives. Additionally, the results indicate that even brief exposure to a change in decision context involving gamification can significantly affect individuals' judgment of technologies, such as by enhancing their perceived usefulness.

In summary, the outcomes of this thesis contribute to existing literature in the above mentioned fields and lay the groundwork for further exploration into the application of gamification and the influence of risk on technology choices. Additionally, these findings motivate the utilisation of gamification in organisational, political, and industrial contexts, including car manufacturing. This encompasses advancing the development of electric cars and their supporting infrastructure, designing suitable behavioural interventions in fleet management and related mobility solutions, and creating effective communication strategies and similar initiatives to promote sustainable technologies.

Structure of This Thesis

The research question outlined above is explored in two studies, denoted as Study 1 and Study 2.

Chapter 2 (Study 1) involves a comprehensive investigation grounded in a TAM specifically adapted to predict individuals' intentions to book a BEV for an upcoming business trip. Integrating a car booking experiment, Study 1 is structured on a 2x2 factorial design. Participants were assigned to one of two differentially risky hypothetical business trips (i.e. factor 1). Additionally, participants were allocated to a condition where gamification was either absent or present in car booking software (i.e. factor 2). After allocation to one of the four experimental conditions, participants were instructed to make bookings between BEVs and conventional cars using car booking software. In accordance with this study design, Study 1 is structured into three sub-studies, denoted as Sub-studies 1.1, 1.2, and 1.3. Each sub-study has a distinct exploratory focus while drawing on the same dataset. Sub-study 1.1 (Chapter 2.1) is dedicated to presenting an adapted TAM designed to predict individuals' behavioural intentions to book a BEV and the exploration of individuals' car type preferences between BEVs and internal combustion engine vehicles (ICEVs) within the context of risky technology usage scenarios (i.e. factor 1). In Sub-study 1.2 (Chapter 2.2), this TAM is expanded with additional predictors and data are examined with the focus on investigating car type preferences under the influence of gamification (i.e. factor 2). Finally, Sub-study 1.3 (Chapter 2.3) specifically explores the interaction between gamification and car choice in risky BEV usage contexts.

Chapter 3 presents Study 2, which utilises a 4x2 factorial design to re-examine the inverted risk-benefit relationship, a concept associated with the affect heuristic, and explores individuals' judgment of BEVs and their car type preferences between BEVs and ICEVs for business trips. Specifically, information was utilised emphasising either the risks or benefits of BEVs (factor 1: high-benefit, low-benefit, high-risk, low-risk), with and without gamification (i.e. factor 2), to manipulate individuals' evaluative affect of BEVs and consequently, the non-manipulated attribute. Through an online experiment, choices between BEVs and conventional cars for business trips were measured using car booking software.

Chapter 4 concerns a general discussion and specific directions for future research of the findings of Studies 1 and 2, followed by implications regarding the utilisation of the TAM and the affect heuristic for technology assessments, implications for the utilisation of gamification, practical implications, an outlook for further research, and limitations of this thesis.

Chapter 2: Study 1 – Application of the Technology Acceptance Model to Explore the Impact of Risk and Gamification on Technology Assessment and Preferences

Structure of Study 1

As described above, Study 1 involves a comprehensive investigation grounded in a TAM specifically adapted to predict individuals' intentions to book a BEV for an upcoming business trip. Integrating a car booking experiment, Study 1 is structured on a 2x2 factorial design. Participants were assigned to one of two differentially risky hypothetical business trip scenarios (i.e. factor 1). Additionally, participants were allocated to a condition where gamification was either absent or present in the car booking software (i.e. factor 2). After allocation to one of the four experimental conditions, participants were instructed to make bookings between BEVs and ICEVs using the car booking software. In accordance with this study design, Study 1 is structured into three sub-studies, denoted as Sub-studies 1.1, 1.2, and 1.3. Each sub-study has a distinct exploratory focus while drawing on the same dataset. Sub-study 1.1 (Chapter 2.1) is dedicated to presenting an adapted TAM designed to predict individuals' behavioural intentions to book a BEV and the exploration of individuals' car type preferences between BEVs and ICEVs within the context of risky technology usage scenarios (i.e. factor 1). In Sub-study 1.2 (Chapter 2.2), this TAM is expanded with additional predictors, and data are examined with the focus on investigating car type preferences under the influence of gamification (i.e. factor 2). Finally, Sub-study 1.3 (Chapter 2.3) specifically explores the interaction between gamification and car choice in risky BEV usage contexts.

Chapter 2.1: Sub-Study 1.1 - Predicting Technology Choice Utilising the Technology Acceptance Model: About Variations in Risky Usage Contexts

Abstract

Sub-study 1.1 examines how differentially risky technology usage contexts influence the reliability of the TAM in predicting technology choice. Specifically, the TAM was adapted to measure the acceptance of BEVs for business trips and an online experiment was conducted to investigate the influence of two differentially risky, hypothetical business trips on choice between BEVs and conventional cars. The results provide evidence that the expected enjoyment of driving a BEV was the primary driver of individuals' behavioural intentions to book a BEV for the low-risk business trip, rather than perceived usefulness and ease of use. According to the findings, only a minority of participants chose a BEV even when the car booking software provided range buffer information, designed to support BEV selection. The results, upon analysing data at an aggregated level, did not uncover a statistically significant association between the choice of car type and affiliation with the low-risk or high-risk group. However, a noteworthy association was observed for participants who opted to withdraw from the car booking experiment rather than selecting a car and were assigned to the high-risk trip. Furthermore, findings on an observational level reveal that using behavioural intentions to predict car choice exhibited a weaker association among participants in the high-risk group compared to those in the low-risk group. Interpreting the results with the affect heuristic indicates that emotions influenced the participants' behavioural responses to higher-risk trips. The findings imply the necessity of considering emotions in future TAM variations to enhance their predictive capacity for technology choices made in risky usage contexts.

Introduction

For more than a decade, the BEV has been argued to be a prominent sustainable alternative to conventional cars with an internal combustion engine (Beuse, 2021; Climate Change Committee, 2023; Fazel, 2014; Presse- und Informationsamt der Bundesregierung, 2022). However, rates of adoption of the BEV vary considerably across countries, suggesting that other issues may influence the decision to use a BEV, such as geographical factors (e.g. settlement structures and corresponding charging infrastructure density) or policies and regulations (e.g. purchase incentives, taxation, parking benefits) (see Wappelhorst et al., 2020). For instance, in 2021 while nearly two thirds (64.5%) of all newly registered cars in Norway were BEVs, the corresponding figure in Germany in 2021 was only 13.6% or even only 3.2% in the United States (Davis & Boundy, 2022; Kraftfahrtbundesamt, n.d.-b; Teslamag, 2022).

Research conducted in Germany indicates that obvious generic obstacles to BEV adoption include the relatively higher purchase price, limited range, extended battery charging duration, or the perceived lack of charging infrastructure availability (Bühler et al., 2014; Verband der TÜV e.V., n.d.). Regarding lower range, a new terminology has arisen in media reporting (e.g. Knorre, 2015; Müller, 2017): *range anxiety* describes the fear of the undesired outcome of becoming stranded with a dead battery with the target destination or next charging station being out of reach. This term, or its equivalent in other countries, has found its way into, for instance, German and Norwegian dictionaries (Loveday, 2013; Müller, 2017). Unlike the availability of charging infrastructure, which can vary from country to country and might as well be a mitigating factor to range anxiety, lower range is still a limitation that applies to all markets. Nevertheless, unlike many other countries, Norway is now a leading BEV market. So what accounts for the variable success of such new technologies?

Technology Acceptance Model and its Variants to Predict Technology Acceptance

To predict the acceptance of technologies, Davis (1986) presented the TAM. Davis's (1986) aim was to determine the influence of the perceived usefulness of an information technology for the job to be done and the perceived ease of use of the technology on individuals' attitudes towards using the technology, and consequently on their decision to use it. Davis's (1986) original TAM is based on Fishbein and Ajzen's (1975) theory of reasoned action. According to the theory of reasoned action, attitudes[24] and subjective norms influence behavioural intentions and thus, actual behaviour (Fishbein & Ajzen, 1975). However, in a subsequent study, Davis et al. (1989) compared the TAM with the theory of reasoned action, including combined versions of the two models. Their findings indicated that attitudes did not fully mediate the effects of perceived usefulness and ease of use on behavioural intentions. Therefore, Davis et al. (1989) proposed an updated TAM variant. Among other changes, this updated TAM variant did not include attitude as a separate predictor but instead behavioural intentions as being the primary predictor of the use of computer-based technologies.

The Role of Emotions in the TAM and the Affect Heuristic

The updated TAM presented by Davis et al. (1989) was not the only adaptation. While the original TAM was tailored to provide predictions of the acceptance of information systems for work purposes, over the past 30 years the TAM has been developed into a variety of versions with different numbers and kinds of predictors, also for different application areas (e.g. Ferri et al., 2020; López-Nicolás et al., 2008; Venkatesh, 2000; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). Regarding electric vehicles, for instance, Fazel's (2014) aim was to measure BEV acceptance for public carsharing. Globisch et al. (2018) and Roemer and Henseler (2022) researched BEV acceptance in the context of commercial use, while Dudenhöffer (2013) aimed to identify the factors explaining why BEVs and hybrid electric vehicles have struggled to gain acceptance for private use.

As mentioned, the TAM variant by Davis et al. (1989) did not include attitude as a separate predictor in the model. However, the four subsequent electric vehicle acceptance studies cited above

[24] According to Fishbein and Ajzen (1975), attitude contains an evaluative but also an affective dimension, which results in an individual's general feeling of liking or disliking towards a stimulus object. Consequentially, it is not difficult to imagine that a person who is generally enthusiastic about the idea of driving a BEV would also be inclined to drive a BEV in the future if given the opportunity. Therefore, while intentions and attitude are distinct concepts, they may still be aligned.

did include a measure for emotions (anger, surprise, fear, etc.) or affect[25] and found them to be predictors for the acceptance of electric vehicles.

As an alternative to the TAM, the affect heuristic (e.g. Slovic et al., 2004) offers another perspective on the role of emotions in judgment and decision-making. The affect heuristic assumes that an evaluation of a risky situation is primarily determined by individuals' emotions and affective responses. While the affect heuristic constitutes a general concept in judgment and decision-making, it has also been examined in the context of technology assessment. Alhakami and Slovic (1994), for example, had participants rate a range of activities (e.g. smoking, automobile travel) and technologies (e.g. nuclear power, microwave ovens) for their risks and benefits. They found an inverse relationship between the perceived risks and benefits: technologies rated as risky were associated with low benefits and vice versa, with evaluative affect being the most important determinant of this relationship (Alhakami & Slovic, 1994). When individuals experience negative affect (i.e. unpleasant emotions) associated with performing a particular behaviour, they are likely to evaluate it negatively across dimensions, such as perceiving low benefits and high risks. Conversely, when individuals experience positive affect (i.e. pleasant emotions), they are more likely to evaluate the behaviour as being high in benefits and low in risks.

Comparing the affect heuristic with the different TAM variants indicates that both theories consider the influence of emotions on judgement and decision-making or technology acceptance, respectively, albeit in different ways. As previously mentioned, within the framework of the original TAM, Davis (1986) asserted that perceived usefulness and ease of use serve as predictors for an individual's attitude towards the item. Precisely, Davis (1986) proposed that an individual's cognitive evaluation of a technology informs their attitude towards it, determining whether the use of the respective technology is perceived as a positive or negative idea. In later variations of the TAM, which did not incorporate attitude as a predictor of behavioural intentions, emotions were instead

[25] According to Slovic et al. (2004), affect refers to the emotional response one has towards a stimulus, whether consciously or unconsciously. It involves categorising the stimulus as either good or bad based on the emotional evaluation.

considered an early predictor in the technology evaluation process. For example, Venkatesh and Bala (2008) incorporated emotions, such as perceived enjoyment or anxiety when envisioning the use of technology, as predictors for perceived ease of use. It is worth noting that the perceived enjoyment and anxiety constituted two out of the 11 predictors for perceived usefulness or ease of use in the model.

In summary, while TAM variations generally consider the influence of emotions, often as one among several factors alongside their emphasis on the cognitive evaluation of technologies, the affect heuristic assigns emotions a central role in individuals' judgments and decisions. This is particularly notable in situations involving risk, as will be introduced below.

The Role of Emotions and Affect in Individuals' Judgments under Risk

As mentioned above, Dudenhöffer (2013) researched electric vehicle acceptance for private use and one particular finding is noteworthy. As part of the study, Dudenhöffer (2013) let each participant drive three different electric cars (BEVs and/or hybrid electric cars) for 20-30 minutes each, including a charging stop. Dudenhöffer (2013) found that it was mainly the enjoyment of driving a BEV (i.e. positive emotions) and range anxiety (i.e. negative emotions) to determine the affective response of the participants before the test drive. After the test drive, however, their affective response towards electric vehicles was primarily guided by negative emotions, specifically, the fear of running out of energy. Dudenhöffer (2013) suggests that the limited range becoming more apparent during the test drive might have outweighed the expected fun. This finding suggests that the applied driving experience primarily evoked a negative affective response towards electric vehicles, which appears to have guided the participants' subsequent responses to the questionnaire. But what provokes such affective responses?

According to the affect heuristic, when imagining possible outcomes, associations, or images derived from past experiences can evoke emotions that are linked to a positive or negative feeling about an option under consideration (Slovic et al., 2004, see also somatic marker hypothesis by Damasio, 1994). In addition, specific elements may augment such affective responses. Loewenstein et al. (2001) and Slovic et al. (2004), for example, exemplify such elements with the vividness of an imagined particular situation or the immediacy of the risky action. These considerations, along with the findings of Dudenhöffer (2013), suggest that simply hearing or reading the term range anxiety might evoke negative associations with BEVs. To explore the notion of range anxiety, Franke et al. (2016) and Rauh et al. (2015b) conducted investigations into factors contributing to the perceived stress reported by BEV drivers, particularly in situations involving critical range situations[26]. Among various factors, participants indicated that trust in the BEV's range estimation and familiarity with the route alleviated perceived stress, while a reduction in the driving range buffer[27] was correlated with an increase in perceived stress (Franke et al., 2016; Rauh et al., 2015b).

In recent years, BEVs have become increasingly prevalent in corporate shared car fleets (Schlütersche Fachmedien GmbH, 2021). Consider an employee preparing for a business trip who needs to decide between selecting a BEV or a combustion engine vehicle from the shared business car fleet. The findings by Dudenhöffer (2013), Franke et al. (2016), and Rauh et al. (2015b) cited above suggest that specific driving contexts may significantly impact an individual's affective responses to the various car options. For example, as indicated above, unfamiliarity with the driving route may evoke negative emotions when envisioning potential challenges in locating a charging station along an unknown route. Consequently, this may lead individuals to perceive BEVs as riskier than ICEVs for the trip, demotivating the choice of a BEV in favour of selecting an ICEV. Conversely, when familiar with the route that lies ahead, the employee might be well aware of available charging infrastructure, potentially eliciting more positive emotions when considering a BEV for the business trip.

In summary, the affect heuristic suggests that affective responses elicited by contemplating BEV choice for specific usage contexts may lead to a differential evaluation of risk for BEVs and

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[26] Rauh et al. (2015b) defined a critical range situation as a BEV driving scenario in which the remaining driving range was only marginally sufficient to complete the intended trip.

[27] The driving range buffer refers to the excess driving range beyond the estimated consumption.

consequently affect BEV choice. Additionally, in the assessment of risky decisions, Loewenstein et al. (2001) and Slovic et al. (2004) argue that emotions may deviate from cognitive judgments. Moreover, within the context of the risk-as-feelings hypothesis, a concept associated with the affect heuristic, Loewenstein et al. (2001) emphasise that emotional responses to risk may even drive behaviour to the extent that individuals might pursue a behaviour they would not have otherwise considered as their best course of action.

The Influence of Risk on the Reliability of the TAM's Prediction of Car Choice

As mentioned above, emotions may be a relevant factor in technology acceptance. Further, the aforementioned considerations demonstrate that both the affect heuristic and the risk-as-feelings hypothesis highlight the role of emotions in risk evaluation. In contrast, the perceived risk of technology usage is not a consistent predictor in variations of the TAM. For instance, while the TAM variations proposed by Davis (1986) and Venkatesh and Bala (2008) did not incorporate perceived risk, it was taken into account by Fazel (2014), Ferri et al. (2020), or Im et al. (2008). These three studies considered perceived risk as a predictor of perceived usefulness or behavioural intentions.

Additionally, it is worth highlighting that further along the decision-making process, TAM variations typically build upon Davis et al.'s (1989) TAM by modelling behavioural intentions as the predictor of behaviour. However, in their review of TAM studies, Bhattacherjee and Sanford (2009) found that intentions predict behaviour with a small to moderate effect size (i.e. with a moderate level of explanatory power). A low to medium effect size suggests that there are other factors that explain why behaviour diverges from intentions; and the considerations above suggest that emotional responses to risk might be among those factors influencing the association between intentions and behaviour. Specifically, the above discussion involving the aforementioned theories, namely the TAM, the affect heuristic, and the risk-as-feeling hypothesis, suggests that emotional reactions to risk could be influencing the prediction of car choice from cognitively assessed behavioural intentions.

Further, these considerations raise the question of the degree to which the TAM can account for the influence of differentially risky technology usage contexts on behaviour or choice? As a result, this investigation aims to determine whether hypothetical business trips with varying risk elements (e.g. route, outside temperature) influence the reliability of the TAM's prediction of car choice.

To explore this research question, the study specifically focuses on technology acceptance of BEVs for business trips within the context of corporate carsharing. Corporate carsharing typically involves employees having access to at least one car that can be booked for business mobility purposes. Related studies, such as those by Globisch et al. (2018) and Roemer and Henseler (2022), examine the acceptance of electric vehicles in commercial use or within commercial car pool fleets. Roemer and Henseler (2022) focused on explaining the acceptance of electric vehicles from the perspective of individual users, namely employees. Globisch et al. (2018) also measured acceptance at an organisational level, examining fleet decision-makers who typically determine the composition of the corporate car fleet, including the decision to integrate electric cars into the fleet. However, since employees ultimately decide whether to use a BEV for their business trips, this study focuses on measuring the acceptance from employee’s perspective.

Due to the aforementioned comparatively low registration rate of BEVs in Germany, the German market was considered ideal for studying technology acceptance for this example. A TAM specifically adapted to assess the acceptance of BEVs for business trips was tested. Additionally, an online experiment was also conducted to examine the influence of two differentially risky business trips on car choice, presenting an attempt to measure system use. This involved randomly assigning the experimental participants to one of two hypothetical business trip scenarios. The participants made car bookings using car booking software and subsequently returned to the questionnaire, which concerned the assessment of the TAM. The hypothetical car fleet in the booking software consisted of an equal number of BEVs and ICEVs, matched in terms of vehicle class and equipment, thus facilitating the examination of the choice between BEVs and ICEVs.

The TAM, specifically adapted to the context of this study, will be introduced below.

Behavioural Intentions and Car Choice

In addition to providing information to the participants about the car booking software, they were informed that the software would estimate personal fuel or battery requirements for the entire roundtrip of the business trip. Moreover, details regarding the range buffer (i.e. excess fuel or range beyond the estimated consumption) were provided for each of the BEVs and ICEVs available in the car booking software, categorised as 0%, 20%, and 100% (see examples in Appendix B). For instance, consider a business trip to the business partner that involves traveling a round trip of 100km. If the car booking software presents a vehicle with a range buffer of 100%, this signifies that the employee would be able to drive an estimated total of 200km. The range buffer information was displayed because Franke et al. (2012) and Rauh et al. (2015a, 2015b) discovered that to mitigate stress, BEV drivers use range buffers to avoid critical range situations where the available battery range is so low that completing the trip seamlessly is at risk.

Therefore, from a rational point of view, car options with sufficient excess range should be available for either of the two hypothetical business trips. However, as mentioned above, feelings about the risk associated with the assigned business trip can diverge from cognitive risk perceptions and ultimately even affect car choice (see Loewenstein et al., 2001; Slovic et al., 2004). The different elements (e.g. route, outside temperature) of the hypothetical business trips may convey different levels of risk when contemplating choice between a BEV or an ICEV. For example, when receiving the information that the outside temperature is 3°C, it is not difficult to imagine that one might want to use the car's heating. However, use of the car's heating system affects the driving range and it would affect the range of BEVs comparatively more than that of conventional cars. Imagining the possible consequences when driving a BEV could include an unplanned search for charging infrastructure or, worse, being stranded without a charging station within reach. Thus, one might experience a negative feeling when imagining driving a BEV for this trip. In contrast, information about an outside temperature of 20°C would not be linked to the assumption that heating is necessary; therefore, the available range would not be constrained as before, ultimately leading to a comparatively better feeling about the idea of driving a BEV.

Hence, in consideration of the varying insights it can be hypothesised that (H1.1) business trips perceived as varying in risk for BEVs will evoke commensurately varying affective responses such that BEV preference is lower for business trips associated with higher risk, vice versa.

Specifically, the assertion made by Loewenstein et al. (2001) that feelings about the risk associated with the assigned business trip can deviate from cognitive risk perceptions and can even influence behaviour not otherwise considered as the best course of action suggests that an individual's affective responses to risky BEV usage situations can also influence the relationship between an individual's behavioural intentions to book a BEV (i.e. the suggested primary predictor of actual behaviour, as proposed by Davis et al., 1989) and their car choice made in the experiment.

Therefore, it can be hypothesised that (H1.2) business trips perceived as varying in risk will influence the reliability of predicting car choice from behavioural intentions.

In the following, the predictors used to measure individuals' behavioural intentions to book a BEV for business trips in this study are introduced.

Perceived Usefulness and Intentions

Changes to technology are introduced with the intention of bringing about improvements for users but may actually not always succeed in that endeavour. Consequently, Davis (1986, p. 26) defined a new technology's perceived usefulness by "the degree to which an individual believes that using a particular system would enhance his or her job performance." Accordingly, for an employee to prefer a BEV to an ICEV, they would need to believe that they can manage the business trip *better* with the BEV than with the ICEV. Specifically, they would need to consider the technical features of a BEV more beneficial (e.g. driving a BEV is comparatively more relaxing due to lower noise emissions at low speeds; higher instant torque, especially when driving off) than the features of an ICEV (e.g. faster refuelling, engine sound)[28]. However, TAM literature on BEV acceptance shows contradictory

[28] For instance, Dudenhöffer (2013) operationalised perceived usefulness by integrating the perceived ecological advantage. However, this study specifically focuses on the technical aspects of BEVs, as suggested by Davis's (1986) definition of perceived usefulness. The measurement of whether individuals associate BEV drivers as contributing to the

results. While Fazel (2014) and Globisch et al. (2018) discovered a positive influence of perceived usefulness on behavioural intentions, Dudenhöffer (2013) did not. Following the findings of Fazel (2014) and Globisch et al. (2018), it can be hypothesised that (H2.1) the perceived usefulness of BEVs will be positively correlated with the behavioural intention to book a BEV.

Perceived Ease of Use and Intentions

According to Davis et al. (1989), the perceived ease of use of a new technology refers to the extent to which a user perceives the new system to be effortless in use. Accordingly, for an employee to prefer a BEV to an ICEV, they would need to believe that driving a BEV for business trips will be easily learned and hassle-free. However, a meta-analysis of 67 TAM studies conducted by King and He (2006) revealed that the proposed influence of perceived ease of use on intentions was found to be non-significant in 30 out of the 67 studies. Conflicting results were also observed in the BEV acceptance literature. Dudenhöffer (2013) did not determine a significant influence of the perceived ease of use on purchase intentions. In contrast, Fazel (2014) and Globisch et al. (2018) found a significant influence of the perceived ease of driving a BEV on behavioural intentions or electric vehicle acquisitions, respectively. These results motivate further investigation into this association. Following Fazel's (2014) and Globisch et al.'s (2018) findings again, it can be hypothesised that (H2.2) the perceived ease of driving a BEV will be positively correlated with the behavioural intention to book a BEV.

Perceived Ease of Use and Usefulness

Davis et al. (1989) discovered that over time, perceived usefulness mediated the effect of perceived ease of use on behavioural intentions, a finding also supported by the results of the meta-analysis conducted by King and He (2006). Therefore, while the perceived ease of use may not always be a significant predictor of intentions, it frequently predicts the perceived usefulness of a

environment or not is conducted in the context of the variable of the perceived image of BEV drivers in Sub-study 1.2 (Chapter 2.2).

technology. Davis (1986) stipulated that if a system is perceived as easier to use, a user would likely expect better performance in task completion. For example, with an easier system, one may need to invest less time in using the system, implying higher productivity. The studies by Dudenhöffer (2013), Globisch et al. (2018), and Fazel (2014) also found a correlation between ease of use and perceived usefulness.

Therefore, it can be hypothesised that (H2.3) the perceived ease of driving a BEV will be positively correlated with the perceived usefulness of BEVs.

Emotions and Perceived Ease of Use

As outlined in the introduction, the affect heuristic attributes emotions a central role in individuals' judgment of behaviours or technologies (e.g. Finucane et al., 2000; King & Slovic, 2014). While the original TAM by Davis (1986) integrated a measure of emotions in the form of individuals' attitude, subsequent TAM variants measured emotions separately from attitude (Davis et al., 1992; Venkatesh & Bala, 2008). Similarly, in the context of electric vehicle acceptance, Globisch et al. (2018) and Fazel (2014) noted that the enjoyment of driving an electric car positively influenced the perceived ease of use. Dudenhöffer (2013) found that the valence of emotions – specifically, positive emotions (i.e. the perceived enjoyment of driving an electric car) and negative emotions (i.e. range anxiety) – predicted the perceived ease of use. However, as outlined in the introduction, after a test drive with electric vehicles, Dudenhöffer (2013) found that primarily negative emotions predicted the perceived ease of use.

In summary, these examples indicate the influence of the valence of emotions on the perceived ease of using a technology. This suggests that the emotions evoked by the thought of choosing a BEV for an upcoming business trip would also predict the perceived convenience of BEVs.

Therefore, it can be hypothesised that (H2.4) the perceived enjoyment of driving a BEV will be positively correlated with the perceived ease of driving a BEV.

Emotions and Perceived Usefulness

Despite the functional shortcomings of BEVs compared to ICEVs, BEVs can be appreciated for specific features, such as their higher instant torque, particularly when starting off (NewMotion, n.d.). This feature can be perceived as useful and appreciated for hedonic reasons. Therefore, driving a BEV for joy, excitement, or similar reasons suggests an association between emotions and the perceived usefulness (i.e. perceived benefits) of BEVs as corroborated by the findings of Alhakami and Slovic (1994) or King and Slovic (2014). Recall that Alhakami and Slovic (1994) found that individuals' evaluative affect towards an item is a strong predictor of their judgments regarding the risks and benefits associated with that item.

The influence of emotions on the perceived usefulness of technologies was not ignored by TAMs. For example, Davis et al. (1992) conducted research on the acceptance of two different types of software for business purposes and noted a positive interaction between enjoyment and usefulness in predicting intentions. Similarly, in the context of adopting (plug-in hybrid) electric vehicles for private use, Schuitema et al. (2013) found that a BEV's instrumental values (e.g. performance, which resembles the notion of the perceived usefulness) directly influenced behavioural intentions but were also largely mediated by perceived driving pleasure. Fazel (2014) found that emotions, specifically the enjoyment of driving a BEV, predicted the perceived usefulness of BEVs.

These examples and theories suggest an association between emotions and the perceived benefits of a technology. Therefore, it can be hypothesised that (H2.5) the perceived enjoyment of driving a BEV will be positively correlated with the perceived usefulness of BEVs.

Emotions and Behavioural Intentions

As mentioned above, variations of the TAM primarily incorporate emotions as antecedents to the two key predictors of behavioural intentions: perceived ease of use and perceived usefulness. Nevertheless, the emphasised central role of affect in individuals' judgments, as per the affect heuristic (e.g. Slovic et al., 2004), also suggests that an association of an individual's emotional responses when contemplating different choice options, such as choosing between a BEV or an ICEV for a business trip, would generally align with their behavioural intentions to book a BEV. For instance, studies conducted by Fazel (2014), Schuitema et al. (2013), and Dudenhöffer (2013) revealed a direct influence of emotions on behavioural intentions within their respective TAM frameworks related to the acceptance of electric vehicles.

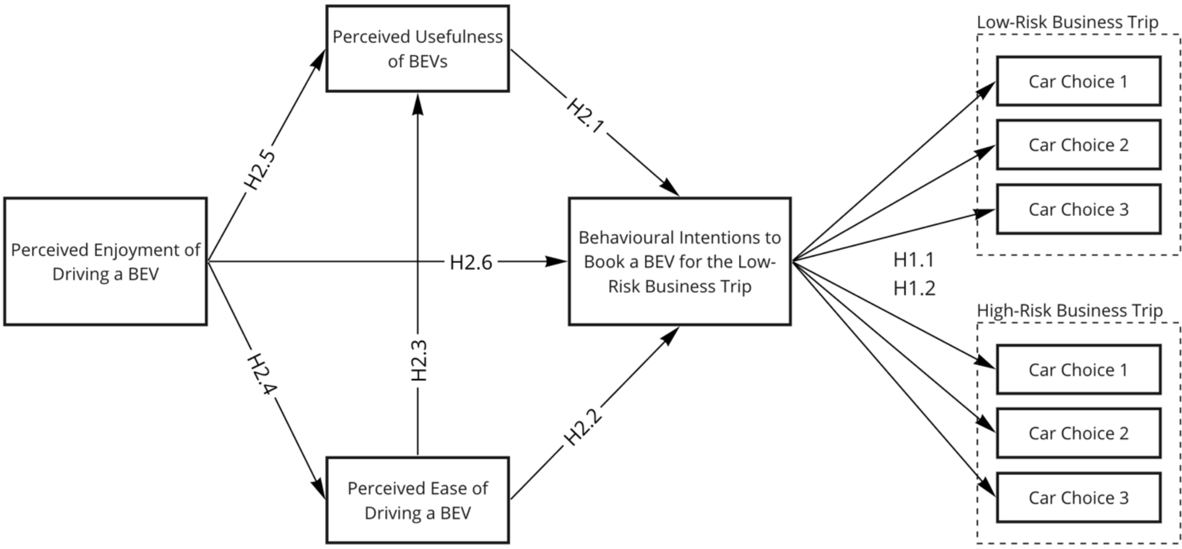
While the original TAM by Davis (1986) and the updated TAM by Davis et al. (1989) primarily focused on the perceived utilitarian aspects of newly introduced workplace technologies, van der Heijden (2004) tested a TAM variant for a hedonic, pleasure-oriented information system, specifically a movie website. His findings indicated that perceived enjoyment and ease of use were the primary predictors of behavioural intentions to use the website while perceived usefulness lost its predominant role in predicting behavioural intentions. Consequently, van der Heijden (2004) suggested that the hedonic value of a technology should not be ignored in product development, even when providing products for a work environment. Consequently, to assess the extent to which the hedonic features of a BEV function as a driver of BEV acceptance, the influence of the expected enjoyment of driving a BEV on behavioural intentions to book a BEV will be examined.

Therefore, it can be hypothesised that (H2.6) the perceived enjoyment of driving a BEV will be positively correlated with the behavioural intention to book a BEV.

Figure 5 displays the theoretical framework and Table 2 presents an overview of the hypotheses.

Figure 5

Theoretical Framework of the Technology Acceptance Model



Note. BEV = battery electric vehicle.

Table 2

List of Hypotheses

No.	Hypotheses
H1.1	Business trips perceived as varying in risk for BEVs will evoke commensurately varying affective responses such that BEV preference is lower for business trips associated with higher risk, vice versa.
H1.2	Business trips perceived as varying in risk will influence the reliability of predicting car choice from behavioural intentions.
H2.1	The perceived usefulness of BEVs will be positively correlated with the behavioural intention to book a BEV.
H2.2	The perceived ease of driving a BEV will be positively correlated with the behavioural intention to book a BEV.
H2.3	The perceived ease of driving a BEV will be positively correlated with the perceived usefulness of BEVs.
H2.4	The perceived enjoyment of driving a BEV will be positively correlated with the perceived ease of driving a BEV.
H2.5	The perceived enjoyment of driving a BEV will be positively correlated with the perceived usefulness of driving a BEV.

No.	Hypotheses
H2.6	The perceived enjoyment of driving a BEV will be positively correlated with the behavioural intention to book a BEV.

Method

Participants

In the context of the comprehensive Study 1, screening questions in the questionnaire were used to recruit participants with the following profile: individuals in Germany whose jobs might require occasional business trips and who considered corporate carsharing as a suitable solution for their regular business mobility were targeted. The final sample comprised 238 participants, with 200 recruited through a panel from Schmiedl Marktforschung GmbH (now Schlesinger Group/Sago) and 38 participants recruited through a car manufacturer in Germany.

Approximately 73% (*n* = 173) of the participants had access to at least one corporate carsharing vehicle, while 24% (*n* = 57) did not have such access. Eight participants (3%) were uncertain about their access to corporate carsharing.

The age of participants was recorded categorically. About 2.1% of participants (*n* = 5) identified as being between 18 and 24 years of age, 33.2% (*n* = 79) between 25 and 34 years, 33.6% (*n* = 80) between 35 and 44 years, 22.3% (*n* = 53) between 45 and 54 years, and 8.4% (*n* = 20) between 55 and 64 years. One person (0.4%) was above the age of 65. Among the participants, 55.5% identified as male (*n* = 132), 44.1% as female (*n* = 105), and one person (0.4%) chose not to respond.

Study Design

As mentioned in the context of the general introduction of Chapter 2, this present Sub-study 1.1 examines the dataset of the overarching Study 1, which also comprises the other two Sub-studies, 1.2, and 1.3. Study 1 is structured on a 2x2 factor between-subjects design. Participants were randomly assigned to one of two differentially risky hypothetical business trips (i.e. factor 1). Additionally, participants were randomly allocated to a condition where gamification was either absent or present in the car booking software (i.e. factor 2). In this present sub-study, data is explored with regards to the first factor, that is, the differentially risky business trips. Refer to Sub-study 1.2 (Chapter 2.2), for the exploration of data regarding factor 2 (i.e. gamification) or Sub-study 1.3 (Chapter 1.3) with regards to the examination of the interaction of both factors, that is, the differentially risky trips and gamification.

As described above, within the framework of the car booking experiment, participants were randomly assigned to one of two business trips, referred to as the *low-risk business trip* or the *high-risk business trip*. The trips were designed to convey a differential degree of risk when imagining driving a BEV for the assigned business trip. Specifically, the two scenarios differed in terms of level of familiarity with the business partner, route familiarity, and weather conditions (see Table 3). Participants rated the perceived risk of both scenarios on a 7-point Likert scale, ranging from (1) *very risky* to (7) *very safe* when imagining driving a BEV. The mean value for the low-risk business trip (M = 5.34, SD = 1.23) indicated that the high-risk business trip (M = 3.27, SD = 1.49)[29] was judged as being more risky. This finding was further corroborated by a Wilcoxon signed-rank test, revealing a significant difference in judgments, Z = -12.19, p < .001.

Table 3

Business Trip Scenarios Used in the Context of the Car Booking Experiment

Low-risk business trip	High-risk business trip
"You are about to visit a business partner who is important but who you know well already. You are well acquainted with the mostly flat route. The weather is sunny and a rather pleasant temperature of about 20°C ."	"You are about to visit a new but important business partner. The route is new to you. It is a wintery but dry day of about 3°C."

[29] The high-risk business trip scenario used for the booking experiment differed from the high-risk business trip scenario subsequently assessed in the questionnaire by containing the additional information that "a charging stop may be necessary" (see Appendix A). Nevertheless, the results, in addition to the pre-test, suggest that the high-risk business trip was perceived as riskier than the low-risk business trip.

Note. The business trip scenarios were translated from German and are based on a scenario used by Franke et al. (2015). Refer to Appendix A for the scenarios in German.

Pre-Test and Planned Missing Design

A pre-test was conducted with eight experts from the automotive industry who assessed the usability of the car booking system, the comprehensibility of the two scenarios, and the number and comprehensibility of the questionnaire items. This assessment was carried out using a *think-aloud* procedure during semi-structured face-to-face interviews. During the pre-test, the eight participants showed increasing fatigue as they completed the questionnaire[30] and the online experiment, indicating a risk of participant drop-out. To address this issue and maintain coverage of the content domain while reducing testing time per participant, a *planned missing design* was employed, following the approach described by Little and Rhemtulla (2013). Planned missing designs involve deliberately omitting certain elements, such as items, to control and manage missing data (Little & Rhemtulla, 2013). Gonzalez and Rutkowski (2010) illustrate the structure of a planned missing design as follows: (Assessment$_a$ (Form$_f$ (Block$_b$ (Unit$_u$ (Item$_i$))))). In this structure, units comprise one or more items (e.g. an item scale) and blocks consist of sets of items or units. A test form contains the different sets of blocks. Eventually, the entire assessment summarises all test forms. Consequently, the level of omission can apply to units as well as entire blocks. In this study, a missing data design was implemented with the level of omission applying to the unit level. This approach involved presenting a random subset of indicators per latent variable to each participant, specifically a random selection of three out of four items per item scale or two out of four items per item scale.

According to Little and Rhemtulla (2013), Pokropek (2011), and Horton and Lipsitz (2001), the condition of data being (completely) missing at random[31] is typically met when employing planned

[30] Alternative terms for planned missing designs include *split questionnaire design* or *matrix sampling*.

[31] Drawing from Rubin's (1976) conceptualisation of missing data patterns, Pokropek (2011) outlines that data missing completely at random indicates that the missingness is unrelated to both the question asked and other variables in the questionnaire. Missing at random signifies that the missing data does not depend on the variable in question when

missing data designs, as is the case in this study. Nonetheless, for value imputation, it is essential to evaluate the pattern of missing data regarding its suitability. Little's test of missing data, conducted using IBM SPSS, confirmed that the data is missing at least at random, thereby supporting the appropriateness of the data for imputation.

However, the suitability of the imputation method (e.g. maximum likelihood, multiple imputation) must be assessed based on the distribution of the data (Raghunathan & Grizzle, 1995). The Kolmogorov-Smirnov and Shapiro-Wilk tests were applied, revealing that none of the variables were normally distributed. Furthermore, a visual inspection of Q-Q-Plots and direct values of skewness and kurtosis yielded mixed findings. Nevertheless, as per Raghunathan and Grizzle (1995), it can be argued that the missing data in this case can be imputed. Raghunathan and Grizzle (1995) created split datasets from an originally full dataset, which displayed both parametric and nonparametric distributions. They observed that multiple imputation was sensitive to skewed data but less sensitive to kurtosis when departing from normality. On a similar note, Horton and Lipsitz (2001) proposed the multiple imputation approach with predictive mean matching to ensure plausible values even if the normality assumption is violated. Raghunathan and Grizzle (1995) suggested that ten imputations provided an optimal trade-off between precision and computational effort compared to a larger number of imputations. Eventually, the multiple imputation approach with predictive mean matching was applied, using ten imputations and IBM SPSS 26 to impute the deliberately missing values.

Procedure

After a brief, general introduction to the study, participants responded to a set of questions designed to filter for the target group (see participants section above). Specifically, these screening questions aimed to determine whether corporate carsharing would be a suitable solution for their

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controlling for another variable (e.g. missing data on age depending on gender) (Pokropek, 2011). Data not missing at random depends on the variable in question (Pokropek, 2011). Ignoring the missing data can lead to biased results and distort the relationship between parameters.

business trips (refer to Appendix A for an excerpt of the screening questions). Throughout this filtering process, any mention of electric mobility was deliberately avoided to prevent priming participants towards this topic, particularly in light of the subsequent online experiment and questions related to the assessment of the TAM. After completing the screening questions and a range of additional items not further discussed in this thesis[32], participants were randomly assigned to one of the four experimental conditions: low-risk control group, low-risk treatment group, high-risk control group, or high-risk treatment group. As mentioned above, this study is based on a 2x2 factorial design. However, only the first factor, perceived risk of the business trip (comprised of the low-risk and high-risk conditions), is addressed in this sub-study. The second factor, gamification (comprising the control and treatment conditions), is examined in Chapters 2.2 and 2.3. Along with the group assignment, each participant was presented the following introduction, regardless of the assigned experimental condition:

"You are now invited to register with the corporate carsharing platform, ve-share[33]. Please assume the following scenario: you and your colleagues have access to a corporate carsharing pool. This pool includes conventional cars with internal combustion engines (gasoline/diesel) as well as fully battery electric cars (with no additional combustion engine). You are about to book an upcoming business trip using the booking software, ve-share. Ve-share is a web application. It is designed to replace conventional methods such as manual booking lists, personal assistance, or digital but non-specialised tools like Outlook. Based on the defined distance of the business trip, ve-share estimates your individual fuel or energy demand for the complete journey.“ (Translated from German, see the original introduction in Appendix A).

Further, before accessing the car booking software, participants were asked to generate and

[32] For example, inquiring about participants' willingness to share a business car.

[33] The car booking software managed a shared fleet consisting of both ICEVs and BEVs in the same number, vehicle class, and equipment. Each BEV and ICEV offered in the car booking software provided information about its available fuel or electric range buffer of 0%, 20%, or 100%, estimated by the software based on the assigned business trip.

enter a code[34] that would also be used for registering with the car booking software. This code ensured user anonymity and allowed for mapping between participants' responses in the questionnaire and their car choice in the booking software. After entering the code, participants received one of two business trip scenarios (see Table 3), along with the following instruction:

"The destination of your business trip has already been entered in ve-share. Please keep this scenario in mind and complete three bookings[35] in ve-share. Return to this questionnaire subsequently."

Participants then clicked on a link to the car booking software, provided in the questionnaire, which opened in a new browser tab. Participants used their previously entered individual code to register on the platform. Upon accessing the car booking software, participants in the control condition (i.e. low-risk control group, high-risk control group) interacted with the booking software without any gamification elements. In contrast, participants in the treatment condition (i.e. low-risk treatment group, high-risk treatment group) experienced the booking software with gamification elements integrated.

After returning to the questionnaire, participants were presented with questions designed to assess the TAM. All participants assessed the TAM-related questionnaire exclusively with regards to imagining the low-risk business trip, irrespective of the business trip assigned in the context of the car booking experiment. Consequently, the TAM, including individuals' behavioural intentions to

[34] The code was based on the following scheme: (1) the first two letters of the father's first name (e.g. HE), (2) the first two letters of the mother's first name (e.g. KE), (3) the last two letters of the participant's first name (e.g. IA), and (4) the first two digits of the participant's birthdate (e.g. 05). This results in the exemplary combination: HEKEIA05.

[35] On the one hand, assigning participants the task of making three car bookings served the purpose of collecting multiple responses per person. On the other hand, the deliberate choice of three bookings was intended to examine the responses of participants assigned to an experimental condition involving gamification, which required them to repeatedly experience the gamification stimulus, as explored in Sub-studies 1.2 (Chapter 2.2) and 1.3 (Chapter 2.3). While it may seem perplexing to complete three bookings for the same scenario, particularly for members of the control group, the pilot study did not indicate that participants would object to completing the three car bookings.

book a BEV, was not assessed for the high-risk business trip. All TAM-related items were measured using a 7-point Likert scale, ranging from (1) *fully disagree* to (7) *fully agree*.

Results

To evaluate the theoretical framework depicted in Figure 5, the assessment will commence with the evaluation of the measurement models, succeeded by the structural model. As elucidated by Hair et al. (2022), a measurement model establishes the relationships between a construct (i.e. latent variable) and its indicators (i.e. items). A structural model concerns the relationships between constructs, such as the hypothesised relationship between perceived usefulness and behavioural intentions (Hair et al., 2022). The evaluation of the measurement model varies based on its type of operationalisation, which can either be reflective or formative. In a reflective measurement model (e.g. behavioural intention), a latent variable causes the indicators. Conversely, in a formative measurement model (e.g. perceived usefulness), the indicators cause a latent variable (Chin & Newsted, 1999; Hair et al., 2022).

To test the hypotheses (see Table 2), the composite-based partial least squares structural equation modelling approach was applied. This approach was selected due to its capability to, for example, handle non-normal data distributions and formative latent variables, both of which are pertinent to this study (Chin & Newsted, 1999; Hair et al., 2020). Perceived usefulness was operationalised as a formative variable, whereas behavioural intention, perceived ease of use, and perceived enjoyment of driving a BEV were operationalised as reflective variables (refer to items in Appendix A for detailed information).

Assessment of the Reflective Measurement Models

For the assessment of the reflective measurement models (see Table 4), the approach of Hair et al. (2022) was followed, assessing convergent validity, discriminant validity, and internal reliability using SmartPLS 4. The assessment of measurement models began at their most granular level, specifically the utilisation of indicators to measure latent variables.

First, to determine indicator reliability, an indicator’s loading should exceed a value of .708.

Squaring this value indicates whether the associated variable explains at least .50 and thus, accounts for at least 50% of the respective indicator's variance. However, for outer loadings (i.e. correlation weights) ranging between .40 and .708, Hair et al. (2022) suggest retaining the indicators once they met the thresholds for composite reliability and average variance extracted (assessment below). This recommendation applied to two indicators of perceived ease of use.

To establish the internal reliability of the latent variables, Cronbach's alpha, composite reliability ρ_C, and the reliability coefficient ρ_A, were utilised. While Cronbach's alpha is deemed to be very conservative and ρ_C is considered too liberal by Hair et al. (2022), they recommend referring to ρ_A. All reliability values preferably range between .70 and .95 and ideally below .90, as values above .90 indicate semantic redundancy of the items associated with a construct (Hair et al., 2022). In summary, internal reliability can be accepted when achieving values within the acceptable range of reliability coefficient ρ_A, which applied to all three reflective variables (see Table 4).

Furthermore, the indicator reliability discussed above is also linked to the convergent validity of a latent variable. Convergent validity was assessed using the average variance extracted, which is calculated as the sum of the squared loadings of a variable, divided by the number of indicators. The average variance extracted should exceed .50, indicating that the indicators associated with a construct explain at least 50% of the indicators' variance (Hair et al., 2022). To significantly increase the average variance extracted, the reverse coded behavioural intention indicator 1 was omitted from the variable.

Discriminant validity is established when a latent variable captures phenomena that are not captured by any other construct in the model. Henseler et al. (2015) and Hair et al. (2022) propose using the heterotrait-monotrait ratio, which requires a maximum threshold of .90 and ideally a value below .85. All heterotrait-monotrait ratio values were below the .90 threshold. Discriminant validity was successfully established for all three reflective variables within the model, namely, behavioural intention, perceived ease of use, and perceived enjoyment of driving a BEV.

Table 4

Reliability and Validity of the Reflective Latent Variables

Variable	Indicator	Convergent validity			Internal consistency reliability			Discriminant validity
		Loadings	Indicator reliability	AVE	CA	ρ_C	ρ_A	HTMT < .90
Behavioural intention	2	.94	.87	.88	.86	.93	.86	Yes
	3	.94	.88					
Perceived ease of use	1	.67	.44	.52	.69	.81	.73	Yes
	2	.60	.36					
	3	.76	.57					
	4	.84	.71					
Perceived enjoyment of driving a BEV	1	.96	.92	.90	.94	.96	.95	Yes
	2	.94	.88					
	3	.94	.89					

Note. As discussed above, behavioural intention indicator 1 was omitted from the model.

AVE = average variance extracted, CA = Cronbach's alpha, HTMT = heterotrait-monotrait ratio.

Assessment of the Formative Measurement Model

The assessment of the formative measurement model of perceived usefulness followed the approach by Hair et al. (2022), encompassing the evaluation of convergent validity, indicator multicollinearity as well as the magnitude and significance of indicator weights[36] (refer to Table 5).

To evaluate the content domain of a formative variable, Hair et al. (2022) propose employing a qualitative approach involving experts of the domain and a comprehensive literature review. Eight automotive experts assessed the indicators subsequently used in this study to measure perceived usefulness. To assess convergent validity, Hair et al. (2022) further recommend correlating the

[36] Hair et al. (2022) state that indicator weights result from regressing the latent variable on its indicators, representing each indicator's relative contribution to forming the construct.

formatively operationalised variable with at least one reflective indicator that adequately captures the domain.

To investigate indicator multicollinearity, Hair et al. (2022) refer to the variance inflation factor, which requires values < 5 and ideally < 3. As per Hair et al. (2022), a substantial correlation among two or more indicators within a formative measurement model affects the estimation of indicator weights and their statistical significance. All three indicators of perceived usefulness ranged below the threshold of 3. Therefore, critical levels of collinearity were not reached.

Further, the assessment of indicator weights (i.e. outer weights in SmartPLS 4) was conducted. Following the approach outlined by Hair et al. (2022), the initial step involved examining the significance of the outer weights. In cases where the outer weights are not statistically significant, Hair et al. (2022) recommend subsequently analysing the outer loading (requiring a value > .50) and the level of significance. If the outer loading is below .50 but significant, the removal of the specific indicator can be considered. Through these procedures, it was observed that perceived usefulness indicator 2 exhibited a non-significant weight but had a significant outer loading, albeit falling below the .50 threshold. In a formative measurement model, each indicator captures a specific and distinct aspect of the construct's domain. The omission of relevant indicators in such a model could potentially alter the nature of the construct, thus affecting its validity (Diamantopoulos & Riefler, 2008; Eberl, 2004; Hair et al., 2022). Consequently, perceived usefulness indicator 2 was retained for content validity of the construct (Hair et al., 2022).

Table 5

Summary of Results for the Formative Latent Variable: Perceived Usefulness

Indicator	Outer weight	Outer loading
1	$.23^{***}$	$.49^{***}$
2	$.06^{n.s.}$	$.41^{***}$
3	$.89^{***}$	$.97^{***}$

$^{***}p < .001$, n.s. = not significant.

Assessment of Measurement Invariance in Low-Risk and High-Risk Groups

As the concluding step in the assessment of the measurement models, an investigation into the measurement invariance of the variables included in this study was undertaken. Although the distinctions in this study involve the utilisation of two experimental groups, the questionnaire used in this study remained consistent across both groups. However, as elucidated by Henseler et al. (2016), group comparisons may be misleading unless the invariance of measures is established. To preclude potential structural differences arising from the alternative group attributing a distinct meaning to a latent variable, Henseler et al. (2016) recommend the application of the measurement invariance of composite models (MICOM) procedure before aggregating (i.e. pooling) the data from the low-risk and high-risk groups for structural analysis. The MICOM procedure involves three steps, encompassing the assessment of configural invariance (step 1), compositional invariance[37] (step 2), and scrutiny for equal mean values and variances (step 3). In step 1, it is required that all composites (i.e. latent variables) exist in all groups, a condition satisfied in this study. MICOM steps 2 and 3 rely on permutation tests conducted with SmartPLS 4. The results of the permutation tests for steps 2 and 3 indicate the establishment of full measurement invariance. Consequently, both groups were pooled for the subsequent structural analysis.

[37] Regardless of the underlying measurement model, whether reflective or formative, structural equation modelling techniques based on variance modelling depict latent variables as composites. This is achieved by generating proxies through linear combinations of the respective indicators for each latent variable (Henseler et al., 2016).

Assessment of the Structural Model

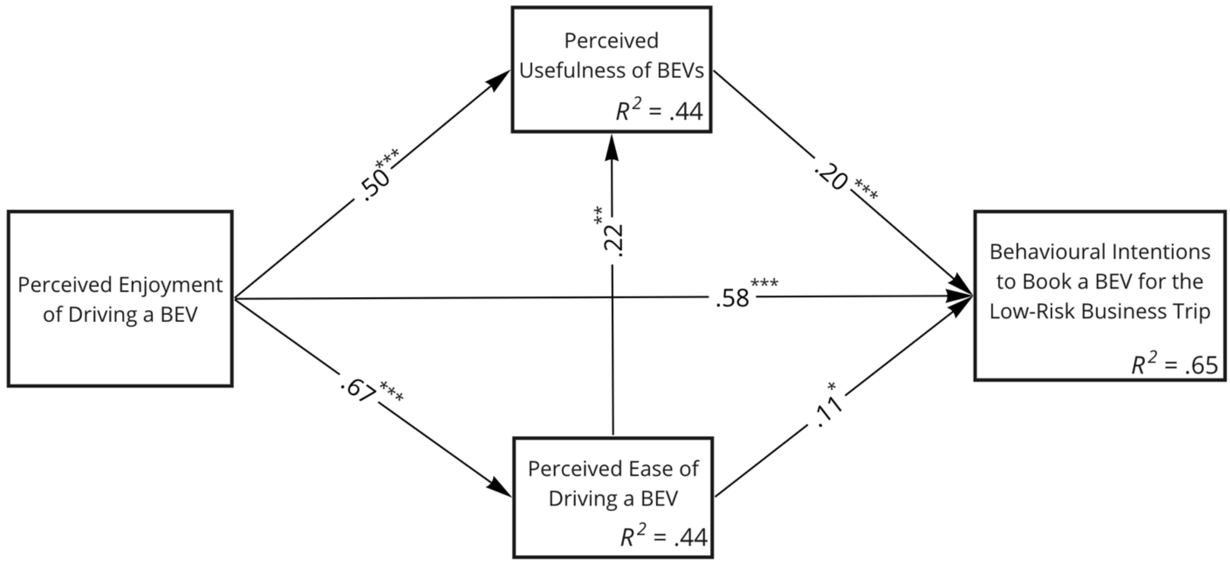
Once again, the approach outlined by Hair et al. (2022) was followed for the evaluation of the structural model using SmartPLS 4. This involved examining collinearity between constructs, assessing the magnitude and significance of relationships among variables, and evaluating the model's explanatory and predictive power.

Firstly, the structural model underwent an assessment for collinearity among the latent variables using the variance inflation factor. This analysis, previously applied at the indicator-level, was now extended to the latent variable level. All latent variables exhibited values below 3, signifying the absence of collinearity concerns among the constructs.

Secondly, to examine hypotheses 2.1 to 2.6, the analysis involved assessing the correlations between variables (refer to Table 6), the path coefficients within the structural equation model (interpreted like standardised regression coefficients), and the f^2 effect sizes (see Figure 6 and Table 7). The f^2 effect size quantifies the explained variance of an endogenous construct (i.e. determinant) per exogenous variable (i.e. predictor). According to Hair et al. (2014), values of .02, .15, and .35 correspond to small, medium, and large effects, respectively.

Figure 6

Structural Model of the Pooled Dataset Combining the Low-Risk and High-Risk Groups



Note. The arrows display path coefficients estimated using SmartPLS 4, interpreted akin to standardised regression coefficients (β) as per Hair et al. (2022).

BEV = battery electric vehicle.

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table 6

Descriptive Statistics and Correlations Between Variables

Variable	*M*	*SD*	1	2	3	4
1. Behavioural intentions	5.03	1.43	-			
2. Perceived usefulness	4.09	1.12	.64***	-		
3. Perceived ease of use	5.22	.82	.61***	.55***	-	
4. Perceived enjoyment	5.56	1.38	.78***	.64***	.67***	-

$^{***}p < .001$.

Table 7

Estimated Effect Sizes of Structural Relationships

Hypothesis	Path	Path coefficient β	t-value	f^2 Effect size
H2.1	PU → BI	$.20^{***}$	3.96	.07
H2.2	PEU → BI	$.11^{*}$	1.90	.02
H2.3	PEU → PU	$.22^{**}$	2.97	.05
H2.4	PED → PEU	$.67^{***}$	20.41	.80
H2.5	PED → PU	$.50^{***}$	6.59	.25
H2.6	PED → BI	$.58^{***}$	9.11	.43

Note. BI = behavioural intention, PU = perceived usefulness, PEU = perceived ease of use, PED = perceived enjoyment of driving a BEV.

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

As hypothesised, all variables displayed positive correlations on a medium to strong scale. Specifically, the results present statistically significant evidence indicating that both the perceived usefulness and the perceived ease of driving a BEV predicted behavioural intentions, thereby supporting hypotheses H2.1 and H2.2. However, the modest f^2 effect sizes for both predictors indicate that they contribute to the variance of behavioural intentions only to a minor extent. As hypothesised (H2.3), perceived ease of use predicted perceived usefulness. However again, the small f^2 effect size of .05 demonstrates that it accounts for little of the variance in perceived usefulness. The perceived enjoyment at the thought of driving a BEV predicted the perceived ease of use as anticipated (H2.4) and explained variance to a large degree. Further, and also as hypothesised (H2.5), the perceived enjoyment of driving a BEV predicted perceived usefulness with a medium f^2 effect size. Finally, considering a BEV fun to drive predicted behavioural intentions to a large degree in terms of explained variance and the size of the path coefficient (H2.6), making it a prominent driver in individuals' judgment of BEVs. Accordingly, the results presented evidence in support of hypotheses 2.1 through 2.6.

Thirdly, the model's explanatory power was assessed using the coefficient of determination, R^2. According to Hair et al. (2014), R^2 values of .75 and above commonly signify a substantial explanation of the variables' variance, while values of .50 and .25 suggest moderate and weak explanations, respectively. In this study, all endogenous constructs were explained at a weak to moderate level (see Figure 6). Among them, behavioural intentions (R^2 = .65) exhibited the highest degree of explained variance.

In a final step, the model's predictive capability was evaluated, indicating the extent to which the model generates generalisable findings (refer to Table 8). For this assessment, Hair et al. (2022) suggest using the $PLS_{predict}$ procedure for the indicators associated with the target construct, i.e. behavioural intentions, within SmartPLS 4.

Firstly, in accordance with this procedure's requirements, both indicators related to behavioural intentions exhibited $Q^2_{predict}$ values greater than zero, indicating predictive power of the model. Secondly, a comparison was made between the root mean square error (RMSE) values of the two indicators linked to behavioural intentions and those of a linear regression model that disregards the specified model for predictions. To assess the model's predictive capacity, comparatively lower RMSE values are required. While the RMSE value of indicator 2 exceeded the value of the linear model, indicator 3 did not. Hence, while the RMSE value of indicator 2 suggested a lack of predictive power, the remaining values for both quality criteria indicate the predictive capacity of the structural model (Hair et al., 2022).

Table 8

Assessment of the Predictive Capacity of the Model

Indicator	$Q^2_{predict}$	RMSE	Linear model
Behavioural intention 2	.59	.97	.94
Behavioural intention 3	.48	1.12	1.13

Note. RMSE = root mean square error.

Determining the Influence of Risk on Car Choice

As described above, the TAM questionnaire administered to all participants focused on assessing the low-risk scenario. Nevertheless, during the booking experiment, participants made three bookings in the booking software, based on the assigned scenario of either the low-risk or high-risk business trip. To examine hypothesis H1.2, separate binary logistic regression analyses were performed for each of the three car bookings in each experimental group, utilising IBM SPSS 28 (Table 9).

Table 9

Binary Logistic Regressions Regarding the Association Between Car Choice and Behavioural Intentions per Car Booking in the Low-Risk and High-Risk Groups

Car Booking	Cox & Snell R^2	Nagel-kerke R^2	*B*	Wald	*p*	*Exp(B)*	Likeli-hood	95% CI	
								LL	*UL*
LR 1	.03	.05	.41	3.64	.056	1.50	50%	.99	2.27
LR 2	.05	.06	.47	4.92	.027	1.61	61%	1.06	2.44
LR 3	.10	.14	.76	9.80	.002	2.14	114%	1.33	3.44
HR 1	.05	.07	.55	4.93	.026	1.73	73%	1.07	2.82

Note. The regression is based on the ordinal independent variable of behavioural intention and the binary dependent variable of car choice (0 = ICEV booked, 1 = BEV booked).

LR = low-risk group, HR = high-risk group, CI = confidence interval, *LL* = lower limit, *UL* = upper limit.

To assess the suitability of the data for binary logistic regression, the omnibus test and the Hosmer-Lemeshow test were applied. The omnibus test examined whether behavioural intentions made a difference in the model predicting car choice. To determine the model fit, the Hosmer-Lemeshow test was employed, which compares observed and expected outcomes through the creation of subgroups.

Regarding the low-risk group, the results demonstrated that all three of three bookings (i.e. bookings 1, 2, and 3) passed both the omnibus test and the Hosmer-Lemeshow test. However, in the high-risk group, bookings 2 and 3 did not pass the omnibus test, indicating that behavioural intentions did not predict car choice in those instances. Notably, the Pseudo R^2 values of the remaining four bookings (i.e. all three bookings of the low-risk group and booking 1 of the high-risk group) indicated that behavioural intentions only added to a very low extent to the prediction of car choice. Furthermore, concerning low-risk scenario booking 1, behavioural intentions did predict car choice, but this association was only statistically significant at the 10% significance level (p = .056).

To explore the relationship between behavioural intentions and the chances for a BEV to be booked, the odds ratio value (i.e. *Exp(B)* value) was converted[38] into estimated probabilities of the event occurring. Despite the non-significant predictive evidence for low-risk group booking 1, the determined odds ratio per booking revealed that all three bookings displayed increasing probabilities for a BEV to be booked as intentions to book a BEV increased. Conversely, the results for high-risk group bookings 2 and 3 did not indicate a relationship between behavioural intentions and their choice of car type. Behavioural intentions were only found to be a statistically significant predictor of car choice in the context of high-risk group booking 1, demonstrating an increasing likelihood of BEVs being selected.

Consequently, the results of the binary logistic regressions above revealed differences in the strength of the relationship between car choice and behavioural intentions between the low-risk and high-risk groups. Specifically, the results indicated a relatively lower reliability in predicting car choice from intentions for the high-risk group. Thus, the results provide statistical evidence in support for hypothesis H1.2, which posits that business trips perceived as varying in risk will influence the reliability of predicting car choice from behavioural intentions.

In the subsequent analysis, hypothesis H1.1 will be examined, postulating that business trips perceived as varying in risk for BEVs will evoke commensurately varying affective responses such that BEV preference is lower for business trips associated with higher risk, vice versa. To investigate this hypothesis, participants' car choices were analysed using absolute figures (as shown in Table 10) and a Chi^2-test of independence to examine the relationship between the differentially risky business

[38] Conversion formula: *(Exp(B)-1)*100*

trips and the selection of car types (see Table 11). Additionally, for a more detailed analysis of preferences, the summation of selected range buffers per car type across the three bookings per experimental group is presented in Table 13.

Table 10

Car Choices in Absolute Numbers for the Low-Risk and High-Risk Groups

Booking	Number of ICEVs booked	ICEV bookings in %	Valid share	Number of BEVs booked	BEV bookings in %	Valid share	Attrition from experiment	Attri-tion in %
Low-risk group								
1	78	64.5%	64.5%	43	35.5%	35.5%	0	0%
2	71	58.7%	60.7%	46	39.3%	39.3%	4	3.3%
3	69	57%	60%	46	38%	40%	6	5%
High-risk group								
1	83	70.9%	70.9%	34	29.1%	29.1%	0	0%
2	72	61.5%	68.6%	33	28.2%	31.4%	12	10.3%
3	67	57.3%	71.3%	27	23.1%	28.7%	23	19.7%

Note. The column depicting the valid share does not incorporate missing data, specifically the data from participants who withdrew from the car booking experiment, as indicated in the column delineating individuals' attrition from the experiment.

BEV = battery electric vehicle, ICEV = internal combustion engine vehicle.

The absolute numbers from Table 10 reveal that the majority in both experimental groups opted for conventional cars over BEVs. While the preference for BEVs remained relatively stable throughout the three bookings in the low-risk group, the number of BEV bookings in the high-risk group exhibited a slight decrease over the three bookings. Additionally, the attrition rate from the experiment, denoting missing bookings, increased in both groups throughout the three bookings, with a more pronounced increase observed in the high-risk condition, approaching 20%, as opposed to the 5% in the low-risk group.

To statistically assess the frequencies in car type preferences between low-risk and high-risk groups, a Chi^2-test of independence was performed (see Table 11). This test determines whether car choice and experimental group assignment are independent or not through the aggregation of data, typically displayed in the form of a contingency table (see Cohen, 1988).

Table 11

Chi^2-Test of Independence for Choice Between Battery Electric Vehicles and Conventional Cars, and Individuals' Membership in the Low-Risk and High-Risk Groups

Car booking	*n*	Chi^2-value	Degrees of freedom	*p*	Cramer's V
1	238	1.14	1	.29	.07
2	222	1.50	1	.22	.08
3	209	2.89	1	.09	.12

While the absolute numbers imply variations in BEV choice across the three bookings per group, the results of the Chi^2-tests for the aggregated choice of car type and experimental group assignment indicate that for none of the three bookings there is statistical evidence supporting an association between individuals' car type selection (BEVs or ICEVs) and their assignment to a low-risk or high-risk business trip. This conclusion is further supported by the low Cramer's V values[39].

However, it is essential to again emphasise the notably high attrition rate from the car booking experiment in the high-risk group, as illustrated in Table 10. The attrition rate was not factored into the results of the aforementioned Chi^2-test due to its classification as missing data. To statistically explore the suggested association between the risk level of the business trip and participants' decision to withdraw from the car booking experiment instead of making a car choice, an additional Chi^2-test was conducted. In this test, missing data was encoded as a third choice option, alongside the selection between BEVs and internal combustion engine vehicles.

[39] According to Cohen (1988), the Cramer's V value signifies the strength of association between variables. Values below .10 indicate a small effect, values of .30 represent medium effects, and values of .50 denote large effects (Cohen, 1988).

Table 12

Chi^2-Test of Independence for Choice Between Battery Electric Vehicles and Conventional Cars or the Decision to Instead Withdraw from the Car Booking Experiment, and Individuals' Membership in the Low-Risk and High-Risk Groups

Car booking	*n*	Chi^2-value	Degrees of freedom	*p*	Cramer's V
1	238	1.14	1	.286	.07
2	238	6.08	2	.048	.16
3	238	13.00	2	.002	.23

In the first booking, no missing values were present as participants who had not booked at least one vehicle were excluded from the study. This exclusion was necessary as the subsequent evaluation of the TAM partly relied on the experiences of the vehicle booking process. As noted above, considering the absolute observations related to car choice and the assigned booking scenario, a higher drop-out rate is evident for participants in the high-risk scenario group compared to the drop-out rate of participants in the less risky scenario group for the second and third bookings. Accounting for this drop-out rate in the statistical analysis revealed a statistically significant association between participants' choices for bookings 2 and 3 and the assigned business trip, as opposed to the results that did not account for the withdrawal rate. Specifically, the results for booking 2, with X^2 (2, n = 238) = 6.08, $p < .05$, and booking 3, with X^2 (2, n = 238) = 13.00, $p < .01$, indicate a statistically significant association between participants' group assignment and their choices. This is further corroborated by weak associations, as demonstrated by Cramer's V values of .16 ($p < .05$) for booking 2 and .23 ($p < .01$) for booking 3. Consequently, integrating individuals' decision to withdraw from the car booking experiment instead of making car choice revealed a statistically significant association with the business trip assignment. This indicated an influence of higher-risk trips on the attrition rate, as evidenced by the absolute figures presented in Table 10.

As described at several junctures in this study, the booking software not only differentiated between ICEVs and BEVs but also displayed the available range buffer per car and car type. Each car was assigned one of three range buffer categories (0%, 20%, or 100%) based on the energy or fuel required for the business roundtrip, covering the journey to the business partner and back to the employer.

Table 13

Total of the Selected Range Buffer Categories per Car Type and Low-Risk and High-Risk Groups Across the Three Bookings

Range buffer	Total BEV bookings low-risk	Share to total in %	Total BEV bookings high-risk	Share to total in %	Total ICEV bookings low-risk	Share to total in %	Total ICEV bookings high-risk	Share to total in %
100%	52	38.5%	33	35.1%	35	16.1%	59	26.6%
20%	59	43.7%	47	50%	142	65.1%	129	58.1%
0%	24	17.8%	14	14.9%	41	18.8%	34	15.3%
Total bookings	135		94		218		222	

Note. BEV = battery electric vehicle, ICEV = internal combustion engine vehicle.

To comprehend the influence of these displayed range buffers on car choice, Table 13 presents the total number of car bookings aggregated across all three bookings, categorised by car type and range buffer. These absolute numbers reveal that cars without a range buffer were the least preferred, irrespective of the chosen car type. Primarily, cars with a 20% range buffer were booked across both car types. Further, the findings suggest that individuals who booked a BEV did exhibit a comparatively greater inclination to choose a 100% range buffer compared to participants who chose an ICEV.

In summary, only a minority of individuals expressed a willingness to use a BEV. Observations indicate that this preference further diminished for the high-risk group across the three bookings, compared to the low-risk group. The results of the Chi^2-test did not yield statistical evidence suggesting an association between individuals' car choice and the assignment to the experimental group. However, it is important to note that after the second of the three bookings, nearly one in five participants (20%) dropped out of the car booking experiment when assigned to the high-risk business trip, compared to only one in twenty in the low-risk group. Incorporating the attrition rate from the car booking experiment into the Chi^2-test as a third choice option revealed a statistically significant association with the assignment to the low-risk and high-risk groups. As a result, the findings do not offer statistical support for hypothesis 1.1, which posited that business trips perceived as varying in risk for BEVs will evoke commensurately varying affective responses such that BEV preference is lower for business trips associated with higher risk, vice versa. Nevertheless, although BEV preference did not vary on a statistically significant basis between groups, the data suggest that participants in the high-risk group demonstrated a tendency to disengage from the car booking experiment rather than choosing any car at all. Additionally, participants who booked a BEV exhibited a higher tendency to opt for a 100% range buffer.

Discussion

This study has provided evidence indicating that the predominant driver behind individuals' behavioural intentions to book a BEV for a low-risk business trip was the expected enjoyment from driving a BEV. While the results did not yield statistical evidence that the perceived risk of the business trip influenced the preference for car type, the data indicated an association between the experimental group assignment and individuals' decision to withdraw from the car booking experiment rather than making a car choice. Specifically, absolute figures suggest that being assigned to the high-risk business trip was linked to a higher propensity of participants' decision to disengage from the car booking experiment. Furthermore, participants chose to disengage from the experiment, despite the car booking software displaying range buffer information for each car, which theoretically should have supported BEV selection. In this context, it is worth noting that individuals who opted for BEVs exhibited a slightly stronger inclination towards cars with a 100% range buffer compared to those who chose ICEVs. Furthermore, the results of the study imply that the reliability of predicting car choice from intentions was lower for higher-risk trips compared to the results of the low-risk group. Consequently, differentially risky BEV usage contexts were shown to influence the reliability of predicting car choice from behavioural intentions, as corroborated by the aforementioned findings.

Davis (1989) proposed perceived usefulness and ease of use to be the primary predictors of behavioural intentions, a proposition corroborated by King and He (2006) in a meta-analysis involving up to 88 TAM studies[40]. Despite recognising that other factors (e.g. subjective norm) may act as predictors of behavioural intentions, King and He (2006) tested and confirmed the significance of the core predictors of Davis's (1989) TAM, specifically, the perceived ease of use and predominantly the perceived usefulness. However, while the results align with the above findings insofar as both factors also predicted behavioural intentions, perceived ease of use and perceived usefulness were not identified as the primary determinants of behavioural intentions in the model of this study. Instead, the data reveal that participants primarily valued BEVs for hedonic reasons, particularly the anticipated driving pleasure, which manifested as the most influential factor in individuals' decision to book a BEV. At first glance, the results seem to deviate from the findings of King and He (2006). However, it is worth noting that King and He (2006) specifically focused on studies that examined the two primary predictors – perceived usefulness and perceived ease of use – from Davis's (1989) TAM. Therefore, while King and He (2006) may have included studies in their meta-analysis that considered the influence of emotions on technology acceptance, it was not the main focus of their analysis.

Nevertheless, considering the comparatively weak influence of perceived usefulness and ease of use in the model of this study, these two key predictors, according to the TAM from Davis (1989) and Davis et al. (1989), will be analysed in more detail in the following. Perceived usefulness and ease of use may serve as primary predictors in the realm of IT systems within organisational contexts as proposed by Davis (1989). However, findings of the meta-analysis by King and He (2006) suggest that the strength of the influence of the predictors on behavioural intentions may vary depending on the type of technology and usage context. Specifically, in their study, King and He

[40] The number of studies included varied depending on the type of effect size under evaluation, such as path coefficients.

(2006) classified the TAM studies they integrated in their analysis into the following three main categories based on the usage types of technologies involved: (1) job-office applications, (2) general technologies (such as email and telecommunications), and (3) internet and e-commerce. Subsequently, King and He (2006) compared the range of beta coefficients for different relationships, such as for the influence of perceived ease of use or perceived usefulness on behavioural intentions. While Davis (1989) originally proposed the TAM for measuring the acceptance of information systems for business purposes, the findings by King and He (2006) illustrated that the magnitude of beta coefficient ranges varied considerably with the examined relationship (e.g. perceived usefulness on behavioural intentions) as well as the type of technology usage (e.g. job-office applications).[41] This indicates that the strength of a relationship may vary with the type of technology and context of usage.

Furthermore, there is also evidence suggesting that factors other than perceived usefulness or ease of use may predominantly predict technology acceptance as applies to this study's findings. For example, the results by van der Heijden (2004) showed that emotions, rather than perceived usefulness or ease of use, were the primary predictor of individuals' behavioural intentions to use a hedonic movie platform. This suggests that depending on the nature (e.g. hedonic or utilitarian) and context of technology usage, predictors other than the perceived usefulness or ease of use, such as emotions, may be more relevant for anticipating individuals' behavioural intentions. A pattern akin to that observed by van der Heijden (2004) is evident in the electric vehicle studies referenced in this study. Specifically, Roemer and Henseler (2022), Dudenhöffer (2013), and Schuitema et al. (2013) found that emotions were a primary factor or, in the case of Fazel (2014), a dominant driver in

[41] For the impact of perceived usefulness on behavioural intentions, King and He (2006) found beta coefficients ranging from approximately .32 to .47 for internet and e-commerce, .41 to .53 for general technologies, and .54 to .68 for job-office applications. For the impact of perceived ease of use on behavioural intentions, King and He (2006) determined the following effect size ranges: .17 to .34 for internet and e-commerce, .14 to .26 for general applications, and .06 to .14 for job-office applications.

predicting the acceptance of electric vehicles (including BEVs or plug-in hybrid electric vehicles) for private or commercial usage. Hence, the results of this study align with the findings of these referenced electric vehicle studies. Therefore, this study's findings corroborate the significance of measuring emotions linked to BEV acceptance and potentially other technologies in predicting individuals' behavioural intentions. This extends beyond the exploration of hedonic information systems in private contexts, as explored by van der Heijden (2004), to predominantly hedonically perceived technologies in typically utilitarian business settings, as indicated by the findings in this study. This conclusion is supported by the work of Davis et al. (1992), who examined computer acceptance in the workplace and highlighted the importance of the enjoyment derived from technology use, even within a business context.

In summary, the considerations above suggest that the perceived enjoyment of driving a BEV may indeed be the primary predictor for BEV acceptance. Although Davis et al. (1989) initially introduced the TAM as a general framework for assessing IT system acceptance in organisational settings, the validity of perceived usefulness, ease of use, or emotions in predicting behavioural intentions may vary when extended to other technology domains (e.g. e-commerce; non-information technologies, as explored in this study), with the nature of the technology (e.g. hedonic or utilitarian), or with the application context (e.g. business, private).

However, the fact that the meta-analysis by King and He (2006) specifically highlighted the relevance of perceived usefulness across different usage domains as opposed to the perceived ease of use for measuring technology acceptance draws particular attention to this predictor. In this study, the data indicate that perceived usefulness only made a small contribution to predicting behavioural intentions to book a BEV for business trips. Furthermore, only a minority of participants booked a BEV. Therefore, the perceived usefulness variable, as measured in this study, will be examined further to provide a deeper understanding of the results described above. Since perceived usefulness is based on a formative measurement model in this study, it is possible to analyse the relative contributions of the three indicators. The relative contribution of each indicator provides specific insights into the perception of the technical performance of BEVs compared to ICEVs.

Indicator 1 measured the influence of charging stops during business trips on the perceived usefulness of BEVs. Recall that according to Davis et al.'s (1989) definition of perceived usefulness, a new technology must deliver superior performance compared to the existing technology to gain acceptance. Therefore, indicator 2 captured participants' perception of whether they can conduct their business trips more efficiently with a BEV than with an ICEV. Indicator 3 concerned the perceived usefulness of specific technical features that are unique to BEVs, such as instant torque when accelerating. The data, specifically the indicator weights, reveal that indicator 3 contributed the most and indicator 1 second most to the perceived usefulness of BEVs. Indicator 2, however, received only limited support from the participants and thus made a very small contribution to measuring the perceived usefulness latent variable. However, since indicator 2 aligns more closely with Davis's (1986) definition but made the smallest contribution, a more detailed examination of this specific indicator will be conducted. On the one hand, the relatively low contribution of indicator 2 initially suggests that the ability to complete a business trip more efficiently with a BEV than with an ICEV is not perceived as relevant for the perceived usefulness of BEVs for business trips. On the other hand, considering that only a minority of participants chose BEVs in the experiment, this result may also imply that for broader acceptance among the population, BEVs need to offer additional technical advantages over ICEVs. This conclusion is supported by Olson's (2013) findings, where research on individuals' product preferences showed a preference for green products when functional trade-offs were not apparent. However, individuals tended to shift to non-green alternatives when facing clear trade-offs between green attributes (e.g. saving energy) and conventional attributes (e.g. performance). Therefore, Olson (2013) recommended addressing functional trade-offs to bridge the green-attitude behaviour gap.

As discussed above, emotions were the primary predictor of individuals' behavioural intentions to book a BEV. Furthermore, the influence of emotions may also pertain to individuals' responses to higher-risk trips as follows. The results of the regression analyses indicate that predicting car choice from behavioural intentions was less reliable for participants that were assigned to the high-risk trip compared to those assigned to the low-risk business trip. Furthermore, while there was no statistical evidence linking car choice to the experimental condition, there is evidence suggesting that the attrition rate from the car booking experiment was associated with the assignment of the high-risk trip. Participants' emotions were not directly assessed during the car booking experiment. Nevertheless, when interpreting the results through the lens of the affect heuristic, the data suggest that the prospect of driving a BEV – or any car, for that matter – for the high-risk business trip elicited negative emotions. This negative emotional response seems to have demotivated car choice, as evidenced by the withdrawal rate from the car booking experiment.

The implied influence of emotions on car choice under risk is further supported by the following observations: in the booking software, three different range buffer categories (0%, 20%, and 100%) were displayed. The distribution of the chosen three range buffer categories per car type across the three bookings reveals that participants opting for a BEV exhibited a relatively higher preference for a 100% range buffer compared to those booking ICEVs. In theory, each individual could have booked a BEV with a 100% buffer. However, interpreting the range buffer preferences in the context of the attrition rate and the generally low preference for BEVs suggests that even a 100% range buffer was not sufficiently large to completely mitigate the perceived risk associated with higher-risk trips. Furthermore, it is also possible that measures other than a range buffer are required to reduce the perceived risk associated with choosing a BEV for a high-risk business trip.

To explore potential explanations for why the technical support provided by the range buffer display did not persuade more participants to choose a BEV or to continue with the car booking experiment, one may refer to a study by Windschitl and Weber (1999). In their research, Windschitl and Weber (1999) investigated the perception of numeric likelihoods of events in different contexts, such as the likelihood of a 5% chance of rain in Madrid compared to a 5% chance of rain in London. Participants were asked to assess their certainty regarding the occurrence of the event. Windschitl and Weber (1999) observed deviations from the provided numeric likelihoods, even when the information was provided by a domain expert, such as a doctor describing medical risks. Windschitl and Weber (1999) attributed the observed deviations to individuals' perceived representativeness of event-context associations as well as their thoughts and feelings based on these associations, although they did not delve further into the proposed influence of feelings. A similar line of reasoning can be found in the risk-as-feelings hypothesis proposed by Loewenstein et al. (2001). According to Loewenstein et al. (2001, p. 271) “feelings about risk are largely insensitive to changes in probability, whereas cognitive evaluations do take probability into account.” The purpose of the range buffer was to address uncertainties surrounding the available BEV range. However, the considerations put forth by Loewenstein et al. (2001) and Windschitl and Weber (1999), as discussed above, further substantiate the conclusion that contemplating the booking of not only a BEV but any vehicle for a high-risk business trip evoked adverse emotions. Consequently, these negative emotions may have intensified the perceived risk associated with BEVs for journeys of elevated risk, concurrently influencing the judgment that the displayed range buffers were considered inadequate for the business trip as evidenced, for instance, in the attrition rate observed in the car booking experiment.

In summary, applying the affect heuristic or the risk-as-feelings hypothesis to interpret the present findings suggests that an emotional response to higher-risk business trips may have influenced participants' willingness to engage in the car booking experiment. Among those who participated and selected a BEV, there was a notable preference for BEVs with a higher range buffer. Since participants' emotions were not directly assessed during the car choice experiment, future studies could explicitly measure the theoretically derived impact of emotions on car choice to advance the comprehension and prediction of technology preferences in contexts characterised by perceived risk. Furthermore, future research could explore alternative strategies beyond the range buffers used in this study to address the suggested impact of negative emotions on car choice for high-risk business trips or similar situations involving BEV usage.

Practical Implications

The following practical recommendations are based on the results presented in this sub-study. Participants associated BEVs with being enjoyable to drive. For fleet managers, policymakers, and car manufacturers, this insight suggests that communications and marketing strategies aimed at encouraging BEV usage should focus on highlighting the enjoyable aspects of driving BEVs to effectively promote BEVs and increase their adoption in corporate fleets.

The findings related to participants' responses to differentially risky business trips, particularly the attrition rate from the car booking experiment, could be valuable for fleet managers in better anticipating fleet usage. Specifically, as business trips perceived as risky may influence employees' car or other mobility choices – especially if there is variation in the available fleet – fleet managers should consider these factors when planning and managing their fleet, particularly regarding capacity usage. Interpreting the range buffer preferences alongside the attrition rate and the generally low preference for BEVs suggests that even a 100% range buffer may not fully mitigate the perceived risk associated with higher-risk trips. Therefore, beyond implementing a range buffer, additional measures may be required to reduce the perceived risk associated with choosing a BEV for a high-risk business trip. One such measure could involve ensuring that the fleet is fully charged[42], which may motivate employees to choose BEVs for their business trips. If not already implemented, fleet managers might consider establishing a practice of employees plugging in BEVs upon returning to the car park, even when the car battery's state of charge is still sufficient for other trips.

While participants demonstrated a willingness to book a BEV, the perceived usefulness of BEVs for business trips in general was rated as average. This suggests that fleet managers should carefully monitor the number of BEVs added to the fleet to maintain proper economic utilisation. A detailed examination of the three indicators of perceived usefulness revealed that current BEV features (e.g. acceleration) predominantly influenced their perceived usefulness. As anticipated, the need to charge during a business trip was a significant factor affecting the perceived usefulness of BEVs. However, the perception that BEVs are more efficient than ICEVs was not a significant factor of their usefulness for business trips. Overall, this suggests that car manufacturers, infrastructure

[42] While a BEV can be charged to 100%, a fleet manager may incentivise charging only up to 80% to extend battery life (see Argue, 2023). This presents a trade-off for fleet managers between optimising battery longevity and potentially achieving a higher usage rate.

providers, and policymakers should continue their efforts to make BEVs more technologically competitive with conventional cars, as supported by international BEV acceptance research (e.g. nearly every second Western European driver expects a range of more than 500km, see Healy et al., 2024).

Limitations

In addition to the specific limitations previously outlined (e.g. the procedure to assess convergent validity of formative variables as suggested by Hair et al., 2022), this study reveals several primary constraints.

Firstly, the questionnaire remained consistent across experimental groups. Consequently, all participants exclusively assessed questionnaire items in the context of envisaging a low-risk business trip. Therefore, the exploration of the impact of risk on the structural relationships within the TAM remains unexplored for participants assigned to a high-risk business trip in the car booking experiment. As a result, the evaluation of behavioural intentions for the high-risk business trip may have revealed a more pronounced association between car choice and behavioural intentions.

Secondly, although the results imply an influence of emotions on car choice, the interpretive scope is limited due to the absence of direct measurements of emotions. Instead, this influence was deduced from observations, relying on the affect heuristic.

Thirdly, concerning the influence of the range buffer on car choice, the absence of a control group – specifically, a group without displayed range buffers in the car booking software – limits a comprehensive elucidation of the actual impact of the three range buffer categories on car choice. Consequently, the influence of the range buffer on car choice can only be estimated and not definitively clarified.

Finally, two considerations merit attention. Firstly, the business trips employed in this study comprised different elements, such as route familiarity or weather conditions. Hence, the precise influence per element on individuals’ responses cannot be determined. Secondly, the conclusions concerning the influence of varying risk levels in usage contexts on car choice are specific to this particular example. Consequently, the results cannot be generalised to other domains or situations. Nevertheless, it is worth emphasising that the observed impact of perceived risk in technology usage contexts on car choice, while applicable to this example, may not be confined solely to this specific case. Therefore, the findings presented here may potentially extend to other domains.

Chapter 2.2: Sub-Study 1.2 - Predicting the Influence of Gamification on Technology Choice Utilising the Technology Acceptance Model: An Experiment on the Effects of Badges

Abstract

Drawing on the dataset from a comprehensive study which incorporates results obtained from a questionnaire designed to assess the TAM and an online experiment, this study expands upon the TAM presented in Sub-study 1.1. This TAM is specifically expanded with additional predictors to investigate the influence of the gamification element badges on the judgment and choice between BEVs and conventional cars. In the context of the online experiment, participants completed three car bookings using a car booking software to explore how badges affected the selection between BEVs and conventional cars for hypothetical business trips. Gamification badges were integrated into the software for the treatment group, while they were absent in the control group. The findings revealed that badges strengthened the relationship between the perceived enjoyment of using the software and individuals' commitment to engage with goals or gamified challenges displayed in the software. Badges enhanced the impact of the perceived usefulness of BEVs on individuals' intention to book a BEV. In the control group, subjective norms were found to predict goal commitment, although this association did not attain statistical significance in the treatment group. Participants' goal commitment had a weak predictive effect on participants' intentions, however, this relationship remained unaffected by the presence of badges. While car choices were predicted by behavioural intentions in two out of three car bookings in both experimental groups, indicating a moderate association, the display of badges was not associated with car choices on a statistically significant basis. Potential strategies for enhancing the effectiveness of gamification interventions are discussed.

Introduction

Games possess the capacity to motivate individuals, encouraging them to invest their leisure time in navigating digital worlds, mastering quests, and overcoming challenges (e.g. Weibel & Wissmath, 2012; Yee, 2006). Games can actively engage players in tasks of increasing difficulty and, on occasion, even develop addictive tendencies in individuals (King et al., 2013; King & Delfabbro, 2020). However, precisely due to their recognised motivational influence, digital games have also served as a source of inspiration in fields beyond game development. Consequently, game elements, such as levels or progress bars[43], have been applied in non-gaming contexts to enhance the enjoyment and engagement in specific activities (Deterding et al., 2011), such as language learning or sporting activities. This approach, commonly known as gamification, has been in circulation for approximately 15 years (Deterding et al., 2011). Gamification is primarily associated with its implementation in digital applications, such as mobile phone applications or other digital services as studies by Gutt et al. (2020) or Hamari and Koivisto (2013) demonstrate. For example, certain game elements, like leaderboards, have been shown to impact individuals' motivation, resulting in increased engagement with incentivised behaviours and improved task performance upon task completion (Boratto et al., 2017; Hamari & Koivisto, 2013; Landers et al., 2017; Landers & Landers, 2014).

To investigate the theoretical underpinnings explaining the aforementioned motivational effects associated with gamification, Krath et al. (2021) conducted a meta-analysis of gamification literature, incorporating 118 different theories. As outlined in the review by Krath et al. (2021), the self-determination theory by Ryan and Deci (2000) emerged as the most frequently cited theory. Ryan and Deci's (2000) self-determination theory pertains to individuals' intrinsic or extrinsic motivation, encompassing a taxonomy of different types of extrinsic motivation to adopt values and associated behaviours. Ryan and Deci (2000) elaborate on these motives in connection with satisfying what they describe as three fundamental psychological needs: autonomy, competence,

[43] Refer to Table 1 for a detailed description of these and various other gamification elements.

and relatedness.

According to the findings of Krath et al. (2021), another frequently applied theory is Davis's (1986) TAM or theories related to the TAM, such as the theory of planned behaviour (Ajzen, 1991) or the theory of reasoned action (Fishbein & Ajzen, 1975). Davis (1986) introduced the TAM with the objective of predicting the acceptance of information systems for business purposes. Specifically, Davis (1986) proposed a framework in which the perceived usefulness of a technology for accomplishing a task and the perceived ease of use of the technology predict an individual's attitudes towards using the technology, and consequently, their decision to use it.

Several studies have used variations of the TAM to explore individuals' intentions to continue using gamified services in the future. For example, Hamari and Koivisto (2013) examined the acceptance of a gamified digital application known as *Fitocracy*, designed for tracking physical exercises. Hamari and Koivisto (2013) identified different social factors, such as the motivation from interacting with the fitness community as predictors of users' intentions to use the gamified fitness app in the future. Similarly, Gumussoy et al. (2023) assessed individuals' intentions to use a gamified sales system by presenting a demo of a gamified sales system to sales employees. They found that the perceived ease of using the gamified sales system mediated the effects of perceived enjoyment of the gamification elements on individuals' intention to use the gamified sales application. Rodrigues et al. (2016) conducted two studies to investigate a gamified online banking application using a TAM variant to measure individuals' intention to use the gamified service. The initial study, conducted in 2012, focused on mutual funds, while the subsequent study, conducted in 2015, examined warrants. In the first study, Rodrigues et al. (2016) found that perceived socialness (i.e. the extent to which the gamified application facilitates meaningful social interaction, such as through the integration of avatars[44]) and perceived ease of use predicted behavioural intentions to use the gamified service. In the second study, Rodrigues et al. (2016) found that perceived socialness and perceived ease of use were not significant predictors of behavioural intentions. Instead, and counter

[44] Refer to Table 1 for a detailed description of this and various other gamification elements.

to the findings of the first study, perceived enjoyment of using the gamified service was a significant predictor. Additionally, several other relationships, such as the influence of ease of use on usefulness, exhibited variations in statistical significance between the two studies.

In summary, the gamification elements used in the three aforementioned studies by Gumussoy et al. (2023), Hamari and Koivisto (2013), and Rodrigues et al. (2016) demonstrated an influence on individuals' behavioural intention to use the gamified service. However, as indicated by the findings of Rodrigues et al. (2016), the perception and influence of a gamification element can vary across different usage contexts that are only slightly different.

Furthermore, although not explicitly addressing gamification, research findings by Richter et al. (2018) indicate that implementing measures to incentivise a specific behaviour could potentially result in adverse effects. Richter et al. (2018) conducted a study in Norway and Germany using variations of information written on a fish-shaped sign to inform shoppers about the existence of sustainable seafood. The sign conveyed that a product carrying the specific certification contributes to sustaining marine resources. Richter et al. (2018, p. 6) used eight variations of signs; one featuring only the sign with sustainable seafood labels and seven sign variations that also differed in their inclusion of descriptive norms (e.g. "28% of all customers buying seafood in our shop yesterday chose MSC/ASC"[45]) to communicate information about other consumers' seafood choices on the previous day. The results showed that in Norway, using the sign alone increased sustainable food choices; however, when a message incorporating descriptive norms was added to the sign, the intervention had no effect. Conversely, in Germany, incorporating normative messages that referred to small reference groups (e.g. 4% or 11%) in combination with the sign resulted in a boomerang effect: sustainable seafood choices decreased compared to the group without the message. Richter et al. (2018) interpret these findings in the context of psychological reactance (see Brehm, 1989). This suggests that customers may have perceived social pressure from the normative message, triggering a fear of potential loss of freedom, leading to their subsequent resistance to the

[45] MSC = Marine Stewardship Council; ASC = Aquaculture Stewardship Council.

incentivised sustainable choice option.

In summary, the findings by Richter et al. (2018) imply that an intervention may even result in an undesirable boomerang effect. However, although Richter et al.'s (2018) study does not provide direct insights into whether gamification elements can be utilised to influence the preferences of different choice options – specifically here to promote the preference for a seemingly more sustainable choice option over its alternative – it does suggest the possibility that gamification elements may interact with the influence of social norms on individuals' choices.

In summary, the existing literature has illustrated the impact of gamification on individuals' intentions to use a gamified service (Gumussoy et al., 2023; Hamari & Koivisto, 2013; Rodrigues et al., 2016). Furthermore, research has indicated that gamification elements can enhance individuals' engagement with incentivised behaviours and improve task performance upon task completion (Boratto et al., 2017; Hamari & Koivisto, 2013; Landers et al., 2017; Landers & Landers, 2014). However, as far as current knowledge extends, no studies have delved into the effects of utilising gamification elements to encourage preferences for a more sustainable technology over its incumbent alternative. While it is worth noting that such attempts may not always yield the desired outcomes as suggested by the earlier findings from Richter et al. (2018), this study aims to investigate the impact of the gamification element badges on the prediction of individuals' behavioural intentions regarding the selection of a more sustainable technology, utilising a TAM, and their subsequent choice between this more sustainable technology and its incumbent alternative.

Battery Electric Vehicles Versus Conventional Cars

To give an example for a sustainable technology and its incumbent alternative, for more than a decade, the BEV has been argued to be a prominent sustainable alternative to conventional cars with an internal combustion engine (Beuse, 2021; Climate Change Committee, 2023; Fazel, 2014; Presse- und Informationsamt der Bundesregierung, 2022). However, rates of adoption of the BEV vary considerably across countries, suggesting that other issues may influence the decision to use a BEV, such as geographical factors (e.g. settlement structures and corresponding charging infrastructure density) or policies and regulations (e.g. purchase incentives, taxation, parking benefits) (see Wappelhorst et al., 2020). For instance, in 2021 while nearly two thirds (64.5%) of all newly registered cars in Norway were BEVs, the corresponding figure in Germany in 2021 was only 13.6% or even only 3.2% in the United States (Davis & Boundy, 2022; Kraftfahrtbundesamt, n.d.-b; Teslamag, 2022). Research conducted in Germany indicates that obvious generic obstacles to BEV adoption include the relatively higher purchase price, limited range, extended battery charging duration, or the perceived lack of charging infrastructure availability (Bühler et al., 2014; Verband der TÜV e.V., n.d.).

Focusing on the German market as an exemplar, it becomes evident that the government has established several objectives and instituted a range of measures to promote electric mobility. As a nation-wide target, the German government initially aimed to achieve one million registered electric vehicles by 2020, but this goal was missed, subsequently postponed to 2022 (ecomento.de, 2019), and eventually achieved in 2021 (Presse- und Informationsamt der Bundesregierung, 2022). Following the accomplishment of one million electric cars, a new goal has been set at 15 million electric vehicles by 2030 (Presse- und Informationsamt der Bundesregierung, 2022). To promote electric vehicle adoption, the government has introduced various incentives, such as tax reductions, subsidies for public charging infrastructure, and other supportive measures (Presse- und Informationsamt der Bundesregierung, 2021). Additionally, there are prohibitions in place that may indirectly contribute to the diffusion of electric vehicles. For instance, the city of Munich has implemented a step-by-step plan for the introduction of a diesel driving ban in Munich's city centre with the aim of reducing local nitrogen dioxide emissions to comply with EU law (Landeshauptstadt München, n.d.-a, n.d.-b).

While the above-mentioned examples illustrate the use of governmental measures aiming at promoting electric vehicle acceptance, there are also indications that demonstrate that electric vehicles do not always receive a welcoming response from the population, as to be illustrated with the following two examples. For instance, electric vehicle drivers in international online communities report instances where designated parking spaces with corresponding charging infrastructure have been deliberately and needlessly occupied by drivers of conventional vehicles (Lambert, 2018). As a second example, users in digital electric vehicle communities have been reporting a trend, predominantly observed in the US, known as *coal-rolling*. In this trend, conventional vehicles are modified by their owners to emit clearly visible clouds of exhaust. Electric vehicle drivers have shared instances in those communities where *coal-rollers* intentionally drive in front of electric vehicle drivers, brake abruptly, and then accelerate to create a cloud of smoke and pollution. In their communities, electric vehicle drivers interpret this behaviour as a way for ICEV drivers to express their opposition to electric vehicles (Grenoble, 2014; Lambert, 2021; Loveday, 2019). In summary, these two examples suggest that battery electric vehicles may not be universally considered a suitable alternative to conventional combustion technology. There is evidence that some people do not merely ignore electric cars but may even react to them with aversion or reactant behaviour. These considerations imply that the implementation of strategies to promote BEVs, such as gamification or the impact of social norms, may not consistently yield the intended motivational effects. In fact, they might even lead to an unintended boomerang effect, as indicated in the study conducted by Richter et al. (2018). Hence, the forthcoming investigation will further explore this phenomenon.

Inclusion of Sub-Study 1.2 as a Component of the Comprehensive Study 1

The foundation of the exploration in this present Sub-study 1 is rooted in the dataset acquired from the comprehensive Study 1. Study 1 involves an exhaustive investigation grounded in a TAM specifically adapted to predict individuals' intentions to book a BEV for an upcoming business trip. Integrating a car booking experiment, Study 1 is structured on a 2x2 factorial design. Participants were assigned to one of two differentially risky hypothetical business trip scenarios (i.e. factor 1)[46]. Additionally, participants were allocated to a condition where gamification was either absent or

[46] Participants were assigned to one of two hypothetical business trips. The first, referred to as the low-risk business trip scenario, was designed to evoke a lower degree of uncertainty when imagining driving a BEV for the business trip compared to the scenario labelled as the high-risk business trip scenario.

present in car booking software (i.e. factor 2). After being allocated to one of the four experimental conditions, participants were instructed to make bookings between BEVs and ICEVs using car booking software. Based on this study design, Study 1 is organised into three sub-studies, referred to as Sub-studies 1.1, 1.2, and 1.3, each with a specific focus but drawing on the same dataset, as follows. Sub-study 1.1 (Chapter 2.1) is dedicated to presenting an adapted TAM designed to predict individuals' behavioural intentions to book a BEV and the exploration of individuals' car type preferences between BEVs and ICEVs within the context of differentially risky technology usage scenarios (i.e. factor 1). In Sub-study 1.2 (Chapter 2.2), this TAM is expanded with additional predictors and data are examined with the focus on investigating car type preferences under the influence of gamification (i.e. factor 2). Sub-study 1.3 (Chapter 2.3) specifically explores the interaction between gamification and car choice within differentially risky BEV usage contexts.

Specifically, this present Sub-study 1.2 explores the influence of factor 2, that is, the influence of gamification on the judgment of BEVs for business trips. In this context, the TAM introduced in Sub-study 1.1 is extended with additional determinants, as suggested by the literature. This theoretical expansion aims to assess the impact of the gamification element badges[47] on the judgment of BEVs for business trips. The exploration further concerns determining the influence of badges on car choices between BEVs and ICEVs.

To concisely outline the procedure, participants in the online experiment were randomly allocated to either the control group, where gamification was absent in the car booking software, or the treatment group, where gamification was incorporated into the software. Further, participants were assigned to one of two hypothetical, differentially risky business trips as further outlined and

[47] Refer to Table 1 for a detailed description of this and various other gamification elements. Among various gamification elements, badges were selected due to their demonstrated effectiveness in motivating individuals to exhibit higher engagement, as shown in previous research (Gutt et al., 2020; Hamari, 2013, 2017).

explored in Sub-study 1.1. Subsequently, participants used car booking software[48] to make their car bookings and then proceeded to the questionnaire used to assess the TAM.

The following section provides an exposition of the theoretical foundations of the original TAM and its various adaptations. Subsequently, it briefly introduces the adapted TAM discussed in Sub-study 1.1, specifically addressing the acceptance of BEVs for business mobility. Following this, the TAM is theoretically expanded by incorporating additional determinants.

TAM Review and Theoretical Extension

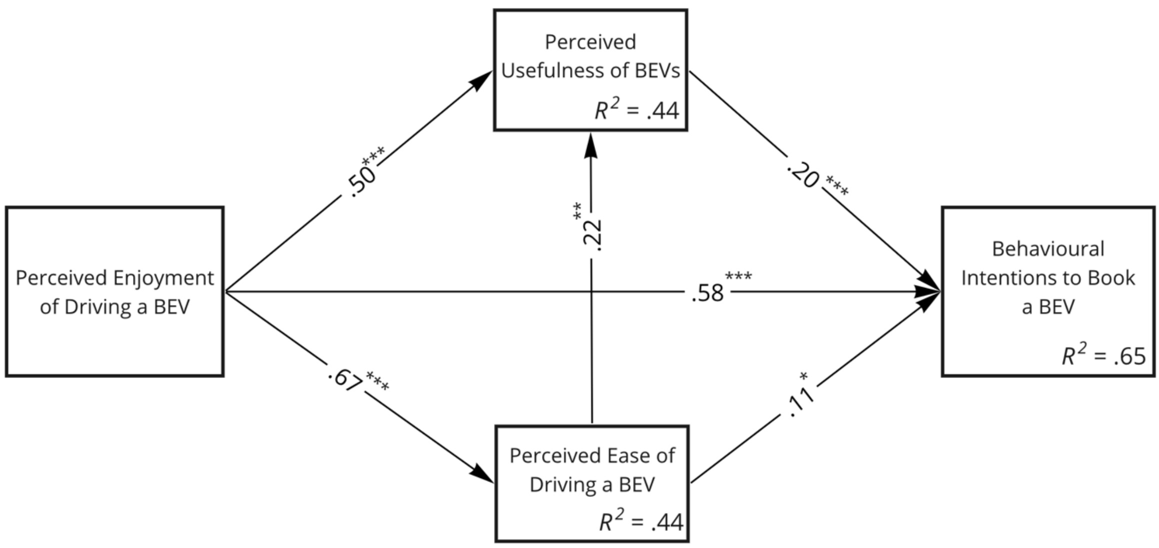
As mentioned above, Davis (1986) proposed the initial TAM with perceived usefulness and ease of use to predict attitude, which was the sole predictor of actual behaviour. In an updated version of this TAM, Davis et al. (1989) suggested using behavioural intentions rather than attitudes as the primary predictor of individuals' use of computer-based technologies. This updated TAM variant was based on the finding that attitudes did not fully mediate the effects of perceived usefulness and ease of use on behavioural intentions. While the original TAM by Davis (1986) was designed to predict the acceptance of information systems for work purposes, the TAM has evolved over the past 30 years into various versions with different numbers and types of predictors (e.g. Venkatesh, 2000; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000) for different application areas including the acceptance of electric vehicles. For instance, Fazel (2014) aimed to measure the acceptance of BEVs for public carsharing. Globisch et al. (2018) researched BEV acceptance in the context of commercial use, while Dudenhöffer (2013) sought to determine the factors influencing the

[48] The hypothetical car fleet in the booking software included BEVs and ICEVs in the same number, vehicle class, and equipment, allowing the choice of BEV or ICEV to be studied. In addition to accessing the booking software, participants received information that the software would calculate their personal fuel or battery requirements for the business roundtrip, that is, to the business partner and back to the employer. Furthermore, each BEV and ICEV listed in the car booking software included details about its range buffer, that is, the excess fuel or battery range beyond the estimated consumption for the round trip, presented in categories of 0%, 20%, or 100% of excess fuel or battery range (as exemplified in Appendix B).

struggle for acceptance of electric vehicles (i.e. BEVs and hybrid electric vehicles) for private use. Roemer and Henseler (2022) analysed the acceptance of BEVs as part of corporate fleets.

Figure 7

Adapted Technology Acceptance Model for Predicting Individuals' Behavioural Intentions to Book a Battery Electric Vehicle for Business Trips



Note. The arrows display path coefficients estimated using SmartPLS 4, interpreted akin to standardised regression coefficients (β) as per Hair et al. (2022). This technology acceptance model is thoroughly elaborated and discussed in Sub-study 1.1 (Chapter 2.1).

BEV = battery electric vehicle.

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Before delving into the theoretical extension of the TAM, the determinants of individuals' intentions regarding the booking of a BEV for business trips will be introduced. As per the experimental findings presented in the previous Sub-study 1.1 (Chapter 2.1), three factors were identified as significant predictors of behavioural intentions to book a BEV: (1) perceived usefulness of BEVs, (2) perceived ease of use of BEVs, and (3) the perceived enjoyment of driving a BEV (refer to Figure 7). The perceived enjoyment of driving a BEV was measured by eliciting individuals' anticipated emotions when envisioning the experience of driving a BEV, including feelings of curiosity, excitement, or joy. Perceived usefulness pertained to the extent to which individuals view driving a BEV, as opposed to a traditional ICEV, as more efficient or consider the technical attributes of a BEV (e.g. lower noise emissions at lower speeds, higher instant torque) as more advantageous when compared to conventional vehicles (e.g. quicker refuelling). Finally, perceived ease of driving a BEV measured individuals' perception of how easy it is to adapt to driving a BEV in contrast to an ICEV. It is noteworthy that the perception of a BEV as enjoyable to drive significantly stood out as the most influential predictor of behavioural intentions, based on relevant effect sizes (i.e. *β* path coefficient, f^2 effect size).

In order to assess the potential effects of gamification badges on predicting behavioural intentions to book a BEV, the following four determinants, recommended by existing literature, are presented. Firstly, the subjective norm associated with driving a BEV for business trips. Secondly, the perceived image of BEV drivers. Thirdly, goal commitment, representing participants' subjective determination to engage with goals or gamified challenges presented to them. Lastly, the perceived enjoyment of using the above mentioned car booking software, utilised in the online experiment to offer participants a selection of various vehicle alternatives.

Behavioural Intentions and Car Choice

As outlined above, studies conducted by Gumussoy et al. (2023), Hamari and Koivisto (2013), and Rodrigues et al. (2016) found gamification to influence individuals' behavioural intention to engage with the respective gamified services. Progressing along the decision-making process, variations of the TAM typically build upon Davis et al.'s (1989) TAM by modelling behavioural intentions as the direct predictor of actual behaviour. Although the three aforementioned studies did not integrate a measure of actual behaviour in their TAMs, other gamification literature provides substantiation for the capacity of gamification to influence actual behaviour. For example, Landers et al. (2017) observed that the introduction of a leaderboard signified an augmentation in individuals' performance (i.e. a greater output generated) during a 12-minute brainstorming activity. Gutt et al. (2020) utilised data from a German Question and Answer community, enriched with badges, to investigate the influence of goal attainment on individuals' efforts to achieve subsequent milestones. According to Gutt et al. (2020), their findings underscored that successful badge achievement (i.e. goal attainment) correlated with sustained efforts to attain subsequent more challenging badges, as long as the badge presented a meaningful challenge to the user. Hamari (2013) conducted a field experiment to examine the impact of badges, attainable through diverse tasks, within a peer-to-peer trading service. According to Hamari (2013), the results indicated that badges did not significantly alter overall behaviour (i.e. usage activity) across all system users, but did exhibit a specific influence on those who actively monitored their own badges as well as those earned by others.

In summary, there is evidence that gamification elements can influence an individual’s behavioural intentions to engage with a gamified service (e.g. Gumussoy et al., 2023; Hamari & Koivisto, 2013; Rodrigues et al., 2016). Furthermore, the three studies cited above by Hamari (2013), Gutt et al. (2020), and Landers et al. (2017) indicate that gamification can also influence behaviour. These observations suggest that gamification elements may not only affect behaviour, but also choice between technology alternatives, such as the preference for BEVs over ICEVs.

Consequently, it is hypothesised that (H1.1) BEV choice will be positively associated with individuals’ behavioural intentions to book a BEV. Further it can be hypothesised that (H1.2) in comparison to the control group without badges, the treatment group with badges will exhibit a comparatively greater preference for BEVs.

Subjective Norm and Perceived Usefulness

When employers introduce new technologies, they also depend on their employees to adopt these new technologies and embrace the corresponding corporate values and behaviours that come with their usage. In this context, a recurring TAM predictor is the subjective norm. The subjective norm originates in Fishbein and Ajzen’s (1975) theory of reasoned action (a model resembling the TAM) and pertains to the perceived social pressure to comply with a specific behaviour. More precisely, Fishbein and Ajzen (1975) state that the subjective norm reflects an individual’s perception of whether important individuals in their life believe they should or should not engage in a particular behaviour.

Venkatesh and Davis (2000), who investigated the acceptance of various information systems, found an association between the subjective norm and the perceived usefulness of the information system under consideration, which they attribute to the degree of value internalisation. Internalisation is rooted in Ryan and Deci's (2000) self-determination theory, which pertains to individuals' intrinsic or extrinsic motivation, encompassing a taxonomy of different types of extrinsic motivation to adopt values and associated behaviours. Ryan and Deci (2000) elaborate on these motives in connection with satisfying what they describe as three fundamental psychological needs: autonomy, competence, and relatedness. In the context of this theory, value internalisation describes the extent to which individuals adopt corporate values and behavioural regulations, ranging from unwillingness or even reactance (see Brehm, 1989) to their full integration[49] (Ryan & Deci, 2000). As per Ryan and Deci (2000), a higher degree of internalisation results in greater commitment, engagement, and persistence, nurturing a sense of self-determination and rendering the associated behaviour more volitional.

The existing literature on the TAM, particularly in the context of electric vehicle acceptance, has also examined the role of the subjective norm as a predictor. Notably, TAMs focusing on electric vehicle acceptance for various usage contexts, such as private, public, or commercial use, as investigated by Fazel (2014), Globisch et al. (2018), and Dudenhöffer (2013), have observed the influence of the subjective norm on the perceived usefulness of electric cars. However, concerning Dudenhöffer's (2013) study, a noteworthy finding emerges: the influence of the subjective norm on the perceived usefulness of electric cars for private use was statistically significant before, but not after participants engaged in a test drive with electric cars. According to Dudenhöffer (2013), this observation suggests that as individuals gain practical experience with electric cars they need to rely less on subjective norms to evaluate the perceived usefulness of BEVs.

[49] According to Ryan and Deci (2000), integration means that the values and behaviours have been assimilated to the self.

In accordance with the suggestions of self-determination theory, particularly for individuals with a higher degree of internalisation (Ryan & Deci, 2000), the considerations above lead to the hypothesis that (H2.1) the subjective norm regarding the use of BEVs for business trips will be positively correlated with the perceived usefulness of BEVs.

Subjective Norm, Image, and Perceived Usefulness

When an individual aligns their technology usage with the subjective norm, it can be inferred that the individual anticipates positive effects on their own image within the pertinent social group. Relatedly, TAM studies investigating IT system acceptance across different organisations, conducted by Venkatesh and Davis (2000) and by Venkatesh and Bala (2008), provide evidence for the impact of the subjective norm on image.

Furthermore, Venkatesh and Davis (2000) theorised that a significant social group can serve as an information source when assessing the usefulness of a technology. Specifically, Venkatesh and Davis (2000) suggest that an employee might perceive an information system as improving their job performance, even if the perceived benefit does not directly come from the system itself but rather from associated social support and the perceived sense of group belonging. The proposition presented by Venkatesh and Davis (2000) suggests that employees who associate BEV drivers with a positive image in their professional environment would consequently consider BEVs as more useful for their own business mobility. This proposition is supported by the statistical evidence they presented. Similarly, Fazel (2014) reported an association between image and the perceived usefulness of BEVs in the context of public carsharing, albeit with statistical significance observed only at the 10% significance level.

Therefore, considering the aforementioned findings by Venkatesh and Davis (2000) and Venkatesh and Bala (2008), it can be hypothesised that (H2.2) the subjective norm regarding the use of BEVs for business trips will be positively correlated with the perceived image of BEV drivers. Furthermore, it can also be hypothesised that (H2.3) the perceived image of BEV drivers will be positively correlated with the perceived usefulness of BEVs.

Subjective Norm and Behavioural Intentions

Above, it was discussed how individuals may adopt behaviours driven by the expectation of having a more positive image within the relevant social group. In the context of self-determination theory, Ryan and Deci (2000) delve more deeply into the range of different motivational drivers of value and behavioural adoption. For example, Ryan and Deci (2000) specifically discuss how individuals may perform a certain behaviour out of perceived social pressure, to avoid guilt or anxiety, or to enhance their self-esteem, pride, and sense of worth. Accordingly, an individual's adoption of a particular behaviour might be driven by the motivation to avoid negative emotions in the first place. For example, a study by Johnson et al. (2018) found how the fear of leaving a negative impression on others can influence their consumption of pro-social goods, such as reusable grocery bags (see Veblen's, 1912, notion of conspicuous consumption).

Similar effects can be observed in TAM literature or literature that is based on theories sharing similarities with TAM. Hartwick and Barki (1994), who tested a model based on the theory of reasoned action (Fishbein & Ajzen, 1975), and Venkatesh and Davis (2000), who tested a TAM to investigate the acceptance of different information systems, found evidence that subjective norms directly influenced behavioural intentions when individuals perceived the system use as mandatory. In summary, these studies indicate how perceived pressure to comply can influence an individual's behavioural intentions with regards to technology acceptance.

Accordingly, it can by hypothesised that (H2.4) the subjective norm regarding the use of BEVs for business trips will be positively correlated with the behavioural intention to book a BEV.

Goal Commitment and Behavioural Intentions

Gamification elements, such as badges or leaderboards, can function as motivational tools, encouraging increased task engagement and persistence, as demonstrated in studies conducted by

Gutt et al. (2020) and Landers et al. (2017).[50] To provide a theoretical framework for explaining the observed effectiveness of gamification elements, both Gutt et al. (2020) and Landers et al. (2002) drew upon Locke and Latham's (2002) goal-setting theory. Furthermore, Gutt et al. (2020) made reference to Bandura's (1982) concept of perceived self-efficacy, which pertains to an individual's personal evaluation of their ability to perform a specific behaviour.

Locke and Latham's (2002) goal-setting theory offers a comprehensive framework for structuring goals as meaningful and potent motivators to enhance performance. This theory examines various goal types, including distal and proximal goals[51], elucidating the mechanisms through which goals operate (e.g. eliciting arousal and a sense of discovery). Additionally, Locke and Latham (2002) discuss the role of goals as mediators of incentives and explore the influence of moderating factors (e.g. feedback, goal commitment, self-efficacy) on the relationship between goal difficulty and specificity, and performance.

Within the context of self-efficacy theory, research by Bandura and Schunk (1981) revealed that individuals made the most progress when working towards proximal goals in contrast to distal goals. Bandura and Schunk (1981) argued that the mastery of subgoals allows individuals to gain a more accurate understanding of their abilities, thereby enhancing their personal efficacy and interest in the tasks. Locke and Latham (2002) postulated a similar notion, wherein Bandura's (1982) concept of self-efficacy served as a moderator for the association between goals and performance.

In summary, these theories suggest that the way goals are presented to individuals can influence their motivation to enhance performance and task engagement. In this context, the

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[50] Gutt et al. (2020) implemented goals with varying difficulty levels in the form of badges within a German Question and Answer community. Their research showed that achieving these goals increased participants' willingness to tackle even more difficult goals. The study conducted by Landers et al. (2017) is introduced in detail in the main text below.

[51] Basically, proximal goals cut down a large goal (e.g. completing a number of tasks) into a number of sub-tasks. Distal goals do not have intermediate goals, but the target to complete the entire set of tasks (see for example Bandura & Schunk, 1981).

research by Landers et al. (2017) and Gutt et al. (2020) suggests that gamification could be considered as a manifestation for designing, structuring, and visually presenting goals to users.

Delving more into goal-setting theory, Locke and Latham (2002) introduced goal commitment being one of the moderating factors on the relationship between goal difficulty and specificity, and individuals' performance. According to Latham and Locke (1991), goal commitment refers to a person's determination to achieve a goal and to persist in pursuing it despite potential setbacks and obstacles. In assessing the success of gamification interventions, Landers et al. (2017) and Hamari (2013, 2017) specifically emphasised the significance of goal commitment as a predictor of success.

Specifically, Hamari (2013, 2017) investigated the impact of badges on individuals' interaction with a peer-to-peer trading service. Among other findings, Hamari (2013) discovered that the gamification intervention influenced participants who regularly monitored their earned badges, and to some extent, also for those who viewed the badges of others. Along with the recommendation to measure goal commitment for future service development, Hamari (2013, 2017) concluded that while badges provide users with clear goals, participants must also be determined to pursue these goals.

To address the second example, Landers et al. (2017) used a 12-minute brainstorming task in their study to compare the performance of a gamification element – a leaderboard – with four distinct goal-setting conditions, ranging from *do-your-best* and *easy* to *difficult* and *impossible* goals. The results of their study revealed that the presence of a leaderboard motivated participants to achieve performance levels comparable to those associated with difficult or seemingly impossible goals, surpassing the performance of individuals in the do-your-best or easy goal conditions. Additionally, Landers et al. (2017) assessed goal commitment and identified it as a direct predictor of the participants' task performance. They also found that goal commitment played a moderating role in the effectiveness of leaderboards. Notably, participants who did not perceive the leaderboard as presenting meaningful goals were not influenced by the leaderboard in their performance within the brainstorming task.

In summary, the above discussions regarding goal-setting (e.g. Bandura & Schunk, 1981; Locke & Latham, 2002) and the gamification literature (Gutt et al., 2020; Hamari, 2013; Landers et al., 2017) suggest that an individual's commitment to engage with presented goals plays a significant role in the efforts of shaping their behaviour. Consequently, these considerations indicate a link between the success of the badges used in the car booking software to promote BEV usage and individuals' commitment to take the presented goals seriously as well as their subsequent willingness to book a BEV.

Therefore, it can be hypothesised that (H2.5) the commitment to engage with disseminated goals (e.g. whether one deems it worthwhile to pursue gamified challenges associated with earning points or badges presented in the car booking software, contingent upon car choice) will be positively correlated with the behavioural intention to book a BEV. Furthermore, it can be hypothesised that (H2.5.2) the gamification element badges will strengthen the relationship between individuals' goal commitment and their behavioural intention to book a BEV, thereby increasing the correlation between these variables.

Subjective Norm, Image, and Goal Commitment

The following section will elucidate the study results by Hamari and Koivisto (2013) to demonstrate the significance of *community* as a driving factor for members to engage with the communicated goals. Hamari and Koivisto (2013) utilised a questionnaire to identify the drivers of individuals' intentions to continue using Fitocracy, a gamified service designed for tracking physical exercises. Among their various findings, Hamari and Koivisto (2013) identified social factors – specifically, the belief that important others expect and support one to perform the gamified target behaviour – and the perceived benefits derived from using the gamified service as robust predictors of both users' attitudes towards the gamified service and their subsequent intention to continue using it. Furthermore, the community's engagement in providing feedback (e.g. through *likes*[52]),

[52] A like typically refers to a simple digital user interaction, often represented by a heart-shaped or a thumbs-up icon, or similar symbol, used on digital platforms to express approval for another user's content.

signalling approval for an individual's behavioural performance, impacted the perceived benefits of using the service and consequently also indirectly affected attitudes. Hamari and Koivisto (2013) concluded that the presence of a community and its underlying network foster active participation, exchange, and meaningful interaction among members, thereby augmenting the benefits associated with the gamified service. Participants were consequently exposed to the attitudes of significant others, made evident through the feedback provided. Hamari and Koivisto (2013) argued that this social interaction would likely strengthen goal commitment, a factor they deemed essential for the success of gamification interventions, as supported by the findings of Landers et al. (2017) described above.

In summary, the insights provided by Hamari and Koivisto (2013) suggest how the social environment can influence individuals' engagement, ambition, and commitment to particular behaviours. Hamari and Koivisto's (2013) findings are consistent with Ryan and Deci's (2000) self-determination theory, suggesting that for the internalisation of values and behaviours to occur, individuals should experience a sense of connection and belonging to the social group that has communicated the goal. According to this account, the more deeply an extrinsically motivated behaviour is internalised, the more a person identifies with the necessary behaviours as part of the self. Ryan and Deci (2000) argue that an increasing degree of internalisation leads to personal commitment, resulting in greater persistence and involvement in the desired behaviour. At this juncture, the theoretical parallels between self-determination theory and Latham and Locke's (1991) concept of goal commitment become evident in relation to the projected success of disseminated goals, as outlined above.

In summary, the insights from the cited literature above suggest a connection between an individual's commitment to disseminated goals and social factors. Therefore, it can be hypothesised that (H2.6) the subjective norm regarding the use of BEVs will be positively correlated with the commitment to engage with disseminated goals. Furthermore, it can be hypothesised that (H2.7) the perceived image of BEV drivers will be positively correlated with an individual's commitment to engage with disseminated goals.

Perceived Enjoyment of Using the Car Booking Software and Goal Commitment

According to Ryan and Deci's (2000) self-determination theory, the intrinsic motivation to use a product solely for the enjoyment derived from its usage is distinct from other benefits or consequences, such as an enhanced image. Nevertheless, the pursuit of goals and the adoption and performance of specific behaviours can also bring joy to extrinsically motivated employees, whom Ryan and Deci (2000) would nevertheless characterise as having internalised the values and behaviours to a comparatively higher degree. Ryan and Deci (2000) posit that the more internalised a behaviour is, the more an employee perceives the activity as part of the self, thus making it self-determined. They argue that the perceived autonomy in carrying out specific behaviours is expected to be linked with higher levels of commitment, improved performance, and greater enjoyment. Considering these insights from Ryan and Deci’s (2000) self-determination theory, it can be inferred that an individual who has internalised relevant organisational values, such as a preference for more sustainable mobility solutions over less sustainable ones, is more likely to approach the exploration and use of software designed for business purposes with inherent pleasure and a spirit of exploration. Consequently, it can once again be inferred that such an individual would also perceive goals disseminated by the employer, for example when linked to car choice, as comparatively more meaningful (see Locke & Latham, 2002).

In accordance with the considerations above, it can be hypothesised that (H2.8) the perceived enjoyment of using the car booking software will be positively correlated with the commitment to engage with disseminated goals.

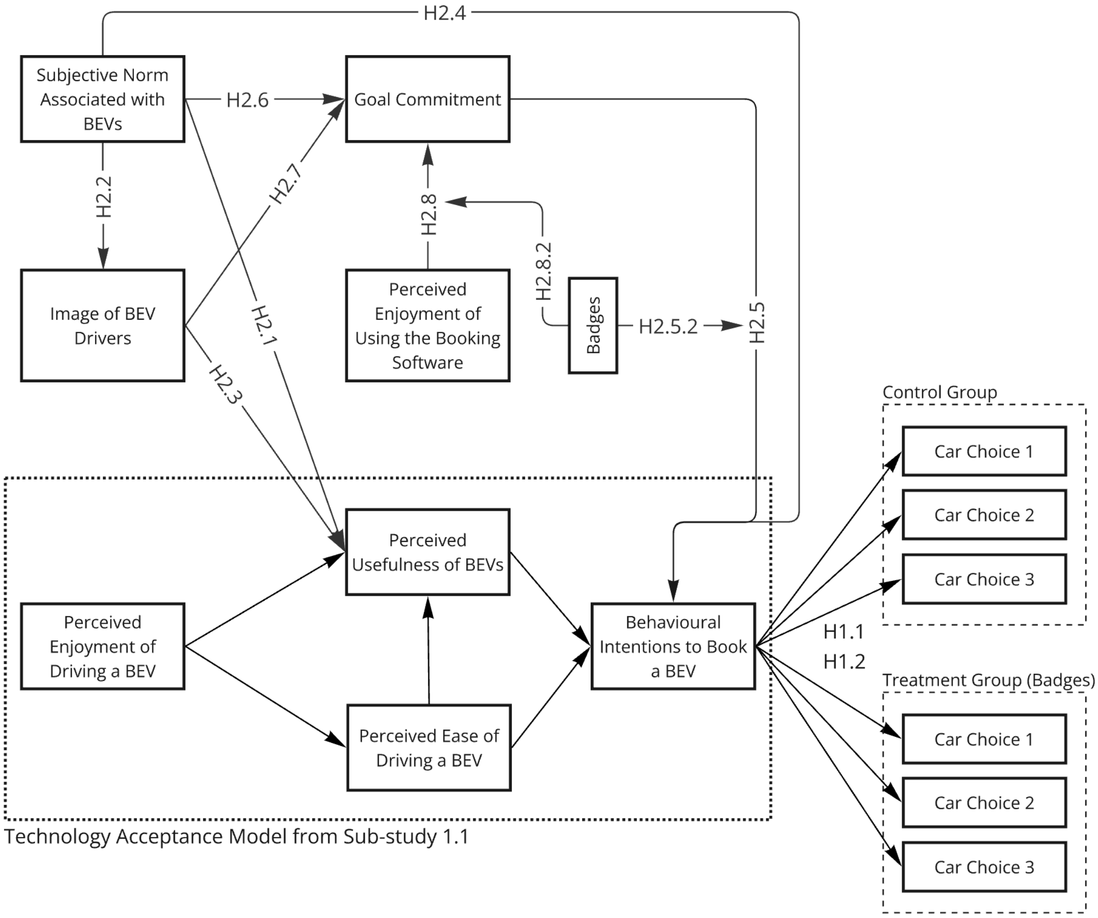
A specific assertion by Locke and Latham (2002) suggests that the introduction of goals can stimulate the exploratory nature of such self-determined employees. Referring to one of four mechanisms explaining why goals influence performance, Locke and Latham (2002, p. 707) argue that "goals affect action indirectly by leading to the arousal, discovery, and/or use of task-relevant knowledge and strategies.” It is therefore not difficult to imagine that digital goals, when presented in the form of points or badges, can similarly evoke a sense of curiosity and joy concerning the exploration and acceptance of these goals in employees who feel that they act self-determined.

Moreover, findings by Codish and Ravid (2015) corroborate that gamification elements can augment the perceived enjoyment of using a car booking software when enriched with gamification: Codish and Ravid (2015) incorporated three distinct gamification elements – badges, leaderboards, and points – into a learning management software used in a university setting. The primary objective was to enhance students' playfulness, characterised by their engagement with the service, curiosity, and enjoyment during interactions with the study materials available within the learning management software. In addition to various other measurements, Codish and Ravid (2015) evaluated students' perceived playfulness and their perception of these three gamification elements at the onset of the experiment (week 2) and its conclusion (week 10). Their findings indicated a link between the perceived enjoyment derived from experiencing badges in the software and the students' perceived playfulness with the learning management software. In summary, within the context of this study, the findings from Codish and Ravid's (2015) research suggest that badges could enhance the perceived enjoyment of using the car booking software, which may, in turn, influence individuals' commitment to exploring and engaging with disseminated digital goals related to car choice.

Therefore, it can be hypothesised that (H2.8.2) the gamification element badges will strengthen the relationship between individuals’ perceived enjoyment of using the car booking software and the commitment to engage with disseminated goals, thereby increasing the correlation between there variables.

Figure 8

Theoretical Expansion of the Technology Acceptance Model with Gamification and the Predictors Subjective Norm, Image, Goal Commitment, and the Perceived Enjoyment of Using the Booking Software



Note. This theoretical extension derives from the technology acceptance model introduced in Sub-study 1.1 (Chapter 2.1).

BEV = battery electric vehicle.

Table 14

List of Hypotheses for the Technology Acceptance Model Extension

No.	Hypotheses
H1.1	BEV choice will be positively associated with individuals' behavioural intentions to book a BEV.
H1.2	In comparison to the control group without badges, the treatment group with badges will exhibit a comparatively greater preference for BEVs.

No.	Hypotheses
H2.1	The subjective norm regarding the use of BEVs for business trips will be positively correlated with the perceived usefulness of BEVs.
H2.2	The subjective norm regarding the use of BEVs for business trips will be positively correlated with the perceived image of BEV drivers.
H2.3	The perceived image of BEV drivers will be positively correlated with the perceived usefulness of BEVs.
H2.4	The subjective norm regarding the use of BEVs for business trips will be positively correlated with the behavioural intention to book a BEV.
H2.5	The commitment to engage with disseminated goals (e.g. whether one deems it worthwhile to pursue gamified challenges associated with earning points or badges presented in the car booking software, contingent upon car choice) will be positively correlated with the behavioural intention to book a BEV.
H2.5.2	The gamification element badges will strengthen the relationship between individuals' goal commitment and their behavioural intention to book a BEV, thereby increasing the correlation between these variables.
H2.6	The subjective norm regarding the use of BEVs will be positively correlated with the commitment to engage with disseminated goals.
H2.7	The perceived image of BEV drivers will be positively correlated with the commitment to engage with disseminated goals.
H2.8	The perceived enjoyment of using the car booking software will be positively correlated with the commitment to engage with disseminated goals.
H2.8.2	The gamification element badges will strengthen the relationship between individuals' perceived enjoyment of using the car booking software and the commitment to engage with disseminated goals, thereby increasing the correlation between these variables.

Note. BEV = battery electric vehicle.

Method

Participants

In the comprehensive Study 1, participants from Germany were recruited based on specific criteria: individuals whose jobs involved occasional business trips and who considered corporate carsharing a viable solution for their regular business mobility. The final sample comprised 238 participants, with 200 recruited through a panel from Schmiedl Marktforschung GmbH (now Schlesinger Group/Sago) and 38 participants recruited through a car manufacturer in Germany. Of the participants, 73% (n = 173) had access to at least one corporate carsharing vehicle, while 24% (n = 57) did not have such access. Eight participants (3%) were uncertain about their access to corporate carsharing. For more detailed information regarding the sample, refer to Sub-study 1.1 in Chapter 2.1.

Study Design

As mentioned above as well as in the context of the general introduction of Chapter 2, this present Sub-study 1.2 examines the dataset of an overarching study, which also comprises the other two Sub-studies, 1.1 and 1.3. Study 1 is structured as a 2x2 factorial between-subjects design. Participants were randomly assigned to one of two differentially risky hypothetical business trips (i.e. factor 1). Additionally, participants were randomly allocated to a condition where gamification was either absent (i.e. control group) or present (i.e. treatment group) in the car booking software (i.e. factor 2). In this present sub-study, data is explored with regards to the second factor, that is, the presence or absence of gamification in the car booking software. Refer to Sub-study 1.1 (Chapter 2.1) for the exploration of data concerning factor 1 (i.e. the differentially risky business trips) or turn to Sub-study 1.3 (Chapter 2.3) for the examination of the interaction between both factors, namely differentially risky trips and gamification.

Procedure

The following section briefly outlines the procedure for the control group, followed by an elaborated description of the procedure for the treatment group. For a more detailed description of the procedure, refer to Sub-study 1.1 (Chapter 2.1).

In the control group, participants were instructed to register and log into the booking software linked in the questionnaire. The booking software managed a shared fleet consisting of an equal number of ICEVs and BEVs with identical vehicle classes (e.g. sedan, SUV) and equipment (e.g. navigation system). Subsequently, participants were asked to mentally prepare for the assigned hypothetical business trip and make three car bookings.[53] After completing the bookings, participants returned to the questionnaire, which concerned the assessment of the TAM.

Participants in the treatment group underwent an identical procedure to those in the control group but, in addition, the booking software was augmented with badges at distinct stages of the booking process, a detailed account of which will be provided below.

Upon registration and logging into the booking software, participants received a welcome notification comprising a title, a description, and a visual representation of the inaugural badge labelled as the *Learner Driver*. Primarily, this initial notification aimed to convey the participant's proficiency level in utilising the company's car fleet. Further, the objective of this preliminary notification was to acquaint the participant with optional challenges linked to their subsequent car choice. In addition to this initial badge, automatically conferred upon login, the booking software enabled participants to earn three additional badges: the *Novice Driver*, *Driver*, or *Race Driver* badges. Over the course of the three car bookings, each participant had the opportunity to achieve all three remaining badges. The rationale for unlocking a badge, that is, the task associated with each badge, was linked to the booked car and its specific characteristics. Specifically, it was associated with the car type (BEV or ICEV) and the available range buffer (refer to completion logic in Table 15). In the event[54] that a participant unlocked another badge through their particular car selection during their booking, a supplementary notification would be displayed upon reviewing the booking confirmation. The notification conveyed congratulations to the participant for unlocking the badge, accompanied by a visual representation of the achieved milestone. Moreover, the notification

[53] The purpose of collecting three bookings was to gather multiple responses per participant, providing participants in the treatment group with more time to become familiar with the gamification badges.

[54] The pages ideally viewed during the booking process, assuming no navigational detours, included (1) the landing page: serving as an overview and introduction to the car booking software, (2) the car list page: a screen presenting car choices and filtering options, (3) the detailed car view: a screen displaying the selected car with all available details, (4) the shopping cart with the selected car: a preview of the confirmation, and (5) the car booking confirmation: a screen confirming the car choice made (refer to Appendix B for examples).

elucidated the criteria that were necessary for earning the specific badge. Additionally, participants were prompted to take on the next challenge by providing a description of the necessary requirements for the subsequent challenge within the same notification. If a participant consciously or unconsciously chose not to participate in the challenge, as evident from their car choice, no notification appeared upon viewing the booking confirmation.

Eventually, after completing the three bookings, participants returned to the questionnaire, which concerned the assessment of the TAM. It is noteworthy that all participants received exclusively a TAM questionnaire related to the low-risk business trip, regardless of the business trip assigned for the booking experiment. Consequently, the TAM, including behavioural intentions, was not evaluated for the high-risk business trip.

Gamification Element Design and Completion Logic

The gamification intervention, implemented using badges, was prominently displayed to all participants within the car booking software of the treatment group. Inspired by Hamari (2017), the design of a badge comprised three essential components: (1) the signifier, (2) the completion logic, and (3) rewards. The specific signifier and reward used in this study are detailed in Table 15. Each of the four badges contained a visual element that illustrated the corresponding skill level, a title, representing the status (e.g. Novice Driver) as well as a description. The description concerned the requirement necessary to achieve the badge, such as to book a BEV that has a 20% range buffer for the upcoming business trip.

To help participants distinguish between the different levels of difficulty[55] associated with car choices, the badge labels (i.e. status/title) were influenced by the studies of Landers et al. (2017) and Hamari (2017). As outlined previously, Landers et al. (2017) compared the performance impact of the gamification element leaderboard across four distinct goal-setting conditions, ranging from do-your-best and easy to difficult and impossible goals. Hamari (2017) utilised badges with corresponding

[55] The level of difficulty (i.e. easy, difficult, impossible) was displayed for each car and car type in the car booking software to clarify the association between the labels and the corresponding difficulty levels.

labels (e.g. *rookie*, *generous*) to describe the activities required to earn those badges. In this study, specific badge labels were chosen to represent different goal types, with the aim of incentivising participants to strive for the achievement of more difficult goals. While badges can be designed in a more neutral manner, such as by using simple ranks (e.g. first, second, third), this study employed more precise labelling tailored to the research context. A pre-test with eight individuals indicated a desire to achieve the different badges; for example, participants reported a motivation to avoid being perceived by others as a Learner Driver. However, it is also not difficult to imagine that such labelling might not appeal to everyone. For instance, being labelled a Race Driver could be polarising and evoke associations with behaviours like speeding, which some individuals may not find desirable. This could diminish the intended meaningfulness of the goal and reduce the motivation to achieve it.

Table 15

Design of the Four Badges Displayed in the Car Booking Software for the Treatment Group

Visual Element				
Status / title	Learner Driver	Novice Driver	Driver	Race Driver
Level of difficulty	None/default	Easy	Difficult	Extremely difficult / impossible
Completion logic	Default badge upon registration. No action required.	For booking an ICEV independent of the chosen range buffer; or a BEV with a 100% range buffer.	For booking a BEV with a 20% range buffer.	For booking a BEV with a 0% range buffer.

Note. Status and title were translated from German.

BEV = battery electric vehicle, ICEV = internal combustion engine vehicle.

The acquisition[56] of the three supplementary badges, namely Novice Driver, Driver, and Race Driver, hinged on an individual's particular car selection and, concomitantly, on two conditions. Firstly, it relied on the range buffer of the car, categorised as 100%, 20%, or 0% of excess fuel or electric range for each car and car type.[57] Secondly, the requirement for each badge was contingent on the car type, i.e. BEV or ICEV.

To unlock the first badge (i.e. Novice Driver) among the three optional badges, an individual could either book an ICEV regardless of the selected range buffer or, alternatively, select a BEV with the maximum available range buffer of 100%. However, the remaining two badges (Driver or Race Driver) were exclusively tied to the booking of a BEV. To attain the Driver badge, participants needed to book a BEV with a range buffer of 20%. For the achievement of the final Race Driver badge, the participant had to book a BEV with a range buffer of 0% excess battery range for the entire business round-trip.[58] Hence, the attainment of two out of the three badges was contingent upon booking

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[56] In addition to promptly displaying the earned badge in the car booking software following the booking of a suitable car, it is noteworthy that a distinct subpage named *achievements* was located within the header bar of the car booking software. This dedicated subpage presented a comprehensive overview of both attained and pending badges, along with their respective requirements. Access to this subpage was restricted to the individual user and inaccessible to others. Refer to Appendix B for an example of this page.

[57] For instance, for a business trip to the business partner that involves traveling a 100km round trip, the car booking software displayed a car with a range buffer of 100%. This 100% range buffer indicates that the employee would be able to drive an estimated total of 200km.

[58] The acquisition of the badges had no predetermined order or dependency in achieving any of the three optional badges. Nevertheless, the booking software incorporated a certain logic in the presentation of notification content, delineating the level of difficulty associated with each badge. In essence, when a participant successfully booked a car, meeting the prerequisites for earning the Novice Driver badge, the booking confirmation presented the next challenge through a subsequent notification. This notification directed the participant to consider booking a BEV with a 20% range buffer to attain the Driver badge with their next booking. If the participant, in turn, booked a car meeting the criteria for the Driver badge, another notification appeared on the booking confirmation screen. This notification outlined the objective of achieving the ultimate badge, referred to as the Race Driver. To accomplish this badge, participants were

BEVs with a reduced range buffer, specifically, either 20% or 0%.

As indicated above, the challenges associated with the respective badges can be considered as reflecting varying levels of difficulty, drawing on insights from the research of Franke et al. (2012) and Rauh et al. (2015a, 2015b). Franke et al. (2012) and Rauh et al. (2015a, 2015b) discovered that, for stress mitigation, BEV drivers utilised range buffers to avoid experiencing critical range situations, where the available battery range is dangerously low, jeopardising the seamless completion of the trip. Hence, a participant contemplating the various cars in relation to the requirements associated with the badges may perceive the execution of the business trip as varying in terms of risk, depending on the car type and corresponding range buffer. This may particularly apply to the perception of BEVs concerning the three available range buffer categories. For example, it is not difficult to imagine that an individual who has contemplated the scenario of a business trip, including information about the external temperature being 3°C, would consider using the car's heating or seat heating based on prior experiences. However, the use of the car's heating system impacts the driving range, affecting BEVs more significantly than ICEVs. Imagining potential consequences when driving a BEV might include an unplanned search for charging infrastructure or, worse, the prospect of being stranded without a reachable charging station. Consequently, individuals may experience negative feelings when contemplating driving a BEV, particularly when considering a lower range buffer, such as 20% excess range, for this business trip.

Pre-Test and Planned Missing Design

For an overview of the pre-test and the implementation of a planned missing design, refer to Sub-study 1.1 in Chapter 2.1.

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required to book a BEV with 0% excess range. Consequently, booking an ICEV did not result in the awarding of a badge at any point after obtaining the Novice Driver badge.

Results

To test the hypotheses within the context of the theoretical extension of the TAM (refer to Figure 8), a composite-based partial least squares structural equation modelling approach was employed due to its capability to, for example, handle non-normal data distributions and formative latent variables[59], both of which are pertinent to this study (Chin & Newsted, 1999; Hair et al., 2020). The four variables subjective norm, image, perceived enjoyment of using the car booking software, and goal commitment were introduced above, building upon the TAM presented in Sub-study 1.1[60] (Chapter 2.1). Subjective norm and image were operationalised as formative variables, while the perceived enjoyment of using the car booking software and goal commitment were operationalised as reflective variables (refer to Appendix A for item details). All items were measured on a 7-point Likert scale, ranging from (1) *fully disagree* to (7) *fully agree*.

Assessment of the Reflective Measurement Models

The assessment of the reflective measurement models followed the approach of Hair et al. (2022) by assessing convergent validity, discriminant validity, and internal reliability using SmartPLS 4. The assessment of the measurement models commenced at their most granular level, that is, the indicators used to measure the two latent variables.

First, to determine indicator reliability, an indicator's loading should exceed .708. Squaring this value indicates whether the associated variable explains at least .50 and thus, accounts for at least 50% of the respective indicator's variance. However, for outer loadings (i.e. correlation weights) ranging between .40 and .708, Hair et al. (2022) suggest retaining the indicators once they met the

[59] In a reflective measurement model (e.g. goal commitment), a latent variable causes the indicators. Conversely, in a formative measurement model (e.g. image), the indicators cause a latent variable (Chin & Newsted, 1999; Hair et al., 2022).

[60] The variables of the TAM outlined in Sub-study 1.1 (Chapter 2.1) comprised the behavioural intentions to book a BEV, the perceived ease of using a BEV, the perceived enjoyment of driving a BEV, and the perceived usefulness of BEVs. All variables, except for perceived usefulness, were operationalised as reflective variables.

thresholds for composite reliability and average variance extracted (see below). This recommendation applied to two of the four indicators of goal commitment (see Table 16).

To establish the internal reliability of the latent variables Cronbach's alpha, composite reliability ρ_C and the reliability coefficient ρ_A were calculated. While Cronbach's alpha is deemed to be very conservative and composite reliability too liberal by Hair et al. (2022), they recommend using reliability coefficient ρ_A. All reliability values preferably range between .70 and .95, and ideally below .90, as values above .90 indicate semantic redundancy of the items associated with a construct. In summary, internal reliability can be accepted when achieving values within the acceptable range of reliability coefficient ρ_A. This applied to the two reflective variables, perceived enjoyment of using the booking software and goal-commitment.

Furthermore, the indicator reliability discussed above is also linked to the convergent validity of a latent variable. Convergent validity was assessed using the average variance extracted, which is calculated as the sum of the squared loadings of a variable, divided by the number of indicators. The average variance extracted should exceed .50, indicating that the indicators associated with a construct explain at least 50% of the indicators' variance (Hair et al., 2022).

Discriminant validity is established when a latent variable captures phenomena that are not captured by any other construct in the model. Henseler et al. (2015) and Hair et al. (2022) propose using the heterotrait-monotrait ratio, which requires a maximum threshold of .90, and ideally a value below .85. All heterotrait-monotrait ratio values were below the .90 threshold. Hence, discriminant validity for the two additional reflective variables (i.e. perceived enjoyment of using the booking software and goal commitment) in the comprehensive model, inclusive of behavioural intentions, perceived ease of use, and perceived enjoyment of driving a BEV, as illustrated in Figure 8, was established (see Table 16).

Table 16

Reliability and Validity of the Reflective Latent Variables

Variable	Indicator	Convergent validity			Internal consistency reliability			Discriminant validity
		Loadings	Indicator reliability	AVE	CA	ρ_C	ρ_A	HTMT < .9
Perceived enjoyment of using the booking software	1	.94	.89	.90	.95	.97	.95	Yes
	2	.95	.90					
	3	.96	.91					
Goal commitment	1	.53	.28	.60	.76	.85	.86	Yes
	2	.66	.47					
	3	.87	.76					
	4	.93	.87					

Note. AVE = average variance extracted, CA = Cronbach's alpha, HTMT = heterotrait-monotrait ratio.

Assessment of the Formative Measurement Models

To assess the formative measurement model of both subjective norm and image, the approach of Hair et al. (2022) was employed, which involves determining convergent validity, indicator multicollinearity, and the size and significance of indicator weights[61] (see Table 17).

To assess the content domain of a formative variable, Hair et al. (2022) suggest following a qualitative approach involving experts and conducting a thorough literature review. Eight automotive experts assessed the indicators used to measure subjective norm and image. To assess convergent validity, Hair et al. (2022) further recommend correlating the formatively operationalised variable with at least one reflective indicator that adequately captures the domain.

To investigate indicator multicollinearity, Hair et al. (2022) refer to the variance inflation factor, which requires values < 5 and ideally < 3. As per Hair et al. (2022), a substantial correlation

[61] Hair et al. (2022) state that indicator weights result from regressing the latent variable on its indicators, hence, representing each indicator's relative contribution to forming the construct.

among two or more indicators within a formative measurement model affects the estimation of indicator weights and their statistical significance. While image indicators 1 and 3 displayed values below 4, all remaining indicators ranged below a variance inflation factor of 3. Therefore, critical levels of collinearity were not reached.

Further, the assessment of indicator weights (i.e. outer weights) was conducted. Following the approach outlined by Hair et al. (2022), the initial step involved examining the significance of the outer weights. In cases where the outer weights are not statistically significant, Hair et al. (2022) recommend subsequently analysing the outer loading (requiring a value > .50) and its level of significance. If the outer loading is below .50 but significant, the removal of the specific indicator can be considered. In line with these procedures, it was observed that image indicator 3 and subjective norm indicators 1 and 5 exhibited non-significant weights but maintained significant outer loadings above the .50 threshold. Following the recommendations of Hair et al. (2022), the three indicators were retained.

Table 17

Summary of Results for Formative Latent Variables

Latent variable	Indicator	Outer weight	Outer loading
Subjective norm	1	$.10^{n.s.}$	$.82^{***}$
	2	$.27^{**}$	$.89^{***}$
	3	$.24^{***}$	$.82^{***}$
	4	$.51^{***}$	$.94^{***}$
	5	$.06^{n.s.}$	$.17^{*}$
Image	1	$.38^{**}$	$.85^{***}$
	2	$.26^{***}$	$.17^{*}$
	3	$.11^{n.s.}$	$.82^{***}$
	4	$.26^{**}$	$.72^{***}$
	5	$.42^{***}$	$.86^{***}$

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$, n.s. = not significant.

As the concluding step in the assessment of the measurement models, an investigation into the measurement invariance of the variables included in this study was undertaken. Although the distinctions in this study involve the utilisation of two experimental groups, the questionnaire used in this study remained consistent across both groups. However, as elucidated by Henseler et al. (2016), group comparisons may be misleading unless the invariance of measures is established. To preclude potential structural differences arising from the alternative group attributing a distinct meaning to a latent variable, Henseler et al. (2016) recommend the application of the MICOM procedure before aggregating (i.e. pooling) the data from the low-risk and high-risk groups for structural analysis. The MICOM procedure involves three steps, encompassing the assessment of configural invariance (step 1), compositional invariance[62] (step 2), and scrutiny for equal mean values and variances (step 3): in step 1, it is required that all composites (i.e. latent variables) exist in all groups, a condition satisfied in this study. MICOM steps 2 and 3 rely on permutation tests conducted with SmartPLS 4. The results of the permutation tests for steps 2 and 3 indicate the establishment of full measurement invariance. Consequently, the data from both the control group and the treatment group were pooled for structural analysis.

Assessment of the Structural Model

Again, the procedure by Hair et al. (2022) was followed to evaluate the structural model through the utilisation of SmartPLS 4. In this process, the extent of collinearity among constructs, the size and significance of the relationships between variables as well as the model's capacity for explanation and prediction were examined.

Initially, the structural model was subjected to a thorough assessment of collinearity among all latent variables within the comprehensive TAM, as illustrated in Figure 8. This evaluation involved the application of the variance inflation factor, as previously discussed in the context of indicator-

[62] Regardless of the underlying measurement model, whether reflective or formative, structural equation modelling techniques based on variance modelling depict latent variables as composites. This is achieved by generating proxies through linear combinations of the respective indicators for each latent variable (Henseler et al., 2016).

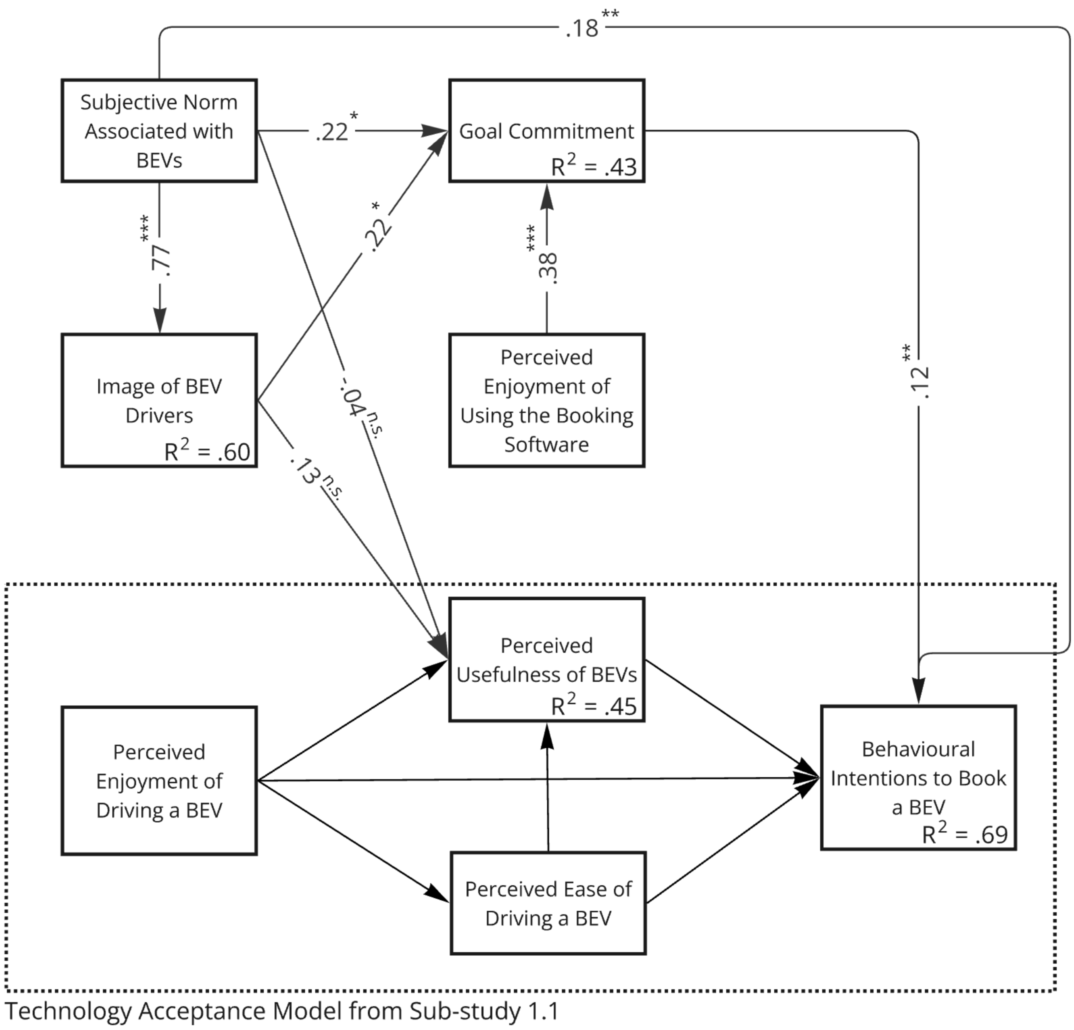
level assessment. The results indicated that all latent variables demonstrated values below 3, signifying the absence of collinearity issues among the constructs.

Secondly, to investigate hypotheses 2.1 to 2.8, analyses were conducted involving the assessment of correlations between variables (see Table 18), the examination of path coefficients within the structural equation model (interpreted as standardised regression coefficients), and the evaluation of f^2 effect sizes (see Figure 9 and Table 19). The f^2 effect size measures the proportion of explained variance in an endogenous construct (i.e. determinant) per exogenous variable (i.e. predictor). In accordance with Hair et al. (2014), values of .02, .15, and .35 define small, medium, and large effects.

The examinations will focus specifically on the hypothesised relationships within the context of this current TAM extension. The complete results of the TAM, encompassing the structural relationships of Sub-studies 1.1 and 1.2, are available in Appendix C.

Figure 9

Structural Model of the Pooled Dataset



Note. The arrows display path coefficients estimated using SmartPLS 4, interpreted akin to standardised regression coefficients (β) as per Hair et al. (2022).

BEV = battery electric vehicle.

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$, n.s. = not significant.

Table 18

Descriptive Statistics and Correlations Between Variables

Variable	*M*	*SD*	1	2	3	4	5
1. Subjective norm	4.83	1.10	-				
2. Image	4.71	1.07	$.78^{***}$	-			
3. Goal commitment	4.46	1.12	$.54^{***}$	$.51^{***}$	-		
4. Enjoyment booking software	4.79	1.40	$.40^{***}$	$.34^{***}$	$.54^{***}$	-	
5. Perceived usefulness	4.09	1.12	$.44^{***}$	$.46^{***}$	$.34^{***}$	$.38^{***}$	-
6. Behavioural intentions	5.03	1.43	$.65^{***}$	$.64^{***}$	$.48^{***}$	$.40^{***}$	$.64^{***}$

$^{***}p < .001$.

Table 19

Structural Relationship Effect Sizes

Hypothesis	Path	Path coefficient β	t-value	f^2 Effect size
H2.1	SN → PU	$-.04^{\text{n.s.}}$	.41	.00
H2.2	SN → IM	$.78^{***}$	28.10	1.51
H2.3	IM → PU	$.13^{\text{n.s.}}$	1.40	.01
H2.4	SN → BI	$.18^{**}$	2.54	.06
H2.5	GC → BI	$.12^{**}$	2.93	.03
H2.6	SN → GC	$.22^{*}$	2.24	.03
H2.7	IM → GC	$.22^{**}$	2.34	.03
H2.8	PEBS → GC	$.38^{***}$	5.82	.21

Note. SN = subjective norm, PU = perceived usefulness, IM = image, BI = behavioural intention, GC = goal commitment, PEBS = perceived enjoyment of using the booking software.

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$, n.s. = not significant.

As hypothesised, all variables demonstrated positive correlations of a medium to strong magnitude (see Table 18). However, concerning the results of the structural model, a statistically significant relationship was neither identified between subjective norm and the perceived usefulness of BEVs, nor between image and perceived usefulness, thereby failing to provide support for hypotheses H2.1 and H2.3. Nevertheless, evidence was found indicating that the subjective norm predicted image and explained a substantial portion of variance, thereby supporting hypothesis H2.2.

Both, subjective norm and goal commitment predicted behavioural intentions, supporting hypotheses H2.4 and H2.5. Furthermore, subjective norm and image predicted goal commitment, providing support for hypotheses H2.6 and H2.7. However, while there is evidence supporting a statistically significant influence of the aforementioned predictor variables, they only explained a small proportion of the variance in the determinant.

Lastly, the perceived enjoyment of using the booking software also predicted goal commitment, exhibiting a medium f^2 effect size. This signifies a moderate explanation of the variance in goal commitment, thereby offering support for hypothesis H2.8. Consequentially, in summary, six out of eight hypotheses were supported.

Table 20

Multigroup Analysis for Assessing the Impact of Badges on the Hypothesised Relationships

Hypothesis	Path	Path coefficient β control group	Path coefficient β treatment group	Difference in effect size
H2.5.2	GC → BI	$.09^{n.s.}$	$.13^{**}$	$.04^{n.s.}$
H2.8.2	PEBS → GC	$.26^{**}$	$.50^{***}$	$.24^{*}$
Not hypothesised	PU → BI	$.08^{n.s.}$	$.25^{***}$	$.18^{*}$
Not hypothesised	SN → GC	$.37^{**}$	$-.01^{n.s.}$	$.38^{*}$

Note. SN = subjective norm, PU = perceived usefulness, BI = behavioural intention, GC = goal commitment, PEBS = perceived enjoyment of using the booking software.

$^{*}p < .05$, n.s. = not significant.

To investigate the hypothesised moderating effects of badges, as outlined in hypotheses H2.5.2 and H2.8.2 (see Table 14), a multigroup analysis was conducted using SmartPLS 4. This approach aimed to identify statistically significant differences between the structural relationships of the control group, where badges were absent in the car booking software, and the treatment group, where badges were present in the software.

Contrary to expectations, no statistical evidence was found in support of H2.5.2, which posited that badges influence the relationship between goal commitment and behavioural intentions. However, significant moderating effects were observed regarding the impact of perceived enjoyment of using the booking software on an individual's commitment to engage with disseminated goals and gamified challenges, as hypothesised in H2.8.2. Notably, the moderation effect of badges was found to be positive, indicating that badges strengthened this association.

Furthermore, beyond the hypothesised effects, the data revealed two additional structural differences between the control group and the treatment group. Firstly, in the absence of badges, the association between perceived usefulness and behavioural intentions did not achieve statistical significance. However, when badges were present in the booking software, a statistically significant and positive relationship was observed in the treatment group. As a result, badges markedly enhanced the impact of perceived usefulness of BEVs on individuals' intentions to book a BEV.

Secondly, a contrasting effect of badges is evident in the relationship between subjective norm and goal commitment. While this association was statistically significant in the control condition, the introduction of badges rendered the relationship non-significant. Consequently, badges appear to have attenuated the strength of the association between the subjective norm associated with booking a BEV and an individual's willingness to engage with disseminated goals.

In the context of the third step in the four-step assessment of the structural model proposed by Hair et al. (2022), the model's explanatory power was examined using the coefficient of determination, R^2. According to Hair et al. (2014), R^2 values of .75 and above typically indicate a substantial explanation of the variables' variance, while values of .50 and .25 suggest moderate and weak explanations, respectively. All endogenous constructs were explained at a weak to moderate level (refer to Figure 9). Among them, behavioural intentions (R^2 = .69) exhibited the highest degree of explained variance.

In a final step, the model's predictive capacity was evaluated, representing the extent to which the model produces generalisable findings (refer to Table 21). For this evaluation, Hair et al. (2022) recommend utilising the $PLS_{predict}$ procedure for the indicators related to the target construct (i.e. behavioural intentions) within SmartPLS 4. To begin, in accordance with this procedure's requirements, both indicators associated with behavioural intentions exhibited $Q^2_{predict}$ values greater than zero, indicating the predictive capability of the model. Subsequently, the RMSE values of the two indicators linked to behavioural intentions were compared with those of a linear regression model that disregards the specified model for predictions. To establish the model's predictive capacity, relatively lower RMSE values are necessary. Although the RMSE value of indicator 2 exceeded the value of the linear model, indicator 3 did not. Therefore, while the RMSE value of indicator 2 implied a lack of predictive power, the remaining values for both quality criteria suggest the predictive capability of the structural model.

Table 21

Predictive Power of Model

Indicator	$Q^2_{predict}$	RMSE	Linear model
Behavioural intention 2	.59	.96	.91
Behavioural intention 3	.53	1.06	1.09

Note. RMSE = root mean square error.

Determining the Influence of Badges on Car Choice

As described earlier, in the context of the car booking experiment, participants were tasked with conducting three car bookings using car booking software. The treatment group was subjected to gamification elements in the form of badges, while the control group utilised the booking software without badges. To examine the first hypothesis (H1.1), which posited that BEV choice would be positively associated with individuals' behavioural intentions to book a BEV, a binary logistic regression analysis was conducted for each of the three bookings within each experimental group using IBM SPSS 28 (see Table 22).

Table 22

Binary Logistic Regressions Regarding Car Choice for Control and Treatment Groups

Booking	Cox & Snell R^2	Nagel-kerke R^2	*B*	Wald	*p*	*Exp(B)*	Likeli-hood	95% CI	
								LL	*UL*
CG 1	.11	.15	.61	11.20	<.001	1.84	84%	1.29	2.63
CG 3	.04	.06	.34	4.12	.042	1.41	41%	1.01	1.97
TG 2	.05	.07	.38	4.94	.026	1.46	46%	1.05	2.05
TG 3	.05	.07	.37	4.75	.029	1.45	45%	1.04	2.03

Note. The regression is based on the ordinal independent variable of behavioural intention and the binary dependent variable of car choice (0 = ICEV booked, 1 = BEV booked).

CG = control group (i.e. no badges displayed in booking software), TG = treatment group (i.e. badges displayed in booking software), CI = confidence interval, *LL* = lower limit, *UL* = upper limit.

To assess the suitability of the data for binary logistic regression, the omnibus test and the Hosmer-Lemeshow test were applied. The omnibus test examined whether behavioural intentions made a difference in predicting car choice within the model. The Hosmer-Lemeshow test was used to determine the model fit by comparing observed and expected outcomes through the creation of subgroups.

With respect to the control group, the findings revealed that bookings 1 and 3 successfully met the criteria of both the omnibus test and the Hosmer-Lemeshow test. In the treatment group, bookings 2 and 3 also satisfied both tests. However, it should be noted that control group booking 2 and treatment group booking 1 did not meet the requirements of the omnibus test, implying that, in those instances, behavioural intentions were not associated with the choice of car type. It is worth highlighting that the Pseudo R^2 values for the other four bookings – namely, control group bookings 1 and 3, and treatment group bookings 2 and 3 – suggested that behavioural intentions contributed to the prediction of car choice only to a minimal degree.

To investigate the association between behavioural intentions and the likelihood of booking a BEV, odds ratio values (i.e. *Exp(B)* values) were transformed into estimated probabilities[63] of the event occurring. The calculated odds ratios revealed that these four bookings demonstrated increasing probabilities for booking a BEV as the intentions to book a BEV increased. Among the four booking scenarios, control group booking 1 exhibited the highest probability, indicating an 84% increase in the likelihood of booking a BEV. Conversely, control group booking 3 displayed the lowest probability, with only a 41% chance of booking a BEV as behavioural intentions increased. In the treatment group, both treatment group bookings 2 and 3 consistently showed probabilities of 46% and 45%, respectively, for booking a BEV.

In conclusion, although car choice was not consistently associated with participants' behavioural intentions to book a BEV across the three bookings for both the control and treatment groups, there is still statistical support for hypothesis 1.1, which posited a positive relationship between individuals' car choice and their intentions to book a BEV.

To assess hypothesis H1.2, which posited that the treatment group would demonstrate a comparatively greater preference for BEVs than the control group, the participants' car choices are presented in absolute numbers (refer to Table 23). Additionally, the relationship between individuals' car choices and their membership in the control group or the treatment group was evaluated using the Chi^2-test of independence (see Table 24).

Table 23

Individuals' Car Choices in Absolute Numbers

Booking	Number of ICEVs booked	ICEV bookings in %	Valid share	Number of BEVs booked	BEV bookings in %	Valid share	Attrition from experiment	Attri-tion in %
Control group (no badges)								
1	77	64.2%	64.2%	43	35.8%	35.8%	0	0%
2	69	57.5%	62.2%	42	35.0%	37.8%	9	7.5%
3	70	58.3%	66.7%	35	29.2%	33.3%	15	12.5%

[63] Conversion formula: *(Exp(B)-1)*100*

Booking	Number of ICEVs booked	ICEV bookings in %	Valid share	Number of BEVs booked	BEV bookings in %	Valid share	Attrition from experiment	Attri-tion in %
Treatment group (badges)								
1	84	71.2%	71.2%	34	28.8%	28.8%	0	0%
2	74	62.7%	66.7%	37	31.4%	33.3%	7	5.9%
3	66	55.9%	63.5%	38	32.2%	36.5%	14	11.9%

Note. The column depicting the valid share does not incorporate missing data, specifically the data from participants who withdrew from the car booking experiment, as indicated in the column delineating individuals' attrition from the experiment.

BEV = battery electric vehicle, ICEV = internal combustion engine vehicle.

Concerning car choices in absolute terms, representing the number of participants who selected each car type, it is evident that more participants opted for ICEVs than BEVs in both experimental groups. Furthermore, the frequency of BEV bookings between the control group and the treatment group only exhibits a slight numerical difference.

As mentioned above, to explore the relationship between car choices and group assignment at an aggregate level, a Chi^2-test of independence was applied, as detailed in Table 24 below. This test determines whether car choice and experimental group assignment are independent or not through the aggregation of data, typically displayed in the form of a contingency table (see Cohen, 1988).

Table 24

Chi^2-Test of Independence for Choice Between Battery Electric Vehicles and Conventional Cars, and Membership in Control and Treatment Groups

Car booking	*n*	Chi^2-value	Degrees of freedom	*p*	Cramer's V
1	238	1.34	1	.25	.075
2	222	.49	1	.48	.047
3	209	.24	1	.63	.034

Overall, the results of the Chi^2-tests for the aggregated choice of car type and experimental group assignment indicate that for none of the three bookings there is statistical evidence supporting an association between individuals' car type selection (BEVs or ICEVs) and their assignment to the control group or treatment group. This conclusion is further supported by the low Cramer's V values.[64]

In summary, while there were minor disparities in car choices between the control group and the treatment group as per the absolute figures, the results of the Chi^2-test indicate that badges did not exert a significant influence on BEV preference. Consequently, the findings did not yield statistical support for hypothesis H1.2, which postulated that the treatment group would exhibit a significantly stronger preference for BEVs compared to the control group.

Discussion

This study presents evidence that the integration of the gamification element badges into the car booking software influenced individuals' judgment of BEVs and their use for business trips. However, this integration did not impact participants' overall preference for BEVs. Specifically, the presence of badges strengthened the relationship between individuals' enjoyment of using the car booking software and their commitment to engage with goals and gamified challenges related to car choice. Notably, a significant relationship between subjective norms and individuals' goal commitment was observed in the control group, whereas it was non-significant in the treatment group. Participants' goal commitment showed a modest, yet statistically significant influence on individuals' intentions to book a BEV. However, contrary to expectations, badges did not further enhance this association. Furthermore, although there was no statistically significant association between the perceived usefulness of BEVs and participants' intentions to book a BEV in the control group, this association was statistically significant and positive in the presence of the badges

[64] According to Cohen (1988), the Cramer's V value signifies the strength of association between variables. Values below .10 indicate a small effect, values of .30 represent medium effects, and values of .50 denote large effects (Cohen, 1988).

intervention. However, while individuals' behavioural intentions to book a BEV were associated with car choice for two out of three car bookings per experimental group, badges were not found to enhance BEV preference.

The preference for conventional cars was observed in the majority of participants across both experimental groups. Additionally, concerning individuals' car selections throughout the three car bookings, a lower frequency of BEV bookings was noted in the treatment group compared to the control group. Initially, this outcome suggests a potential attenuation of individuals' inclination towards BEVs due to the incorporation of gamification in this study. Such a behavioural response could be construed as a boomerang effect (see Brehm, 1989), akin to the psychological reactance identified in Richter et al.'s (2018) investigation into the promotion of sustainable fish consumption. However, there are additional indications that do not align with this conclusion. Despite a lower choice of BEVs in the treatment group, the data reveals a steady increase, rather than a decline, in the number of BEV bookings across the three bookings. In contrast, the control group exhibited a decrease in BEV bookings. These observations do not substantiate the conclusion of a reactant response to gamification badges. Furthermore, despite disparities in absolute figures, the observed differences were not statistically significant for any of the three bookings between the two experimental groups. Therefore, there is no empirical evidence supporting the hypothesised positive influence of badges on car choice. Conversely, there is also no statistical evidence of a boomerang effect resulting from the badges intervention.

Although badges did not directly influence the choice of car, their impact extended to several relationships within the TAM, which was utilised in this study to predict participants' behavioural intentions regarding the booking of BEVs. The subsequent analysis will explore these findings in greater detail, aiming to enhance the comprehension of participants' responses to the gamification stimulus.

The results of this study indicate that the gamification element badges positively influenced two relationships. On the one hand, the results revealed a positive association between the perceived usefulness of BEVs for business trips and individuals' behavioural intentions to book a BEV.

This relationship was not found to be significant in the control group. The observed influence of the intervention suggests that badges increased the perceived utility or value associated with BEVs. This change in the perceived value of an object due to an attribute that inherently does not carry any added functionality or monetary value resembles the findings of a study by Ayton et al. (2022), who observed a similar effect, however, in a different application context. In their study, Ayton et al. (2022) examined the influence of attaching blue plaques to buildings in the London area, referring to notable men and women who had previously lived in this estate. Through a comparison of price changes before and after the installation of new plaques with property prices in the same neighbourhood for a specific measurement period, Ayton et al. (2022) found that this item increased the prices of properties with plaques by 27% compared to houses without plaques. To explain this observation, Ayton et al. (2022) refer to the theory of magical contagion, fundamentally stating that the perceived value of objects changes once they have come into contact with a known person. The buildings in the study by Ayton et al. (2022), despite being adorned with a blue plaque, did not distinguish themselves through higher construction quality or amenities and yet experienced an increase in value. Essentially, the same applies to BEVs and their complementary badges in this study: the BEVs in this study were not previously driven by a known person or used in any related context that would justify them being perceived as more useful than the other cars available in the shared fleet. Furthermore, none of the BEVs changed in terms of their functionality, such as available driving range or other performance-related features. Nevertheless, the findings of this study imply that badges appear to have enhanced the perceived value and associated benefits of BEVs for business trips and, consequently, individuals' intention to book a BEV.

On the other hand, badges reinforced the association between the perceived enjoyment of using the car booking software and participants' goal commitment. Consequently, individuals who experienced greater pleasure from utilising the gamified car booking software were more inclined to engage with and commit to disseminated goals or gamified challenges associated with car choice.

However, apart from these two determined effects of badges on individuals' perception of the booking software and the perceived usefulness of BEVs, badges were not found to extend to individuals' behavioural intentions and car choice. In their respective gamification studies, Hamari (2013) and Hamari and Koivisto (2013) advocate the inclusion of Locke and Latham's (2002) goal commitment as a predictor for the success of gamification strategies. Recall the results of Landers et al. (2017), who found that goal commitment played a moderating role in the effectiveness of leaderboards. Specifically, participants who did not perceive the leaderboard as representing meaningful goals also did not exhibit changes in their performance during the brainstorming task. Relatedly, in the context of facilitating goal commitment, Locke and Latham (2002) referred to goal importance, which concerns the perceived importance of the outcome related to achieving the goal. This implies that, in conjunction with the manner in which the goals were presented to them (i.e. the leaderboard), participants in the study conducted by Landers et al. (2017) deemed the outcomes of performing well in the brainstorming task as worthwhile pursuits. In the context of their findings, Landers et al. (2017) recommended that practitioners measure goal commitment early in the implementation phase to anticipate the envisaged effect of an intervention. While there was a significant relationship between goal commitment and individuals' behavioural intentions to book a BEV in this study, commitment only weakly explained intentions as well as badges did not significantly moderate this association. Interpreting the findings suggests that individuals may have considered achieving badges in the software to be an amusing experience, but changing their car choice solely to earn the badges might not have been regarded as a worthwhile outcome, not even in a hypothetical setting. Consequently, the findings suggests that goal commitment can be considered a precursor to the observations made in the car booking experiment. Furthermore, the findings also suggest that the implementation of badges in this study may require modifications to influence individuals' intentions and subsequent choices, as will be further elaborated in the course of this discussion.

The TAM utilised in this study was expanded to include the two social factors: subjective norm and image. Results demonstrated a direct, but weak influence of subjective norm on the behavioural intentions to book a BEV. As previously outlined in the introduction, scholars such as Hartwick and Barki (1994) or Venkatesh and Davis (2000) argue that subjective norms directly influence behavioural intentions when individuals perceive the use of the system as mandatory. Therefore, the results imply that participants were aware that choosing to book a BEV instead of an ICEV would be socially compliant and, consequently, a reasonable decision. Further, both, subjective norm and image, weakly predicted goal commitment in the control group. However, in the treatment group, badges attenuated the significant influence of subjective norm on goal commitment, rendering this association statistically non-significant. This suggests that individuals in the control group depended on their social environment to assess their participation in disseminated goals and challenges. In contrast, within the treatment group, badges seemed to serve as a more pertinent source of information compared to their corporate reference peers.

Furthermore, data showed that neither subjective norm, nor image statistically significantly predicted the perceived usefulness of BEVs. The fact that perceived usefulness did not mediate the effects of social factors on individuals' intentions implies that their corporate environment may not have served as a source of information for evaluating the benefits of BEVs. Specifically, Venkatesh and Davis (2000) claim that such missing mediation indicates a lower degree of value internalisation and identification with their reference peers when evaluating new corporate technology.

Interpreting the results described above using Ryan and Deci's (2000) self-determination theory, and specifically their taxonomy of extrinsic motivation, suggests that participants in this study could be attributed a form of extrinsic motivation[65] characterised by lower internalisation of values and behavioural regulations. Specifically, Ryan and Deci (2000) describe that such individuals derive motivation for performing a particular behaviour from perceiving social pressure, avoiding guilt or anxiety, or enhancing their self-esteem, pride, and feelings of worth. Moreover, a new set of values and their corresponding behavioural regulations might even be considered controlled and alienated,

[65] Ryan and Deci (2000) introduced a taxonomy categorising extrinsic human motivation into four types, ranging from initial unwillingness or reactance to the full integration of relevant corporate values and behavioural regulations. They argue that a higher degree of internalisation leads to increased commitment, engagement, and persistence, fostering a sense of greater self-determination among individuals.

potentially even leading to individuals responding with reactance. However, as argued above, the results in this study do not provide evidence to support the assumption of the influence of psychological reactance. Consequently, although the influence of subjective norm on behavioural intentions was low, the considerations above nevertheless imply that individuals who stated their intention to book a BEV in the future might have been driven, among other factors, by the motivation to please their business environment.

Overall, the influence of social factors within the TAM was notably weak, which might also affect the anticipated influence of gamification interventions on individuals' behaviours and choices. For instance, Hamari and Koivisto (2013) emphasise the significance of community and network effects in the success of gamification interventions. Specifically, insights from Hamari and Koivisto's (2013) study on badges in a fitness tracking application indicate that a human network can enhance the influence of social factors on users of the gamified service. This network, specifically the sports community, exerted an influence on various factors in the model predicting usage intentions. For example, it directly and indirectly affected individuals' attitudes and intentions towards the service, such as the perceived benefits of using the gamified service or the recognition received from other users, which can be generated through social feedback elements such as likes[66] (Hamari & Koivisto, 2013). Consequently, Hamari and Koivisto (2013) underscored the significance of promoting a community dedicated to shared goals for the success of gamification. They argue that creating a community that enables active participation and meaningful interaction, while allowing individuals to experience the benefits of using the system, can enhance their willingness to use the service. Therefore, Hamari and Koivisto (2013) emphasise that elements encouraging social interaction are pivotal in creating engaging and valuable services. Moreover, Hamari and Koivisto (2013) explicitly suggest fostering an interactive community where people can act in competition with each other.

This recommendation by Hamari and Koivisto (2013) finds further support in a field-

[66] A like is a digital interaction where a user expresses their approval or interest in a post or activity of another person by clicking a button, often represented as a heart or thumbs-up icon, signalling their support.

experiment by Hamari (2013). Hamari (2013) implemented badges in a peer-to-peer trading service and found that badges did not impact behaviour, specifically usage activity, for all system users. Instead, badges did affect those individuals who predominantly monitored their own badges and to some extent also those of others. The observation by Hamari (2013) implies that the influence of comparing their individual progress as well as the progress of important others can be an incentive to engaging with the service and to consequently adapt behavioural regulations for the aim of progressing.

While Hamari's (2013) research primarily focuses on the impact of badges on individuals' engagement with gamified services, there is additional evidence suggesting that the visibility of actions can also influence individuals' choices between products and their eco-friendly alternatives. For instance, Griskevicius et al. (2010) explored how the desire for status influences the preference for less luxurious green products (with pro-environmental features) versus equally priced luxurious non-green products (offering superior luxury and performance). Specifically, in their study, Griskevicius et al. (2010) investigated various products and provided scenarios to participants in the treatment group aimed at eliciting status motives, such as the desire for social status and prestige. Furthermore, participants were assigned to one of two conditions in which they were asked to imagine shopping in a public or private setting (e.g. in a physical store or online). The results showed that in the control group (where no status motives were induced), participants preferred the luxurious non-green variant, regardless of whether they were shopping in public or private. However, in the treatment condition, which emphasised status motives, individuals' preferences shifted towards less luxurious green products when imagining shopping in a public setting. Conversely, when participants envisioned shopping online, the treatment group increased their preference for the more luxurious non-green version, which Griskevicius et al. (2010) attribute to costly signalling (a notion related to conspicuous consumption, see Veblen, 1912). Consequently, their study highlights the impact of status motives and the visibility of choices on individuals' preferences for eco-friendly products compared to non-green alternatives.

While the findings of Hamari (2013) and Griskevicius et al. (2010) are not entirely consistent, they collectively suggest that the visibility and tracking of one's own activities, coupled with the signalling of one's behaviour to others, in conjunction with the desire for status, may function as motivating factors for engaging in specific behaviours and influencing choices.

In the car booking software, the badges earned or yet to be earned were visible only to the individual and not to other users of the car booking software. Nevertheless, participants were able to view their individual progress. On the one hand, this limitation in signalling their behaviours to important others may have reduced the anticipated impact of badges on individuals' intentions and car selections, as specifically suggested by Griskevicius et al. (2010). On the other hand, participants had the opportunity in the car booking software to view their own progress, which Hamari (2013) identified as a relevant factor to the success of gamification. Insights from a study conducted by Bandura and Schunk (1981) provide further understanding of potential reasons why the results did not demonstrate an influence of gamification on car choice as hypothesised. In the context of self-efficacy theory, Bandura and Schunk (1981) exposed students to mathematical tasks under varying goal conditions. Their results showed that individuals made the most progress when striving for proximal goals, compared to three other goal type conditions: distal goals, no goals, and the control group[67]. According to Bandura and Schunk (1981), the experience of successfully mastering a set of mathematical tasks by breaking them into attainable subgoals improved their veridical self-knowledge of capabilities. This, in turn, increased their personal efficacy and intrinsic interest in mathematical tasks that had previously held little appeal to them as well as their motivation to engage with more challenging goals. Relatedly, Locke and Latham (2002) emphasised that perceived self-efficacy serves as a facilitator of goal commitment. A similar effect can be found in the gamification study conducted by Gutt et al. (2020). Gutt et al. (2020) introduced goals of varying

[67] In the proximal goal condition, students received advice or suggestions regarding suitable intermediate goals in the context of the final goal. In the distal goal condition, students were solely provided with the final goal. In the no-goal condition, students were instructed to complete as much as possible within the given time. In the control group, no performance indication was provided whatsoever (see Bandura & Schunk, 1981).

difficulty levels utilising badges within a German Question and Answer community. According to the results from Gutt et al. (2020), upon successfully achieving a goal, participants exhibited a heightened willingness to undertake more challenging tasks, thereby motivating them to exert greater effort in pursuing subsequent, more difficult goals.

In conclusion, the two previously mentioned studies by Bandura and Schunk (1981) and Gutt et al. (2020) share the commonality that participants were able to actively engage with tasks, consequently confirming their actual abilities, which in turn motivated them to engage with tasks of higher difficulty. In contrast, participants in this study were only exposed to hypothetical usage scenarios and had no opportunity to approach experimenting with BEVs in an easier setting (i.e. less risky setting) to gain confidence in their skills for tackling goals of higher difficulty. Interpreting these results through the lens of self-efficacy theory (Bandura, 1982) and the specific gamification literature above implies that the incremental confirmation of knowledge enabled by proximal goal setting serves as a fundamental lever for approaching tasks with higher levels of difficulty. Consequently, individuals who, for example, perceive driving a BEV with a lower range buffer as more risky and consequently more challenging (i.e. difficult) compared to a BEV with a higher range buffer may need to gain practical experience in less challenging situations before attempting more difficult usage situations.

In summary, badges were identified as having a positive impact on the perception of the car booking software and the perceived benefits of BEVs. However, the results of this study also suggest that individuals' overall commitment to participate in goals and gamified challenges associated with car choice did not extend to an enhanced BEV preference. When interpreting the findings of this study in the context of goal-setting theory, self-efficacy theory, self-determination theory, and other above cited literature, it is important to consider the following factors as premises for effectively setting up gamification interventions. Literature suggests that a community that shares common goals and values is pivotal for the success of gamification interventions. Such a community might also recognise the importance of the respective goals being represented in the form of the chosen gamification element and commensurately consider the outcomes associated with that element as valuable pursuits. The above cited literature further suggests that a successful gamification intervention may rely on a community that facilitates meaningful and rewarding interactions, allows individuals to track their own progress, supports monitoring and observation, encourages competition with significant peers, and enables comparisons with individuals of importance, which can reinforce the commitment of individuals. Consequently, the insights from this study, paired with the aforementioned recommendations, serve as an inspiration for future research to discover whether gamification elements can in fact not only influence performance and engagement but also technology choice.

Practical Implications

The following practical recommendations are based on the results presented in this sub-study. While there was no statistical evidence for the effect of badges on car choice, badges did enhance the influence of the perceived enjoyment of using the car booking software on employees' commitment to engaging with goals and gamified challenges. For software designers, organisations, and fleet managers this indicates that encouraging employees to explore the software could create a more engaging and enjoyable user experience. This, in turn, may motivate them to discover new car options or other features within the car booking software with greater enthusiasm and satisfaction. Thus, incorporating such gamification elements might be beneficial in promoting BEV usage.

Although there was no statistically significant association between the perceived usefulness of BEVs and participants' intentions to book a BEV in the control group, this association became statistically significant and positive in the presence of the badges intervention. For car manufacturers and software designers this insight suggests that gamification badges encouraged individuals to consider booking a BEV. This finding implies that such design elements could be applied in related BEV areas. For example, original equipment manufacturers (e.g. car manufacturers, charging infrastructure providers) and software designers could use gamification to promote the usage of specific charging stations. This could include encouraging the use of alternating current (AC) charging, which involves slower charging speeds, over direct current (DC) charging, which involves faster charging speeds but could impact battery capacity in the long term (see Argue, 2023).

The results indicated that badges did not influence the relationship between participants' commitment to engaging with digital goals and gamified challenges and their intention to book a BEV, as further evidenced by no changes in car preferences. As highlighted by Landers et al. (2017) and Hamari (2013, 2017), goal commitment is a relevant predictor of the success of gamification interventions. Consequently, measuring goal commitment could be a valuable tool for software designers when pre-testing gamification interventions. This could serve as an early indicator of whether the intended intervention will achieve the desired effects or if adjustments are necessary. The results may guide software designers in better understanding the potential impact of gamification elements on their target user groups. Additionally, considering factors such as age, gender, experience, company size, and other factors, may provide further insights into specific user preferences. For example, Koivisto and Hamari (2014) found that gender and age influenced the perception of a gamified fitness application.

As noted above, the strengthened association between the enjoyment of using the booking software and goal commitment through the gamification intervention suggests that individuals derived pleasure from interacting with gamification badges. However, the data also indicates that changing their car choice solely to earn badges might not have been perceived as worthwhile, even in a hypothetical setting. Therefore, if fleet managers do not (wish to) apply the TAM in its entirety, they might consider measuring employees' goal commitment in relation to their intentions to engage with the target system. This approach could help anticipate whether the gamified service, or the act of gamifying the service, would be perceived as valuable by potential users. These considerations may also extend to software and technologies beyond BEVs, car booking software, and fleet management in general.

Limitations and Directions for Future Research

In addition to the specific statistical limitations previously discussed, the primary limitations identified in this study are outlined below.

A limitation of this study arises from the hypothetical nature of the car booking experiment, wherein participants did not actually book cars from a genuine car fleet or for a real business trip. This hypothetical setup may have constrained the impact of social factors, as participants lacked the opportunity for meaningful social interactions, a factor explicitly emphasised by Hamari and Koivisto (2013) for the effectiveness of gamification interventions. In accordance with the recommendations of Bandura and Schunk (1981), badges in the form of proximal goals were presented; however, the experiment's hypothetical nature imposed a notable limitation. Despite the indications from Bandura and Schunk (1981), proposing that practical experience might enable individuals to progressively cultivate confidence in their skills and thereby encourage them to voluntarily pursue more challenging goals, participants in this study were not given the opportunity to experiment with the technologies and their skills. Consequently, the absence of practical experience may have limited the anticipated effectiveness of the badges intervention. Accordingly, future studies could investigate whether the combination of proximal goal setting and gamification, within an experimental framework that enables participants to actively explore their own skills and capabilities, enhances the accessibility of new technologies for individuals and, consequently, influences technology choice.[68]

Furthermore, whether badges proved effective in the study by Hamari (2013) was contingent on the frequency with which individuals monitored their own progress and, to some extent, on viewing the progress of others. Consequently, the limited time available to participants for engaging with the badge system in the context of the car booking experiment may have been a constraining factor. Participants could only form a spontaneous impression of the presented gamification

[68] There is other literature corroborating the projected effect on technology choice: Rogers' (1983) theory of diffusion of innovation refers to trialability being one of the factors which enhance innovation adoption.

elements, potentially leaving insufficient time for progress tracking. Additionally, participants were unable to receive feedback from their peers regarding their engagement with the service, as suggested by the network effect outlined by Hamari and Koivisto (2013). While Landers et al. (2017) observed an impact of their gamification intervention on performance, they also considered the 12-minute brainstorming task used in their study as a relatively brief period for an individual to fully comprehend the novelty of the leaderboard and the associated goal requirements. The prompt response observed among participants in the context of this study yields valuable insights into individuals' reactions to gamification interventions. However, it remains uncertain whether the intervention would have exerted a significant influence on car choices had participants been afforded the opportunity to gain experience with various challenges, allocate time for self-progress monitoring, and engage in meaningful interactions with significant others. This question remains unaddressed in this study, presenting an avenue for exploration in future studies.

This study exclusively examined one product pair, comprising one sustainable product and its conventional alternative, which may restrict the generalisability of findings concerning the influence of gamification on other technology choices. While the insights presented in this study might be applicable to other domains, it is recommended that future studies broaden their scope to encompass a diverse array of technologies, including research in social environments beyond the business context. This inclusive approach would enhance a comprehensive assessment of the impact of gamification on technology choice.

Finally, this study exclusively focused on a singular gamification element, namely badges, potentially limiting the understanding of the impact of various gamification elements or their combined effects on technology choices. Consequently, future studies could explore various elements or their combinations to comprehend their specific influence on technology choices.

Chapter 2.3: Sub-Study 1.3 - Exploring the Effects of Gamification on Technology Choice in Risky Usage Contexts

Abstract

This study is based on the dataset derived from a comprehensive study structured on a 2x2 factorial design. Participants were assigned to one of two differentially risky hypothetical business trip scenarios (i.e. factor 1) and further allocated to a condition where gamification was either absent or present in car booking software (i.e. factor 2). Factor 1 was examined in Sub-study 1.1, factor 2 was examined in Sub-study 1.2, and this study investigates the interaction of both factors. Specifically, with the aim to explore how gamification badges affect car type preference between BEVs and conventional cars, participants were randomly assigned to either a low-risk or high-risk business trip. Subsequently, based on the assigned trip, participants conducted three car bookings using car booking software, with badges being absent in the control group and present in the treatment group. The results suggest that badges did not motivate BEV preference over conventional cars, regardless of the associated risk level in the business trip. While aggregated data of the three car bookings did not reveal an influence of badges in either business trip context, regression analyses revealed variations in the strength of the association between car choice and behavioural intentions across the four experimental conditions. In the low-risk control group (i.e. badges absent in the software), intentions consistently predicted car choices in all three bookings, but this association was less reliable when participants were exposed to the badges intervention (i.e. low-risk treatment group). Furthermore, the results indicate an association between participants' decision to withdraw from the car booking experiment, rather than selecting any car, and their assignment to a high-risk trip. These observations are discussed in the context of the affect heuristic, suggesting that participants may have experienced negative emotions prompted by badges or higher-risk trips.

Introduction

Game-like elements such as levels, leaderboards, or progress bars[69], recognised for their motivational impact in conventional gaming, have been integrated into non-gaming contexts (Deterding et al., 2011) with the objective of enhancing individuals' enjoyment, engagement, and task performance in specific activities, as demonstrated in numerous studies (Boratto et al., 2017; Gutt et al., 2020; Hamari & Koivisto, 2013; Landers et al., 2017; Landers & Landers, 2014). This approach, commonly referred to as gamification, is predominantly associated with its utilisation in digital applications, encompassing mobile phone applications and other digital services, spanning various domains such as language learning (e.g. Duolingo, see Bilham, 2021) or sporting activities. For instance, Hamari and Koivisto (2013) conducted a field experiment investigating the integration of badges within a platform designed for monitoring individuals' physical exercise routines. The convergence of fitness and gamification, exemplified by this case, is a recurring theme not only in academic literature but also in commercial applications. Prominent sports tracking applications, such as Strava, Adidas Running, and Nike Run Club, incorporate various gamification elements, including leaderboards, points, badges, social feedback, and others. Similarly, hard- and software manufacturer Apple has integrated a badge system designed to motivate individuals to consistently track their activities and monitor progress using their smartwatches. Overall, these mentioned applications and systems appear to be designed with the objective of inspiring users to pursue individual activity goals, engage in friendly competition, and provide a means to easily share the results of their workouts and personal improvements.

With goal-setting theory, Locke and Latham (2002) introduced a comprehensive framework for designing goals as meaningful and potent motivators to enhance individuals' performance. In this context, the utilisation of gamification elements can also be viewed as manifestations of goals, designed to playfully acquaint individuals with challenges. These challenges often start with a certain level of simplicity to alleviate uncertainties and usually progress in complexity. The approach of

[69] Refer to Table 1 for a detailed description of these and various other gamification elements.

subdividing larger goals into smaller sub-goals, referred to as proximal sub-goals by Bandura and Schunk (1981), was further investigated by Locke and Latham (2002) or, in the context of gamification, by Gutt et al. (2020). Gutt et al. (2020), who analysed data from a German Question and Answer community enriched with badges, investigated the impact of goal attainment on individuals' efforts to reach subsequent milestones. According to Gutt et al. (2020), their findings underscore that the successful achievement of badges (i.e. goal attainment) is associated with individuals' sustained efforts to attain subsequent, more challenging badges, provided that the badge represents a meaningful challenge to the user. Accordingly, the findings by Gutt et al. (2020) suggest that, despite the escalation in difficulty levels as individuals progress, there persists a motivation to strive for more challenging objectives.

However, the perceived difficulty of a task and the confidence in successfully mastering it may not exclusively depend on the predefined difficulty level of a specific goal. It can be assumed that the perception of task difficulty is also influenced by other factors, such as the context or situation in which the task is carried out. To illustrate, envision the following challenge, derived from an actual challenge presented in one of the previously mentioned commercial applications designed for tracking physical activities, from a user's perspective: imagine that upon opening the application, a notification prompts the user to participate in a physical challenge. This challenge entails covering a distance of 15 kilometres within the next week to earn a specific number of points within the application. Hence, in this instance, the level of difficulty is contingent upon accomplishing the 15 kilometres within the specified timeframe. When evaluating the task, the cyclist may express confidence in their abilities (see Bandura, 1982, and the notion of self-efficacy)[70], quickly concluding that they are in good shape and well capable of cycling 15 kilometres in the next week. However, considering the individual's preference for outdoor instead of indoor cycling, the cyclist additionally checks the weather forecast. Initiated by the weather forecast revealing a temperature of 3°C and

[70] Bandura's (1982) notion of self-efficacy pertains to an individual's personal evaluation of their ability to perform a specific behaviour.

constant rain for the upcoming days, thoughts may shift to recalling previous negative experiences while cycling in such situations, such as slipping on wet surfaces and incurring injuries. An elicited rush of negative emotions might now instead demotivate the cyclist from engaging in the now rather risky endeavour. Consequently, the cyclist might now harbour some scepticism about the likelihood of successfully completing this challenge and the earning of the projected points.

In summary, Locke and Latham (2002) define goal difficulty as the likelihood of task success. However, although the task might seem manageable in isolation, the example above indicates that assessing the level of difficulty of the challenge may also extend to judging the perceived risk associated with the context in which the desired behaviour linked to the challenge is to be performed.

The above example also serves to illustrate that an individual's emotions can play a pivotal role in evaluating a challenge for its perceived risk and in contemplating whether engaging in it is a prudent choice. Zajonc (1980), who explored the impact of emotions on judgment and decision-making, asserted that affective responses to stimuli often constitute the initial reactions and can occur more rapidly than cognitive processes. Correspondingly, when considering whether to engage in a risky endeavour, the affect heuristic (e.g. Slovic et al., 2004), which attributes a central role to emotions in judgment and decision-making, indicates that emotional responses evoked by images of potential consequences can influence one's decision about participating in risky activities. Specifically, according to the affect heuristic (Slovic et al., 2004, 2007), a positive emotional response to a stimulus would likely serve as an encouragement to participate in the incentivised activity, while the experience of negative emotions would more likely act as a deterrent to engaging in the activity. Moreover, as discussed within their risk-as-feelings hypothesis, a concept related to the affect heuristic, Loewenstein et al. (2001) emphasise that emotions may even drive behaviour to the extent that individuals might pursue a course of action they would not have otherwise considered as their best course of action. Both Zajonc (1980) and Slovic et al. (2004, 2007) contend that even the mere exposure to specific words can evoke positive or negative emotions. Consequently, simply evaluating a weather forecast may trigger positive or negative emotions in relation to the judgment of a particular activity. Hence, while a forecast of 3°C and rain might elicit negative emotions, conversely, on a typical cloudless summer day of 20°C, the cyclist contemplating whether to engage with the challenge would not be predisposed to perceiving the situation as risky, but the individual might instead feel quite content and enthusiastic about the specific challenge.

In summary, the cyclist example presented above illustrates that the perceived difficulty of a task can extend beyond its inherent complexity, as defined solely by the task requirements, to include the evaluation of one's skills needed for task completion. Moreover, the example indicates that the perceived risk associated with the gamified task may also vary with the specific context of behavioural performance associated with the task. These considerations suggest that contemplating such risky contexts of behavioural performance could influence individuals' willingness to engage with the specific challenge.

Existing literature has demonstrated the motivational power of gamification elements. As previously mentioned, Gutt et al. (2020) specifically showed that the successful attainment of badges was linked to sustained efforts to achieve subsequent, more challenging badges, provided that the badge presented a meaningful challenge to the user. Nonetheless, while gamification has been studied and proven effective in terms of increasing individuals' engagement with tasks and their performance (e.g. Hamari, 2013, 2017; Landers et al., 2017), its efficacy in the context of motivating specific technology preferences for risky usage contexts remains unexplored.

Hence, the objective of this study is to examine the influence of gamification elements on technology choices in risky technology usage contexts.

The investigation of this research objective is founded on the dataset from a comprehensive study (labelled Study 1), organised into three foundational analyses referred to as Sub-studies 1.1, 1.2, and 1.3 (with Sub-study 1.3 representing the current investigation). The findings of Sub-study 1 are expounded upon in Chapter 2.1, and the results of Sub-study 1.2 are outlined in Chapter 2.2. Both are succinctly summarised below.

Summary of Results from Sub-*S*tudies 1.1 and 1.2

The overarching objective of the comprehensive study (i.e. Study 1) was to investigate individuals' preferences for car types within a shared corporate car fleet designated for business trips in Germany.[71] An online car booking experiment was conducted to examine the influence of the gamification element badges[72] on the choice between BEVs and ICEVs in two distinct business trip scenarios characterised by varying levels of risk. As detailed in the forthcoming methodology section, a 2x2 factorial between-subjects design was utilised. Participants were randomly assigned to either a hypothetical low-risk business trip or a high-risk business trip. Furthermore, participants were divided into two groups: the control group, where gamification badges were absent in the car booking software, and the treatment group, where badges were present in the software. Participants were instructed to conduct three car bookings based on their assigned trip using the car booking software. Within the software, participants were presented a hypothetical car fleet comprising an equal number of BEVs and ICEVs. The cars were matched in terms of vehicle class and equipment, allowing for choice between BEVs and ICEVs to be studied. Subsequently, participants completed a questionnaire designed to assess a TAM[73] specifically adapted to this research context.

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[71] This technology pair was specifically selected because BEVs, the touted sustainable alternative to ICEVs, exhibits a relatively slower rate of adoption in the German market (13.6% of newly registered cars were all-electric in 2021) compared to other markets, such as Norway (64.5% in 2021), thereby presenting an interesting example and market to be studied (Kraftfahrtbundesamt, n.d.-b; Teslamag, 2022).

[72] Among various gamification elements, badges were selected due to their demonstrated effectiveness in motivating individuals to exhibit higher engagement, as shown in previous research (e.g. Gutt et al., 2020; Hamari, 2013, 2017).

[73] To predict the acceptance of technologies, Davis (1986) introduced the TAM with the goal of gauging the impact of perceived usefulness and perceived ease of use of an information technology in the context of job-related tasks. The TAM aims to elucidate how these factors influence individuals' attitudes towards using the technology and, consequently, their decision to use it.

Below, the findings of Sub-studies 1.1 (Chapter 2.1) and 1.2 (Chapter 2.2) will be concisely outlined, with a focus on the impact of the respective interventions on car choice and their influence on predicting car choice from behavioural intentions (refer to Figure 10).

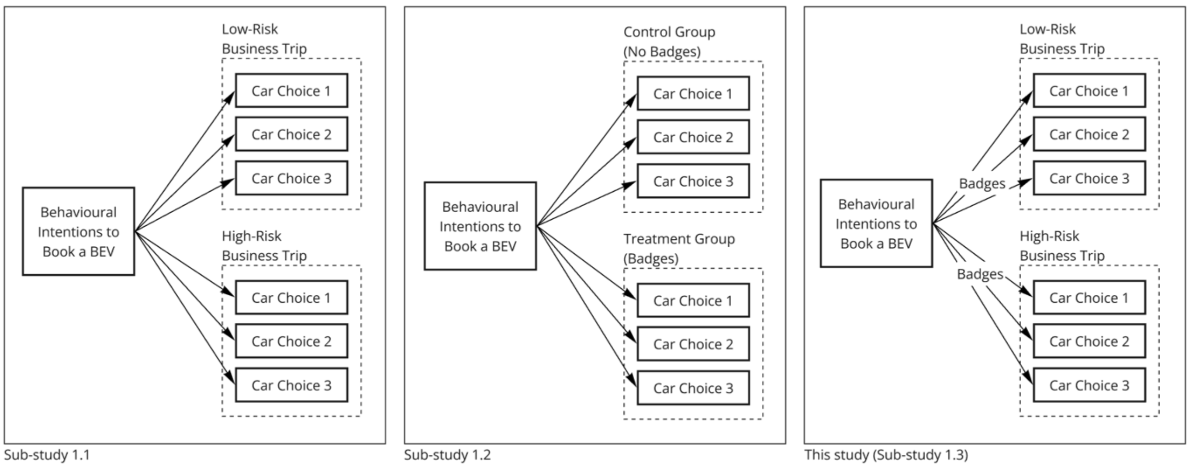
In Sub-study 1.1, data analysis focused on elucidating the influence of the two differentially risky, hypothetical business trips on the choice between BEVs and ICEVs. Consequently, Sub-study 1.1 did not explore a possible interaction with gamification but analysed data on an aggregated basis. The results did not demonstrate a statistically significant association between the choice of car type and the classification into the low-risk or high-risk group. Nevertheless, a notable association was observed for participants who opted to withdraw from the car booking experiment instead of making car choice and their assignment to a higher-risk trip. Furthermore, regarding the prediction of car choice from behavioural intentions, the findings indicated a comparatively weaker association among participants in the high-risk group in contrast to those in the low-risk group, with the latter exhibiting a stronger association.

In Sub-study 1.2, the data examination focused on investigating the influence of the gamification element badges on predicting both individuals' behavioural intentions and their actual choices between BEVs and ICEVs. Consequently, Sub-study 1.2 did not explore the influence of differentially risky BEV usage contexts on the results but analysed data on an aggregated basis. The results did not demonstrate a statistically significant association between the choice of car type and the display of badges in the car booking software. Furthermore, BEV choice exhibited an association with behavioural intentions in two out of three car bookings in both the control group (i.e. badges absent in the software) and the treatment group (i.e. badges present in the software), indicating a moderate association.

Consequently, the precise impact of presenting gamification badges and the level of risk associated with the business trips remained unexplored in the preceding Sub-studies 1.1 and 1.2, as further illustrated in Figure 10. This aspect will be the focus of investigation in the present study.

Figure 10

Comparison of the Focus Between the Two Sub-Studies and the Present Study



Note. BEV = battery electric vehicle.

Method

Participants

In the comprehensive Study 1, participants from Germany were recruited based on specific criteria: individuals whose jobs involved occasional business trips and who considered corporate carsharing a viable solution for their regular business mobility. The final sample comprised 238 participants, with 200 recruited through a panel from Schmiedl Marktforschung GmbH (now Schlesinger Group/Sago) and 38 participants recruited through a car manufacturer in Germany. Of the participants, 73% (*n* = 173) had access to at least one corporate carsharing vehicle, while 24% (*n* = 57) did not have such access. Eight participants (3%) were uncertain about their access to corporate carsharing. For more detailed information regarding the sample, refer to Sub-study 1.1 in Chapter 2.1.

Study Design

As previously mentioned, the comprehensive study was based on a 2x2 factorial between-subjects design. Factor 1 involved two differentially risky hypothetical business trips, referred to as the low-risk and high-risk business trips (see Table 25). Factor 2 pertained to the absence (i.e. control group) or presence of the gamification element badges (i.e. treatment group) in the car booking software. Participants were randomly assigned to one of the four experimental groups. As stated above, the sample consisted of 238 participants, with 62 participants assigned to the low-risk control group, 58 participants to the high-risk control group, 59 participants to the low-risk treatment group, and another 59 participants to the high-risk treatment group.

Below, factors 1 and 2 are briefly outlined. For more details on the hypothetical business trips and the study procedure, see Sub-study 1.1 (Chapter 2.1). For a comprehensive description of the requirements for acquiring the supplementary badges, refer to Sub-study 1.2 (Chapter 2.2).

Factor 1: Low-Risk and High-Risk Business Trips

The business trips were designed to convey a differential degree of risk when imagining driving a BEV for the assigned business trip. Specifically, the two scenarios differed in terms of level of familiarity with the business partner, route familiarity, and weather conditions (see Table 25).

Table 25

Business Trip Scenarios Used in the Context of the Car Booking Experiment

Low-risk business trip	High-risk business trip
"You are about to visit a business partner who is important but who you know well already. You are well acquainted with the mostly flat route. The weather is sunny and a rather pleasant temperature of about 20°C ."	"You are about to visit a new but important business partner. The route is new to you. It is a wintery but dry day of about 3°C."

Note. The business trip scenarios were translated from German and are based on a scenario used by Franke et al. (2015). Refer to Appendix A for the scenarios in German.

Factor 2: Gamification Element Design & Completion Logic

The gamification intervention, implemented through the use of badges, was prominently displayed to all participants within the car booking software of the treatment group. Inspired by Hamari (2017), the design of a badge comprised three essential components: (1) the signifier, (2) the completion logic, and (3) rewards. The specific signifier and reward used in this study are detailed in Table 26. Each of the four badges contained a visual element that illustrated the corresponding skill level, a title, representing the status (e.g. Novice Driver) as well as a description. The description concerned the requirement necessary to achieve the badge, such as to book a BEV that has a 20% range buffer for the upcoming business trip.

Table 26 displays the four badges utilised in the experiment.

Table 26

Design of the Four Badges Displayed in the Car Booking Software for the Treatment Group

Visual Element				
Status / title	Learner Driver	Novice Driver	Driver	Race Driver
Level of difficulty	None/default	Easy	Difficult	Extremely difficult / impossible
Completion logic	Default badge upon registration. No action required.	For booking an ICEV independent of the chosen range buffer; or a BEV with a 100% range buffer.	For booking a BEV with a 20% range buffer.	For booking a BEV with a 0% range buffer.

Note. Status and title were translated from German.

BEV = battery electric vehicle, ICEV = internal combustion engine vehicle.

Results

To assess the impact of the gamification intervention on the relationship between behavioural intentions and choices of car type for the two distinctively risky business trips, the presentation of results will commence with reference to the evaluation of the measurement model for behavioural intentions to book a BEV. Subsequently, the presentation of results will explore the association between gamification badges and car choice for participants in the low-risk group, followed by the analysis for participants in the high-risk group.

The measurement model of behavioural intentions[74] adhered to the recommended procedure by Hair et al. (2022). Summarising the results, all internal reliability values, including Cronbach's alpha, composite reliability ρ_C, and the reliability coefficient ρ_A, fell between the range of .70 and .95. Therefore, internal reliability is acceptable for behavioural intentions. Convergent validity was assessed using the average variance extracted. However, to significantly improve the average variance extracted, the reverse-coded behavioural intention indicator 1 was omitted from the measurement model. Consequently, behavioural intentions were measured with the remaining indicators 2 and 3. Finally, utilising the heterotrait-monotrait ratio, discriminant validity was successfully established for all reflective variables within the model, including behavioural intentions. For a detailed description of the assessment, refer to Sub-study 1.1 (Chapter 2.1).

Analysis of the Influence of Badges on Car Choices for the Differentially Risky Business Trips

To explore the association between the choice of car type, gamification, and the differentially risky business trips, the following analyses were conducted: to ascertain the association between the display of badges and individuals' car type preferences, participants' car choices were analysed using both absolute numbers and the Chi^2-test of independence. Additionally, to determine the association between behavioural intentions[75] and individuals' car choices, a binary logistic regression was

[74] Behavioural intentions was measured on a 7-point Likert scale, ranging from (1) *fully disagree* to (7) *fully agree*.

[75] Behavioural intentions of all participants, regardless of their originally assigned business trips, were assessed for the low-risk business trip in the car booking experiment.

conducted for each of the three bookings per experimental group. These analyses were performed using SPSS 28.

The presentation of results begins with the low-risk control and treatment groups, followed by the results for the high-risk groups.

Results for the Low-Risk Control Group and Low-Risk Treatment Group

To determine the influence of badges on car type preference for the low-risk group, Figure 11 and Table 27 present the absolute numbers of individuals who booked either a BEV or an ICEV for each of the three bookings, for both the control and treatment groups.

Table 27

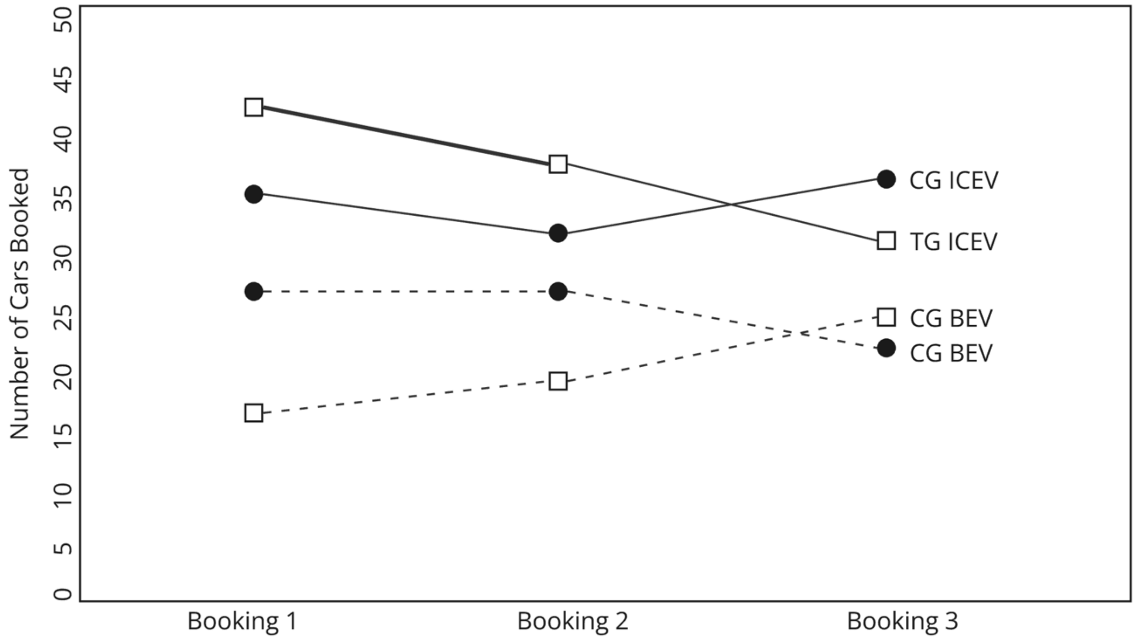
Car Choices of Participants in Absolute Numbers for Low-Risk Control and Treatment Groups

Booking	Number of ICEVs booked	ICEV bookings in %	Valid share	Number of BEVs booked	BEV bookings in %	Valid share	Attrition rate across groups	Share
Low-risk control group (no badges)								
1	35	56.5%	56.5%	27	43.5%	43.5%	0	0%
2	32	51.6%	54.2%	27	43.5%	45.8%	3	4.8%
3	37	59.7%	62.7%	22	35.5%	37.3%	3	4.8%
Low-risk treatment group (badges)								
1	43	72.9%	72.9%	16	27.1%	27.1%	0	0%
2	39	66.1%	67.2%	19	32.2%	32.8%	1	1.7%
3	32	54.2%	57.1%	24	40.7%	42.9%	3	5.1%

Note. BEV = battery electric vehicle, ICEV = internal combustion engine vehicle.

Figure 11

Visualisation of Participants' Car Choices in Absolute Numbers for Low-Risk Control and Treatment Groups



Note. TG ICEV = treatment group internal combustion engine vehicle, CG ICEV = control group internal combustion engine vehicle, TG BEV = treatment group battery electric vehicle, CG BEV = control group battery electric vehicle.

Data presented in Table 27 and Figure 11 demonstrate that ICEVs dominated in both the control group and the treatment group. Furthermore, the control group counted more BEV bookings than the treatment group. Soft trends in car type preferences can be observed in both groups. In the control group, the trend suggests that over the three bookings, fewer BEVs were booked in favour of conventional cars. In contrast, in the treatment group, the preference for BEVs steadily increased, while the numbers of combustion vehicles decreased consistently. In the final booking, the number of BEVs booked in the treatment group equalled and even slightly surpassed that of the control group.

To test whether these observed differences are statistically significant between groups, a Chi^2-test of independence was performed to examine the association between individuals' choice between BEVs and ICEVs and the presence or absence of the badges intervention (see Table 28). This test determines whether car choice and experimental group assignment are independent or not through the aggregation of data, typically displayed in the form of a contingency table (see Cohen, 1988).

Table 28

Chi^2-Test of Independence for Choice Between Battery Electric Vehicles and Conventional Cars, and Membership in Low-Risk Control and Treatment Groups

Booking	*n*	Chi^2-value	Degrees of freedom	*p*	Cramer's V
1	121	3.56	1	.06	.17
2	117	2.07	1	.15	.13
3	115	.37	1	.54	.06

Overall, for none of the three bookings related to the low-risk business trip, there is statistical evidence supporting that badges had a significant impact on participants' car choice, as indicated by the corresponding Cramer's V[76] values per booking, which suggest a weak association between the variables. Therefore, despite the subtle trends in choices suggested by the absolute figures above, the introduction of badges did not result in a significant variation in car choices.

To evaluate the predictive capability of behavioural intentions to book a BEV concerning car choice, binary logistic regressions were conducted for each car booking within both the control group and the treatment group (refer to Table 29).

[76] According to Cohen (1988), the Cramer's V value signifies the strength of association between variables. Values below .10 indicate a small effect, values of .30 represent medium effects, and values of .50 denote large effects (Cohen, 1988).

Table 29

Binary Logistic Regressions Regarding Car Choice for Low-Risk Control and Treatment Groups

Booking	Cox & Snell R^2	Nagel-kerke R^2	*B*	Wald	*p*	*Exp(B)*	Likeli-hood	95% CI	
								LL	*UL*
CG 1	.17	.23	.81	8.36	.004	2.24	124%	1.30	3.87
CG 2	.09	.13	.52	4.84	.028	1.69	69%	1.06	2.68
CG 3	.10	.13	.56	4.79	.029	1.75	75%	1.06	2.89
TG 3	.10	.14	.51	4.84	.03	1.66	66%	1.06	2.62

Note. The regression is based on the ordinal independent variable of behavioural intention and the binary dependent variable of car choice (0 = ICEV booked, 1 = BEV booked).

CG = control group, TG = treatment group, CI = confidence interval, *LL* = lower limit, *UL* = upper limit.

To assess the suitability of the data for the regression, the omnibus test and the Hosmer-Lemeshow test were applied. The omnibus test determines whether the independent variable, specifically behavioural intention, makes a difference in the model to predict the employees' car choices in the booking software. To determine the model fit, the Hosmer-Lemeshow test was applied, which compares the observed to the expected outcome by the creation of subgroups.

While all three bookings of the control group passed the omnibus test, treatment group bookings 1 and 2 did not pass the omnibus test, which implies that behavioural intentions were not a contributing factor in predicting individuals' car choice when imagining the low-risk business trip scenario. All four bookings that passed the omnibus test also passed the Hosmer-Lemeshow test. However, it is worth mentioning that the Pseudo R^2 values indicate that behavioural intentions only added to a very low extent to the prediction of car choice.

To further analyse the relationship between behavioural intentions and the chances for a BEV to be booked, the value representing the odds ratio (i.e. the *Exp(B)* value) was converted[77] into the estimated likelihood of the event to happen. With respect to the prediction of car choice from

[77] Conversion Formula: *(Exp(B)-1)*100*

behavioural intentions, the results of the control group imply that higher intentions to book a BEV were also associated with an increasing likelihood of BEVs to be booked for each of the three bookings. The probabilities ranged from 124% at the first booking to 75% at the third booking. A steady decline in BEV preference can also be noted in the absolute numbers (refer to Figure 11), with BEV preference decreasing and a greater number of ICEVs being booked in the final booking.

In summary, while variations in car choices can be noted, the outcomes of the Chi^2-tests indicate that there were no statistically significant associations in car preferences between the control and treatment groups across the three bookings. These findings suggest that the inclusion of gamification badges did not exert a significant impact on participants' car choices in favour of BEVs when individuals were exposed to the low-risk business trip. However, in contrast to the Chi^2-test, which operates on aggregated data, binary logistic regressions, functioning at the level of individual observations, may be considered as presenting more nuanced results. The regression analyses suggest that, in the control group, car choices were associated with behavioural intentions in all three car booking cases. However, under the influence of the badges intervention in the car booking software, the regressions reveal that car choice was significantly related to individuals' behavioural intentions to book a BEV only for the first of the three bookings. This indicates a significant divergence between the chosen car type and individuals' behavioural intentions when exposed to the gamification intervention.

Results for the High-Risk Control Group and High-Risk Treatment Group

The same procedure, as applied above, was used to examine the impact of gamification in the context of the high-risk business trip. Accordingly, Table 30 and Figure 12 depict the absolute numbers of individuals who selected either a BEV or an ICEV for each of the three bookings in both the control group and the treatment group for the high-risk business trip. Additionally, to assess the associations between car choices and the badges intervention, a Chi^2-test of independence was conducted (see Table 31).

Table 30

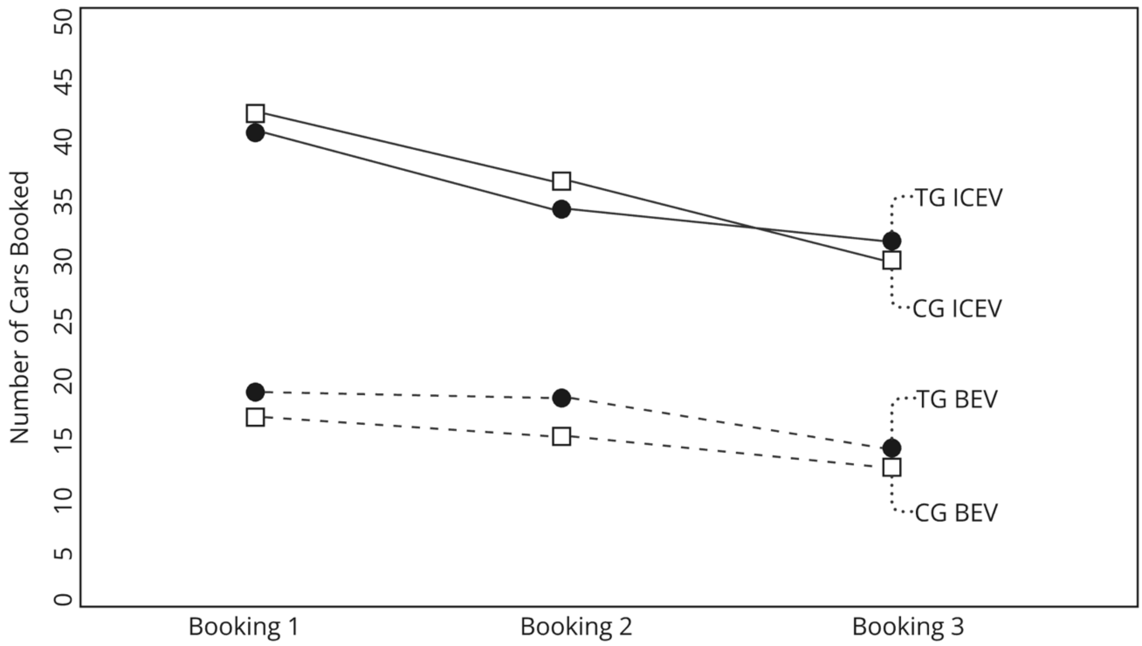
Car Choices of Participants in Absolute Numbers for High-Risk Control and Treatment Groups

Booking	Number of ICEVs booked	ICEV bookings in %	Valid share	Number of BEVs booked	BEV bookings in %	Valid share	Attrition rate across groups	Share
High-risk control group (no badges)								
1	42	72.4%	72.4%	16	27.6%	27.6%	0	0%
2	37	63.8%	71.2%	15	25.9%	28.8%	6	10.3%
3	33	56.9%	71.7%	13	22.4%	28.3%	12	20.7%
High-risk treatment group (badges)								
1	41	69.5%	69.5%	18	30.5%	30.5%	0	0%
2	35	59.3%	66.0%	18	30.5%	34.0%	6	10.2%
3	34	57.6%	70.8%	14	23.7%	29.2%	11	18.6%

Note. BEV = battery electric vehicle, ICEV = internal combustion engine vehicle.

Figure 12

Visualisation of Participants' Car Choices in Absolute Numbers for High-Risk Control and Treatment Groups



Note. TG ICEV = treatment group internal combustion engine vehicle, CG ICEV = control group internal combustion engine vehicle, TG BEV = treatment group battery electric vehicle, CG BEV =

control group battery electric vehicle.

Table 30 and Figure 12 present data illustrating the absolute number of car choices, emphasising that ICEVs continued to dominate bookings in both the control and treatment groups. Notably, compared to the two low-risk groups, there was a lower incidence of bookings for BEVs. Unlike the preferences observed for both low-risk groups, the high-risk control and treatment groups displayed a consistent choice pattern, seemingly unaffected by the treatment. In essence, the absolute numbers do not suggest a discernible difference in BEV preference between both experimental groups.

Nevertheless, to ascertain the statistical significance of these observations, a Chi^2-test of independence was executed to examine the association between car type choice and the badges intervention (refer to Table 31).

Table 31

Chi^2-Test of Independence for Choice Between Battery Electric Vehicles and Conventional Cars, and Membership in High-Risk Control and Treatment Groups

Car booking	*n*	Chi^2-value	Degrees of freedom	*p*	Cramer's V
1	117	.12	1	.73	.03
2	105	.32	1	.57	.06
3	94	.01	1	.92	.01

Overall, for none of the three bookings regarding the high-risk business trip there is statistical evidence supporting that badges are associated with individuals' car choice, as corroborated by the low Cramer's V value. Consequently, car choice did not significantly vary with the badges intervention.

To evaluate the predictive capacity of behavioural intentions to book a BEV in relation to car choice, binary logistic regressions were conducted for each car booking within both the control and treatment groups (refer to Table 32).

Table 32

Binary Logistic Regressions Regarding Car Choice for High-Risk Control and Treatment Groups

Booking	Cox & Snell R^2	Nagelkerke R^2	*B*	Wald	*p*	*Exp(B)*	Likelihood	95% CI	
								LL	*UL*
CG 1	.08	.12	.53	3.95	.05	1.70	70%	1.01	2.86
TG 2	.10	.14	.61	4.25	.04	1.84	84%	1.03	3.27

Note. The regression is based on the ordinal independent variable of the behavioural intention and the binary dependent variable of car choice (0 = ICEV booked, 1 = BEV booked).

CG = control group, TG = treatment group, CI = confidence interval, *LL* = lower limit, *UL* = upper limit.

Results show that control group bookings 2 and 3 and treatment group bookings 1 and 3 did not pass the omnibus test. This implies that behavioural intentions were not a contributing factor in predicting individuals' car choice when assigned to the high-risk business trip. Accordingly, only control group booking 1 and treatment group booking 2 passed the omnibus test. Further, these two remaining bookings also passed the Hosmer-Lemeshow test. However, it is worth mentioning that the Pseudo R^2 values indicate that behavioural intentions only added to a low extent to the prediction of car choice.

To further analyse the relationship between behavioural intentions and the chances for a BEV to be booked, the value representing the odds ratio (i.e. the *Exp(B)* value) was converted[78] into the estimated likelihood of the event to happen: for control group booking 1, the estimated likelihood showed a 70% chance of participants booking a BEV if their intentions increased by one unit. Treatment group booking 2 displayed an estimated likelihood of 84%.

In summary, the results of individuals' car choices in absolute terms and the Chi^2-test did not indicate an influence of badges on car type preferences. Hence, the findings suggest that the inclusion of gamification badges in the car booking software did not influence participants' car choices in favour of selecting BEVs when exposed to the high-risk business trip. Furthermore, car

[78] Conversion Formula: *(Exp(B)-1)*100*

choice was only weakly associated with behavioural intentions[79] in both the control and treatment groups, indicating no separable influence of badges. Consequently, participants' assessments of their behavioural intentions only weakly aligned with their car choices for higher-risk trips.

Car Booking Experiment Attrition Rate

As evident from Tables 27 and 30, there is a notable attrition rate from the car booking experiment, indicating the number of participants who chose to withdraw from the car booking experiment instead of making a car choice throughout the three bookings. Specifically, in both high-risk groups, the attrition rate exceeded that of both low-risk groups. While the maximum dropout rate among both low-risk groups across the three bookings remained at 5%, approximately 20% of participants in the high-risk groups disengaged after the second booking.

In Sub-study 1.1 (Chapter 2.1), a Chi^2-test of independence was conducted to explore whether an association exists between individuals' decisions to make car choices or withdraw from the experiment and their assignment to the low-risk or high-risk business trip. The results demonstrated a statistically significant association between the attrition rate and individuals' business trip assignment. Specifically, the results indicated a higher withdrawal rate for participants that were assigned to a high-risk trip.

However, incorporating the attrition rate as an additional choice option into the above examinations of the present study – specifically, in the association between individuals' car choice and their membership in either (1) the low-risk control group or the low-risk treatment group or (2) the high-risk control group or the high-risk treatment group – did not yield statistically significant results. Consequently, the results of the Chi^2-test of independence did not indicate a statistical association regarding the attrition rates for either of the two additional examinations (refer to Appendix D for detailed results).

Consequently, the findings suggest that the perceived riskiness of the high-risk business trip

[79] Behavioural intentions of all participants, regardless of their originally assigned business trips, were assessed for the low-risk business trip in the car booking experiment.

influenced individuals' decision to withdraw from the experiment, regardless of exposure to the badges intervention.

Discussion

The findings of this exploration reveal that the incorporation of the gamification element badges in the car booking software did not incentivise participants to prefer BEVs over ICEVs, whether in the context of low-risk or high-risk business trips. ICEVs remained the predominant choice in all four experimental conditions: the low-risk control group, low-risk treatment group, high-risk control group, and high-risk treatment group. Examination of data at an aggregated level did not show a statistically significant impact of gamification on individuals' preferences for car types. This implies that the presence or absence of gamification had no considerable effect on participants' choices. However, at an observational level, the results show that the low-risk control group demonstrated higher reliability in predicting car choices based on behavioural intentions when gamification was absent from the car booking software, and lower reliability when gamification was present. Further, the statistical explorations confirm the findings regarding the association between individuals' attrition rate from the car booking experiment and their assignment to either a low- or high-risk trip, as reported in Sub-study 1.1 (Chapter 2.1). Specifically, the data indicate that participants' withdrawal from the car booking experiment was influenced by the perceived risk associated with higher-risk business trips, while the presence of gamification elements in the software had no discernible impact on their decisions.

The statistical analyses do not provide evidence that the spontaneous exposure to gamification motivated participants to exhibit a greater willingness to engage with BEVs in differentially risky BEV usage contexts. Indeed, the noted reduced preference for BEVs in the low-risk treatment group could potentially indicate a boomerang effect, as described within Brehm's (1989) concept of psychological reactance. Brehm’s (1989) notion of a boomerang effect implies that the threatened choice alternative became more appealing in response to the promotional or social influence efforts. If participants indeed responded with reactance to the display of BEV-promoting badges in the software, this would imply that they engaged in behaviour aimed at reinstating their sense of autonomy (see Brehm, 1989), which could explain the observed preference for the non-promoted ICEVs. However, given that this study encompassed three car bookings, it is worth noting that the preference for BEVs in the low-risk treatment group increased progressively across these three bookings, even surpassing the number of BEVs booked by the low-risk control group in the final booking. Consequently, this observed trend does not support attributing reactant behaviour to the badges promoting BEVs concerning individuals' car choices.

Nevertheless, differences can be noted in the association between car choice and behavioural intentions for the two low-risk groups in this study, which may be attributable to individuals' affective responses to the intervention as follows. The gamified tasks involving the two most challenging objectives, namely the acquisition of the Driver badge and the Race Driver badge, required booking a BEV with an excess range of 20% and 0%, respectively. However, as illustrated by research conducted by Bühler et al. (2014) and the Verband der TÜV e.V. (n.d.) in Germany, perception studies related to BEVs have identified various obstacles, one of which is the more limited range of BEVs compared to conventional vehicles. Concerning this limited driving range, the term range anxiety has frequently arisen in journalistic discussions about BEVs, as highlighted by Balch (2014), or in the context of early reports from individuals who have experimented with BEVs for private trips, as indicated by the reports of Harloff (2014) and Knorre (2015). Range anxiety refers to the apprehension of the undesirable scenario of being stranded due to a depleted battery (Loveday, 2013; Rauh et al., 2015b), with the intended destination or the next charging station being out of reach. Therefore, while the gamification tasks aimed to provide participants with meaningful and engaging challenges, it is not difficult to imagine that perceived risks associated with driving a BEV could have increased after participants read the badge requirements associated with the car's range.

This interpretation aligns with findings from Finucane et al. (2000) and King and Slovic (2014) regarding their exploration of the inverted risk-benefit correlation, a concept linked to the affect heuristic (see Slovic et al., 2004). Specifically, in both studies, participants received information that either highlighted the risks or benefits of either well-established technologies, as exemplified in the study by Finucane et al. (2000), or innovations with which participants had no prior experience, as illustrated in the study by King and Slovic (2014). Both Finucane et al. (2000) and King and Slovic (2014) observed that highlighting one attribute (e.g. higher benefit) often led to a corresponding change in the rating of the non-manipulated attribute (e.g. lower risk) in the majority of cases. In both studies, participants rated the attributes in an affectively congruent manner for the majority of items; for example, items perceived as high in risk, were rated as having low benefits, and vice versa. Finucane et al. (2000) and King and Slovic (2014) implied that affect presents the common basis for individuals' judgments of the risks and benefits of items. Using the findings by Finucane et al. (2000) and King and Slovic (2014) to interpret the results of both the low-risk control group and the low-risk treatment group suggests that the information presented to the participants during the gamification tasks may have elevated the perceived risk of using BEVs for business trips in the treatment group compared to the control group. According to the affect heuristic, this heightened risk may have elicited negative emotions towards BEVs and consequently discouraged the choice of BEVs for the low-risk treatment group. This is evidenced by the weak association between car choices and behavioural intentions for the first two of the three bookings, especially when compared to the results of the low-risk control group.

Furthermore, the observed increase in preference for BEVs of the low-risk treatment group throughout the three bookings suggests that individuals may have engaged in more analytical thinking and evaluations of the current situation. As described by Slovic et al. (2004), rational decision-making entails the integration of both the so-called experiential system and the analytic system. According to Slovic et al. (2004), the former is primarily grounded in emotion and affect, yielding rapid responses, while the latter is characterised by slower, logic-based, and evidence-driven processing, along with more deliberate and conscious decision-making. Consequently, throughout these three booking experiences, the consistent rise in BEV preference within the low-risk treatment group indicates that the increasing integration of both systems may have fostered a somewhat more favourable inclination towards BEVs. Specifically, when users repeated the bookings under the same scenario two more times, it may have encouraged them to rely less on their initial, relatively BEVdiscouraging gut feelings. Participants may have progressively integrated additional information, such as the available range buffers, or evaluated their estimated likelihood of any adverse outcomes (e.g. getting stranded) through a more analytical approach. In particular, the observations from the third booking of the low-risk treatment group, supported by the statistically significant association between behavioural intentions and car choice, imply that participants may have arrived at a different conclusion regarding BEVs compared to their initial car choice.

In summary, interpreting the results of both low-risk groups through the affect heuristic suggests that the gamification stimulus may have potentially heightened the perceived risks associated with BEVs for individuals. Consequently, the affective responses of the participants in the low-risk treatment group, at least during the first two out of the three car bookings, may have been comparatively less positive towards BEVs.

In the course of analysing the results of both high-risk groups, it is important to note that all participants evaluated their behavioural intentions to book a BEV solely based on the low-risk business trip. When examining the results of the high-risk control and treatment groups, one might initially conclude that the study's findings, including those from the Chi^2-test and the weak association between behavioural intentions and car choices, are solely attributable to this limitation. Certainly, this does not exclude the possibility that participants, if they had been given the opportunity to also assess their behavioural intentions for the high-risk business trip, may as well have expressed different intentions that would have predicted car choices more reliably. Nevertheless, the comparatively higher attrition rate of participants in both high-risk groups suggests an influence of the contemplation of the high-risk business trip on individuals' responses. While the drop-out rate of both low-risk groups was approximately 5%, the rate for both high-risk groups reached approximately 20% after the second car booking. Consequently, upon completing the second car booking, every fifth participant of the high-risk groups decided to withdraw from the car booking experiment and instead continue with the questionnaire. As it can be derived from Sub-study 1.1 (Chapter 2.1), the results indicated a link between individuals' assignment of a high-risk trip and their decision to withdraw from the car booking experiment. Furthermore, the findings do not imply an influence of badges on the attrition rate.

Once again, one can turn to the affect heuristic to investigate why a certain number of participants in both the high-risk control and treatment groups chose to withdraw from the car booking experiment. The interpretation of the observations through the affect heuristic, and particularly the risk-as-feelings hypothesis by Loewenstein et al. (2001)[80], suggests that the idea of booking a car for the high-risk condition could have triggered negative emotions. These negative emotions may have ultimately led the identified portion of high-risk group participants to disengage from the online experiment, while still participating in the subsequent phases of the study.

In their elaborations of the risk-as-feelings hypothesis, Loewenstein et al. (2001) referred to a study conducted by Welch (1999), which illustrates how participants often *chicken out* from engaging in risky behaviours when the risk is perceived as imminent. This example can specifically serve to understanding the disengagement-behaviour of the participants as observed in this study. In the study by Welch (1999, as cited in Loewenstein et al., 2001), participants were asked to perform a task in which they would tell a joke in front of their class the following week in exchange for $1. Furthermore, 50% of the participants watched a 2-minute fear-inducing film clip. Subsequently, the participants were asked to make a choice regarding whether they would proceed with telling the joke or not. In the absence of fear induction, 33% of the 30 participants agreed to tell a joke in the following week, whereas only 6% of the 32 participants in the fear-induction group were willing to do so. In the second measurement, conducted immediately prior to telling the joke, the results indicated that when participants were asked whether they would reconsider their decision, only 13% of those in the non-fear induction group and none in the fear induction group were willing to

[80] Essentially Loewenstein et al. (2001) argue on context of their risk-as-feelings hypothesis that particularly in situations involving risk, emotions can exert such significant influence that they might not only diverge from cognitive judgments but even drive behaviour.

proceed with the joke[81] (Welch, 1999, as cited in Loewenstein et al., 2001). Loewenstein et al. (2001) concluded that participants were less inclined to engage with risky behaviours as influenced by the temporal proximity of the risk or when fear had been induced by the scary movie clip. Consequently, for the participants in this study, this observation may imply that reading the high-risk business trip scenario may have induced negative emotions, such as fear or anxiety, in participants. Although the business trip was only hypothetical, it might have triggered emotions that discouraged individuals from carrying out the requested car booking behaviour.

In addition to the affect heuristic, other theories such as the theory of cognitive dissonance (Festinger, 1957) could shed light on the observed behaviour. In essence, Festinger's (1957) concept of cognitive dissonance pertains to a state of psychological discomfort due to conflicting beliefs. This discomfort motivates individuals to resolve the conflict and seek a state of consistency while avoiding situations that would trigger dissonance. Although the entire online booking experiment was merely hypothetical, interpreting the observations in the context of the above mentioned theories suggests that participants may have found themselves in a conflict regarding their choice of vehicles between BEVs and ICEVs, which was further intensified by negative emotions that were elicited by the high-risk business trip. Consequently, discontinuing the booking experiment can be interpreted as a strategy, driven by an individual’s emotions and motivated by the urge to escape the stressful conflict situation, regain composure, and continue with the remainder of the study.

Nevertheless, while the aforementioned theories were used to interpret the results of the participants that were assigned to the high-risk business trip, further investigation in future studies is necessary to provide a more comprehensive understanding of the psychological mechanisms that drove participants’ choice to disengage rather than choose any car for the hypothetical high-risk business trip.

[81] While the first measurement was statistically significant at the 5% significance level, the difference between the fear-induced and no-fear-induced groups did not reach statistical significance in the second measurement.

Some concluding considerations pertain to the earlier-discussed observations that the BEV preference of the low-risk treatment group was initially lower compared to the control group. As outlined above, one factor contributing to the lower preference for BEVs could be that the gamification tasks were aligned with the car's range. This alignment may have elicited negative emotions, which initially discouraged participants from considering BEVs for their business trips. Consequently, to enhance the intended motivating effect of gamification regarding sustainable decisions, a potential solution might involve redefining gamification tasks in connection with other goals that are less likely to evoke negative emotions when considering BEVs as an option. While this could be a viable approach, the findings of Franke et al. (2012) do not necessarily constrain the badge design utilised in this study. With the aim to examine the infamous concept of range anxiety, Franke et al. (2012) conducted research where participants drove electric vehicles over a six-month period. Franke et al. (2012) gained insights that individuals adapted to the available range, using a rule-of-thumb estimation based on experiences with similar trips to estimate the required battery range. Furthermore, Franke et al. (2012) reported that about half of the participants (19 out of 36) viewed the range as a challenge or problem-solving task rather than a threatening encounter to be avoided. These results do not argue against setting goals based on range as an appropriate approach to improve the accessibility of electric vehicle range and portray it less as a risk and more as an exciting challenge for individuals.

However, Franke et al.'s (2012) study also highlights another crucial factor, as previously discussed in Sub-study 1.2 (Chapter 2.2), which is experience. As outlined, theories such as Bandura's (1982) self-efficacy theory, insights from goal-setting theory (e.g. Locke & Latham, 2002), and findings derived from applying both theories to research on gamification in the context of proximal goal-setting (Gutt et al., 2020) suggest that establishing goals with gradually increasing difficulty is a prerequisite for successful goal-setting. Participants can start with simple tasks, systematically explore their knowledge and skills, build self-confidence, and thus gain the confidence to tackle more challenging goals (e.g. Bandura & Schunk, 1981; Gutt et al., 2020). Therefore, in line with the insights derived from the aforementioned studies, future research could explore the potential impact of combining proximal goal-setting and gamification within an experimental framework. This approach, i.e. facilitating participants to actively explore their own abilities and skills, may warrant investigation to determine whether it can enhance the accessibility of new technologies for individuals and, consequently, influence their technology choices. Such approaches, along with additional suggestions for enhancing the effectiveness of gamification interventions, are discussed in greater detail in Sub-study 1.2 (Chapter 2.2).

Practical Implications

The following practical recommendations are based on the results presented in this sub-study. As discussed above, the findings suggest that for software designers, organisations, or fleet managers, combining excess battery range (i.e. range buffer) with gamification to promote BEV usage might not be the most effective approach. However, it was also noted that when introducing a new system or functionality, individuals may require time to adapt and gain experience with the new stimulus. This adjustment period could lead to varying responses in how individuals judge a system or behaviour over time, as demonstrated by Bandura and Schunk (1981) and Venkatesh and Bala (2008). Given the need for further research to provide clearer guidance for the industry, software designers, organisations, and fleet managers might consider integrating gamification with activities or challenges beyond remaining range. For instance, gamification could be utilised by software designers, organisations, and fleet managers to encourage the initial selection of a BEV over an ICEV, regardless of the car's remaining range. Once drivers have adopted a BEV, new goals could be introduced to promote eco-driving practices (i.e. achieving lower energy consumption in kilowatt-hours (kWh)/100km, see Günther et al., 2020; Degirmenci & Breitner, 2023), or direct users to charging stations offering more affordable rates per kWh. Additionally, to extend battery longevity, findings by Argue (2023) suggest promoting the use of slower AC chargers over faster DC chargers and encouraging charging when the battery is between 20% and 80% capacity, among other strategies.

Limitations

The limitations of this study base on the limitations presented in Sub-study 1.1 (Chapter 2.1; predicting BEV choice for risky usage contexts) and Sub-study 1.2 (Chapter 2.2; investigating the impact of gamification on behavioural intentions and car choice). Nevertheless, for the interpretation of the results of this study, it is worth emphasising the following two limitations again.

Firstly, the questionnaire did not differ between groups, meaning that the questionnaire items were only assessed with regard to the low-risk business trip scenario. Consequently, the influence of risk on the structural relationships of the TAM remains unexplored for the high-risk group. As a result, measuring behavioural intentions for the high-risk business trip may well have revealed a stronger association between car choice and behavioural intentions.

Secondly, although the present results suggest an influence of emotions on car choice, the conclusions are limited because emotions were not directly measured but were inferred from the observations with reference to the affect heuristic.

Conclusion of Study 1

As described above, Study 1 involves a comprehensive investigation grounded in a TAM specifically adapted to predict individuals' intentions to book a BEV for an upcoming business trip. Study 1 is structured on a 2x2 factorial between-subjects design that further incorporates a car booking experiment. Participants were assigned to either a hypothetical low-risk business trip or a high-risk business trip scenario (i.e. factor 1). Additionally, participants were allocated to a condition where gamification was either absent (i.e. control group) or present (i.e. treatment group) in the car booking software (i.e. factor 2). After allocation to one of the four experimental conditions, participants were instructed to make bookings between BEVs and ICEVs using the car booking software. Below summarises the key findings across the explorations of the Sub-studies 1.1, 1.2, and 1.3 (Chapters 2.1, 2.2, and 2.3, respectively).

The outcomes of the TAM closely align with the findings of related TAM variants. Notably, variables such as perceived usefulness and ease of using BEVs, subjective norms associated with driving a BEV, and the perceived image of BEV drivers all demonstrated statistically significant associations with individuals' behavioural intentions to book a BEV. The data showed that the perceived enjoyment of driving a BEV was the predominant driver of individuals' behavioural intentions to book a BEV.

The introduction of badges in the car booking software had an impact on various relationships within the TAM. Notably, in the control group, a significant relationship was observed between subjective norms and individuals' commitment to engage with disseminated goals and gamified challenges, while this association was non-significant in the treatment group. Furthermore, although there was no statistically significant link between the perceived usefulness of BEVs and participants' intentions to book one, this association became significant and positive in the presence of badges. Gamification also strengthened the association between the perceived enjoyment of using the booking software and individuals' commitment to engage with goals and gamified challenges related to car choice presented in the software. Furthermore, participants' goal commitment had a modest influence on individuals' intentions to book a BEV. However, contrary to expectations, badges did not further enhance this association.

Only a minority of participants opted for a BEV within the car booking experiment and the results did not reveal a statistically significant association between the choice of car type and the experimental conditions. Nevertheless, except for the low-risk control group, data indicated variations in the reliability of car choice predictions based on behavioural intentions across the remaining three experimental conditions. Specifically, for these conditions, behavioural intentions were only weakly associated with individuals’ car choice. While the findings suggest that gamification influenced this association for the low-risk treatment group, the analyses for the high-risk control group and the high-risk treatment group revealed a different pattern regarding individuals' choices: regardless of the treatment, the results indicated that participants assigned to a high-risk trip were linked to a statistically significantly higher attrition rate from the car booking experiment compared those assigned to a low-risk trip. Accordingly, those participants chose to withdraw from the experiment instead of making any car choice.

Consequently, badges did not motivate participants to favour BEVs over conventional cars, regardless of the assigned experimental condition. Interpreting the above-described observations through the lens of the affect heuristic suggests that participants may have experienced negative emotions, prompted by the gamification element badges or the assignment of the higher-risk trip.

The findings of this study extend the existing literature focused on influencing sustainable behaviours and choices of individuals (e.g. Chang et al., 2016; Richter et al., 2018; Thaler & Sunstein, 2014). Furthermore, they contribute to the gamification literature, specifically addressing the comprehension of the impact of gamification on the selection of technologies (e.g. Gutt et al., 2020; Hamari, 2013, 2017; Landers et al., 2017). The findings also contribute to the TAM literature, particularly in the context of the acceptance of BEVs (e.g. Dudenhöffer, 2013; Fazel, 2014; Roemer & Henseler, 2022) and in terms of the influence of gamification on technology judgment.

Chapter 3: Study 2 - Gamifying Technology Choices: A Re-Examination of the Risk-Benefit Association

Study 2 - Gamifying Technology Choices: A Re-Examination of the Risk-Benefit Association

Abstract

Contemporary literature within the context of the affect heuristic highlights that individuals' assessments of activities or technologies in terms of their risks and benefits are often inversely related, grounded in their general evaluative affect. In an experimental setting, this study utilised information emphasising either the risks or benefits of BEVs to manipulate individuals' evaluative affect towards BEVs and consequently, the non-manipulated attribute. Furthermore, with the aim of enhancing these expected effects and corresponding choices, this information was further supplemented by the gamification elements points and a leaderboard. Specifically, choices between BEVs and conventional vehicles for business trips were measured using car booking software. The results reveal an inverse correlation between risks and benefits, aligning with the inverted risk-benefit correlation. Contrary to expectations, the provided information did not significantly alter the respective non-manipulated attribute. Furthermore, individuals' evaluative affect of BEVs was linked to their decision to book a BEV. While the majority of participants booked a BEV in all four control group conditions, car type preference did not statistically vary between these four conditions. Conversely, car choice exhibited significant variations among the four treatment group conditions. Moreover, in a pairwise comparison of the experimental conditions per manipulated attribute, statistically significant differences in car type preferences were observed between the control group and the treatment group, except for participants who received the low-risk condition. The findings of this study underscore the potential of gamification to extend beyond enhancing performance, as extensively demonstrated in the literature, to also influence technology choices.

Introduction

In the literature, the processing of information by humans is commonly categorised into two modes of thinking. For example, Kahneman (2012) subdivides these into system 1 (i.e. thinking fast) and system 2 (i.e. thinking slow), while Slovic et al. (2004) refer to the experiential system and the analytic system. According to Slovic et al. (2004), the analytic system utilises logic and reason, processes information more slowly and with a higher level of consciousness compared to the experiential system. Slovic et al. (2004) claim that the experiential system is driven by affective responses, incorporates past experiences and mental images, and operates with a faster processing speed compared to the analytic system.

In a related vein, the position was taken by Zajonc (1980) that emotions are often the initial reactions to situations being evaluated. Zajonc (1980) illustrated this claim with the vivid example of getting introduced to a previously unknown person. According to Zajonc (1980), such an encounter would likely be accompanied by the immediate experience of a feeling of attraction or repulsion, and thus imply a judgment of the other person. The following example substantiates the illustration by Zajonc (1980): Burchard (2009) referenced findings from a study by Kube (2009), which examined the connections between primary school teachers in Germany and various names. Certain names consistently received evaluations indicative of greater politeness and academic proficiency in children, while other names were linked to children displaying behavioural challenges and an increased likelihood of rudeness or disruptive behaviour (Kube, 2009, as cited in Burchard, 2009). This example suggests that the mere hearing of a name appears to have served as a social marker for primary school teachers, prompting a rapid categorisation of students into specific groups based on behaviour, educational potential, and other factors. Consequentially, as suggested by Zajonc (1980), the mere mention of an individual's name, even in the absence of a personal encounter, has the capacity to elicit a positive or negative emotional response towards that person.

By asserting that emotions often constitute the initial reactions to situations under evaluation, Zajonc (1980) presented a position contrary to the prevailing assumption in the literature at that time. According to Zajonc (1980), such contemporary literature typically posited that emotions were the result of significant cognitive evaluations. For example, the theory of reasoned action by Fishbein and Ajzen (1975) builds on the assumption that emotions are a product of cognitive processes. Fishbein and Ajzen (1975, p. vi) explicitly assert the position that they "view humans as rational animals who systematically utilize or process the information available to them." In the context of their presented theory, Fishbein and Ajzen (1975) proposed that an individual’s beliefs about the consequences of performing a behaviour informed their attitude (i.e. evaluative affect), that is, their general liking or disliking towards that stimulus object. Further, they stated that a person’s normative beliefs informs their subjective norm, which reflects a person's perception of whether important individuals in their life believe they should or should not engage in a particular behaviour (Fishbein & Ajzen, 1975). In the model, both attitude and subjective norm served as predictors of an individual’s intentions regarding the performance of a specific behaviour and, subsequently, actual behaviour. Loewenstein et al. (2001) characterised such theories as taking a consequentialist perspective, asserting that individuals base their decisions on the assessment of anticipated consequences of choice alternatives. While consequentialist models, such as the theory of reasoned action, also encompass the influence of emotions, they typically refer to anticipated emotions – those expected to be experienced if one chooses to engage in a particular behaviour (Loewenstein et al., 2001).

In addition to arguing that affective responses can occur much more swiftly than cognitive processes, Zajonc (1980) further contends that while affect will invariably be present in the context of cognitive processes, the reverse is not necessarily true. Zajonc (1980) and Slovic et al. (2004, 2007) assert that merely hearing a particular word can elicit positive or negative feelings. Slovic et al. (2007) classify this feeling-based judgment and decision-making under the concept of the affect heuristic. Mental images and associations that emerge facilitate the rapid categorisation of the received stimulus – whether it is perceived as good or bad, liked or disliked, positive or negative, and so forth (Slovic et al., 2007).

By specifically referring to risk as a feeling in the context of the affect heuristic, Slovic et al. (2004) emphasised how emotions can guide risky decisions, such as determining whether mildly odorous milk remains suitable for consumption or not. In this context, Slovic et al. (2004) assert that evaluations of risky situations are predominantly shaped by individuals' affective responses, whether consciously or unconsciously (Slovic et al., 2004). Aligned with the affect heuristic and the related risk-as-feelings hypothesis presented by Loewenstein et al. (2001), there is a distinct emphasis on the significant influence of emotions in the evaluation of risky events or behaviours during the decision-making process. While Slovic et al. (2004) and Loewenstein et al. (2001) both assume that emotions can profoundly impact the assessment of a risky event or behaviour at the moment of decision-making and can even deviate from cognitive risk assessments, Loewenstein et al. (2001) further argue that such deviance can be so strongly that one might depart from what they would otherwise view as their best course of action.

While the affect heuristic is a general concept of judgement and decision-making, it has nevertheless also been used for the assessment of technologies. Alhakami and Slovic (1994), for example, had participants rate a range of activities and technologies (e.g. nuclear power) for their perceived risks and benefits. They found an inverse relationship between individuals' judgments of the risks and benefits associated with these technologies: technologies rated as risky were associated with low benefits, and vice versa. Further, individuals' evaluative affect was found to be a reliable predictor of this relationship. For example, when individuals experience negative affect towards a specific item, they are inclined to evaluate this item as having low benefits and high risks. Conversely, when individuals experience positive affect towards an item, they are more likely to evaluate this item as having high benefits and low risks (see Alhakami & Slovic, 1994).

Based on the assumption that influencing the favourability of one attribute (e.g. benefit) would impact an individual's comprehensive affective evaluation of the manipulated item and consequently also alter the judgment of the non-manipulated attribute (e.g. risk), Finucane et al. (2000) re-examined the inverse correlation of risks and benefits. In their study, Finucane et al. (2000) deliberately highlighted either the risks or benefits of a technology by presenting participants with statements that advertised either the risks or the benefits of the technology in question (i.e. high-benefit, low-benefit, high-risk, and low-risk). They found that, for example, when the information described the technology as low risk appears to have primed their affective response. Their affective response led to an increase in the perceived benefits of the technology. The manipulation worked in 50% of trials, while in 16% of trials, the effect was opposite to the intended manipulation. The remaining 33% did not change in either direction (Finucane et al., 2000).

This association was again confirmed in a study by King and Slovic (2014), who tested the above described risk-benefit association specifically for product innovations, that is, products that individuals would not have had the chance to test or otherwise acquire much knowledge about. In their study, they also presented information to participants designed to manipulate one of the four conditions (i.e. high-benefit, low-benefit, high-risk, or low-risk). Their manipulation worked in 59% of trials, while in 14% of cases the effect was opposite to the intended manipulation; 27% of trials showed no change (King & Slovic, 2014).

In the studies by Finucane et al. (2000) and King and Slovic (2014), participants were exposed to statements that emphasised either the benefits or risks of technologies, leading to a discernible impact on their evaluative affect towards the manipulated items. Literature presents a myriad of ways which concern the presentation of information to individuals with the aim of influencing their behaviour or choices[82]. For example, an approach that has been found to influence individuals' attitudes and, consequently, their behaviours is the concept of gamification (Landers, 2014). In gamification, conventional game elements, such as points, levels, progress bars, and others[83], have found application in non-game contexts with the aim to amplify individuals' engagement in specific tasks and task performance (Deterding et al., 2011), as also demonstrated empirically (Boratto et al., 2017; Hamari & Koivisto, 2013; Landers et al., 2017; Landers & Landers, 2014). Gamification has been in circulation for approximately 15 years and is primarily associated

[82] Examples of schematic approaches to behaviour change encompass nudges (Thaler & Sunstein, 2014), mindspace (Dolan et al., 2012), normative messaging (e.g. Cialdini et al., 1990; Richter et al., 2018), and other persuasive concepts.

[83] Refer to Table 1 for a detailed description of these and various other gamification elements.

with its implementation in digital applications, such as mobile phone and smartwatch applications, or other digital services (Deterding et al., 2011).

For instance, Hamari (2017) conducted a two-year field experiment, encompassing one year of observation before the intervention and another year of observation during the intervention, involving a peer-to-peer trading service. This service aims at facilitating the sharing of assets, including carpooling as well as the buying and selling of goods and services. The intervention incorporated the gamification element badges[84]. According to Hamari (2017), badges were designed with the aim to present various goals to users, such as their general usage activity on the platform, posting trade proposals, completing transactions, and their engagement with various other activities. The results of Hamari's (2017) study revealed a significant influence of badges on a variety of user activities, including more active usage of the service, increased commenting, and participation in other activities. While Hamari (2017) measured actual user behaviour, the study did not include measurement variables to explain potential psychological effects. Nonetheless, Hamari (2017) assumed that gamification elements, by presenting users with goals as a motivational mechanism, would lead to an increase in positive emotions, such as satisfaction or self-efficacy, upon achieving those goals.

Landers et al. (2017) tested goal-setting theory (e.g. Locke & Latham, 2002)[85] to understand the attributed motivational effects of gamification elements. Landers et al. (2017) conducted a 12-minute brainstorming task to compare the performance of the gamification element leaderboard with four distinct goal-setting conditions, ranging from do-your-best, easy to difficult and impossible' goals.[86] The results of their study revealed that the presence of a leaderboard motivated participants

[84] Refer to Table 1 for a detailed description of this and various other gamification elements.

[85] Locke and Latham's (2002) goal-setting theory aims to provide a comprehensive framework for structuring goals as meaningful and potent motivators to enhance performance.

[86] In the 12-minute brainstorming task, participants were required to list as many uses for a knife as possible. Specifically, participants had to list 15 uses for the easy goal, 39 for the difficult goal, and 53 uses to attain the impossible goal.

to achieve performance levels comparable to those associated with difficult or seemingly impossible goals, surpassing the performance of individuals in the do-your-best or easy goal conditions. Consequently, gamification, at least in the form of leaderboards as tested by Landers et al. (2017), can be considered a specific form of presenting goals to users.

When examining commercial smartphone or smartwatch applications, such as for the purpose of tracking one's sporting activities or language skills[87], the presentation of goals and challenges with gamification elements is typically implemented with a focus on rewarding users (e.g. points, badges, increase in ranking compared to others) for accomplishing tasks. The implications for not achieving a goal are either not implemented or only implicitly evident. If only implicitly evident, a user might simply remain at the current level, thus missing out on collecting new points, achievements, or badges. If more explicitly implemented, failure can, for example, result in the active loss of points, ranking positions, or gameplay lives, sometimes accompanied by a waiting period before the user can take on the challenge again. In summary, gamification elements can be used to convey both benefits (such as gaining points, advancing in the leaderboard) and risks (such as losing points, descending in the leaderboard) associated with engaging in specific behaviours.

As previously noted, Finucane et al. (2000) and King and Slovic (2014) observed that exposing participants to information presented in the form of statements promoting either the risks or benefits of products and technologies influenced individuals' overall evaluative affect towards that specific item as well as towards the attribute which was not emphasised by the specific information. Consequently, the above considerations suggest that gamification elements could equally be utilised to influence an individual's judgment of a technology, including its perceived risks and benefits.

Past research has addressed the application of gamification to enhance individuals' engagement and task performance (e.g. Boratto et al., 2017; Gutt et al., 2020; Landers et al., 2017) and investigated the influence of gamification on individuals' perceptions of gamified services and

[87] Sports tracking applications that integrate gamification elements: e.g. Strava, Adidas Running, or Nike Run Club. Language learning application that integrates gamification elements: e.g. Duolingo.

their intention to use such services in the future (e.g. Hamari & Koivisto, 2013). Furthermore, although not specifically addressing gamification, past research explored the use of information to influence individuals' judgment of items, including technologies (e.g. Finucane et al., 2000; King & Slovic, 2014). However, to the best of current knowledge, the aforementioned literature has not examined whether the identified inverted risk-benefit relationship, as explored by Finucane et al. (2000) and King and Slovic (2014), also holds true for the application of gamification. Specifically, it has not been investigated whether gamification can alter an individual's overall affective evaluation of technologies, along with their associated risks and benefits.

Therefore, this study specifically investigates whether gamification elements can influence the inverse relationship between perceived risks and benefits and, consequently, also influence the choice between technologies.

To explore this identified research gap, choice between BEVs and ICEVs from a shared fleet of corporate cars for business mobility purposes was utilised as a research example. For more than a decade, the BEV has been argued to be a prominent sustainable alternative to conventional cars with an internal combustion engine (Beuse, 2021; Climate Change Committee, 2023; Fazel, 2014; Presse- und Informationsamt der Bundesregierung, 2022). Given the comparatively low registration rate of BEVs in Germany[88], the German market was considered ideal for studying the judgment of BEVs for this specific example.

To explore the influence of gamification on individuals' judgment of BEVs for business trips in the context of the inverse relation of perceived risks and benefits, the experimental procedure closely followed the methods employed by Finucane et al. (2000) and King and Slovic (2014). In this study, an online car booking experiment using car booking software was conducted to assess the impact of gamification on hypothetical car choice. Participants were randomly assigned to one of

[88] For instance, in 2021 while nearly two thirds (64.5%) of all newly registered cars in Norway were BEVs, the corresponding figure in Germany in 2021 was only 13.6% or even only 3.2% in the United States (Davis & Boundy, 2022; Kraftfahrtbundesamt, n.d.-b; Teslamag, 2022).

four experimental conditions per control group or treatment group. Aligned with the studies of Finucane et al. (2000) and King and Slovic (2014), the control group received information deliberately highlighting either the risks or benefits of BEVs. In contrast to the two cited studies, the treatment group's four experimental conditions were additionally expanded with gamification. Furthermore, a questionnaire was employed to gauge individuals' perceived risks and benefits of BEVs as well as their evaluative affect towards BEVs, both before and after the car booking experiment. The hypothetical car fleet in the car booking software comprised an equal number of BEVs and ICEVs, matched in vehicle class and equipment, which enabled the choice between BEVs and ICEVs to be studied.

Subsequently, additional insights from the literature regarding the judgment of BEVs will be introduced, and the risk-benefit association will be presented in more detail. Along with this, the hypotheses used in the context of this study will be outlined.

Literature Review

While the introduction primarily focused on the findings of Alhakami and Slovic (1994), Finucane et al. (2000), and King and Slovic (2014), the identification of an inverse correlation between perceived risks and benefits dates back to a study by Fischhoff et al. (1978). In their study, 30 activities and technologies were evaluated, including alcoholic beverages, food preservatives, high school and college football, and hunting. In a similar study, Slovic et al. (1991) had participants rate 33 items for their risks and benefits. Those items primarily encompassed pharmaceuticals (e.g. vaccines), some medical devices (e.g. X-rays), and a range of other technologies (e.g. nuclear power). By comparing the means per attribute (i.e. risk or benefit), the results indicated a negative correlation for the items. Building upon the data from the study by Slovic et al. (1991), Alhakami and Slovic (1994) conducted additional analyses and identified a statistically significant inverse correlation for most items. This implied that items perceived as high in risk were also judged to be low in benefit, and vice versa. Alhakami and Slovic (1994) conducted another test with 40 items and additionally assessed participants' overall evaluative affect towards these items. As mentioned above, in this re-examination, Alhakami and Slovic (1994) discovered that an individual's general evaluative affect served as a predictor for the risk-benefit correlation. Once more, Alhakami and Slovic (1994) found an inverse relationship between the perceived risks and benefits of the judged items. Alhakami and Slovic (1994) noted that strong negative correlations were associated with negative affect towards the judged item, while weak negative correlations were linked to favourable attitudes. Moreover, when comparing the distance of means per attribute, Alhakami and Slovic (1994) reported that pronounced positive or negative evaluations would exhibit larger differences between evaluated risks and benefits, while items judged towards the middle of the evaluation scale would correspond to smaller distances.

Alhakami and Slovic (1994) concluded that the observed inverse relationship was indicative of a confounding in individuals' minds and linked to their overall affective evaluation. For their interpretation of the findings, Alhakami and Slovic (1994) referred to cognitive consistency theory (e.g. Heider, 1946) to theoretically explain the implied confounding between risks and benefits. For example, in his exploration of balance theory, Heider (1946) delved into interpersonal relationships to illustrate how individuals strive for attitudinal balance. Heider (1946) argued that conflicts may emerge when there is a perceived imbalance, for example, among individuals, objects, and the attitudes associated with them, leading individuals to seek cognitive balance through actions or cognitive restructuring, such as making excuses. Consequently, within the framework of their findings, Alhakami and Slovic (1994) contend that if individuals uphold a favourable attitude towards an activity or technology, their inclination for cognitive consistency would prompt them to judge the respective item as high in benefits and low in risks. Conversely, the opposite pattern would emerge for items towards which individuals harbour an unfavourable attitude.

As indicated above, the studies by Fischhoff et al. (1978), Slovic et al. (1991), Alhakami and Slovic (1994), and Finucane et al. (2004) explored a wide spectrum of items, including individuals' perceptions of *cars* and *automobile travel*. For instance, while Alhakami and Slovic (1994) did not identify an inverse correlation for the item *motor vehicles* in general, they did observe an inverse correlation specifically for automobile travel, although these categories were not specified in greater detail. Moreover, Finucane et al. (2000) discovered an inverse correlation for cars, which was further strengthened when individuals were tasked with judging cars in a time-pressure condition. Finucane et al. (2000) argued that under time pressure, individuals would rely more heavily on their affective responses towards the item being evaluated, rather than engaging in cognitive evaluations. In summary, the above considerations indicate an inverse correlation between the perceived risks and benefits for cars in general.

The Inverse Correlation Between the Perceived Risks and Benefits of BEVS

However, given that BEVs have only become more widely available in the recent decade, these aforementioned results may, but do not necessarily apply to the judgment of BEVs. BEVs have constituted the majority in registration numbers compared to the registration of conventional cars in, for example, Norway (31% in 2018, 65% in 2021, 79% in 2022) (Ferris, 2022; Johnson, 2023). However, while registration rates are significantly lower in other countries, such as Germany (1% in 2018, 13.6% in 2021, 17.7% in 2022) (Kraftfahrtbundesamt, n.d.-a, n.d.-b, n.d.-c), the increasing registration rate may suggest a growing positive attitude towards BEVs.

In this context, the subsequent exposition of study findings seeks to elucidate the nature of risks and benefits associated with BEVs, particularly in the domain of business mobility. The investigation commences with a scrutiny of potential risks linked to BEVs.

While BEVs have been presented as a sustainable alternative to ICEVs, study findings pertaining to research conducted in Germany indicated a decrease in the proportion of individuals, namely from 75% in 2013 to 58% in 2019, who perceive BEVs as environmentally friendly (Aral Aktiengesellschaft, n.d.-a, n.d.-b). This decrease may, for instance, originate from concerns related to the ascribed carbon dioxide advantage of BEVs compared to ICEVs. Research examining the ascribed CO_2 advantage has produced varied conclusions, depending on the scope of the assessment and contributing factors, such as the underlying electricity mix[89] (e.g. Abdul-Manan, 2015; Buberger et al., 2022; Buchal et al., 2019; European Environment Agency, n.d.; Helmers et al., 2020; Jochem et al., 2015). Moreover, among other factors, frequently cited barriers of BEV adoption include the prolonged charging duration compared to refuelling ICEVs, limited range, perceived insufficiency of charging infrastructure, and the higher purchase price (Bühler et al., 2014; Egbue & Long, 2012; Schuitema et al., 2013; Verband der TÜV e.V., n.d.). In a related study, Roemer and Henseler (2022) explored individuals' acceptance of BEVs for business mobility within corporate fleets and found similar results. Specifically, Roemer and Henseler (2022) conducted surveys at three distinct time points: prior to usage (t_0), after three months of usage (t_1), and subsequently after six months (t_2) of BEV utilisation for business mobility. At the third measurement (t_2), the researchers discovered that perceived risks associated with BEVs, such as insufficient range, challenges in locating charging stations, and prolonged recharging times, exerted a significant and negative influence on individuals' intentions to utilise a BEV in the ensuing six months. It is worth noting that participants initially received training, support (e.g. telephone hotlines), guidance (e.g. information packages), and other assistance. Roemer and Henseler (2022) assume that this association may have turned out statistically significant so late, because with progressed usage time, barriers such as available range or charging infrastructure availability may have gained importance.

With regards to possible benefits associated with BEV usage, the results of Study 1 in this thesis (Chapter 2) provide some indications of the perception of BEVs for business trips. Study 1 investigated individuals' acceptance of BEVs from a shared car fleet for business purposes. The results showed that individuals anticipated driving a BEV for business trips to be a joyful experience. Additionally, functional benefits, such as higher instant torque than ICEVs, influenced individuals' intentions to choose a BEV for a hypothetical business trip. Relatedly, Roemer and Henseler (2022)

[89] The electricity mix refers to the primary energy sources used to generate electricity, including the burning of fossil fuels (e.g. coal, gas), nuclear power, renewable sources (e.g. wind power, solar, hydropower), and others (Ritchie et al., 2020b).

discovered that the perceived enjoyment of driving a BEV statistically significantly influenced the participants' intentions to drive a BEV for future business trips once participants had gained some practical BEV driving experience.

In summary, the considerations outlined above suggest that individuals contemplating the choice of a BEV, for example, for business travel, may be aligned with various risks (e.g. insufficient range) and benefits (e.g. joy of driving) associated with driving a BEV. Applying the inverse relationship between perceived risks and benefits within the context of evaluating BEVs implies that individuals with a generally positive attitude towards BEVs are likely to perceive them as possessing high benefits and low risks. Conversely, those with a negative attitude towards BEVs are expected to perceive them as high in risks and low in benefits.

Therefore, it can be hypothesised that (H1) individuals' evaluative affect towards BEVs will be correlated with the inversely related perceived benefits and risks of BEVs.

Evaluative Affect Towards BEVs and Car Choice

As mentioned above, Slovic et al. (2004) argue that humans process information through a dual-process, comprising the so-called experiential system and the so-called analytic system. These systems operate in parallel, each depending on the other for guidance (Slovic et al., 2004). When judging risky decisions, however, Loewenstein et al. (2001) as well as Slovic et al. (2004) claim that emotions might diverge from cognitive judgments. Furthermore, Loewenstein et al. (2001) emphasise that emotions may even drive behaviour to the extent that individuals might pursue a course of action which they usually would not have viewed as their best course of action.

In summary, the considerations presented by Slovic et al. (2004) and Loewenstein et al. (2001) suggest a significant influence of emotions on individuals' decisions. This implies that an individual's evaluative affect towards BEVs would likely be linked to their choice of cars between BEVs and ICEVs for business trips.

Therefore, it can be hypothesised that (H2) BEV choice will be positively associated with individuals' evaluative affect towards BEVs.

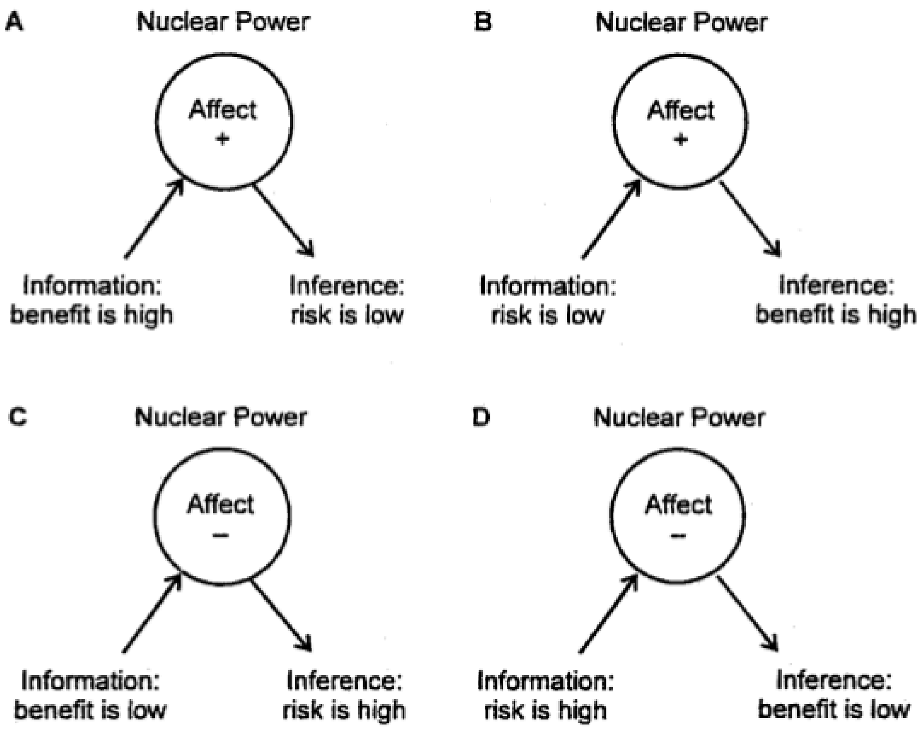
Manipulation of Affective Attributes

As delineated above, Finucane et al. (2000) and King and Slovic (2014) undertook a reassessment of the inverse relationship between the perceived risks and benefits of items. Participants in their studies were exposed to statements endorsing either the risks or benefits of products and technologies, using four distinct conditions: the high-benefit, low-benefit, high-risk, and low-risk condition. In both studies, these statements specifically promoted one attribute (either risk or benefit), thereby influencing individuals' overall evaluative affect towards that item and subsequently altering their judgment of the non-manipulated attribute (refer to Figure 13). In both studies, the manipulation worked as intended in at least in 50% of trials. Hence, the above considerations suggest that presenting participants with information that highlights the risks or benefits of BEVs for business trips would similarly impact individuals' evaluative affect towards BEVs and, consequently, also influence the non-manipulated attribute (refer to Table 33).

Consequently, it can be hypothesised that (H3) manipulating one BEV attribute (e.g. BEVs being high in benefits) will concomitantly influence the non-manipulated attribute (i.e. BEVs being low in risk).

Figure 13

The Framework for Intentional Shifts in Evaluative Affect through Risk or Benefit Manipulation Proposed by Finucane et al. (2000)



Note. Figure presenting the theoretical model from Finucane et al. (2000, p. 9).

Table 33

Manipulations of Benefit and Risk Information and Their Hypothesised Effects on the Non-Manipulated Attribute of Battery Electric Vehicles

Information content	Predicted effect on non-manipulated attribute
BEV benefit is high	Perceived risk of BEVs decreases
BEV benefit is low	Perceived risk of BEVs increases
BEV risk is high	Perceived benefit of BEVs decreases
BEV risk is low	Perceived benefit of BEVs increases

Manipulation of Affective Attributes with Gamification

Gamification literature has demonstrated that gamification can influence individuals' attitudes and intentions regarding the use of a specific gamified service in the future (Gumussoy et al., 2023; Hamari & Koivisto, 2013; Rodrigues et al., 2016) as well as affect their enjoyment of interacting with the respective gamified application (e.g. Codish & Ravid, 2015; Mitchell et al., 2020). This suggests that gamification could also impact individuals' affective responses to a target object. For example, in Study 1 (refer to Chapter 2), the integration of the gamification element badges in a car booking software was found to strengthen the association between the perceived usefulness (i.e. perceived benefits) of BEVs and participants' intentions to book a BEV for future business trips. Study 1 did not explicitly address any specific negative consequences associated with engaging in a task (e.g. losing points if a challenge was not successfully mastered). Nevertheless, the results of Study 1 imply that a BEV was perceived more beneficial once it was presented along with gamification badges. Therefore, in the context of this investigation, the results of Study 1 suggest that gamification elements have the potential to amplify the perceived benefits or risks associated with a choice option.

Considering the insights presented above and drawing upon the studies by Finucane et al. (2000) and King and Slovic (2014), it can be inferred that linking a BEV to the anticipated consequence of losing an asset, such as a badge or points, would correspondingly indicate a diminished perception of BEV benefits and, consequently, an increased perception of risk. Conversely, aligning the choice of a BEV with the expected outcome of acquiring gamification assets would imply perceiving BEVs as more advantageous and less risky (see Figure 15).

Therefore, it can be hypothesised that (H3.2) augmenting the manipulation of one BEV attribute with gamification will strengthen the effects postulated in hypothesis 3 (H3). Accordingly, extending the manipulation of one BEV attribute with gamification (e.g. emphasising the benefits of BEVs and rewarding BEV selection with a gamification asset) will concomitantly strengthen the influence on the non-manipulated attribute (i.e. BEVs being perceived as low risk).

Variation in Car Type Preference Across Experimental Conditions

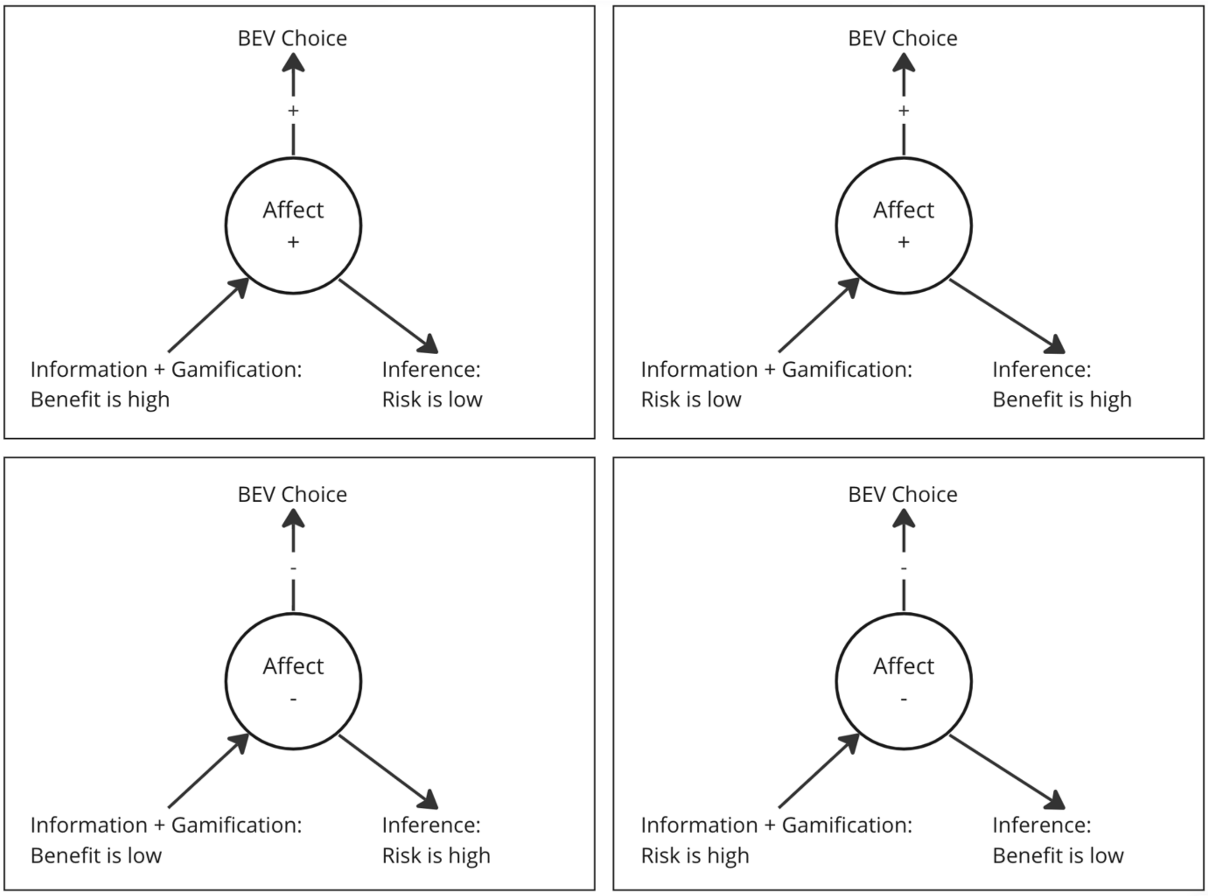
It can be posited that manipulating the risks or benefits of BEVs may not only influence the evaluative affect towards BEVs but could also extend to individuals' preferences for car types, specifically their choice between a BEV or an ICEV. For example, when participants are presented with information that specifically underscores the advantages of BEVs for business trips, in accordance with the risk-benefit association, the evaluative affect towards BEVs is expected to become more positive, while perceived risks should decrease. Given that emotions are considered predictors of behaviour, as noted by Slovic et al. (2004) and Loewenstein et al. (2001), it can be assumed that individuals' car choices will align with their general evaluative affect. Consequently, it can be inferred that when making car choices under the high-benefit and low-risk conditions, there will be a higher proportion of bookings for BEVs compared to the low-benefit and high-risk conditions. In line with the aforementioned considerations, it can further be presumed that this variation in car type preferences will be more pronounced with the addition of gamification.

Therefore, it can be hypothesised that (H4) car type preferences will exhibit variations across experimental conditions (i.e. high-benefit, low-benefit, high-risk, low-risk). Furthermore, it can be hypothesised that (H4.2) car type preferences will exhibit variations across experimental conditions, and these variations will be augmented by the introduction of gamification (i.e. high-benefit + gamification, low-benefit + gamification, high-risk + gamification, low-risk + gamification).

Figure 14 illustrates the theoretical model depicting the hypothesised influence of gamification on the inverse relationship between risks and benefits. Table 34 provides a summary overview of the hypotheses.

Figure 14

Theoretical Model Involving Gamification in the Information Used to Influence Evaluative Affect and the Non-Manipulated Attribute



Note. BEV = battery electric vehicle.

Table 34

List of Hypotheses

No.	Hypotheses
H1	Evaluative affect towards BEVs will be correlated with the inversely related perceived benefits and risks of BEVs.
H2	BEV choice will be positively associated with individuals' evaluative affect towards BEVs.
H3	Manipulating one BEV attribute (e.g. BEVs being high in benefits) will concomitantly influence the non-manipulated attribute (i.e. BEVs being low in risk).
H3.2	Augmenting the manipulation of one BEV attribute with gamification will strengthen the effects postulated in hypothesis 3 (H3).

H4	Car type preferences will exhibit variations across experimental conditions (i.e. high-benefit, low-benefit, high-risk, low-risk).
H4.2	Car type preferences will exhibit variations across experimental conditions and these variations will be augmented by the introduction of gamification (i.e. high-benefit + gamification, low-benefit + gamification, high-risk + gamification, low-risk + gamification).

Note. BEV = battery electric vehicle.

Method

Participants

Screening questions in the questionnaire were used to recruit participants with the following profile: individuals in Germany whose jobs might require occasional business trips and who considered corporate carsharing as a suitable solution for their regular business mobility were targeted.[90] The final sample comprised 361 participants of whom 279 were recruited through a panel from Gapfish GmbH, 40 participants were recruited via the panel provided by Prolific, and an additional 42 participants were primarily recruited through a car manufacturer in Germany and other companies.

Approximately 76.2% (*n* = 275) of the participants had access to at least one corporate carsharing vehicle, while 21.6% (*n* = 78) did not have such access. Eight participants (2.2%) were uncertain about their access to corporate carsharing.

The age of participants was collected in categorical groups. About 3% of participants (*n* = 11) identified as being between 18 and 24 years of age, 27.1% (*n* = 98) were between 25 and 34 years old, 30.5% (*n* = 110) were between 35 and 44 years, 20.5% (*n* = 74) between 45 and 54 years, and 16.3% (*n* = 59) were between 55 and 64 years. Nine participants (2.5%) were above the age of 65.

Among the participants, 74.2% identified as male (*n* = 268), 25.5% as female (*n* = 92), and one person (0.3%) chose not to respond.

[90] Essentially, the screening questions aimed to determine whether corporate carsharing would be a suitable solution for participants' business trips. These questions are identical to those used in Study 1 (see Appendix A).

Study Design

The car booking experiment utilised a 2x4 factorial between-subjects design. Participants were randomly assigned to either the control group (*n* = 180) or the treatment group (*n* = 181). Subsequently, they were allocated to one of the four conditions within their respective groups, namely a high-benefit, low-benefit, high-risk, or low-risk condition. Gamification was absent in the control group, whereas it was introduced in the treatment group through the inclusion of points and a leaderboard within the car booking software.

The control group comprised 44 participants in the high-benefit condition and 46 participants in the low-benefit condition. Meanwhile, the treatment group included 46 participants in the low-risk condition. The remaining conditions, namely the high-risk control group, the low-risk control group, the high-benefit treatment group, the low-benefit treatment group, and the high-risk treatment group, each consisted of 45 participants.

Experimental Stimuli: Business Trip Scenarios of the Control Group

In the context of the car booking experiment, all participants, regardless of their assigned experimental condition, received a hypothetical business trip scenario. In any of the four conditions per control group or treatment group, the scenario prompted participants to envision a business trip where they needed to book a car from the shared corporate car fleet using car booking software. The scenario also provided information on how colleagues and managers judged the use of BEVs for business trips, thereby conveying a social norm[91], even if only for hypothetical peers. The respective scenario was designed to manipulate the perceived risks and benefits of BEVs per experimental condition. In both high-benefit conditions (i.e. high-benefit control group, high-benefit treatment

[91] In the context of the theory of reasoned action, Fishbein and Ajzen (1975) propose that the subjective norm serves as a predictor of individuals' intentions to perform a particular behaviour. According to Fishbein and Ajzen (1975), the subjective norm reflects a person's perception of whether important individuals in their life believe they should or should not engage in a particular behaviour. This suggests that the utilisation of normative messaging could amplify the intended attribute manipulation in this study.

group), colleagues and managers were portrayed as considering BEVs as functionally advantageous for business trips. Conversely, in low-benefit conditions, colleagues and managers were described as considering BEVs as functionally less advantageous for business trips. In high-risk conditions, colleagues and managers highlighted possible negative consequences of using a BEV, whereas low-risk conditions portrayed BEVs as safe and reliable for business trips (see Tables 35 and 36).

Table 35

Scenarios Presented to the Control Group in the Context of the Car Booking Experiment

High-benefit
You are aware that your supervisor and colleagues endorse electromobility because they believe that battery electric cars provide several significant advantages for business trips.
Low-benefit
You are aware that your supervisor and colleagues do not hold a high opinion of electric cars because they believe that electric cars lack some important features that would be useful for business trips.
High-risk
You are aware that your supervisor and colleagues approach electric cars with great caution because they believe that driving electric cars for business trips entails numerous risks and a lack of reliability, potentially leading to missing a business appointment in the worst-case scenario.
Low-risk
You are familiar with the route to your business partner by heart. Therefore, you are aware that numerous charging stations are available along the route. Your colleagues have also reported the reliability of electric cars and mentioned that they have not had any unexpected experiences on business trips so far.

Note. Scenarios were translated from German. Refer to Appendix F for the scenarios in German. Further, prior to receiving one of the scenarios, all participants received the following introduction: “A business trip is approaching. For this journey, you need to book a car from the shared corporate car fleet. The fleet comprises conventional cars with an internal combustion engine and recently added battery electric cars.”

Experimental Stimuli: Business Trip Scenarios of the Treatment Group

The subsequent section briefly highlights the differences in the scenarios used in the treatment group (see Table 36) compared to those in the control group (see Table 35). Firstly, the normative resonance in the four scenarios of the treatment group was comparatively more pronounced, resembling injunctive messaging[92]. Secondly, the anticipated gains or losses of gamification points (so-called *karma points*) linked to the choice of car type and the projected changes in the departmental ranking (i.e. leaderboard) were included in each treatment group scenario and subsequently visually integrated into the car booking software.

Specifically, for participants assigned to the high-benefit condition, the business trip scenario provided information that booking a BEV would award 100 karma points, thereby elevating the individual to the top position on the department leaderboard (i.e. position 1 of 15). In contrast, booking a conventional car would award only 10 karma points and would not affect an individual's position in the department ranking (i.e. position 5 of 15).

In the low-benefit condition, booking a BEV was awarded only 20 karma points, while booking an ICEV was awarded 25 karma points. Regardless of the chosen car type, the position in the department ranking (i.e. position 6 out of 15) would remain unchanged.

Selecting a BEV in the high-risk condition would imply a deduction of 100 karma points and a drop in the leaderboard from position 5 of 15 to the second last position (i.e. 14 of 15). In contrast, booking an ICEV would award 10 karma points, with no change in the ranking.

In the low-risk condition, participants were awarded an equal amount of karma points, regardless of the choice of car type. Independent of the chosen car type, participants would progress from position 6 of 15 to 5 of 15.

[92] Injunctive norms typically refer to what is morally approved or disapproved, specifying how individuals are expected to behave (e.g. Cialdini et al., 1990).

Table 36

Scenarios Presented to the Treatment Group in the Context of the Car Booking Experiment

High-benefit
In the car booking software, karma points are displayed, the amount of which can vary depending on the car choice. Karma points are akin to collecting points or coins in video games. You are aware that your supervisor and colleagues endorse electromobility: they believe that electric cars offer a range of significant advantages for business trips. Therefore, the team has decided that booking a battery electric car will be rewarded with a 10-fold score (equivalent to 100 karma points). By booking a battery electric car, you would secure the first position (i.e. position 1 out of 15) in the departmental competition, which includes your supervisor. In comparison, booking a conventional car earns 10 karma points. Your position (5 out of 15) would remain unchanged for booking a conventional car.
Low-benefit
In the car booking software, karma points are displayed, the amount of which can vary depending on the car choice. Karma points are akin to collecting points or coins in video games. You are aware that your supervisor and colleagues do not hold a high opinion of electric cars because they believe that electric cars lack some important features that would be useful for business trips. Therefore, the team has decided that fewer karma points (20 points) will be awarded for booking an electric car compared to booking a combustion engine vehicle (25 points). Regardless of the car type (electric car or combustion engine) you book, your position (6 out of 15) in the departmental ranking, which includes your supervisor, will remain unchanged.
High-risk
In the car booking software, karma points are displayed, the amount of which can vary depending on the car choice. Karma points are akin to collecting points or coins in video games. You are aware that your supervisor and colleagues approach electric cars with great caution because they believe that driving electric cars for business trips entails numerous risks and a lack of reliability, potentially leading to missing a business appointment in the worst-case scenario. Therefore, the team has decided that booking an electric car results in a deduction of 100 karma points. By booking an electric car, you would drop from the 5th position to the second-to-last position (i.e. position 14 out of 15) in the departmental competition, which includes your supervisor. For comparison, booking a combustion engine vehicle earns 10 karma points. Your position remains unchanged.

Low-risk
In the car booking software, karma points are displayed, the amount of which can vary depending on the car choice. Karma points are akin to collecting points or coins in video games. You are familiar with the route to your business partner by heart. Therefore, you are aware that numerous charging stations are available along the route. Your colleagues have also reported the reliability of electric cars and mentioned that they have not had any unexpected experiences on business trips so far. Therefore, the team has decided that booking an electric car should earn the same number of karma points as booking a combustion engine vehicle. Regardless of the car type (combustion engine or electric car) you choose, you would move up from position 6 to position 5 out of 15 in the departmental competition, which includes your supervisor.

Note. Scenarios were translated from German. Refer to Appendix F for the scenarios in German. Further, prior to receiving one of the scenarios, all participants received the following introduction: “A business trip is approaching. For this journey, you need to book a car from the shared corporate car fleet. The fleet comprises conventional cars with an internal combustion engine and recently added battery electric cars.”

Pre-Test

A pre-test involving eight experts from the automotive industry was conducted to evaluate the usability of the car booking system, the comprehensibility of the scenarios, and the clarity of the questionnaire items, utilising a think-aloud procedure during semi-structured face-to-face interviews. Subsequent to the pre-test, minor adjustments were made based on the feedback received.

Procedure

After completing a set of screening questions, each participant rated three 11-point semantic scaled items spanning from *dislike* to *like*, *bad* to *good*, and *negative* to *positive*, to capture their affective evaluations of BEVs for business trips. Additionally, participants were presented with a single item for rating the perceived risks (11-point semantic scale ranging from (1) *very risky* to (11) *very safe*) and benefits (11-point semantic scale ranging from (1) *not beneficial at all* to (11) *very beneficial*) associated with using a BEV for business trips (refer to Appendix E for the detailed items).

Subsequently, participants were randomly assigned to one of eight experimental conditions, each representing a hypothetical business trip scenario as described in Tables 35 and 36 above.

The following outlines the procedure for the control group, followed by a description of the procedure for the treatment group. In the context of the assigned scenario, participants were instructed to select a car using the car booking software, which was accessible through the questionnaire. This car booking software managed a shared fleet comprising an equal number of ICEVs and BEVs with identical vehicle classes (e.g. sedan, SUV) and other specifications (e.g. range buffer > 20%[93]). Within the software, participants were first shown a page presenting the car fleet, including all available car options. Once the participant made their selection, they were directed to a page asking them to confirm or cancel their chosen car. Upon confirming their choice, participants were presented with a booking confirmation page detailing the chosen car type and its configuration, thereby concluding the car booking experiment.

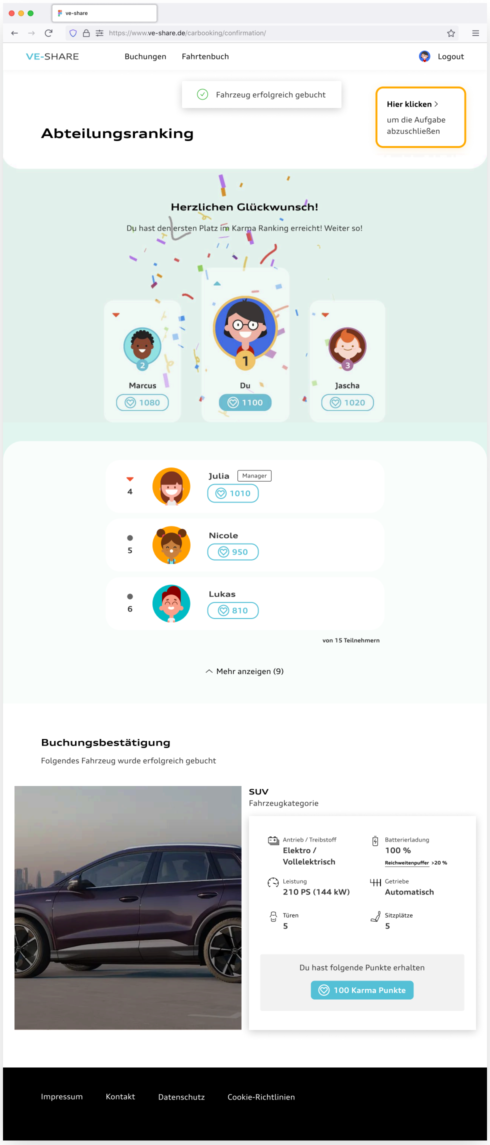
Participants in the treatment group followed the same procedure as those in the control group. Additionally, each car option was associated with the specific number of karma points to be awarded or deducted as defined by each experimental condition (see Table 36). Following the selection of a car, participants were directed to a dedicated page designed for confirming or cancelling their choice. This page also repeatedly displayed the projected number of karma points to be earned or lost upon confirming their car selection. Upon confirmation of their car choice, participants proceeded to the booking confirmation page, described above. In addition to the view of the control group described earlier, this page also incorporated the updated leaderboard (refer to the example in Figure 15), illustrating the adjusted karma point balance and the individual's current position in the ranking among the 14 other participants.

[93] Within the car booking software, information for each BEV and ICEV was presented, specifying that the car's range buffer (i.e. excess fuel or range beyond the estimated consumption) exceeded 20% for the business roundtrip. As a result, for a business trip to the designated partner involving a 100km round trip, the car booking software indicated that the selected car with >20% range buffer would provide a driving capacity of at least 120km.

Following the completion of the car booking process in the software, all participants (in both the control and treatment groups) returned to the questionnaire. The survey continued by revisiting the same set of items mentioned above, assessing individuals' attitudes towards BEVs, along with their perceived risks and benefits associated with BEVs.

Figure 15

Example of the Confirmation Page in the Car Booking Software for the Treatment Group



Note. This screen variant of the car booking confirmation page was presented to participants in the high-benefit treatment group when they chose to book a BEV instead of a conventional car. Refer to Appendix G for more examples of the car booking software and the different conditions.

Results

The procedure of Finucane et al. (2000) or King and Slovic (2014) was predominantly followed to investigate the inverse relationship between the perceived risks and benefits of BEVs. Statistical analyses were conducted using IBM SPSS 28.

In this study, the variables of evaluative affect, perceived risks, and perceived benefits of BEVs were measured twice: t_0 denotes the measurement taken before individuals participated in the car booking experiment, and t_1 refers to the measurement taken after their participation in the experiment. As described above, the evaluative affect scale comprises three items on an 11-point semantic scale ranging from 1 (*dislike/bad/negative*) to 11 (*like/good/positive*). With Cronbach's alpha values of $\alpha(t_1)$ = .97 and $\alpha(t_2)$ = .98, the internal reliability of the scale is deemed acceptable, albeit suggesting potential semantic redundancy[94]. As mentioned above, perceived risk and benefit are each based on a single item, assessed using an 11-point semantic scale ranging from 1 (*very safe/not beneficial*) to 11 (*very risky/very beneficial*) (refer to Appendix E for detailed item descriptions).[95] The means and standard deviations for individuals' evaluative affect, perceived benefits, and perceived risks of BEVs for both measurements are presented in Table 37.

Table 37

Descriptive Statistics for Control and Treatment Groups

Group	*n*	Affect(t_0)		Benefit(t_0)		Risk(t_0)		Affect(t_1)		Benefit(t_1)		Risk(t_1)	
		M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
CG	180	8.49	2.76	7.76	2.85	4.16	2.73	8.59	2.75	8.01	2.87	3.99	2.79
TG	181	7.73	2.94	6.96	3.0	4.40	2.84	7.75	3.08	7.12	2.98	4.60	2.93

[94] According to Hair et al. (2022), reliability values preferably range between .70 and .95 and ideally below .90 as values above .90 indicate semantic redundancy of the items associated with a construct.

[95] For statistical analysis, perceived risk was recoded from a scale of (1) *very risky* to (11) *very safe* to a scale of (1) *very safe* to (11) *very risky*.

Note. The data present the ratings of evaluative affect, perceived risk, and perceived benefit before engaging in the car booking experiment (t_0) and after participating in the car booking experiment (t_1). CG = control group, TG = treatment group.

To investigate the first hypothesis (H1), which posited that evaluative affect towards BEVs will be correlated with the inversely related perceived benefits and risks of BEVs, correlations were computed between the variables of evaluative affect, perceived risks, and perceived benefits for the control and treatment groups, for both measurements t_0 and t_1. Prior to this analysis, the six variables were examined for normality of data distribution. The Kolmogorov-Smirnov test indicated a high level of significance ($p < .001$) for each tested variable, suggesting that the data did not follow a normal distribution. This conclusion was further supported by an examination of the respective histograms. Hence, because the variables were not normally distributed, Spearman rank correlations were computed (refer to Table 38).

Table 38

Correlations Across Participants Between Evaluative Affect, Perceived Risk, and Perceived Benefit for Control and Treatment Groups

	Control group		Treatment group		Control group		Treatment group	
	Affect(t_0)	Risk(t_0)	Affect(t_0)	Risk(t_0)	Affect(t_1)	Risk(t_1)	Affect(t_1)	Risk(t_1)
Risk	-.73**	.	-.79**	.	-.79**	.	-.82**	.
Benefit	.83**	-.79**	.79**	-.72**	.87**	-.84**	.86**	-.85**

** $p < .01$ (one-tailed).

The correlations reveal a pronounced[96] and statistically significant inverse relationship ($p < .01$) between the perceived risks and benefits of BEVs for both the control group and the

[96] According to Hemmerich (n.d.-b), the guidelines for interpreting Pearson Product-Moment correlation can be utilised to interpret the Spearman's ρ correlation coefficients. Regarding the Pearson correlation coefficient, Cohen (1988) considers values of $r = .10$ as a small effect, values of $r = .30$ as a medium effect, and values of $r = .50$ as a large effect.

treatment group, both before and after their participation in the car booking experiment. Additionally, evaluative affect demonstrated a positive correlation with perceived benefits and a negative correlation with perceived risks of BEVs across both groups and measurements. Consequently, the findings support hypothesis 1 (H1), affirming the inverse relationship between evaluated risks and benefits of BEVs for business trips and their association with individuals' evaluative affect.

Recall that in the control group, participants were exposed to one of four experimental conditions where they received a statement promoting one attribute, either highlighting BEVs as high/low in benefits or risks for business trips. The treatment group was presented with the same statements, augmented with gamification, and the car booking software incorporated the gamification extension, which was not included for the control group. To assess whether the non-manipulated attributes changed after exposure to the specific condition, as hypothesised in hypotheses H3 and H3.2, the examination followed the procedure outlined by Finucane et al. (2000). Hence, t-values were calculated per experimental condition to determine alterations in judgments of BEVs (see Table 39). Specifically, the procedure for calculating the t-values for both manipulated and non-manipulated attributes was as follows, using the perceived benefit of the control group exposed to the high-benefit condition (i.e. CGHB) as an example:

1. The mean difference in ratings for the non-manipulated attribute before (t_0) and after (t_1) the car booking experiment was computed. The mean of perceived benefit before the experiment ($M(CGHB_{Ben}, t_0)$ = 7.0) was subtracted from the mean of perceived benefit after the experiment ($M(CGHB_{Ben}, t_1)$ = 7.25).
2. Subsequently, the mean difference in ratings ($M(Ben_{Diff})$ = .25) for the non-manipulated attribute was divided by the pooled standard error[97] of the mean to yield the t-value ($t(CGHB_{Ben}) = \frac{.25}{.4804}$ = .52).

[97] Pooled standard error = $\sqrt{\frac{SE_1^2+SE_2^2}{2}}$

3. Steps one and two were repeated for the respective manipulated attributes, both before and after the experiment, to calculate the corresponding t-values.

Table 39

T-Values for Manipulated and Non-Manipulated Attributes Across Two Measurements in Four Experimental Conditions for Control and Treatment Groups

		Control group			Treatment group	
	n	Risk	Benefit	*n*	Risk	Benefit
High-benefit	44	-.43 n.s.	.52 n.s.	45	-.35 n.s.	.96 n.s.
Low-benefit	46	.49 n.s.	.12 n.s.	45	-.15 n.s.	.61 n.s.
High-risk	45	-.11 n.s.	.35 n.s.	45	1.70*	-.34 n.s.
Low-risk	45	-1.71*	1.49 n.s.	46	-.05 n.s.	.19 n.s.

**p* < .05 (one-tailed), n.s. = not significant.

Concerning hypotheses H3 and H3.2, the manipulation of an attribute across all eight conditions did not elicit a change in the non-manipulated attribute, as hypothesised. This finding remained consistent for the four conditions within the control group and the four conditions within the treatment group.

Nevertheless, the data unveiled two statistically significant alterations pertaining to a manipulated attribute associated with the perceived risk of BEVs. In the low-risk condition of the control group, the results indicate a reduction in the perceived risk associated with BEVs. Consequently, a noteworthy change is evident for the manipulated attribute (i.e. low-risk) but not for the non-manipulated attribute (i.e. perceived benefits). Additionally, in the high-risk condition of the treatment group, perceived risk significantly increased after participants' exposure to the condition portraying BEVs as high in risk. Nevertheless, the non-manipulated attribute (i.e. benefits) did not decrease as anticipated. Neither the information alone nor the information extended with gamification succeeded in augmenting the non-manipulated attribute as expected. Consequently, the results do not provide substantiating evidence for hypotheses H3 and H3.2.

To investigate hypothesis H2, which posits an association between car choice and evaluative affect, a binary logistic regression was conducted for car bookings in both the control group and the treatment group. Due to the non-normal distribution of the evaluative affect variable, an assessment was made to determine whether the four experimental conditions could be pooled per control group and treatment group for the purpose of conducting binary logistic regressions. Specifically, a Kruskal-Wallis test was employed to assess whether a significant difference existed among the four experimental conditions within both the control and treatment groups at time points t_0 and t_1 (Walther, 2022). The results did not indicate statistically significant differences between the four experimental conditions per group ($p_{CG, t0} = .128$, $p_{CG, t1} = .119$, $p_{TG, t0} = .444$, $p_{TG, t1} = .448$) (Walther, 2022). Consequently, the results were pooled for subsequent statistical analyses, allowing for the examination of the relationship between individuals' evaluative affect and their car choice within both the control and treatment groups before and after participating in the car booking experiment.

However, it is important to note that for interpreting the results of the binary logistic regression, the Kolmogorov-Smirnov test revealed significant differences in the distributions of affect between the pooled data for the control group and the treatment group at both measurement points, t_0 and t_1 ($p_{t0} < .05$, $p_{t1} < .05$). Furthermore, the application of a Mann-Whitney-U test revealed a statistically significant difference of evaluative affect between the control group and the treatment group for the two measurements, $U_{t0} = 13668.50$, $Z = -2.67$, $p < .01$ and $U_{t1} = 13588.50$, $Z = -2.75$, $p < .01$ (Hart, 2001; Hemmerich, n.d.-a; Mann & Whitney, 1947).

Table 40 presents the results pertaining to individuals' evaluations of evaluative affect before (t_0) and after (t_1) participating in the car booking experiment.

Table 40

Binary Logistic Regression Analyses Regarding the Association Between Car Choice and Evaluative Affect

Booking	Cox & Snell R^2	Nagel-kerke R^2	*B*	Wald	*p*	*Exp(B)*	Likeli-hood	95% CI	
								LL	*UL*
CG(t_0)	.22	.31	.44	31.95	<.001	1.55	55%	1.33	1.80
CG(t_1)	.28	.38	.52	36.45	<.001	1.68	68%	1.42	1.99
TG(t_0)	.16	.22	.32	25.74	<.001	1.37	37%	1.22	1.55
TG(t_1)	.17	.23	.32	27.27	<.001	1.37	37%	1.22	1.54

Note. The regression is based on the ordinal independent variable of evaluative affect towards BEVs and the binary dependent variable of car choice (0 = ICEV booked, 1 = BEV booked).
CG(t_0) = control group before participating in the car booking experiment, TG(t_0) = treatment group before participating in the car booking experiment, CG(t_1) = control group after participating in the car booking experiment, TG(t_1) = treatment group after participating in the car booking experiment.
CI = confidence interval, *LL* = lower limit, *UL* = upper limit.

To evaluate the suitability of the data for binary logistic regression, both the omnibus test and the Hosmer-Lemeshow test were applied. The omnibus test assessed whether evaluative affect made a difference in the model predicting car choice. Model fit was assessed using the Hosmer-Lemeshow test, which compares observed and expected outcomes by creating subgroups. Both the control group and treatment group passed the omnibus test and the Hosmer-Lemeshow test.

To explore the relationship between evaluative affect and the likelihood for a BEV to be booked in the control group, the odds ratio value (i.e. *Exp(B)* value) was converted[98] into estimated probabilities of the event occurring. The computed odds ratio for the control group displayed increasing probabilities of 55% for a BEV to be booked as individuals' evaluative affect towards BEVs increased, based on assessments made before participating in the car booking experiment. The

[98] Conversion formula: *(Exp(B)-1)*100*

estimated likelihood further rose to 68% after participation in the experiment. In contrast, the treatment group indicated a comparatively lower likelihood of booking a BEV, with a consistent 37% at both measurements. In summary, the data supports hypothesis 2 (H2), indicating a link between evaluative affect towards BEVs and car choice.

To examine hypotheses H4 and H4.2, which propose that car choices will vary across experimental conditions and to a more pronounced extent when enhancing the experimental conditions of the treatment group with gamification, individuals' car choices per car type and condition are presented in Table 41. Additionally, to assess whether the observed variations between the conditions of the control group and the treatment group were statistically significant, a Chi^2-test of independence was conducted for the four conditions per group (see Table 42). Pairwise comparisons for each manipulated attribute (e.g. high-benefit) across the control and treatment groups were also performed (see Table 43). The Chi^2-test of independence determines whether car choice and experimental group assignment are independent or not through the aggregation of data, typically displayed in the form of a contingency table (see Cohen, 1988).

Table 41

Car Choices as Percentages Per Car Type, Experimental Condition, and Control and Treatment Groups

	Control group				Treatment group			
	High-benefit	Low-benefit	High-risk	Low-risk	High-benefit	Low-benefit	High-risk	Low-risk
n	44	46	45	45	45	45	45	46
BEV share	57%	61%	62%	78%	87%	33%	27%	65%
ICEV share	43%	39%	38%	22%	13%	67%	73%	35%

Table 42

Chi^2-Test of Independence for Choice Between Battery Electric Vehicles and Conventional Cars, and Membership in Control and Treatment Groups

Group	*n*	Chi^2-value	Degrees of freedom	*p*	Cramer's V
Control group	180	4.96	3	.18	.17
Treatment group	181	42.75	3	<.001	.49

Note. The Chi^2-test was used to determine whether car choice was associated with the assignment to one of the four experimental conditions within both the control and treatment groups.

In the control group, the majority of participants opted to book a BEV across all four conditions. Notably, the highest percentage of BEV bookings, at 78%, occurred when participants were exposed to the low-risk condition. It is noteworthy that the high-benefit condition exhibited the fewest BEV bookings, with only 57% selecting BEVs. The low-benefit and high-risk conditions demonstrated a similar level of BEV preference, each at 61% and 62%, respectively. Furthermore, as mentioned above, a Chi^2-test of independence was conducted to determine whether the assigned condition was associated with individuals' choice between BEVs and ICEVs (see Table 42). With regards to the control group, the results of the Chi^2-test did not reveal a statistically significant association, indicating no significant variation in car choice based on the assigned condition. Additionally, Cramer's V[99] suggested only a weak association between the experimental condition and car choice.

Conversely, in the treatment group, the results indicate a variation in preference for BEVs based on the assigned experimental condition. Specifically, BEV preference was more pronounced in the high-benefit condition, increasing from 57% in the control group to 87% in the treatment group. In the low-benefit condition of the treatment group, BEV preference decreased to 33%, compared to

[99] According to Cohen (1988), the Cramer's V value signifies the strength of association between variables. Values below .10 indicate a small effect, values of .30 represent medium effects, and values of .50 denote large effects (Cohen, 1988).

61% in the control group. With the addition of gamification in the high-risk group, BEV preference further decreased to 27% in the treatment group, in contrast to 62% in the control group. Lastly, in the low-risk condition of the treatment group, 65% of participants chose BEVs, indicating a lower preference for BEVs compared to the control group where 78% selected a BEV. Nevertheless, BEVs still constituted the majority choice in the low-risk treatment condition. Moreover, the results of the Chi^2-test of independence revealed a statistically significant association between individuals' car choices and their assignment to one of the four experimental conditions. The findings are further supported by the Cramer's V value, indicating a moderate association between car choice and the assigned condition.

In summary, there is no statistical evidence indicating a significant variation in car choice across the four experimental conditions of the control group. However, there is statistical evidence suggesting a significant variation in car choice across the four experimental conditions of the treatment group. Consequently, the data presents mixed findings regarding hypothesis H4.

Finally, to further evaluate whether the observed differences in choices between the control group and the treatment group (H4.2) are statistically significant, a Chi^2-test was conducted per manipulated attribute across the control group and the treatment group (see Table 43).

Table 43

Chi^2-Tests of Independence for Choice Between Battery Electric Vehicles and Conventional Cars, and Membership in Control and Treatment Groups, in Relation to Pairwise Comparisons per Manipulated Attribute

Booking	*n*	Chi^2-value	Degrees of freedom	*p*	Cramer's V
High-benefit	89	9.81	1	.002	.33
Low-benefit	91	6.92	1	.009	.28
High-risk	90	11.52	1	<.001	.36
Low-risk	91	1.76	1	.19	.14

Note. The Chi^2-test of independence focused on comparing values across conditions (i.e. manipulated attribute), such as comparing car choices between participants assigned to the high-benefit control condition and those in the high-benefit treatment condition.

The results display a statistically significant association between being either assigned to the control group or treatment group and participants' car choices for three of four conditions. Thus, the data suggest that the introduced gamification elements, that is, the leaderboard and the associated karma points, exerted a significant influence on the preference for BEVs or ICEVs for three of the four manipulated attributes. Specifically, BEV preference appears to have varied significantly for the high-benefit, low-benefit, and the high-risk conditions as anticipated, but not for the low-risk condition. Furthermore, the corresponding Cramer's V values indicate a moderate association between car choice and individuals' assignment to the high-benefit, low-benefit, and high-risk conditions, and a weak association for participants in the low-risk condition. Thus, due to the absence of a statistically significant difference for the low-risk condition, the data offers mixed evidence for hypothesis H4.2, which posited that the observed variations in car choice will be augmented with the addition of gamification.

Discussion

In this study, the results revealed an inverse correlation between the perceived risks and benefits of BEVs as well as individuals' general evaluative affect was strongly associated with the judgment of BEVs for their risks and benefits, thereby aligning with the previous findings in the context of the inverted relationship between risks and benefits (Alhakami & Slovic, 1994; Finucane et al., 2000; King & Slovic, 2014). Furthermore, individuals' evaluative affect towards BEVs was significantly linked to their opting for BEVs. However, the information used in this study with the aim to manipulate one attribute (i.e. risk or benefit) of BEVs was not found to influence the non-manipulated attribute, neither in the control group, nor in the treatment group. While the manipulation of individuals' judgment of BEVs was not found effective, the results of the car booking experiment nevertheless demonstrate compelling evidence that the gamification elements utilised in this study had a significant impact on participants' choice of car type. Specifically, the control group predominantly chose BEVs in the car booking experiment across all four experimental conditions and participants did not exhibit a statistically significant variation in car type preferences. Conversely, the treatment group's choice of car type aligned with the manipulation of risks and benefits as intended in three out of four conditions. BEV preference significantly increased in the high-benefit treatment condition. Most participants opted for an ICEV in the low-benefit and high-risk treatment conditions, thereby exhibiting car type preferences that were in stark contrast to preferences in the control group. However, while also the majority of the low-risk condition chose a BEV as expected, the participants assigned to this treatment condition did not exhibit an increase in BEV preference as anticipated. Concludingly, the observed variation in car type preferences within and between groups suggests that gamification could be applied not only to enhance individuals' performance and engagement with tasks, as demonstrated by numerous studies (e.g. Boratto et al., 2017; Gutt et al., 2020; Hamari & Koivisto, 2013; Landers et al., 2017), but also to influence choices between different technologies.

As mentioned above, the results of the present study do not indicate that the statements used in the context of the car booking experiment led to a statistically significant variation in the choice of car type in the control group. However, car choices significantly varied for the high-benefit, low-benefit, and high-risk conditions when gamification was added to the statements as well as displayed in the car booking software.

The results of a study by Hsee (1999) suggest why gamification has evidently influenced car type preferences. While many utilitarian consequentialist studies focus on measuring individuals' decisions involving monetary gains or losses, Hsee (1999) conducted a study measuring the anticipated joy regarding product usage and the predicted choice of products. In Hsee's (1999) study, the products were not associated with a monetary value but instead varied in assigned points, which Hsee termed *pseudo values*. With these pseudo values, Hsee (1999) referred to a feature that aimed at creating the illusion of value without actually being of value, a concept that thus resembles the gamification element points. In his study, Hsee (1999) randomly assigned participants to a condition with points or a condition without points. In the condition without points, participants could choose between task 1, which lasted for 50 minutes and was rewarded with a Beatles CD, or task 2, which lasted for 60 minutes and was rewarded with a Barbra Streisand CD. In the condition with points, the completion of task 1 was rewarded 50 points and task 2 with 90 points. For 50 points the participant could get a Beatles CD and for 90 points the participant could redeem a Barbra Streisand CD. Participants of both conditions were initially asked to predict which CD would bring them more joy and which of the two tasks they would choose. According to Hsee (1999), participants in the no-point group exhibited no inconsistency between their predictions and decisions, as they predominantly predicted and chose the Beatles CD. However, Hsee (1999) noted a significant inconsistency among participants in the points group. Specifically, although the predicted CD preference did not differ statistically significantly from the preferences of the other group, the majority of participants in this group chose the task rewarded with the Streisand CD. Hsee (1999) concluded that points had a greater impact on decisions than on preferences. The points seemed to steer participants' decisions away from their predictions towards the option that offered them higher value, thereby giving the value attribute more weight in their decision than in their prediction. In interpreting his findings, Hsee (1999) posited that participants might engage in two distinct cognitive processes. Specifically, during their predictions, individuals may envision the experience of consuming the chosen option. However, during the actual decision-making process, individuals would tend to prioritise the option with the highest value, neglecting the consideration of future outcomes.

In a wholly different context, Ayton et al. (2022) observed a comparable effect, specifically an enhancement in the perceived value of an object through its association with an item that inherently holds minimal monetary value. Ayton et al. (2022) examined the influence of attaching blue plaques to buildings in the London area where notable men and women previously lived. Through a comparison of price changes before and after the installation of new plaques with property prices in the same neighbourhood, Ayton et al. (2022) found that, during the measurement period, this item increased the prices of properties with plaques by 27% compared to houses without plaques. Ayton et al. (2022) invoke the theory of magical contagion, which fundamentally explains how items acquire perceived value after coming into contact with a known person, to elucidate this observation.

In this study, the integration of gamification elements, which have no monetary value, appears to have influenced the evaluation of BEVs and ICEVs. Specifically, in the low-benefit and high-risk conditions, the results of the treatment group, when compared to the control group, indicate a shift in car choice from a majority preference for BEVs to a majority preference for conventional cars. The utilisation of findings from Hsee (1999) and Ayton et al. (2022) to interpret the results of this study suggests that participants in the control group may have chosen the type of vehicle they perceived as most suitable for their business trip, as indicated by the significant correlation between BEV choice and participants' evaluative affect for BEVs. Although evaluative affect was also associated with BEV choice in the treatment group, participants evidently leaned towards the option that offered the most points and the greatest advancement in the department ranking.

While Hsee (1999) had participants assess the predicted enjoyment of both choice options, evaluative affect in this study was measured only for BEVs and not for ICEVs. Consequently, one could argue that ICEVs might have been the choice option that would have conveyed an equally significant or even greater sense of enjoyment if it had been assessed. Nevertheless, the results of the control group also serve as an indicator of the preferences of the treatment group, as the treatment group differs only in the addition of gamification. Since participants in the control group consistently preferred BEVs over ICEVs across all four conditions, the results of the control group also highlight the explicit influence of gamification on car choice, which varied significantly in the treatment group.

The intentional alignment of an individual's choice of vehicle type with points lacking tangible value may be surprising. To theoretically delineate such puzzling decisions, which Hsee et al. (2003) termed as *rationalistic* (intentionally distinguished from *rational*), Hsee et al. referred to the concept of *lay rationalism*. In a multitude of studies, Hsee et al. (2003) observed the deviation between individuals’ predicted consumption experience, that is, their enjoyment of consuming a product, and their actual decision for a product, a distinction Hsee et al. (2003) termed as being influenced by *cold factors*. With these rationalistic, cold attributes, Hsee et al. (2003) alluded to factors that one could consider as being *better* or *more meaningful* in terms of economic value, quantity, functionality, or similar magnitudes.

Hsee et al. (2003) argued that when individuals deviate from their predicted consumption experience – and thus from their feelings (termed *hot factors*) – this might conflict with literature on affect-driven decisions (e.g. Loewenstein et al., 2001; Slovic et al., 2004), which suggests that decisions are often driven by affective responses to choice options. However, Hsee et al. (2003) also argue that making a rational decision may itself engender pleasure (a *hot feeling*), as may apply to this study. It is not difficult to imagine that participating in collecting gamification points and the pursuit of maintaining or climbing up positions in the department ranking, even overtaking one's superior manager, may bring joy, and perhaps even greater joy, when making this decision rather than contemplating whether driving with a BEV or an ICEV will bring greater joy during the business trip. As previously outlined and demonstrated in the cited literature, engaging with gamified services can elicit excitement and bring enjoyment (see results of Study 1 regarding the perceived enjoyment of using the car booking software; Codish & Ravid, 2015; Mitchell et al., 2020); however, this was not measured in the present study.

While the study results suggest that participants in the treatment group seemed to predominantly orient themselves toward, as termed by Hsee et al. (2003), rationalistic, cold gamification points, there is another factor in this study that may have added a hot, emotional note to the arguably cold points. The leaderboard used in this study was based not only on the collection of points but, more precisely, on the accumulation of so-called karma points. Although initially just an unassuming prefix, one can refer back to the example mentioned in the introduction by Zajonc (1980) and Slovic et al. (2004, 2007): they emphasised that merely hearing a certain word can evoke positive or negative feelings, which might be the case when reading the word karma.

According to Jones (2014), karma originates from the Buddhist belief that one's actions in this present life have consequences, influencing one's present and future lives. Good actions lead to positive outcomes, such as rebirth in a pleasant environment, while bad actions lead to negative outcomes, such as rebirth in an unpleasant environment (Jones, 2014). Drawing upon this religious notion, combining the completion of tasks with enhanced karma can be observed in different platforms, such as Todoist, a service with the aim to enhance task productivity, or the international public discussion platform Reddit. Reddit, for example, implemented gamification in the form of what they termed karma points, which the Reddit (n.d., para. 1) platform hosts describe as “fake internet points”. On Reddit, any user can create a post or comment on other posts. These posts or comments can be rated by other users based on what they judge will bring positive or negative karma to the author of the post. Relatedly, on Todoist, users may lose karma points if they fail to complete a task within four days (todoist, n.d.).

Hence, in line with the affect heuristic (Slovic et al., 2007), it is not difficult to imagine that encountering the term karma in connection with points being awarded or deducted for car choice may have triggered thoughts about potential positive or negative future consequences for oneself. Such associations may or may not have influenced individuals’ choices in favour of options that award karma and do not deduct it, as eventually evidenced in the results.

A study by Wiese (2023) highlights a similar influence, referred to as the concept of karmic nudging. In Wiese’s (2023) investigation, messages were used to prime karma-related thoughts before participants engaged in an anonymous online game involving coin flipping or dice rolling. In this game, participants had the opportunity to earn extra money if their coin flip or die roll matched the result displayed on the screen. The honest reporting of the result (i.e. side of the coin or number on the die) relied on the integrity of the participant. Wiese (2023) found evidence that using such messages could reduce cheating for financial gains and, consequently, enhance individuals’ honesty. Although the focus of this study is not on promoting honesty in relation to the concept of karma, the results nonetheless suggest that a particular belief in the existence of karma – linked to the potential of positive outcomes or the avoidance of negative consequences – may have prompted individuals to contemplate the specific consequences of their car choices for their personal future. This belief could thus be an influencing factor for the observed vehicle selections in the treatment group.

The considerations above, along with the insights from Wiese (2023), suggest that the expansion of points by the addition of the term karma may have influenced individuals' choice of vehicles. However, since there is no control group exposed solely to points without the extension of the term karma, this indicated influence cannot be isolated. Subsequent research could explore whether a belief in karma affected the impact of gamification on vehicle choices or if participants were driven solely by rationalistic aspects, as suggested by the findings of Hsee (1999) and Hsee et al. (2003).

While the karma points served as the basis for the leaderboard, which was visible only to the treatment group, both groups were presented with scenarios that included the opinions of hypothetical colleagues and a superior manager regarding the use of BEVs for business trips, specifically, whether they viewed BEVs to be advantageous or risky. Although participants in the study were informed about the beliefs of important individuals in their professional environment, this did not result in a significant variation in the choice of car type among control group participants. Therefore, the results suggest that indications of social norms, at least to a certain extent, did not have a discernible impact on car choices.

In the four scenarios presented to the treatment group, the opinions expressed by colleagues and an individual's manager were accentuated through the incorporation of gamification. In contrast to the control group, the opinions of peers were presented more strongly as recommendations, resembling the concept of injunctive norms by specifying explicit actions that should be taken or avoided (see Cialdini et al., 1990). Depending on the assigned experimental condition, the scenarios outlined how the team evaluated BEVs as either beneficial or risky, which influenced their collective decision to award or deduct a specific number of points for booking a BEV or an ICEV. Although the associated leaderboard could only be accessed after participants confirmed their car choices, the use of the leaderboard and the anticipated consequences of selecting a specific vehicle type, with regard to expected changes in the department ranking, were unequivocally explained in each scenario. Deliberating on a choice while envisioning that the consequences of one's decision would be visible to peers through the leaderboard suggests that conspicuous consumption may have motivated individuals to modify their decisions to achieve the most advantageous outcome in the departmental ranking. Veblen (1912) introduced the term conspicuous consumption in 1899, which delineates humans' overt display of luxury products to demonstrate their abundance of available time, (pecuniary) strength, etc. with the aim of enhancing their image or status. In various domains, individuals have been observed to adjust their choices between product alternatives based on perceived status enhancement, not only for luxury products (e.g. Nelissen & Meijers, 2011) but also in the context of conspicuous consumption of pro-social goods (e.g. Johnson et al., 2018) or environmentally friendly goods (e.g. Griskevicius et al., 2010). Study results by Griskevicius et al. (2010), for example, indicate how the visibility of one's behaviour can be a potent driver of individuals' choices. In their study, Griskevicius et al. (2010) presented treatment group participants with scenarios designed to evoke status motives (such as the desire for social status and prestige). Participants were also asked to imagine that they were either shopping in a public or private setting (e.g. in a physical store or online). The results showed that in the control group (where no status motives were induced), participants preferred the luxurious non-green variant, regardless of whether they were shopping in public or private. However, in the treatment condition, which elicited status motives, individuals' preferences shifted towards less luxurious green products when imagining shopping in a public setting. Conversely, when participants envisioned shopping online, the treatment group increased their preference for the more luxurious non-green version, which Griskevicius et al. (2010) attribute to costly signalling (a notion related to conspicuous consumption, see Veblen, 1912). The findings of Griskevicius et al. (2010) emphasise the impact of status motives and the visibility of decisions on individuals' product preferences. Interpreting the results of this study in light of the insights from Griskevicius et al. (2010) suggests that the leaderboard, which renders one's decisions transparent to significant others, may have influenced the vehicle choices of individuals compared to the non-visibility of activities in the control group conditions. However, this potential effect requires further investigation in future studies.

The considerations above suggest that participants in the treatment group appeared to deliberately choose the vehicle type that would convey the greatest perceived value to them or, conversely, choose the option that would avoid losses, specifically in the high-risk condition. Comparing the results of the high-risk control condition to the high-risk treatment condition revealed a majority preference for BEVs in the control group shifting to a majority preference for ICEVs in the treatment group. As a reminder, in the high-risk treatment group, the outcome was described such that booking a BEV would result in a deduction of karma points, while choosing an ICEV would be rewarded with karma points. Given that participants had to choose between technologies associated with gains and losses, albeit non-monetary in nature, an interpretation of the results using prospect theory is plausible. Prospect theory, introduced by Kahneman and Tversky (1979), provides a theoretical alternative to the expected utility theory, which they consider as a descriptive model for decision-making under uncertainty. Kahneman and Tversky (1979) conducted a series of experiments primarily focusing on gambling scenarios with various configurations of gain and loss scenarios. In doing so, Kahneman and Tversky (1979) identified various effects, such as the certainty effect. Specifically, Kahneman and Tversky (1979) described that participants exhibited risk-averse tendencies when presented with choices offering certain gains. Conversely, participants demonstrated a risk-seeking inclination when the decision options involved certain losses. Within the framework of the theory, Kahneman and Tversky (1979) presented a value function based on their empirical findings, illustrating that losses carry a greater psychological weight than equivalent gains. Thus, the loss of $100 would be perceived as more impactful than a gain of an equivalent amount, i.e. $100. In this study, the high-risk treatment condition combined the hypothetical opinions of colleagues and a manager, stating that driving a BEV is not very reliable for business trips, with a team decision that BEVs should be avoided for business trips. Booking a BEV was described as being aligned with a deduction of 100 karma points and projected to result in a drop in the department ranking to the second last position. In contrast, booking an ICEV was rewarded with 10 karma points, but it did not result in any change in ranking position. In consideration of Kahneman and Tversky's (1979) prospect theory, by presenting two distinct choices with defined outcomes, the high-risk scenario presented here left no room for ambiguity. Therefore, while participants in the control group exhibited a preference for choosing a BEV, participants in the treatment group, in accordance with the expectations of prospect theory, avoided the option associated with losses and a significant decline in the department ranking. Instead, they preferred the option that awarded some karma points and hinted at no changes in the ranking.

Furthermore, participants may have chosen the car type perceived as less risky. As illustrated in the results, in the high-risk condition of the treatment group, perceived risk significantly increased after participants encountered the statement endorsing BEVs as high-risk as well as the car booking experiment. This implies that the scenario and/or car booking experience may have triggered negative emotions when considering a BEV choice for an upcoming business trip, in alignment with the affect heuristic (e.g. Loewenstein et al., 2001; Slovic et al., 2004).

Finally, the findings suggest that gamification exerted no discernible impact on participants in the low-risk group. While there was no statistically significant difference in vehicle choices between the groups, the low-risk scenario employed in the control group indicated an influence on individuals' judgments: the perceived risk of BEVs in the control group significantly decreased in the second measurement. Despite this observation for the control group, the incorporation of gamification elements did not achieve a change in the evaluation of either the perceived benefits or risks associated with BEVs.

In conclusion, this study did not find evidence that the scenarios influenced the judgment of the non-manipulated attribute, as suggested by prior research (e.g. Finucane et al., 2000; King & Slovic, 2014). Furthermore, car choices did not exhibit statistically significant variations in the control group as expected. However, car choices displayed significant variations in three out of four experimental treatment group conditions when comparing the results with the control group. The preference for BEVs was not only enhanced or attenuated as intended by the use of gamification. Moreover, even the predominantly preferred car type was significantly affected by the gamification intervention. Specifically, in the low-benefit and high-risk conditions, ICEVs were preferred, while for the high-benefit condition, BEV preference was even more pronounced. The results of this study give rise to intriguing considerations. On the one hand, in line with Hsee’s (1999) and Hsee et al.’s (2003) findings related to lay rationalism, participants might have opted for the cold, rationalistic choice option offering more points, disregarding the choice option that would provide greater enjoyment (i.e. choosing a BEV, as indicated by the choices of the control group), as suggested by the affect heuristic. On the other hand, the foregoing discussion suggests that the majority of participants might have chosen ICEVs in two of the four treatment conditions, driven by positive or negative emotions associated with pursuits of good karma, the avoidance of negative karma, the enjoyment derived from engagement in the gamified setting (e.g. Codish & Ravid, 2015; results of Sub-study 1.2, see Chapter 2.2; Mitchell et al., 2020), or the motivation to mitigate negative feelings (as indicated by the increase in perceived risk of BEVs in the high-risk treatment condition at t_1) when contemplating booking a BEV for a risky business trip. These considerations align with the affect heuristic but warrant further investigation.

This study has yielded new insights into the efficacy of gamification in contexts beyond the scope of the existing literary focus on enhancing individuals' engagement and performance. The findings presented here indicate that the application domain can extend to the choice between technologies, or more specifically, the choice between a sustainable technology and its conventional alternative. The results lay the groundwork for exploring the implied effects in future research and underscore the need for further investigation. Additionally, they suggest potential applications in commercial contexts related to technology choice, which will be discussed in detail below.

Practical Implications

The following practical recommendations are based on the results presented in this study. As discussed above, the findings highlight the potential of gamification not only to enhance performance, as extensively demonstrated in the literature (e.g. Boratto et al., 2017; Gutt et al., 2020; Landers et al., 2017), but also to influence technology choices. For organisations, fleet managers, software designers, car manufacturers, and policymakers, the results suggest that gamification leaderboards can significantly influence individuals' choices of car type.

However, on a more detailed level, it is important for software designers to carefully consider the specific implementation of gamification elements, including leaderboards. For example, seemingly minor details, such as using the term *karma* alongside gamification points could notably influence individuals' responses to such interventions. As mentioned above, this aspect, which was not controlled for in this study, underscores the need for further research.

For software designers, organisations, and fleet managers, the findings offer mixed results regarding the use of social factors to promote BEV choice. On the one hand, experimental scenarios that conveyed a social norm associated with BEVs for business trips did not result in significant variation in car choice. This suggests that communication strategies based on social norms may not be particularly effective in this context.[100] On the other hand, the leaderboard, which relies on social comparison, proved to be impactful. The results indicate that the leaderboard, by making individuals' decisions visible to significant others, influenced car choices in comparison to the non-visibility of choices in the control group. While this finding warrants further investigation, particularly concerning the precise design elements of a leaderboard implementation[101], it suggests to car manufacturers, organisations, fleet managers, and software designers that making activities visible to important others could be an effective strategy for influencing car choices.

As outlined in the introduction, gamified commercial applications typically focus on rewarding users, with the loss of points either not implemented or not emphasised. However, the findings of this study demonstrate that both the awarding and loss of points can significantly affect individuals' car choices. Specifically, participants tended to select options that maximised point gains (and ranking position) or those that avoided point losses (and ranking position) and awarded at least

[100] For example, the study by Richter et al. (2018) demonstrated how minor changes to the presented social norm – such as varying the percentages of reference groups, omitting percentages altogether, or displaying only a sign – can influence individuals' product choices in different ways. These variations may be effective for one user group but could potentially provoke psychological reactance (see Brehm, 1989) in another.

[101] For example, further research would be required to determine the individual influences of the visualisation of the graphical elements, the precise implementation of the ranking system, the consequences of points being awarded or not awarded, the user's current or future balance, the size of the group participating in the gamified challenge and consequently, in the ranking, as well as other factors.

some points. For software designers this result suggests that incorporating the loss of points could be an effective method for promoting specific technology choices. However, this approach requires careful consideration as it is not difficult to imagine that losing points could negatively affect users' enjoyment of the gamified application (see Degirmenci & Breitner, 2023)[102], potentially driving users away. Therefore, the trade-off between influencing individuals' choices and maintaining their enjoyment as well as their intentions to engage in a gamified environment warrants further investigation and caution when implementing such elements in a commercial context. Nevertheless, for software designers and fleet managers the findings indicated that individuals tended to choose options that offered the greatest improvement in points and ranking, as evidenced by the majority preferring a BEV in the high-risk control group and an ICEV in the high-risk treatment group.

Overall, while the results do not allow for a clear disentanglement of the factors that influenced individuals' choices – whether due to positive or negative emotions associated with the pursuit of good karma or the avoidance of negative karma, the enjoyment of engaging in the gamified setting, or the motivation to avoid negative emotions – the findings nonetheless support the use of gamification elements in a commercial context.

Limitations

This study is subject to three primary limitations, which will be briefly outlined below.

Firstly, this study exclusively focused on a singular comparison between an established technology and its proposed sustainable alternative. This limitation may impact the generalisability

[102] Degirmenci and Breitner (2023) conducted a field-study to promote BEV eco-driving (i.e. lower energy consumption in kWh per 100 km driving) through gamification integrated into a mobile application used during BEV driving. They tested three groups: (1) a control group not exposed to gamification, (2) a group that was exposed to gamification with visual stimuli, and (3) a group exposed to gamification with both auditory and visual stimuli. The results showed that energy consumption was reduced in the group exposed to auditory-visual cues. However, participants in this group also reported lower enjoyment and reduced intentions to continue using the gamified eco-driving application compared to those in the visual-only group.

of the findings regarding the influence of gamification on other technology choices. Therefore, future studies could broaden their scope to encompass a diverse range of technologies, comprehensively assessing the impact of gamification, including research in social environments beyond the business context.

Secondly, this study only measured individuals' subjective assessment of affect regarding BEVs, potentially limiting the scope of feelings experienced during the study. In the future, alternative methods for measuring affect could be considered. Relatedly, King and Slovic (2014), for example, suggested measuring the physiological states corresponding to individuals’ feeling states.

Thirdly, the study was conducted without a break between the two measurements. However, for instance, King and Slovic (2014) incorporated filler tasks between both assessments, spanning approximately 30 minutes. Hence, participants recalling their previous responses from the initial measurement may have influenced their judgment of evaluative affect, risks, and benefits of BEVs, potentially motivating consistent ratings of the items in alignment with their earlier judgments. This potential recall effect could have influenced the findings of this study.

Chapter 4: General Discussion

Introduction

This thesis examined the impact of changes in the context of technology use, evaluated through the TAM and the affect heuristic, on the assessment and preference of BEVs in comparison to conventional cars. Subsequently, a synthesis of the key findings from both studies forming the foundation of this thesis is presented. This synthesis is accompanied by theoretical and practical implications, an outlook for further research, and the primary limitations of this thesis. The findings are structured into three clusters summarising the results:

The first cluster provides a synopsis regarding the influence of various predictors on individuals' intentions to book a BEV, as determined through the application of an adapted TAM, and examines the outcomes of the affect heuristic, with a focus on a re-examination of the inverse relationship between the perceived risks and benefits associated with BEVs.

The second cluster provides a summary of changes in technology usage contexts (e.g. risky BEV usage situations, expansion of the decision-making context for car choice through gamified gains and losses) and the resulting effects on individuals' judgments of BEVs.

The third cluster encapsulates a summary of the influence of changes in technology usage contexts on preferences for car types, coupled with other pertinent observations as well as the association between car choice and individuals' behavioural intentions or evaluative affect towards BEVs.

Perceived Risks, Benefits, the Expected Enjoyment of Driving a BEV, and Other Predictors of Individuals' Intentions to Book a BEV or Their Evaluative Affect Towards BEVs

The outcomes of the TAM of Study 1 align predominantly with the findings of related TAM variants, showing that individuals' behavioural intentions to book a BEV were predicted by the perceived usefulness and ease of use of BEVs. However, in contrast to other frequently cited TAM variants (e.g. Venkatesh & Bala, 2008), evidence was presented showing that the primary driver behind individuals' intentions to book a BEV was the anticipated enjoyment derived from driving it. This underscores the significance of the hedonic aspects of technologies and emotions in predicting behavioural intentions, even when they are utilised within a business context. Furthermore, the results of this study revealed a significant impact of the subjective norm associated with BEVs, the image linked to BEV drivers, an individual's commitment to engage with disseminated goals and gamified challenges embedded in the car booking software, and the perceived enjoyment of using the car booking software on individuals' intentions to book a BEV.

In Study 2, the re-examination of the affect heuristic in the context of the inverse relationship between perceived risks and benefits revealed an inverse correlation between the perceived risks and benefits of BEVs for both the control group and the treatment group (including gamification) before and after their participation in the car booking experiment. Furthermore, individuals' general evaluative affect was strongly linked to the judgment of BEVs regarding their risks and benefits.

In summary, the anticipated enjoyment of driving a BEV emerged as the primary predictor of behavioural intentions and the outcomes of the adapted TAM were largely in accordance with findings from related TAMs in the context of BEV acceptance (e.g. Fazel, 2014; Roemer & Henseler, 2022). Additionally, the results of the risk-benefit association were consistent with previous literature findings (e.g. Alhakami & Slovic, 1994; Finucane et al., 2000; King & Slovic, 2014).

The Influence of Changes in Technology Usage Contexts on the Judgment of BEVs

In Study 1, the inclusion of badges in the car booking software exerted an influence on several TAM relationships. Specifically, badges enhanced the relationship between individuals' enjoyment of using the car booking software and their commitment to engage with goals and gamified challenges presented in the car booking software. Furthermore, while a significant relationship between subjective norms and individuals' goal commitment was established in the control group, this association became non-significant when badges were displayed in the software. Additionally, although no statistically significant association existed between the perceived usefulness of BEVs and participants' intentions to book a BEV in the control group, this association became statistically significant and positive in the presence of the badges intervention.

In the re-examination of the inverse relationship between the risks and benefits of BEVs in Study 2, the information used to manipulate either the risks or benefits of BEVs did not influence the non-manipulated attribute in either the control group or in the treatment group, which integrated gamification. Nevertheless, two statistically significant changes were observed regarding the manipulated attribute of perceived risk of BEVs. In the low-risk condition of the control group, the results indicate a decrease in the perceived risk associated with BEVs. Additionally, in the high-risk condition of the treatment group, perceived risk significantly increased after participants were exposed to the statement and booking system that promoted BEVs as high risk.

In summary, the incorporation of the gamification element badges into the car booking software was observed to influence several TAM relationships in Study 1. In Study 2, the manipulation of the risks or benefits of BEVs, including the integration of gamification, was only found to evoke minor changes in individuals' judgment of the manipulated risk attribute. Hence, despite the two observed changes in the manipulated attribute, Study 2 was largely not found to replicate the findings from past literature (see Finucane et al., 2000; King & Slovic, 2014).

The Impact of a Change in Technology Usage Context on BEV Preference and Their Prediction

In Study 1, the data revealed that BEVs were the preferred choice for only a minority of participants. Moreover, the inclusion of the gamification element badges in the car booking software did not motivate participants to prefer BEVs over ICEVs, regardless of whether the business trips were characterised as low-risk or high-risk. Hence, while Davis et al. (1989) proposed behavioural intentions as a predictor of actual behaviour, the results of Study 1 showed variations in the reliability of predicting car choices based on behavioural intentions depending on the experimental condition. Specifically, for participants in the low-risk control group (i.e. without gamification), behavioural intentions consistently predicted individuals' car choices in all three car bookings. However, this association was notably weak for the low-risk treatment group, suggesting an influence of the badges intervention. Furthermore, the association between car choice and intentions was weak for both the high-risk control group and the high-risk treatment group. Although the results did not indicate an influence of gamification on this association, they revealed that participants assigned to a high-risk trip were associated with a statistically significantly higher attrition rate from the car booking experiment. Additionally, participants chose to withdraw from the experiment instead of selecting any car type, despite the car booking software displaying range buffer information for each car and car type, which theoretically should have supported BEV selection. Notably, individuals opting for BEVs exhibited a slightly stronger inclination towards cars with a 100% range buffer compared to those choosing ICEVs.

In Study 2, the results of the car booking experiment provide compelling evidence that the utilised gamification elements had a significant impact on participants' choice of car type. Notably, the majority of control group participants consistently chose BEVs in the car booking experiment across all four experimental conditions. In contrast, the treatment group's choice of car type exhibited significant variations in three out of four conditions, aligning with the intended manipulation: BEV preference significantly increased in the high-benefit condition. Furthermore, the majority of participants in the treatment group chose an ICEV in the low-benefit and high-risk treatment conditions, indicating car type preferences that were markedly different from those in the corresponding control group conditions. However, while the majority of participants in the low-risk conditions opted for a BEV, individuals assigned to the treatment condition did not exhibit the expected increase in BEV preference. Furthermore, participants’ evaluative affect towards BEVs was significantly associated with their selection of BEVs in both the control group (absence of gamification in the scenario and car booking software) and the treatment group (presence of gamification).

In summary, the findings of Study 1 suggest an influence of gamification and/or higher-risk trips on individuals' responses in the car booking experiment. On the one hand, the inclusion of the gamification element badges influenced individuals’ responses, as evidenced by the weakened association between participants' intentions to book a BEV and their actual car choices in the low-risk treatment group. On the other hand, a statistically significant association was observed between participants assigned to a high-risk business trip and their decision to withdraw from the car booking experiment, compared to participants with a low-risk business trip. The results of Study 2 indicate that the information presented in the control group did not lead to statistically significant variations in car choices. In contrast, the addition of gamification elements in the treatment group resulted in significant variations in car type preferences. While Study 1 demonstrated variations in the predictive capacity of behavioural intentions concerning a change in context, in Study 2, evaluative affect was consistently linked to car choice in both the control group and the treatment group across both measurements.

Theoretical Implications of Using the Technology Acceptance Model or the Affect Heuristic for Technology Assessment

Regarding the research aim of this thesis, the following section shall provide a concise overview of the value of the applied theories, the TAM and the affect heuristic, with regards to their benefits and drawbacks regarding the judgment, acceptance, and choice of technologies, based on the insights derived from both studies in this thesis.

Benbasat and Barki (2007) criticised the multitude of extensions of the TAM, arguing that it has led to theoretical chaos. It cannot be denied that the TAM has been adapted to different contexts, which also applies to Study 1. However, the flexibility of the model regarding the number and type of predictors may well be to the TAM's advantage. By applying the TAM, valuable insights can be gained, ranging from capturing general perceptions of a technology to examining responses at a granular level. With regards to the level of granularity, a factor that is not exclusive to the TAM but may be relevant for the specific research objective is the choice of measurement model for the latent variables (i.e. formative or reflective). For instance, as demonstrated in the measurement of the formative variable perceived usefulness of BEVs in Study 1 and the corresponding insights gained from an analysis of the individual contribution per indicator, the use of a formative measurement model can, for example, assist product designers or developers in identifying specific areas for technology improvement as will be further discussed in the practical implications.

Furthermore, in Study 1, the TAM was adapted to this research context. This adaptation revealed that the expected enjoyment of driving a BEV was the strongest predictor of individuals' behavioural intentions to book a BEV. This observation aligns with findings in related BEV studies (e.g. Fazel, 2014; Roemer & Henseler, 2022) and contrasts with other popular TAM variants in the field of IT acceptance in business environments, such as the TAM by Venkatesh and Bala (2008). The findings of Study 1 suggest the relevance of assessing the perceived emotions associated with technology usage as a determinant of behavioural intentions. This relevance extends not only to predominantly hedonic information systems in a private usage context, as indicated by research by van der Heijden (2004), but also to the domain of primarily hedonically perceived technologies used in a utilitarian business context, as indicated by the results in this study.

According to the affect heuristic, emotions are a primary determinant of how individuals judge a technology, activity, or similar entities for their risks and benefits. In the context of a re-examination of the inverse relationship between the perceived risks and benefits of innovations, King and Slovic (2014) argued that individuals are more likely to rely on their affect in early judgments of new technologies for their risks and benefits rather than systematically evaluating a product's individual attributes. This highlights a potential limitation of the TAM's approach to measuring individuals' intentions to use a new technology. Specifically, King and Slovic (2014) argue that the TAM, along with related theories (e.g. the theory of reasoned action), primarily relies on the cognitive processes of individuals for technology evaluation. According to King and Slovic (2014), these cognitive processes involve individuals carefully forming their attitudes based on acquired knowledge and information, leading to decisions. However, for risky decisions (e.g. Loewenstein et al., 2001), decisions made under time pressure (e.g. Finucane et al., 2000), or when evaluating new technologies (e.g. King & Slovic, 2014), the affect heuristic suggests that individuals are more inclined to rely on their affective response (Slovic et al., 2004). For example, interpreting the findings of Study 1 with regards to the comparatively higher attrition rate from the car booking experiment of participants who were assigned higher-risk trips with the affect heuristic or the risk-as-feelings hypothesis implies that an emotional response to higher risk trips may have influenced their decision to disengage from the car booking experiment rather than selecting any car.

In summary, while the measurement of predicting car choice from behavioural intentions in Study 1 and evaluative affect in Study 2 is not directly comparable due to nuanced differences, as will be further discussed in the limitations, the results of both studies nevertheless suggest that the association between car choice and individuals' intentions to book a BEV appeared to be more susceptible to influences in the decision-making context than applies to the measurement of evaluative affect, as per the findings of Study 2. Nevertheless, among other factors, the predictive validity of the different theories may further depend on the stage of product development, the nature of the product (e.g. business or pleasure), individuals' experience gained or knowledge about the specific technology, or the desired level of granularity in assessing individuals' responses to technologies. Ultimately, theory choice does not have to be a binary decision. Each theory discussed in this thesis contributes a valuable piece to the puzzle of understanding the various factors influencing sustainable car choice under varying contextual influences.

Theoretical Implications for the Utilisation of Gamification to Motivate Choice of Innovative and Sustainable Technologies

Among other critiques raised in the context of gamification, Bogost (2011) cautioned against a one size fits all mentality, emphasising the danger of reducing essential insights from the gaming industry solely for the purpose of enhancing customer loyalty. Nevertheless, those typical gamification elements criticised by Bogost (2011), including points, badges, and leaderboards, were utilised in the two studies underlying this thesis. They served as a means to alter the decision context of individuals with the aim of influencing technology choice between the argued sustainable alternative of BEVs and ICEVs. While it is worth mentioning that between the conduction of Study 1 (in 2019) and Study 2 (in 2023), the attitude towards BEVs may have become more positive in German society, as noted in the increased registration rates from 1% in 2018 to 17.7% in 2022 (Kraftfahrtbundesamt, n.d.-c, n.d.-b), pronounced variations in the efficacy of gamification on car type preferences across both studies can be observed. In summary, Study 1 showed that a minority of participants chose a BEV, while the majority of the control group in Study 2 preferred a BEV.

Despite the findings of Study 1 suggesting that the use of gamification did not motivate BEV choice, BEV or ICEV preference varied significantly within the gamified group in Study 2. In Study 1, gamification was found to strengthen some structural relationships in favour of BEV perception. Conversely, in Study 2, gamification barely influenced the judgment of BEVs contrary to expectations but exerted a pronounced impact on the preference of car type.

The findings of this thesis contribute to the understanding of how even a brief exposure to a change in decision context involving gamification can alter individuals' perceptions of technologies, as specifically indicated by the results of Study 1. Furthermore, the results of Study 2 have provided new insights into the efficacy of gamification in contexts beyond the scope of the existing literature, which predominantly focuses on enhancing individuals' engagement and performance (e.g. Boratto et al., 2017; Gutt et al., 2020; Hamari & Koivisto, 2013; Landers et al., 2017; Landers & Landers, 2014). Specifically, the findings of Study 2 indicate that the application domain may extend to the choice between technologies, or more specifically, the choice between a sustainable technology and its conventional alternative. The results pave the way for exploring the implied effects in future research and suggest its application in commercial contexts, as will be further discussed in the practical implications.

The Observed Added Value of Gamification: An Interpretation Utilising the Notions of Lay Rationalism and Magical Contagion

In Study 1, it was discovered that the gamification element badges transformed the initially non-significant association between the perceived usefulness of BEVs and the behavioural intentions to book a BEV into a statistically significant and positive relationship. This suggests that badges enhanced the perceived value and associated benefits of BEVs for business trips, consequently influencing individuals' intention to book a BEV. In Study 2, for three out of four experimental conditions in the treatment group, it was observed that participants adjusted their car type preference to align with the car types advertised through gamification. In various research contexts, literature has reported similar observations of an item evidently gaining value by adding an attribute that inherently appears to have little or no monetary value (e.g. Ayton et al., 2022, referring to the theory of magical contagion; Hsee et al., 2003, and their concept of lay rationalism). In the context of the findings of this thesis, these insights suggest that the utilised gamification element may have elicited what Hsee et al. (2003) termed as rationalistic behaviour, wherein individuals prefer an object perceived as better or more meaningful in terms of economic value, quantity, functionality, or similar magnitudes. However, future research could explicitly investigate whether these theories are applicable to gamification, as suggested by the results of this thesis.

The Belief in Karma and the Efficacy of Gamification

The gamification points used in the context of the leaderboard in Study 2 were referred to as karma points. The observations from Study 2 suggest that specific beliefs in the existence of karma may prompt individuals to reconsider the consequences of their car choices in relation to potential impacts on their personal future. Specifically, individuals might adapt their behaviours to attain positive outcomes or avoid negative consequences. This belief in karma could be a contributing factor to the observed influence of gamification in Study 2. However, as there was no control group in Study 2 exposed solely to points without the extension of the term karma, this indicated influence cannot be isolated. Consequently, future research could investigate whether the belief in karma affected the impact of gamification on car choices or if participants were primarily driven by rationalistic aspects, as suggested by the findings of Hsee (1999) and Hsee et al. (2003).

Self-Efficacy: Giving Individuals the Opportunity to Validate Their Skills

Research by Bandura and Schunk (1981) on self-efficacy theory and Gutt et al.'s (2020) research involving gamification within the context of goal-setting theory and self-efficacy theory share the commonality that participants' active engagement with tasks confirmed their actual abilities, thereby motivating them to engage with tasks of higher difficulty. However, participants in both studies of this thesis were only exposed to hypothetical technology usage scenarios and had no opportunity to experiment with BEVs in an *easier* setting (i.e. potentially a less risky setting) to gain confidence in their skills for tackling goals of higher difficulty. Interpreting the findings of this thesis through the lens of self-efficacy theory implies that the incremental confirmation of knowledge, enabled by proximal goal setting, may serve as a fundamental lever for approaching tasks with higher levels of difficulty. Consequently, individuals who perceive BEVs with a lower range buffer as riskier and challenging compared to a BEV with a higher range buffer might need to accumulate practical experience in less challenging situations first before considering more difficult goals. This lack of practical experience may have limited the effectiveness of the intervention, specifically the gamification intervention in Study 1. Future research could explore whether combining proximal goal setting with gamification in an experimental framework, which allows participants to actively explore their own skills and capabilities, can enhance the accessibility of new technologies for individuals, thereby influencing (sustainable) technology choices.

Tracking One's Own Activities and the Activities of Others

In addition to the suggested pivotal role of being able to explore one's skills and abilities, it is noteworthy that in Study 1, participants had the opportunity to track their own progress in badge achievement within the car booking software. However, this did not exert a noticeable motivational influence on BEV choice. Conversely, in Study 2, a leaderboard was integrated into the software, allowing for a comparison with (hypothetical) significant others, which was found to yield a statistically significant influence on individuals' car type preferences. Although each study has a different focus, findings from Hamari (2013) on gamification and from Griskevicius et al. (2010) on conspicuous consumption suggest that the visibility and tracking of one's own activities, along with implicit references to the behaviour of others and a desire for status, may serve as motivating factors for engaging in specific behaviours and influencing choices.

However, as it remains unclear under which circumstances tracking one's own progress is more motivating or beneficial than sharing progress publicly in the context of gamification, future research could explore the factors that determine when tracking one's own progress is more motivating for sustainable choices than comparing it with the progress of (important) others, and vice versa.

The Role of Value Internalisation in Predicting the Success of Gamification Interventions

Regarding the determined influence of social factors (i.e. subjective norm and image) in predicting individuals' behavioural intentions to book a BEV in Study 1, Ryan and Deci's (2000) self-determination theory suggests that the individuals in this study could be attributed a form of extrinsic motivation, characterised by lower internalisation of values and behavioural regulations. Ryan and Deci (2000) describe that such individuals derive motivation for performing a particular behaviour from perceiving social pressure, avoiding guilt or anxiety, or enhancing their self-esteem, pride, and feelings of worth. Moreover, a new set of values and their corresponding behavioural regulations might even be considered controlled and alienated. Although the influence of subjective norm on behavioural intentions was low, the insights from self-determination theory nevertheless suggest that individuals who expressed a willingness to book a BEV in the future might have been driven, among other factors, by the motivation to please their business environment.

Overall, the influence of social factors on individuals' behavioural intentions to book a BEV within the TAM was notably weak. Consequently, this diminished influence of social factors may also affect the anticipated influence of gamification interventions. Hence, future research could specifically explore whether value internalisation is a predictor for the success of gamification interventions, similar to the attributed predictive role of goal commitment suggested by Hamari (2013, 2017) or Landers et al. (2017).

Utilising Goal-Commitment as a Predictor of the Success of Gamification Interventions

Locke and Latham (2002), within the context of goal-setting theory, along with scholars in the gamification literature (e.g. Landers et al., 2017; Mitchell et al., 2020), have addressed that presented goals should be meaningful to individuals to be effective. In this regard, when assessing the success of gamification interventions, Landers et al. (2017) and Hamari (2013, 2017) specifically emphasised the significance of goal commitment as a predictor of success.

In Study 1, the introduction of badges did not demonstrate an enhancement of the influence of individuals' willingness to engage with disseminated goals and gamified challenges on individuals' intentions to book a BEV. The interpretation of the findings suggests that while individuals may have found achieving badges to be an amusing experience, as indicated by the strengthened association between the enjoyment of using the booking software and goal commitment, changing their car choice solely to earn badges might not have been considered a worthwhile outcome, even in a hypothetical setting. For practical application, this suggests that measuring goal commitment alone does not provide insights into why individuals do not perceive the presented goals as worthwhile or meaningful. Nevertheless, measuring goal commitment could be employed for pre-testing gamification interventions and serve as an early indicator of whether the intended intervention will yield the desired effects or whether adjustments are necessary, as will be further discussed below.

Practical Implications

The following practical recommendations are drawn from the findings of Study 1 (including the Sub-studies 1.1, 1.2, and 1.3) and Study 2, offering valuable insights for car manufacturers, fleet managers, policymakers, and software designers on the acceptance and promotion of BEVs within the context of business mobility.

The outcomes of the TAM in Study 1 indicate that individuals' behavioural intentions to book a BEV were, among other factors, predicted by the perceived usefulness of BEVs. A detailed examination of the three indicators of the perceived usefulness of BEVs revealed that current BEV features, such as faster acceleration compared to conventional cars and the usability of BEVs during business trips in terms of charging, were the primary factors in defining the perceived usefulness. However, perceiving BEVs as more efficient than conventional cars did not significantly determine the perceived usefulness. This finding suggests that car manufacturers, infrastructure providers, and policymakers should continue their efforts to enhance the technological competitiveness of BEVs relative to conventional cars, aligning with international BEV acceptance research (e.g. nearly half of Western European drivers expect a range of more than 500km, see Healy et al., 2024).

While the overall perceived usefulness of BEVs for business trips was rated as average, and only a minority of participants chose a BEV in Study 1, this suggests that organisations and fleet managers may need to carefully monitor the number of BEVs to be added to the fleet to ensure proper economic utilisation of the car fleet. In contrast, the majority of participants in Study 2 preferred a BEV. This shift in preference, contrasting with the findings of Study 1, suggests that attitudes towards BEVs may have evolved over the time between the two studies, conducted in 2019 and 2023. For organisations and fleet managers, a positive change in attitudes further encourages the consideration of BEVs in corporate fleets, particularly when fleet expansion is necessary and when BEVs align with the mobility patterns of employees.

The findings of Study 1 revealed that the primary driver behind individuals' intentions to book a BEV was the anticipated enjoyment derived from driving it, underscoring the importance of hedonic aspects even within a business context. For organisations, fleet managers, policymakers, and car manufacturers, this insight suggests that communications and marketing strategies aimed at encouraging BEV usage should focus on highlighting the enjoyable aspects of driving BEVs to effectively promote their adoption, for instance, in corporate fleets.

Results from Study 1 also showed that for participants in the low-risk control group (i.e. without gamification), behavioural intentions consistently predicted car choices across all three car bookings. However, this association was notably weak within the low-risk treatment group, suggesting an influence of the badges intervention. Study 2 further indicates that the information provided to the control group did not lead to statistically significant variations in car choices, whereas the addition of gamification elements in the treatment group resulted in significant variations. Previous literature (e.g. Bandura & Schunk, 1981; Venkatesh & Bala, 2008) has highlighted that when a new system or functionality is introduced, users may require time to adapt and gain experience with the new stimulus. This period of adjustment could lead to varying responses in system judgment or behaviour over time. Therefore, it may be advisable for organisations and fleet managers to monitor employees' behaviours at multiple measurement points to determine whether the desired effect is occurring and inform decisions about potential amendments to the intervention.

Although there was no statistically significant association between the perceived usefulness of BEVs and participants' intentions to book a BEV in the control group of Study 1, this association became statistically significant and positive in the presence of the badges intervention. For car manufacturers and software designers, this finding indicates that incorporating gamification badges influenced individuals to consider booking a BEV. However, the gamification badges did not incentivise participants to prefer BEVs over ICEVs, whether in the context of low-risk or high-risk business trips. Thus, the insights from Study 1 may also suggest to software designers, organisations, and fleet managers that associating the battery's range buffer with gamification badges to promote BEV usage may not be the most effective approach. Given the need for further research to provide clearer guidance for the industry, it may be beneficial for software designers to consider integrating gamification with activities or challenges that extend beyond the remaining range. For instance, gamification could be utilised by software designers, organisations, and fleet managers to encourage the initial selection of a BEV over an ICEV, regardless of the car's remaining range. Once drivers have adopted a BEV, new goals could be introduced to playfully encourage eco-driving practices (i.e. achieving lower energy consumption in kWh/100km, see Günther et al., 2020; Degirmenci & Breitner, 2023), or direct users to charging stations offering more affordable rates per kWh. Furthermore, for original equipment manufacturers (e.g. car manufacturers, charging infrastructure providers) and software designers, the insights from Study 1 suggest that similar design elements could be transferrable to related BEV areas. To extend battery longevity (see Argue, 2023), gamification could be utilised to encourage the use of slower AC chargers over faster DC chargers, and to promote charging when the battery is between 20% and 80% capacity, among other strategies.

In Study 1, the presence of badges did enhance the influence of perceived enjoyment of using the car booking software on employees' commitment to engaging with goals and gamified challenges. This suggests that individuals may have found the process of earning badges to be an enjoyable experience. For software designers, organisations, and fleet managers this implies that encouraging employees to explore the software using gamification badges could lead to a more engaging and enjoyable user experience, allowing them to discover new car options or other features within the car booking software. Consequently, the use of such gamification elements may be beneficial in promoting BEV usage.

In contrast to Study 1, the findings of Study 2 demonstrate how the use of leaderboards resulted in a significant variation in car choice, highlighting the potential of gamification to extend beyond merely enhancing performance, as extensively documented in the literature (e.g. Boratto et al., 2017; Gutt et al., 2020; Landers et al., 2017), to also influencing technology choices. For organisations, fleet managers, software designers, and car manufacturers, these results suggest that gamification leaderboards can significantly impact individuals' decisions regarding car type selection.

The results of Study 1 indicated that gamification badges did not influence the relationship between participants' commitment to engaging with digital goals and gamified challenges and their intention to book a BEV for the upcoming business trip, as further evidenced by the absence of changes in car preferences. As previously noted, Landers et al. (2017) and Hamari (2013, 2017) emphasised the importance of goal commitment as a predictor of the success of gamification interventions. If organisations including fleet managers lack the capacity or do not wish to apply the TAM in its entirety, they might consider measuring employees' goal commitment in relation to their intentions to engage with the target system. This approach could help anticipate whether employees would consider engaging with the presented goals and challenges as worth pursuing. Relatedly, measuring goal commitment could be utilised by software designers when piloting gamification interventions, providing an early indication of whether the intended intervention will achieve the desired effects or if amendments are needed. These findings may guide software designers in better understanding the potential impact of gamification elements on target user groups.

Gamified commercial applications typically focus on rewarding users, while the loss of points is either not implemented or not emphasised. However, the findings of Study 2 demonstrated that both the awarding and loss of gamification points can significantly influence individuals' car choices. Specifically, participants tended to choose options that maximised point gains (and ranking position)[103] or those that avoided point losses (and ranking position) while still awarding some points. For instance, the scenario presented to the high-risk treatment group – where selecting a BEV was associated with a point deduction and selecting an ICEV resulted in the awarding of a few points – was linked to an increased perceived risk of BEVs. In contrast, the perceived risk of BEVs remained unchanged in the high-risk control group, where gamification was absent. In the high-risk control group, the majority of participants chose a BEV, whereas in the high-risk treatment group, the majority opted for an ICEV. This finding suggests that participants chose the car type they perceived as less risky in this specific situation. For software designers this result suggests that incorporating the loss of points could be an effective method for promoting specific technology choices. However, this approach requires careful consideration, as it is not difficult to imagine that losing points could adversely affect users' enjoyment of the gamified application (see Degirmenci & Breitner, 2023)[104], potentially leading to disengagement. Therefore, the trade-off between influencing individuals' choices and maintaining their enjoyment as well as their intentions to engage in a gamified environment warrants further investigation and caution when using such elements in commercial contexts.

When designing gamification elements, software designers should carefully consider the specifics of their implementation. For instance, seemingly minor details, such as using the term *karma* alongside gamification points could significantly influence individuals' responses to such interventions. This aspect was not controlled for in this study, highlighting the need for further

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[103] The influence of changes in ranking position cannot be disentangled from the study results.

[104] Degirmenci and Breitner (2023) conducted a field-study to promote BEV eco-driving (i.e. lower energy consumption in kWh per 100 km driving) through gamification integrated into a mobile application used during BEV driving. They tested three groups: (1) a control group not exposed to gamification, (2) a group that was exposed to gamification with visual stimuli, and (3) a group exposed to gamification with both auditory and visual stimuli. The results showed that energy consumption was reduced in the group exposed to auditory-visual cues. However, participants in this group also reported lower enjoyment and reduced intentions to continue using the gamified eco-driving application compared to those in the visual-only group.

research. Additionally, considering additional factors such as age, gender, experience, and company size could provide deeper insights into specific user preferences. For example, Koivisto and Hamari (2014) found that gender and age influenced the perception of a gamified fitness application. Overall, while the results of Study 2 do not allow for a clear disentanglement of the specific factors that influenced individuals' choices – whether due to positive or negative emotions associated with the pursuit of good karma or the avoidance of negative karma, the enjoyment of engagement in the gamified setting, or the motivation to avoid negative emotions – the findings nonetheless support the use of gamification elements in a commercial context.

The results of Study 1 indicate that the subjective norm influenced participants' commitment to engage with goals and challenges. However, this statistically significant association became non-significant when gamification badges were introduced in the car booking software for the treatment group. For (software) designers, organisations, and fleet managers, this observation suggests that in the absence of gamification, individuals are more likely to rely on the opinions of their corporate peers. When considering the implementation of a communication campaign, such as one based on corporate testimonials, this finding implies that individuals in the control group depended on their social environment to assess their participation in disseminated goals and challenges. In contrast, within the treatment group, badges appeared to serve as a more pertinent source of information compared to the opinions of their corporate peers, potentially rendering such a campaign less effective.

The results of Study 2 present mixed outcomes regarding the use of social factors to promote BEV choice. On the one hand, conveying a corporate social norm associated with BEVs for business trips through experimental scenarios did not result in a significant variation in car choice within the control group (i.e. without gamification). For software designers, organisations, and fleet managers this suggests that communication strategies based on social norms may not be particularly effective, at least in this particular context. On the other hand, the use of a leaderboard in the treatment group, which leverages social comparison by design, proved to be impactful. Specifically, the results indicate that the leaderboard, by making individuals' decisions visible to significant others, influenced car choices compared to the non-visibility of activities in the control group. While further investigation is needed, particularly regarding the precise design elements of a leaderboard implementation, this finding suggests to car manufacturers, organisations, fleet managers, and software designers that making activities visible to important others could be an effective strategy for influencing individuals' car choices.

Overall, the two studies present a mixed picture regarding the reactions of individuals to social influence. Organisations and fleet managers who wish to implement communication campaigns or gamification should ideally test these interventions first and track the responses across different measurement points. As demonstrated by Richter et al. (2018)[105], even small differences in communication can lead to significant behavioural changes, including potential reactance, among the target audience.

The findings of Study 1 indicate a statistically significant association between participants assigned to a high-risk business trip and their decision to withdraw from the car booking experiment, compared to participants with a low-risk business trip. Moreover, participants chose to withdraw from the experiment instead of selecting any car type, despite the car booking software displaying

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[105] Specifically, Richter et al. (2018) conducted a study in Norway and Germany using variations of information written on a fish-shaped sign to inform shoppers about the existence of sustainable seafood. The sign conveyed that a product carrying the specific certification contributes to sustaining marine resources. Richter et al. (2018, p. 6) used eight variations of signs; one featuring only the sign with sustainable seafood labels and seven sign variations that also differed in their inclusion of descriptive norms (e.g. "28% of all customers buying seafood in our shop yesterday chose MSC/ASC"[105]) to communicate information about other consumers' seafood choices on the previous day. The results showed that in Norway, using the sign alone increased sustainable food choices; however, when a message incorporating descriptive norms was added to the sign, the intervention had no effect. Conversely, in Germany, incorporating normative messages that referred to small reference groups (e.g. 4% or 11%) in combination with the sign resulted in a boomerang effect: sustainable seafood choices decreased compared to the group without the message. Richter et al. (2018) interpret these findings in the context of psychological reactance (see Brehm, 1989). This suggests that customers may have perceived social pressure from the normative message, triggering a fear of potential loss of freedom, leading to their subsequent resistance to the incentivised sustainable choice option.

range buffer information for each car and car type, which theoretically should have supported BEV selection. Notably, individuals opting for BEVs exhibited a slightly stronger inclination towards cars with a 100% range buffer compared to those choosing ICEVs. Interpreting the range buffer preferences in the context of the attrition rate and the generally low preference for BEVs suggests that even a 100% range buffer was not sufficiently large to completely mitigate the perceived risk associated with higher-risk trips. This indicates that measures beyond providing a range buffer may be required to reduce the perceived risk of choosing a BEV for a high-risk business trip. For example, fleet managers should closely monitor their fleet and ensure that all vehicles are fully charged. If not already implemented, this could involve establishing a protocol requiring employees to plug in BEVs upon their return to the car park, even if the car battery's state of charge is still adequate for other trips. Although charging a BEV beyond 80% may negatively impact battery longevity (see Argue, 2023), employees might be more inclined to choose a BEV over an ICEV for business trips if the state of charge is consistently high, presenting a trade-off for fleet managers.

Outlook for Further Research

Beyond the future research avenues previously discussed, the following outlook highlights broader avenues that warrant further investigation. These areas may also extend beyond the current focus on promoting BEVs over ICEVs for business trips, as outlined below.

Degirmenci and Breitner (2023) researched the influence of gamification on eco-driving behaviour using BEVs, focusing on the use of audio signals and silent feedback to provide real-time behavioural feedback. Their study revealed that the gamification elements vary in how enjoyable and effective they are at changing behaviour. For instance, while silent visual feedback alone was not effective at improving eco-driving behaviour, the addition of auditory signals led to improvements, although it also reduced the perceived enjoyment and individuals' intentions to continue using the gamified service. Similarly, Sailer et al. (2017) examined the effects of various gamification elements (e.g. badges, teammates) and their associated mechanisms (e.g. teammates conveying a sense of relevance or badges providing cumulative feedback) on the fulfilment of basic psychological needs, as defined by Ryan and Deci (2000), such as the need for competence. They concluded that the effectiveness of gamification is contingent upon the specific design elements and their psychological impact. In alignment with Degirmenci and Breitner's (2023) mixed findings on the impact of gamification on user behaviour, Studies 1 and 2 of this thesis also presented mixed results regarding its influence on individuals' car type choices. Consistent with the insights from this thesis, Degirmenci and Breitner (2023) suggested that future studies should explore "where" gamification is effective, in "which context", and determine the "how and when not" (p.278). Further exploration is necessary to disentangle the effects of different gamification elements, considering their specific design, including sensory elements (e.g. visual, auditory), combinations involving more than one gamification element, and context-specific applications. Such research is crucial for better anticipating the effects of gamification on decision-making within varying levels of risk in technology usage situations. Additionally, the medium through which gamification is conveyed (e.g. smartwatch, smartphone, virtual reality headsets) may influence user experience and responses.

Building on the exploration of business mobility undertaken in this thesis, future research could extend this focus from business trips to include employees' mobility choices for their regular commutes. However, the insights gained from this thesis need not be confined to the specific context of carsharing and business mobility; they could also be tested and explored in various (electric) mobility settings. For instance, encouraging a shift from individual motorised transport to public transport could be further investigated, as demonstrated in related studies. Lieberoth et al. (2018), for example, compared the effectiveness of nudges, gamification, and health framing in motivating commuters to switch from cars to public transport. Similarly, Zimmermann et al. (2023) utilised digital nudging to increase commuters' use of public transport. Therefore, it may be valuable to explore mobility choices involving gamification within different risk contexts, particularly in application areas similar to those examined in this research, such as public transport and shared mobility concepts that facilitate multi- and seamless inter-modal transport[106], including the so-called last mile[107]. This could encompass BEVs for public (electric) carsharing (see Fazel, 2014), ridepooling[108] (see Burghard & Scherrer, 2022), and the use of different vehicle types, such as (electric) bicycles, electric scooters, and others. Future research could also extend beyond mobility choices, targeting entirely different categories of technologies, products, or services, such as those in the domains of food or fashion.

In summary, further exploration of the combination of gamification and differentially risky technology usage contexts remains a promising avenue for research. Future studies should investigate the design of gamification elements at a more granular level, particularly in relation to specific risk situations in technology use, with the aim of better anticipating individuals' behaviours and choices between technologies. Such insights could enhance the generalisability of gamification elements and ultimately lead to more effective intervention design decisions across various application contexts.

Limitations

In addition to the limitations addressed in Studies 1 and 2, the following will outline the eight primary limitations of both studies.

First, in Study 1, it is noteworthy that the questionnaire remained consistent across groups. Specifically, all participants, irrespective of the assigned type of business trip, assessed a majority of questionnaire items by imagining booking a car for the low-risk business trip, including those related

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[106] Schoch (2024) defines multi-modal transport as the availability of various mobility options (e.g. bus or train) for completing a trip. In contrast, inter-modal transport refers to the use of different modes of transport within a single journey, such as taking a bus to the train station, travelling by train, and then switching to an electric scooter for the last mile.

[107] The last mile refers to the final segment of a journey, typically the remaining few hundred metres to the destination that an individual must cover after using public transport, such as trains or buses (Haas, 2018).

[108] Burghard and Scherrer (2022) define ridepooling as the shared transportation of multiple, unrelated individuals based on their individual travel preferences.

to behavioural intentions. Consequently, the impact of risk on the structural relationships within the TAM remains unexplored for the high-risk group. The assessment of behavioural intentions for the high-risk business trip might have uncovered a more pronounced association between car selection and behavioural intentions.

Second, while the findings of Study 1 imply an impact of emotions on car choice, the conclusions are constrained due to the absence of direct measurement of emotions in this study. Instead, this effect was inferred from observations, drawing upon the affect heuristic.

Third, in Study 2, the assessment of affect was confined to individuals' subjective evaluations concerning BEVs, potentially limiting the range of emotions individuals may have experienced within the study. For future investigations, alternative methods for assessing affect could be considered, such as measuring individuals' emotional states through physiological measures, as advocated by King and Slovic (2014).

Fourth, while Study 1 specifically measured behavioural intentions to book a BEV in the context of a low-risk business trip, Study 2 assessed evaluative affect towards BEVs for business trips in general, without referencing a specific trip. This disparity in measurement introduces a limitation in the direct comparability of the measurements of intentions and evaluative affect between the two studies.

Fifth, in both Study 1 and Study 2, the assessment of behavioural intentions and evaluative affect exclusively pertained to BEVs, with no measurement conducted in relation to ICEVs. Including assessments of ICEVs could have provided additional clarity regarding individuals' responses to the car booking experiments and their car choices, potentially alleviating the need for extensive interpretation of the results.

Sixth, Study 2 was conducted without a break between the two measurements. However, for instance, King and Slovic (2014) incorporated filler tasks between both assessments, spanning approximately 30 minutes. Hence, participants in Study 2 recalling their previous responses from the initial measurement may have influenced their judgment of evaluative affect, risks, and benefits of

BEVs, potentially motivating consistent ratings of the items in alignment with their earlier judgments. This potential recall effect could have influenced the findings of this study.

Seventh, a primary limitation applicable to both studies resides in the hypothetical nature of the car booking experiments. Participants neither booked cars from an authentic car fleet nor for an actual business trip. This hypothetical setup may, for example, have constrained the potential impact of social factors, as participants lacked the opportunity for meaningful social interactions – an element explicitly advocated by Hamari and Koivisto (2013) as relevant to the effectiveness of gamification interventions, particularly pertaining to Study 1.

Finally, this study exclusively examined one product pair, comprising one sustainable product and its conventional alternative, which may restrict the generalisability of findings concerning the influence of gamification on other technology choices. Therefore, future studies could broaden their scope to encompass a range of diverse technologies, aiming to comprehensively assess the impact of gamification, including research in social environments beyond the business context.

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Appendices

Appendix A

Screening Questions, Introduction to the Car Booking Experiment, and TAM Questions in Study 1

Screening Questions

Table A1

Screening Question: Assessing Participants' Business Mobility Patterns

Introduction to scale	„Welchen Mobilitätsgrad erfordert Ihr momentaner Beruf? Bitte wählen Sie die Antwortalternative, die Ihrer überwiegenden geschäftlichen Mobilität am nächsten kommt."
Choice option 1	„Ich bin nie auf Geschäftsfahrt. Mein momentaner Beruf erfordert das nicht."
Choice option 2	„Ich bin gelegentlich auf Geschäftsfahrt, aber das ist ungewöhnlich. Meistens findet man mich an meinem täglichen Arbeitsplatz."
Choice option 3	„Ich bin öfters auf Geschäftsfahrt. Geschäftsfahrten sind nichts Besonderes für mich."
Choice option 4	„Ich bin fast nie an einem festen Arbeitsplatz anzutreffen."
Choice option 5	„Das betrifft mich nicht (z. B. momentan arbeitssuchend, Student, o. Ä.)."
Choice option 6 including open text field	„Anderes Mobilitätsprofil."

Note. Selecting options 4, 5, or 6 marked the end of the questionnaire, as participants did not meet the criteria of the target group.

Table A2

Screening Question: Assessing the Suitability of Corporate Carsharing for Participants' Business Mobility Patterns

Introduction to scale	„Corporate Carsharing ist das Teilen von Autos für Geschäftsfahrten. Anders als ein Dienstwagen steht ein Corporate Carsharing Auto (auch Poolfahrzeug) nicht allein einer Person zur Verfügung. Bitte bewerten Sie die folgenden Statements. Stellen Sie sich vor, dass Corporate Carsharing in Ihrer Firma verfügbar ist.

	Rufen Sie sich dabei Ihre übliche Mobilität in Erinnerung, z. B. durchschnittliche Reisedistanz oder Reisehäufigkeit.“
Item 1	„Im Großen und Ganzen stellt Corporate Carsharing ein geeignetes Konzept für die Durchführung meiner Geschäftsfahrten dar.“
Item 2	„Im Großen und Ganzen ist Corporate Carsharing eine Lösung, die zu meinem durchschnittlichen Mobilitätsverhalten passt (z. B. Distanz, Dauer und Häufigkeit der Geschäftsfahrten).“

Note. The items were assessed using a 7-point Likert scale, ranging from (1) *fully disagree* to (7) *fully agree*. Participants who tended to disagree (i.e. selecting options 1, 2, or 3 on the Likert scale) regarding item 1 were directed to the question presented in Table A3. Those who selected options 4 to 7 were also presented with the second item from the scale and continued with the questionnaire.

Table A3

For Participants Who Selected Rather Disagree, Disagree, or Fully Disagree in the Question Presented in Table A2, the Following Final Question was Shown

Introduction to scale	„Gemäß der vorherigen Frage scheint es, als sei Corporate Carsharing keine adäquate Lösung für Sie. Bitte unterstützen Sie uns mit einem Einblick darüber, warum das der Fall ist. Sie können mehr als einen Grund auswählen. Um meine Geschäftsfahrten durchzuführen, stellt Corporate Carsharing keine relevante Lösung für mich dar, weil...“
Choice option 1	„...ich einen persönlichen Dienstwagen habe.“
Choice option 2	„...ich auf zu vielen Dienstreisen bin.“
Choice option 3	„...ich ein Spezialfahrzeug brauche (Transporter, speziell ausgerüstetes Fahrzeug, o. Ä.).“
Choice option 4 including open text field	„Anderer Grund.“

Note. For participants shown this question, it marked the end of the questionnaire, as they did not meet the criteria of the target group.

Introduction to Car Booking Experiment

The following introduction was used before the participants were assigned to either the low-risk business trip or high-risk business trip:

„Sie werden nun auf die Corporate Carsharing Plattform *ve-share* eingeladen. Bitte nehmen Sie dabei folgendes an: Sie und Ihre Kollegen haben Zugriff auf einen Corporate Carsharing Pool. Dieser Pool besteht aus konventionellen Verbrennern (Benziner/Diesel) sowie reinen Elektroautos (ohne zusätzlichen Verbrennungsmotor). Sie sind dabei eine anstehende Geschäftsfahrt über die Buchungssoftware ve-share zu buchen. Ve-share ist eine Webapplikation. Sie ersetzt konventionelle Methoden wie die Reservierung über eine händische Liste, die Assistenz oder digitale, aber nichtspezialisierte Hilfsmittel wie Outlook. Anhand der definierten Distanz der Geschäftsfahrt schätzt ve-share Ihren individuellen Treibstoff- bzw. Energiebedarf für die Gesamtstrecke.“

TAM Items

All TAM items were measured using a 7-point Likert scale, ranging from (1) *fully disagree* to (7) *fully agree*.

Table A4

Items of Behavioural Intentions

Introduction to scale	„Bitte bewerten Sie Elektroautos für sich persönlich. Für welchen Fahrzeugtyp entscheiden Sie sich bezüglich der anstehenden Geschäftsfahrt (Szenario)?“*
Item 1	„Im Großen und Ganzen würde ich den Verbrenner einem Elektroauto vorziehen, um meine anstehende Geschäftsfahrt durchzuführen.“
Item 2	„Ich kann mir vorstellen, spontan ein Elektroauto für die anstehende Geschäftsfahrt zu buchen.“
Item 3	„Im Großen und Ganzen beabsichtige ich, das Elektroauto und nicht den Verbrenner zu buchen, um die anstehende Geschäftsfahrt zurückzulegen.“

Reference: Venkatesh & Bala (2008), Fazel (2014).

Table A5

Items of Perceived Enjoyment of Driving a BEV

Introduction to scale	„Bitte versetzen Sie sich in die Situation, dass Sie nun die anstehende Geschäftsfahrt (Szenario) mit dem Elektroauto durchführen. Wie fühlen Sie sich dabei?“*
Item 1	„Ich glaube, insgesamt hätte ich Spaß daran, die Geschäftsfahrt (Szenario) mit dem Elektroauto durchzuführen.“*
Item 2	„Ich glaube, es ist spannend, die anstehende Geschäftsfahrt (Szenario) mit einem Elektroauto zurückzulegen.“*
Item 3	„Ich glaube, dass das Fahren eines Elektroautos meine Neugier weckt.“

Reference: Venkatesh & Bala (2008), Dudenhöffer (2013), Fazel (2014).

Table A6

Items of the Perceived Usefulness

Introduction to scale	„Was halten Sie von der Erweiterung eines Corporate Carsharing Pools um Elektroautos?“
Item 1	„Ich denke, Elektroautos sind nicht von Vorteil für meine Geschäftsfahrten, sobald ich während einer Geschäftsfahrt (inkl. des Aufenthalts beim Geschäftspartner) einen Ladestopp einlegen muss.“
Item 2	„Ich denke, dass ich meine Geschäftsfahrten mit einem Elektroauto nicht effizienter durchführen kann als mit einem Verbrenner.“
Item 3	„Ich denke, dass die Eigenschaften von Elektroautos nützlich für die Durchführung meiner Geschäftsfahrten sind (z. B. leiser bei geringen Geschwindigkeiten, schlupffreier Antrieb, direktes Drehmoment).“

Reference: Rogers (1983), Moore & Benbasat (1991), Venkatesh & Bala (2008), Fazel (2014).

Table A7

Items of the Perceived Ease of Use

Introduction to scale	„Ein Elektroauto kann sich vom Verbrenner in Funktionen oder Fahrverhalten, z. B. dem Bremsverhalten (Rekuperation), der Lautstärke, dem sofortigen Drehmoment und entsprechender Beschleunigung, unterscheiden. Bitte versetzen Sie sich in die Situation, die anstehende Geschäftsfahrt (Szenario) mit einem Elektroauto zurückzulegen. Bewerten Sie den empfundenen Schwierigkeitsgrad dieses Vorhabens."*
Item 1	„Ich denke, es ist einfacher, ein Elektroauto als einen konventionellen Verbrenner zu fahren."
Item 2	„Ich denke, das Fahren eines Elektroautos ist nicht anders als das Fahren eines Verbrenners."
Item 3	„Ich denke, mir fällt es genauso leicht, mich an das Verhalten eines Elektroautos oder an das eines Verbrenners zu gewöhnen."
Item 4	„Ich denke, mir fällt es genauso leicht, mich an die Funktionen eines Elektroautos zu gewöhnen wie an andere Funktionen, z. B. an einen Tempomat."

Reference: Moore & Benbasat (1991), Venkatesh & Bala (2008), Dudenhöffer (2013), Fazel (2014).

Table A8

Items of Image

Introduction to scale	„Bitte denken Sie an Ihre Kollegen und Vorgesetzten. Inwiefern beeinflusst die Fahrzeugwahl eines Kollegen dessen Profil innerhalb Ihres Unternehmens?"
Item 1	„Insgesamt beeinflusst die Wahl eines Elektroautos das Image eines Mitarbeiters positiver als die Wahl eines Verbrenners."
Item 2	„Ich denke, wenn ein Mitarbeiter ein Elektroauto statt eines Verbrenners bucht, dann möchte er Aufmerksamkeit erregen."
Item 3	„Ich denke, dass die Wahl eines Elektroautos statt eines Verbrenners einen positiven Einfluss auf das Ansehen eines Kollegen hat."
Item 4	„Ich denke, dass Arbeitskollegen, die Elektroautos buchen, beabsichtigen, umweltfreundlich zu handeln."
Item 5	„Ich denke, dass Arbeitskollegen, die ein Elektroauto buchen, innovativer erscheinen."

Reference: Moore & Benbasat (1991), Venkatesh & Bala (2008), Fazel (2014).

Table A9

Items of Subjective Norm

Introduction to scale	„Inwiefern würde Ihr Unternehmensumfeld die Wahl eines Elektroautos statt eines Verbrenners für Ihre anstehende Geschäftsfahrt (Szenario) anerkennen?"*
Item 1	„Ich denke, mein Arbeitgeber würde die Wahl eines Elektroautos positiv zur Kenntnis nehmen."
Item 2	„Ich denke, meine Kollegen würden meine Wahl eines Elektroautos positiv anerkennen."
Item 3	„Ich denke, meine Vorgesetzten würden meine Entscheidung unterstützen, ein Elektroauto auszuwählen."
Item 4	„Ich denke, meine Geschäftspartner würden meine Wahl eines Elektroautos positiv wahrnehmen."
Item 5	„Ich denke, meine Kunden würden nicht von mir erwarten, dass ich ein Elektroauto fahre."

Reference: Dudenhöffer (2013), Venkatesh & Bala (2008), Fazel (2014).

Table A10

Items of Goal Commitment

Introduction to scale	„Bitte nehmen Sie folgendes an: Auf ve-share werden Ihnen zu erreichende Ziele angezeigt, die mit der Fahrzeugwahl verknüpft sind. D. h. mit einem bestimmten Fahrzeugprofil (z. B. verfügbarer Reichweitenpuffer) können Sie Punkte oder digitale Badges freischalten."
Item 1	„Ich denke, es ist schwer über ve-share dargestellte Ziele ernst zu nehmen."
Item 2	„Offen gesagt, es kümmert mich nicht, ob ich die dargestellten Ziele erreiche oder nicht."
Item 3	„Ich fühle mich dazu verpflichtet die mit den Herausforderungen verbundenen Ziele zu verfolgen."
Item 4	„Ich denke, es lohnt sich die Herausforderungen zu meistern."

Reference: Klein et al. (2001), Landers et al. (2017).

Table A11

Items of the Perceived Risk When Assessed in the Context of the TAM

Introduction to scale	„Ein Risiko beschreibt die wahrgenommene Unsicherheit hinsichtlich eines Ergebnisses bzw. der Konsequenzen eines Verhaltens. Das Risikoempfinden entspricht einer sehr persönlichen und intuitiven Wahrnehmung. Bitte bewerten Sie im Folgenden das Risikolevel.“
Low-risk business trip	„Das Fahren eines Elektroautos zu einem Geschäftspartner, der wichtig ist und den Sie bereits gut kennen. Sie sind mit der überwiegend ebenen Wegstrecke zu Ihrem Geschäftspartner gut vertraut. Das Wetter ist sonnig und mit 20°C von recht angenehmer Temperatur.“
High-risk business trip	„Das Fahren eines Elektroautos zu einem neuen, aber wichtigen Geschäftspartner. Die Route ist Ihnen noch unbekannt. Ein Ladestopp könnte nötig sein. Es ist ein winterlicher, jedoch trockener Tag bei etwa 3°C.“

Reference: Franke et al. (2015).

Table A12

Low-Risk and High-Risk Business Trip Scenarios Used in the Context of the Car Booking Experiment

Low-risk business trip	„Sie besuchen einen Geschäftspartner, der wichtig ist und den Sie bereits gut kennen. Sie sind mit der überwiegend ebenen Wegstrecke zu Ihrem Geschäftspartner gut vertraut. Das Wetter ist sonnig und mit 20°C von recht angenehmer Temperatur.“
High-risk business trip	„Sie besuchen einen neuen, aber wichtigen Geschäftspartner. Die Route ist Ihnen noch unbekannt. Es ist ein winterlicher, jedoch trockener Tag bei etwa 3°C.“

Reference: Franke et al. (2015).

*When referring to the *scenario*, the participant was asked to recall the low-risk business trip.

Appendix B

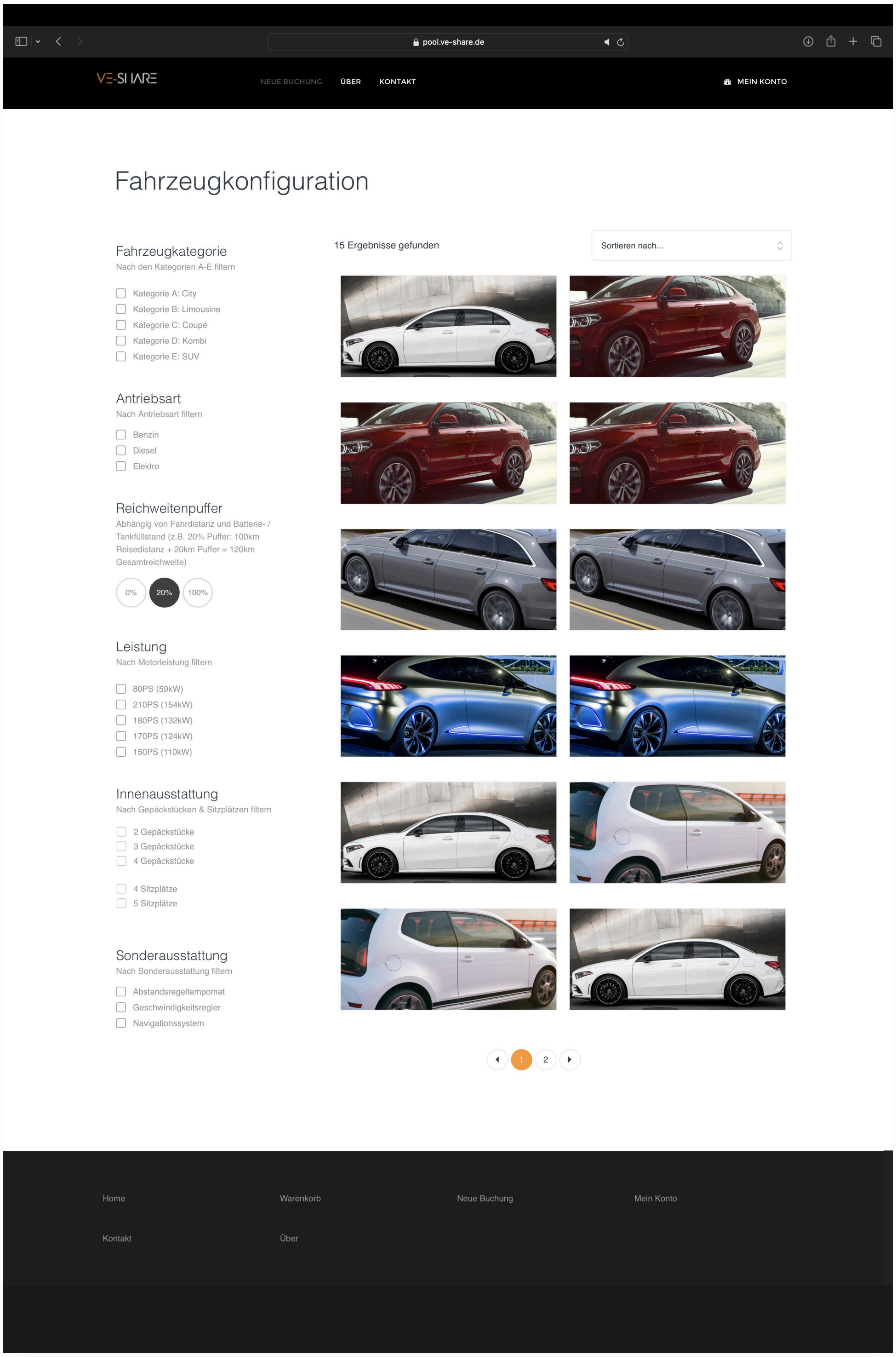
Examples of the Car Booking Software Utilised in Study 1 and Implementation Details

Study 1 utilised car booking software being based on a Wordpress (www.wordpress.com) template. The following provides an overview of the car booking flow, starting with a sample from the control group, followed by a set of screens from the treatment group.

Excerpt of the Car Booking Process of the Control Group

Figure B1

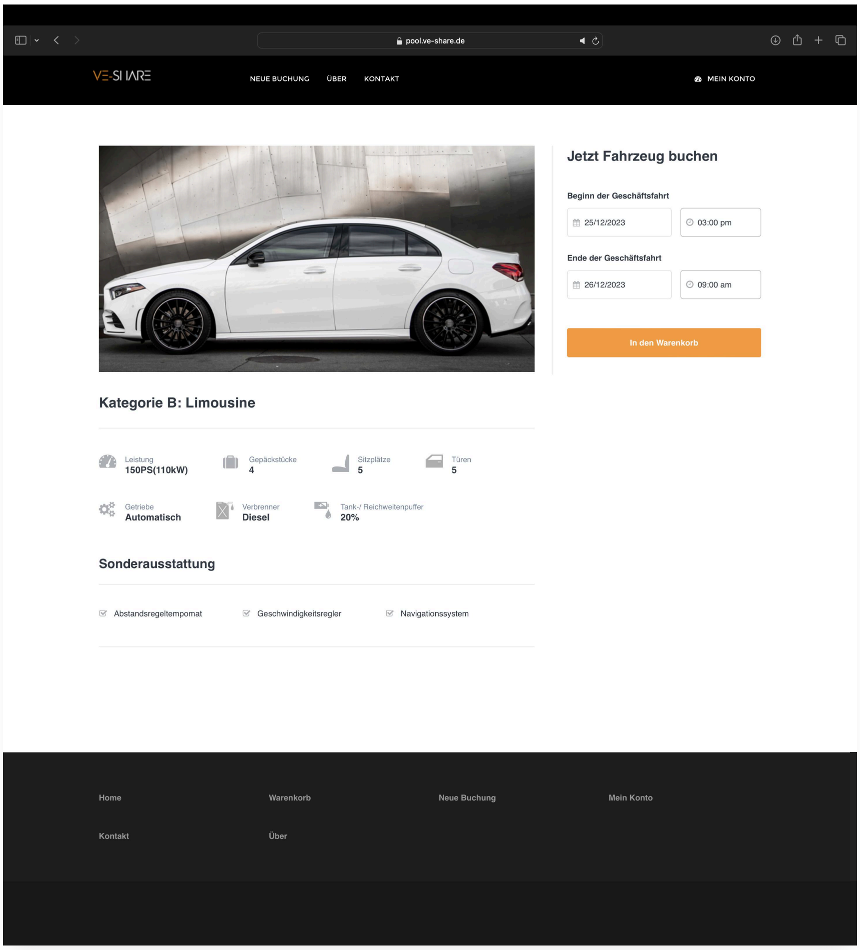
Car Selection Page Displayed to Participants in the Control Group



Note. The car selection page displays the car fleet along with filtering options. The 20% car range buffer filter has been applied to demonstrate the filtering options.

Figure B2

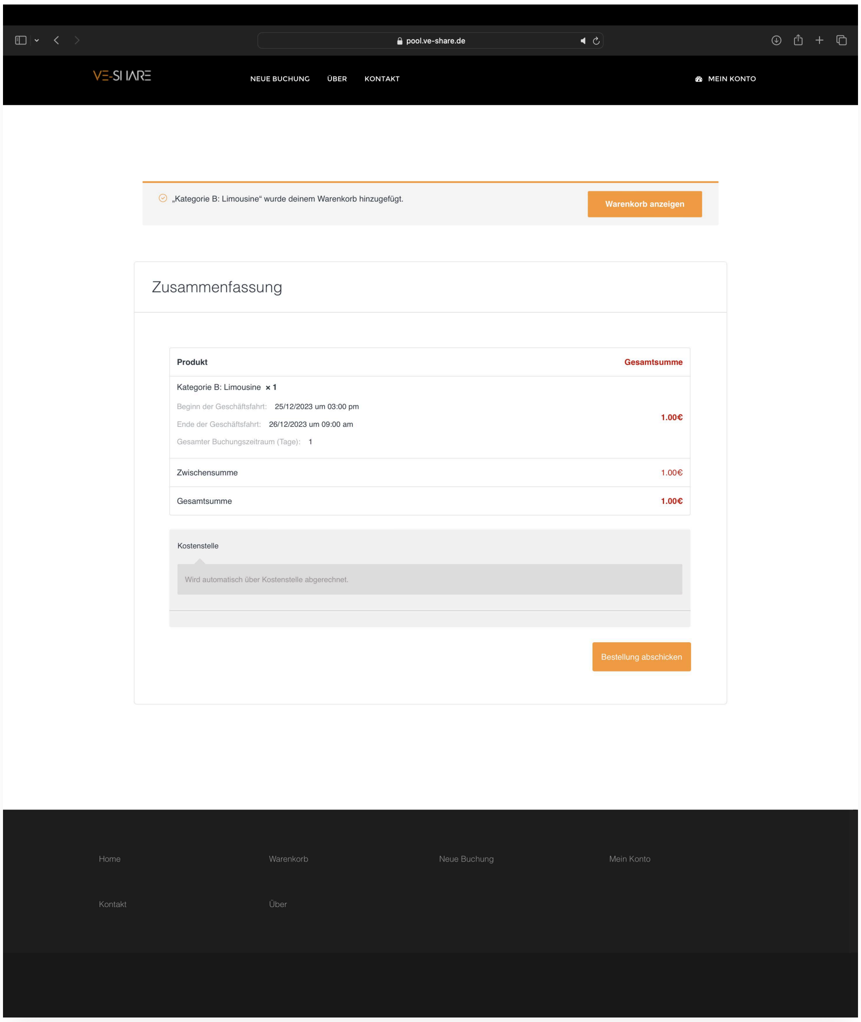
Detailed View of the Selected Car Displayed to Participants in the Control Group



Note. This screen is displayed after selecting a car from the previous car selection page. Dates and times on the calendar have been filled in for illustration purposes.

Figure B3

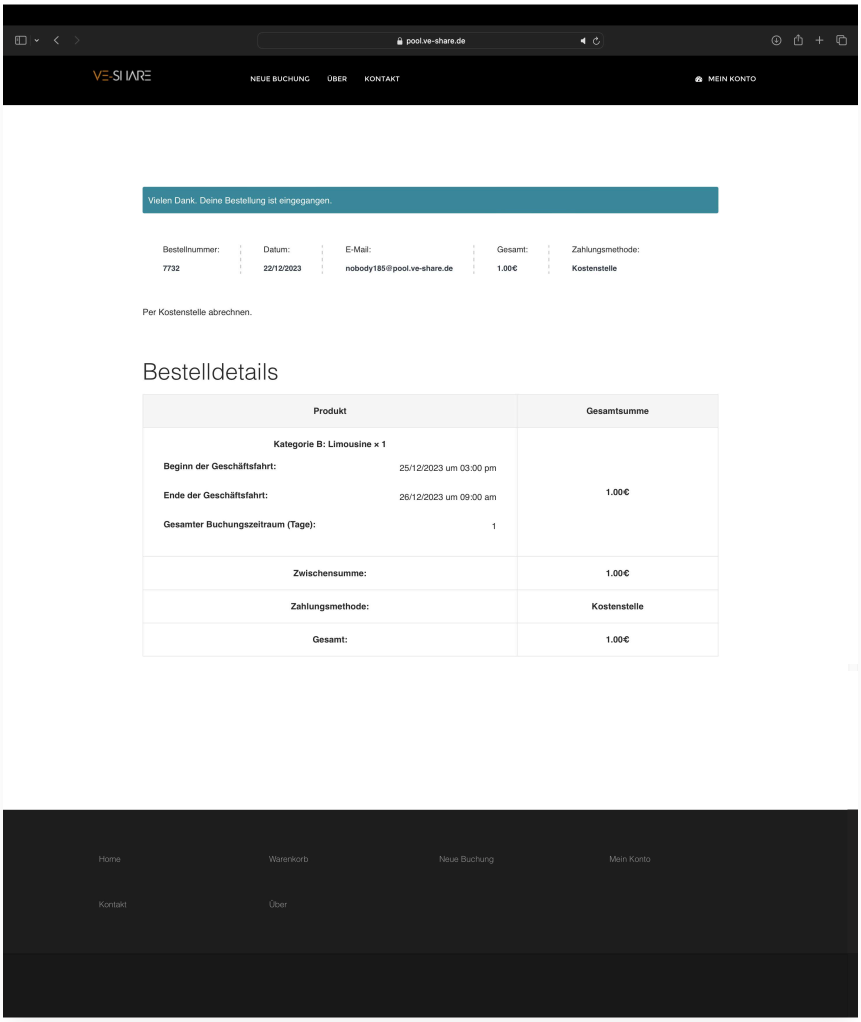
Overview of the Car to be Booked Displayed to Participants in the Control Group



Note. This screen provides details of the car to be booked.

Figure B4

Car Booking Confirmation Displayed to Participants in the Control Group

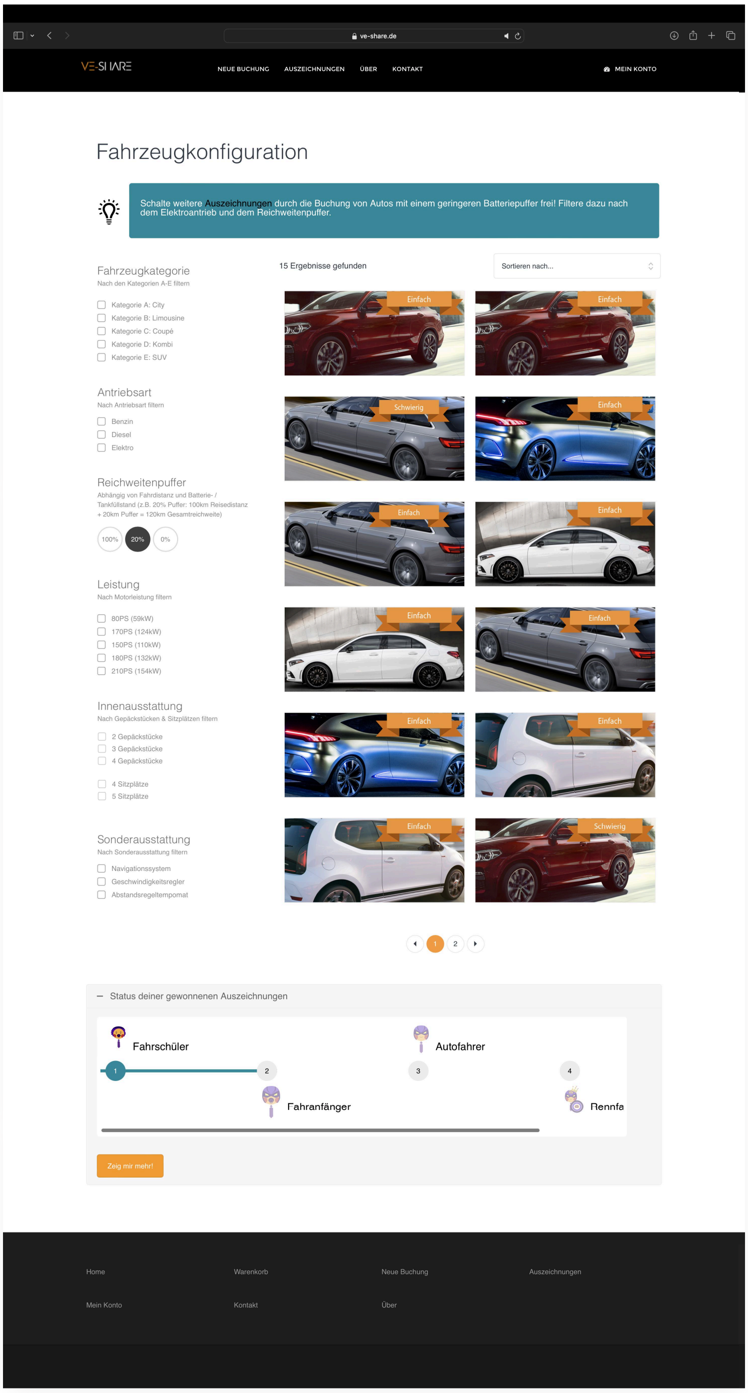


Note. The car booking confirmation serves as the concluding screen of the booking process.

Car Booking Process of the Treatment Group

Figure B5

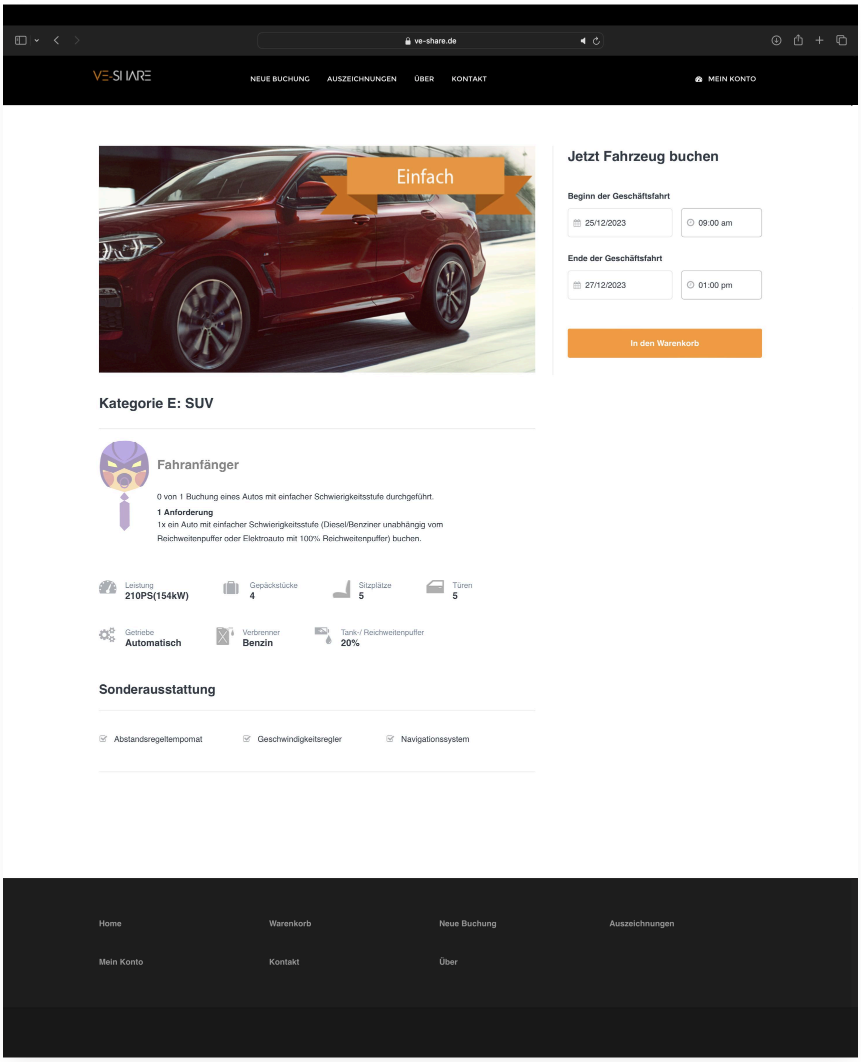
Car Selection Page Displayed to Participants in the Treatment Group



Note. The car selection page exhibits the car fleet alongside filtering options. The 20% car range buffer filter has been applied to showcase the filtering options. This page includes information about the gamification badges associated with an individual's car choice.

Figure B6

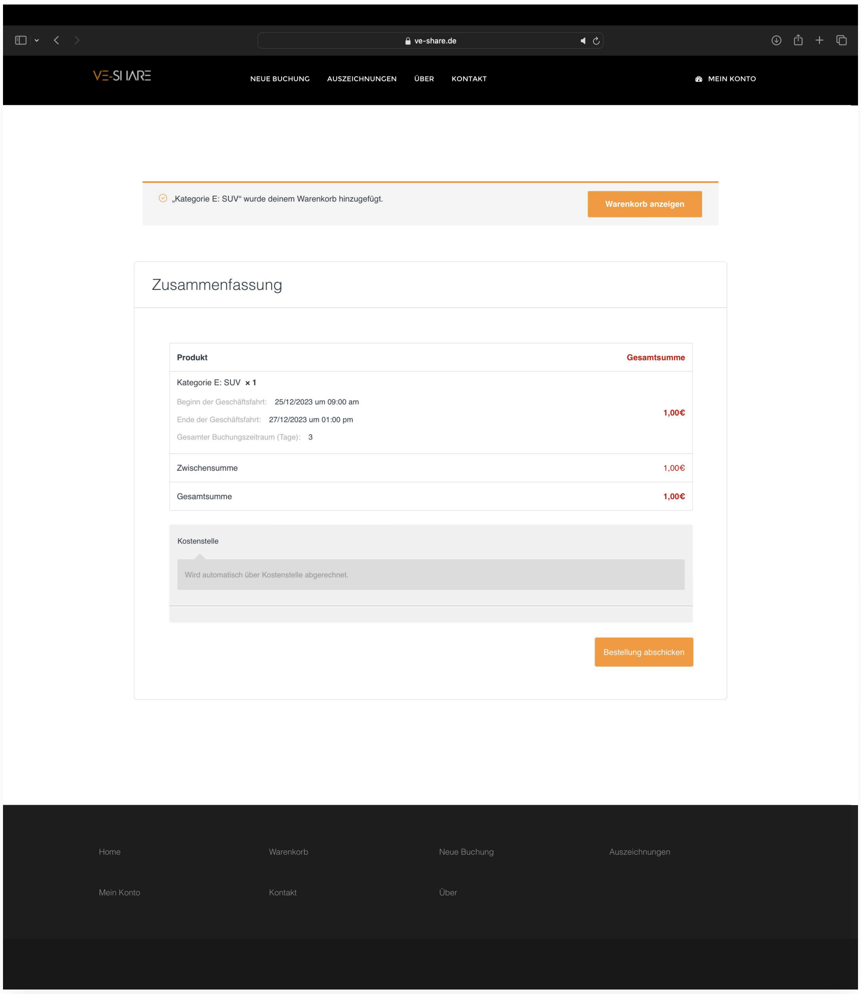
Detailed View of the Selected Car Displayed to Participants in the Treatment Group



Note. This screen is presented after selecting a car from the previous car selection page. Dates and times on the calendar have been filled in for illustrative purposes. This page also provides information about whether the selected car is associated with achieving a gamification badge or not.

Figure B7

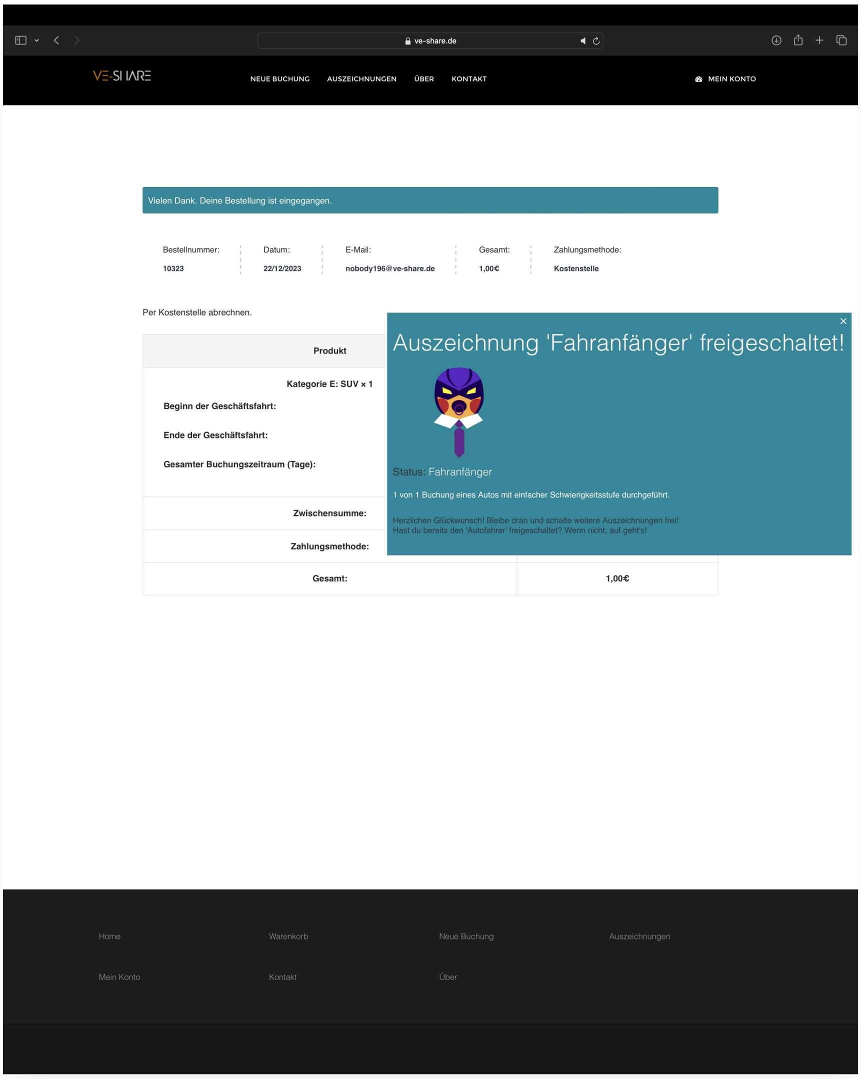
Overview of the Car to be Booked Displayed to Participants in the Treatment Group



Note. This screen provides details of the car to be booked.

Figure B8

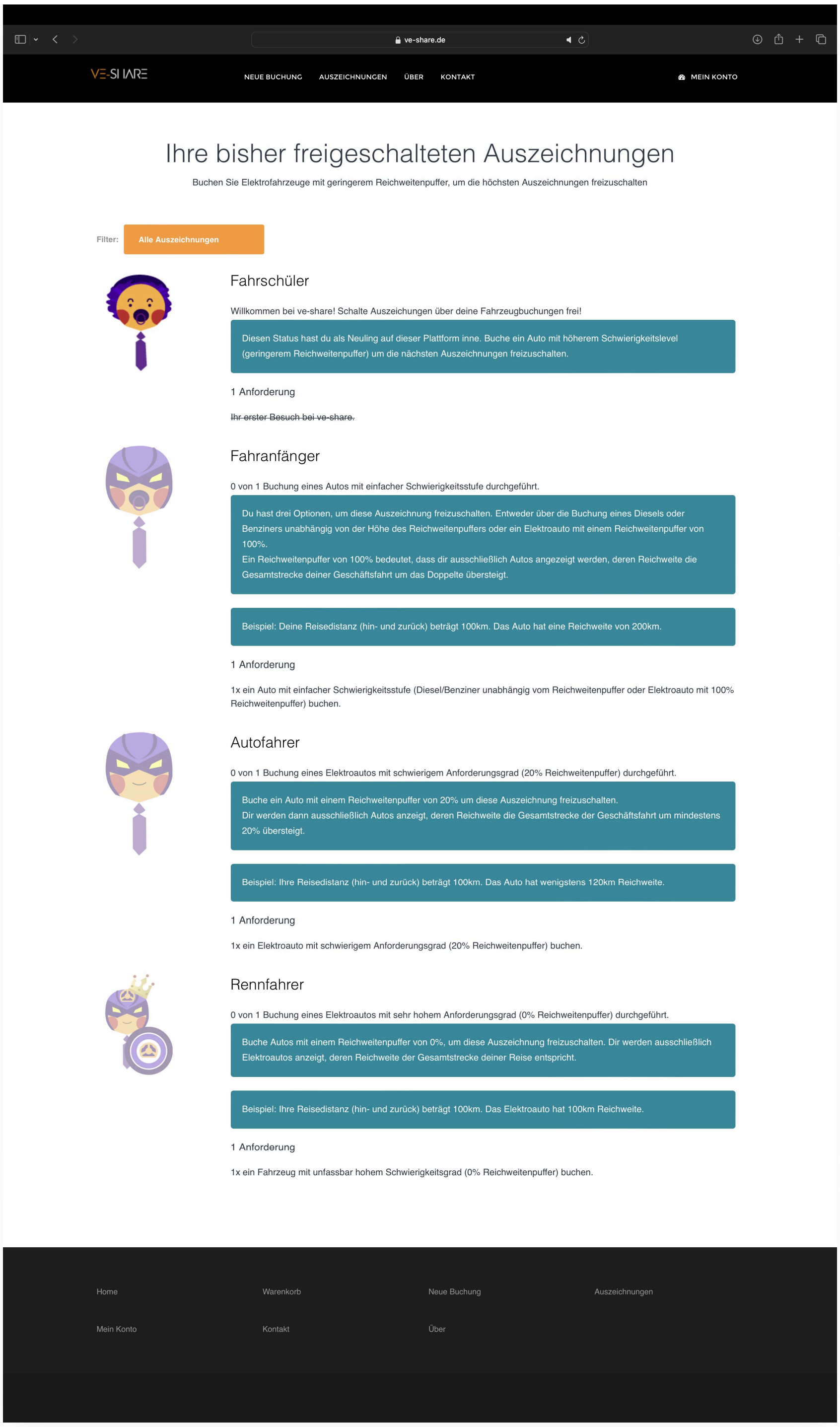
Car Booking Confirmation Displayed to Participants in the Treatment Group



Note. The car booking confirmation serves as the concluding screen of the booking process. If a car was selected that was associated with earning a new badge, the badge is displayed along with this car booking confirmation.

Figure B9

List of Achievements



Note. This dedicated subpage, located within the header bar of the car booking software, presented a comprehensive overview of both attained and pending badges, along with their respective requirements. Access to this subpage was restricted to the individual user and was inaccessible to others.

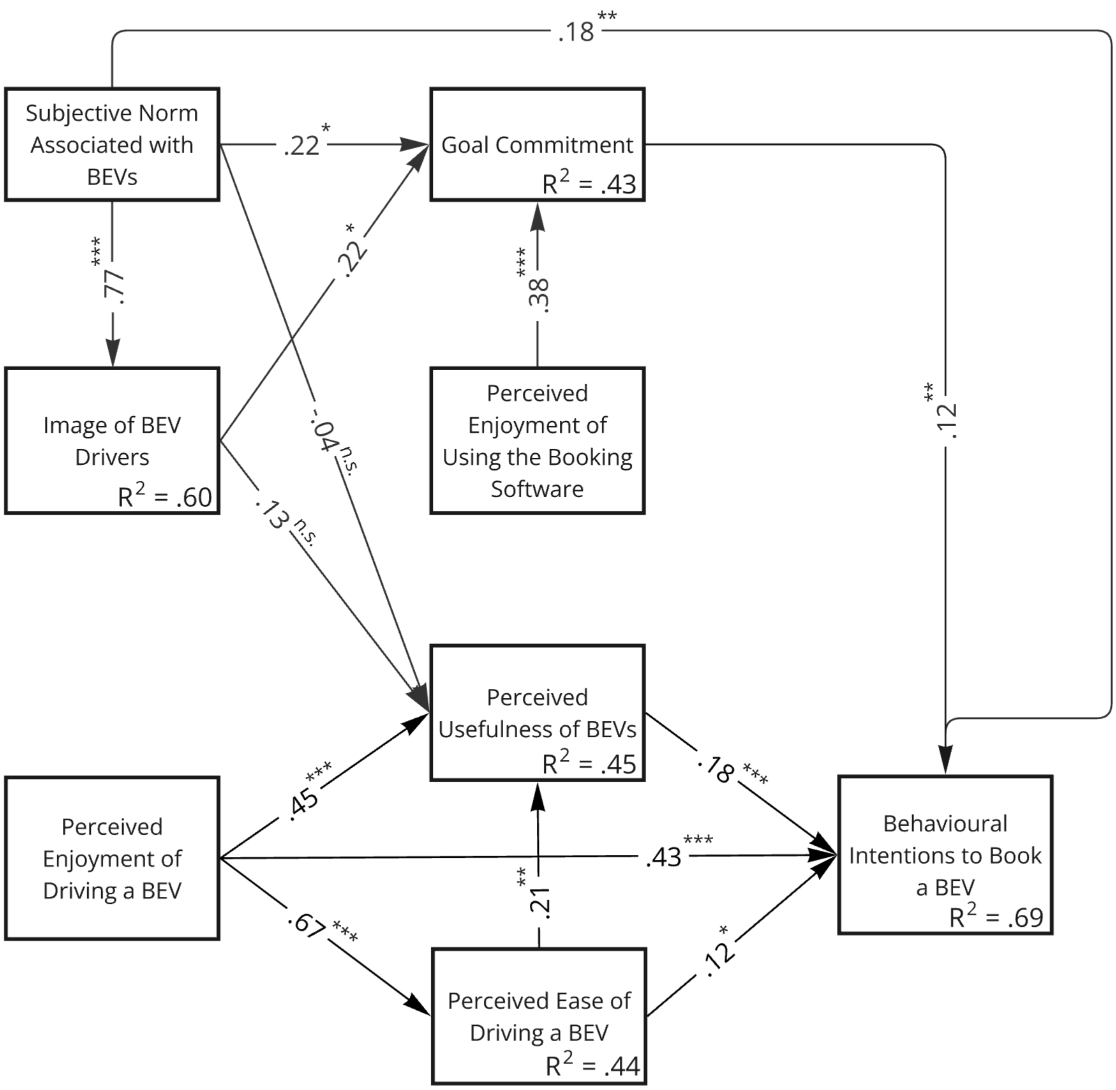
Appendix C

Comprehensive TAM of Study 1

The TAM below incorporates the results of the Sub-studies 1.1 and 1.2.

Figure C1

Comprehensive Technology Acceptance Model



Note. The arrows display path coefficients estimated using SmartPLS 4, interpreted akin to standardised regression coefficients (β) as per Hair et al. (2022).

BEV = battery electric vehicle.

Table C1

Structural Relationship Effect Sizes

Path	Path coefficient β	t-value	f^2 Effect size
PU → BI	$.18^{***}$	3.65	.06
PEU → BI	$.12^{*}$	1.93	.02
PEU → PU	$.21^{**}$	2.91	.05
PED → PEU	$.67^{***}$	20.41	.80
PED → PU	$.45^{***}$	5.14	.15
PED → BI	$.43^{***}$	6.67	.22
SN → PU	$-.04^{n.s.}$	.41	.00
SN → IM	$.78^{***}$	28.10	1.51
IM → PU	$.13^{n.s.}$	1.40	.01
SN → BI	$.18^{**}$	2.54	.06
GC → BI	$.12^{**}$	2.93	.03
SN → GC	$.22^{*}$	2.24	.03
IM → GC	$.22^{**}$	2.34	.03
PEBS → GC	$.38^{***}$	5.82	.21

Note. BI = behavioural intention, PU = perceived usefulness, PEU = perceived ease of use, PED = perceived enjoyment of driving a BEV, SN = subjective norm, PU = perceived usefulness, IM = image, GC = goal commitment, PEBS = perceived enjoyment of using the booking software.

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$, n.s. = not significant.

Appendix D

Results of the Chi^2-Tests of Independence Regarding Study 1

The following section presents the results of Chi^2-tests of independence based on membership in either the high-risk or low-risk experimental condition. This analysis considers individuals' decisions to withdraw from the car booking experiment as an additional choice option, in conjunction with their selection between BEVs or ICEVs.

Table D1

Chi^2-Test of Independence for Choice Between Battery Electric Vehicles and Conventional Cars or the Decision to Instead Withdraw from the Car Booking Experiment, and Individuals' Membership in the Low-Risk Control and Treatment Groups

Car booking	*n*	Chi^2-value	Degrees of freedom	*p*	Cramer's V
1	121	3.56	1	.06	.17
2	121	3.01	2	.22	.16
3	121	.45	2	.80	.06

Table D2

Chi^2-Test of Independence for Choice Between Battery Electric Vehicles and Conventional Cars or the Decision to Instead Withdraw from the Car Booking Experiment, and Individuals' Membership in the High-Risk Control and Treatment Groups

Car booking	*n*	Chi^2-value	Degrees of freedom	*p*	Cramer's V
1	117	.12	1	.73	.03
2	117	.32	2	.85	.05
3	117	.09	2	.96	.03

Appendix E

Items of Study 2

All items were measured using a 11-point semantic scale.

Table E1

Items of Evaluative Affect

Introduction to scale	„Als Elektroauto (auch E-Auto, elektrisches Auto, elektrisch betriebenes Auto) wird im weitesten Sinne ein Automobil bezeichnet, das mindestens einen Elektromotor zum Antrieb nutzt. Diese Studie konzentriert sich auf rein batterieelektrische Autos, sogenannte BEV (englisch: battery electric vehicle). Elektroautos sind in den vergangenen Jahren auch vermehrt Teil betrieblicher Fahrzeugflotten geworden. Bitte stellen Sie sich vor, dass Ihnen eine Geschäftsfahrt bevorsteht und Ihr Arbeitgeber Ihnen dafür ein Elektroauto bereitstellt. Was halten Sie spontan von der Idee? Bitte bewerten Sie dazu aus dem Bauch heraus folgende Wortpaare:“
Item 1	„Gefällt mir nicht“ / „Gefällt mir“
Item 2	„Schlecht“ / „Gut“
Item 3	„Negativ“ / „Positiv“

Reference: Alhakami & Slovic (1994), Finucane et al. (2000), King & Slovic (2014).

Table E2

Perceived Risk

Introduction to scale	„Ganz allgemein, wie riskant finden Sie den Einsatz von Elektroautos für Geschäftsfahrten?“
Single item	„Äußerst riskant“ / „Äußerst sicher“

Reference: Alhakami & Slovic (1994), Finucane et al. (2000), King & Slovic (2014).

Table E3

Perceived Benefits

Introduction to scale	„Ganz allgemein, wie vorteilhaft empfinden Sie den Einsatz von Elektroautos für Geschäftsfahrten?“
Single item	„Äußerst unvorteilhaft“ / „Äußerst vorteilhaft“

Reference: Alhakami & Slovic (1994), Finucane et al. (2000), King & Slovic (2014).

Appendix F

Scenarios Used in Each of the Four Experimental Conditions per Group in Study 2

Table F1

Four Experimental Conditions of the Control Group

High-benefit	Eine Geschäftsreise steht bevor. Für diese Fahrt müssen Sie jetzt noch ein Fahrzeug aus der Fahrzeugflotte Ihres Arbeitgebers buchen. Die Flotte besteht aus Verbrennern und kürzlich hinzugefügten Elektroautos. Sie wissen, dass Ihr Vorgesetzter und Ihre Kollegen Unterstützer von Elektromobilität sind, denn sie denken, dass Elektroautos eine Reihe markanter Vorteile für Geschäftsfahrten bieten.
Low-benefit	Eine Geschäftsreise steht bevor. Für diese Fahrt müssen Sie jetzt noch ein Fahrzeug aus der Fahrzeugflotte Ihres Arbeitgebers buchen. Die Flotte besteht aus Verbrennern und kürzlich hinzugefügten Elektroautos. Sie wissen, dass Ihr Vorgesetzter und Ihre Kollegen nicht viel von Elektroautos halten, denn sie denken, dass Elektroautos einige wichtige Features vermissen lassen, die nützlich für Geschäftsfahrten wären.
High-risk	Eine Geschäftsreise steht bevor. Für diese Fahrt müssen Sie jetzt noch ein Fahrzeug aus der Fahrzeugflotte Ihres Arbeitgebers buchen. Die Flotte besteht aus Verbrennern und kürzlich hinzugefügten Elektroautos. Sie wissen, dass Ihr Vorgesetzter und Ihre Kollegen Elektroautos mit großer Vorsicht begegnen, denn sie denken, dass das Fahren von Elektroautos für Geschäftsfahrten mit vielen Risiken und mangelnder Verlässlichkeit einhergeht, sodass man im schlimmsten Fall seinen Geschäftstermin verpassen könnte.
Low-risk	Eine Geschäftsreise steht bevor. Für diese Fahrt müssen Sie jetzt noch ein Fahrzeug aus der Fahrzeugflotte Ihres Arbeitgebers buchen. Die Flotte besteht aus Verbrennern und kürzlich hinzugefügten Elektroautos. Die Strecke zu Ihrem Geschäftspartner kennen Sie auswendig. Deshalb wissen Sie, dass entlang der Strecke zahlreiche Lademöglichkeiten zur Verfügung stehen. Auch Ihre Kollegen haben von der Verlässlichkeit von Elektroautos berichtet und dass sie bisher kein unerwartetes Erlebnis auf Geschäftsreisen hatten.

Reference: Finucane et al. (2000), King and Slovic (2014).

Table F2

Four Experimental Conditions of the Treatment Group

High-benefit	Eine Geschäftsreise steht bevor. Für diese Fahrt müssen Sie jetzt noch ein Fahrzeug aus der Fahrzeugflotte Ihres Arbeitgebers buchen. Die Flotte besteht aus Verbrennern und kürzlich hinzugefügten Elektroautos. In der Buchungssoftware werden sogenannte *Karma Punkte* angezeigt deren Höhe mit der Fahrzeugwahl variieren kann. Karma Punkte sind vergleichbar mit dem Sammeln von Punkten oder Münzen in Videospielen. Sie wissen, dass Ihr Vorgesetzter und Ihre Kollegen Unterstützer von Elektromobilität sind: Sie denken, dass Elektroautos eine Reihe markanter Vorteile für Geschäftsfahrten bieten. Deshalb hat das Team entschieden, dass die Buchung eines Elektroautos mit 10-facher Punktzahl (also 100 Karma Punkten) belohnt wird. Bei der Buchung eines Elektroautos würden Sie die erste Position (d. h. Position 1 von 15) im Abteilungswettbewerb inklusive Ihres Vorgesetzten erreichen. Zum Vergleich: Für die Buchung eines Verbrenners werden 10 Karma Punkte vergeben. An Ihrer Position (5 von 15) würde sich nichts ändern.
Low-benefit	Eine Geschäftsreise steht bevor. Für diese Fahrt müssen Sie jetzt noch ein Fahrzeug aus der Fahrzeugflotte Ihres Arbeitgebers buchen. Die Flotte besteht aus Verbrennern und kürzlich hinzugefügten Elektroautos. In der Buchungssoftware werden sogenannte *Karma Punkte* angezeigt deren Höhe mit der Fahrzeugwahl variieren kann. Karma Punkte sind vergleichbar mit dem Sammeln von Punkten oder Münzen in Videospielen. Sie wissen, dass Ihr Vorgesetzter und Ihre Kollegen nicht viel von Elektroautos halten, denn sie denken, dass Elektroautos einige wichtige Features vermissen lassen, die nützlich für Geschäftsfahrten wären. Deswegen hat das Team entschieden, dass für die Buchung eines Elektroautos weniger Karma Punkte (20 Punkte) als für die Buchung eines Verbrenners (25 Punkte) vergeben werden. Unabhängig dessen welchen Fahrzeugtypen (Elektroauto oder Verbrenner) Sie buchen, ändert sich nichts an Ihrer Position (6 von 15) im Abteilungsranking inklusive Ihres Vorgesetzten.

High-risk	Eine Geschäftsreise steht bevor. Für diese Fahrt müssen Sie jetzt noch ein Fahrzeug aus der Fahrzeugflotte Ihres Arbeitgebers buchen. Die Flotte besteht aus Verbrennern und kürzlich hinzugefügten Elektroautos. In der Buchungssoftware werden sogenannte *Karma Punkte* angezeigt deren Höhe mit der Fahrzeugwahl variieren kann. Karma Punkte sind vergleichbar mit dem Sammeln von Punkten oder Münzen in Videospielen. Sie wissen, dass Ihr Vorgesetzter und Ihre Kollegen Elektroautos mit großer Vorsicht begegnen denn sie denken, dass das Fahren von Elektroautos für Geschäftsfahrten mit vielen Risiken und mangelnder Verlässlichkeit einhergeht sodass man im schlimmsten Fall seinen Geschäftstermin verpassen könnte. Deswegen hat das Team entschieden, dass die Buchung eines Elektroautos zu einem Abzug von 100 Karma Punkten führt. Bei der Buchung eines Elektroautos würden Sie von Platz 5 auf den vorletzten Platz (d. h. Position 14 von 15) im Abteilungswettbewerb inklusive Ihres Vorgesetzten zurückfallen. Zum Vergleich: Für die Buchung eines Verbrenners werden 10 Karma Punkte vergeben. An Ihrer Position ändert sich nichts.
Low-risk	Eine Geschäftsreise steht bevor. Für diese Fahrt müssen Sie jetzt noch ein Fahrzeug aus der Fahrzeugflotte Ihres Arbeitgebers buchen. Die Flotte besteht aus Verbrennern und kürzlich hinzugefügten Elektroautos. In der Buchungssoftware werden sogenannte *Karma Punkte* angezeigt deren Höhe mit der Fahrzeugwahl variieren kann. Karma Punkte sind vergleichbar mit dem Sammeln von Punkten oder Münzen in Videospielen. Die Strecke zu Ihrem Geschäftspartner kennen Sie auswendig. Deshalb wissen Sie, dass entlang der Strecke zahlreiche Lademöglichkeiten zur Verfügung stehen. Auch Ihre Kollegen haben von der Verlässlichkeit von Elektroautos berichtet und dass sie bisher kein unerwartetes Erlebnis auf Geschäftsreisen hatten. Deswegen hat das Team entschieden, dass man für die Buchung eines Elektroautos genauso viele Karma Punkte erhalten sollte wie für die Buchung eines Verbrenners. Unabhängig davon für welchen Fahrzeugtypen (Verbrenner oder Elektroauto) Sie sich entscheiden, würden Sie von Position 6 auf Position 5 von 15 im Abteilungswettbewerb inklusive Ihres Vorgesetzten aufrücken.

Reference: Finucane et al. (2000), King and Slovic (2014).

Appendix G

Examples of the Car Booking Software Utilised in Study 2 and Implementation Details

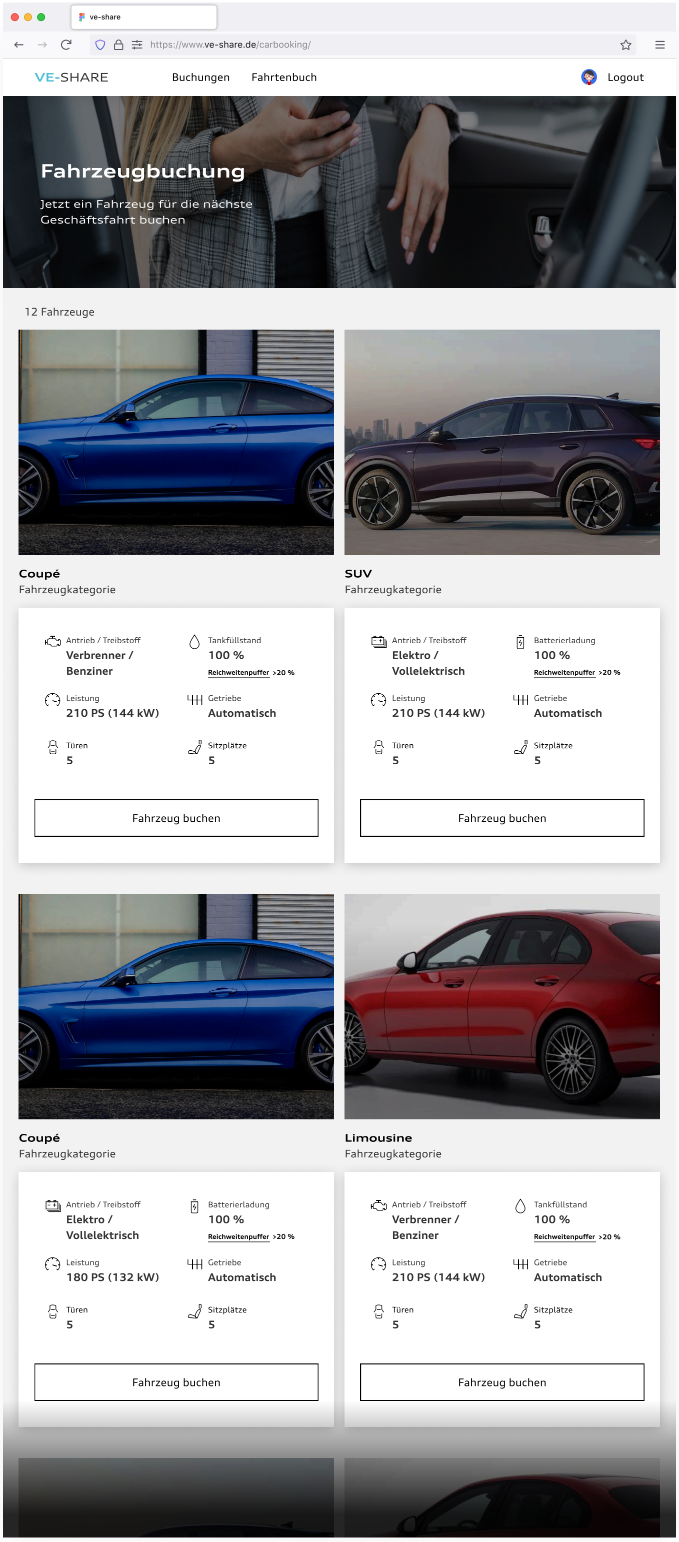
Study 2 employed a digital prototype presenting the car booking software, designed with the Figma (www.figma.com) software. Car choice was measured using the Maze (www.maze.co) software, which tracks individuals' navigation through the software and their car choices. The designs utilise avatars based on the designs by Saif (n.d.).

Furthermore, the following section provides an excerpt featuring the most relevant screens from the experimental conditions of the car booking experiment. While the four conditions of the control group remained consistent in terms of the design of the car booking software, the car booking software presented in the context of the four experimental conditions of the treatment group underwent design variations. This appendix commences with the screens of the control group, followed by the sample screens of the treatment group.

Excerpt of the Car Booking Process of the Control Group

Figure G1

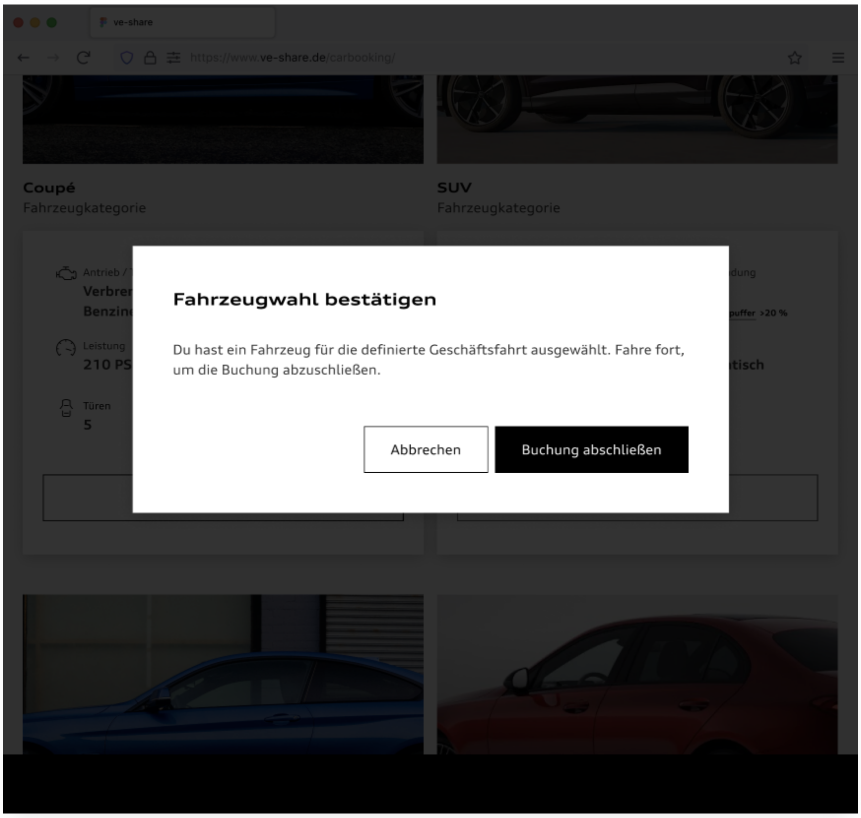
Car Selection Page Displayed to Participants in the Control Group



Note. This screen displays a truncated view of the car selection page, presenting the car fleet.

Figure G2

Confirmation of Car Selection Displayed to Participants in the Control Group

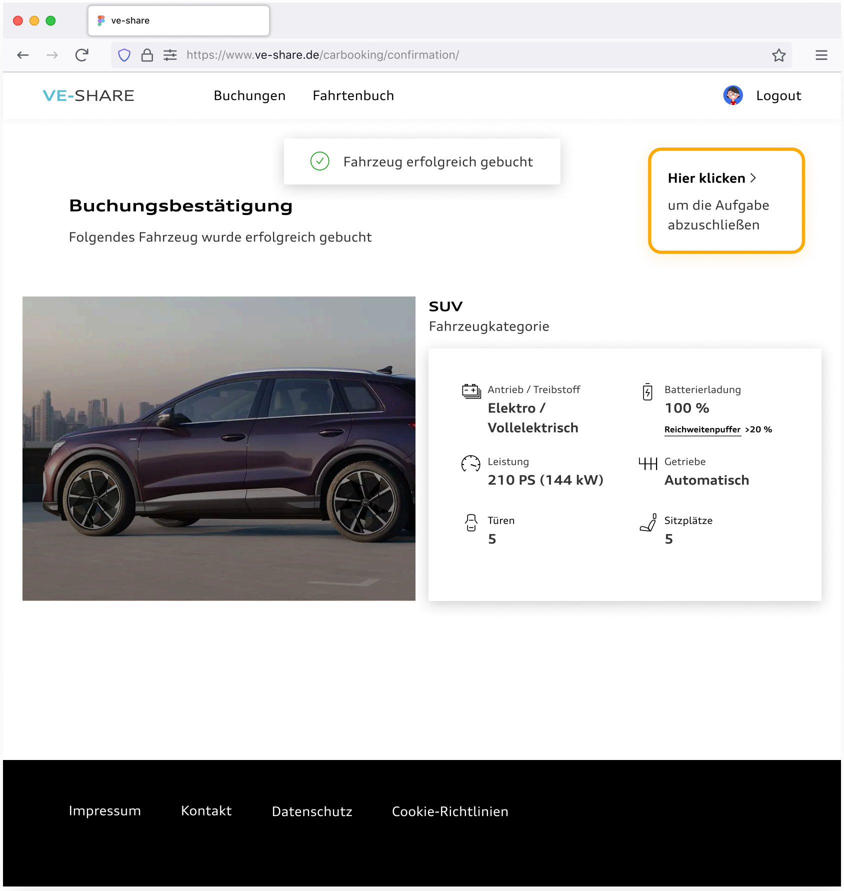


Note. This screen was presented to participants upon selecting a car for their upcoming business trip.

Participants were required to confirm their choice before finalising their booking.

Figure G3

Car Booking Confirmation Displayed to Participants in the Control Group

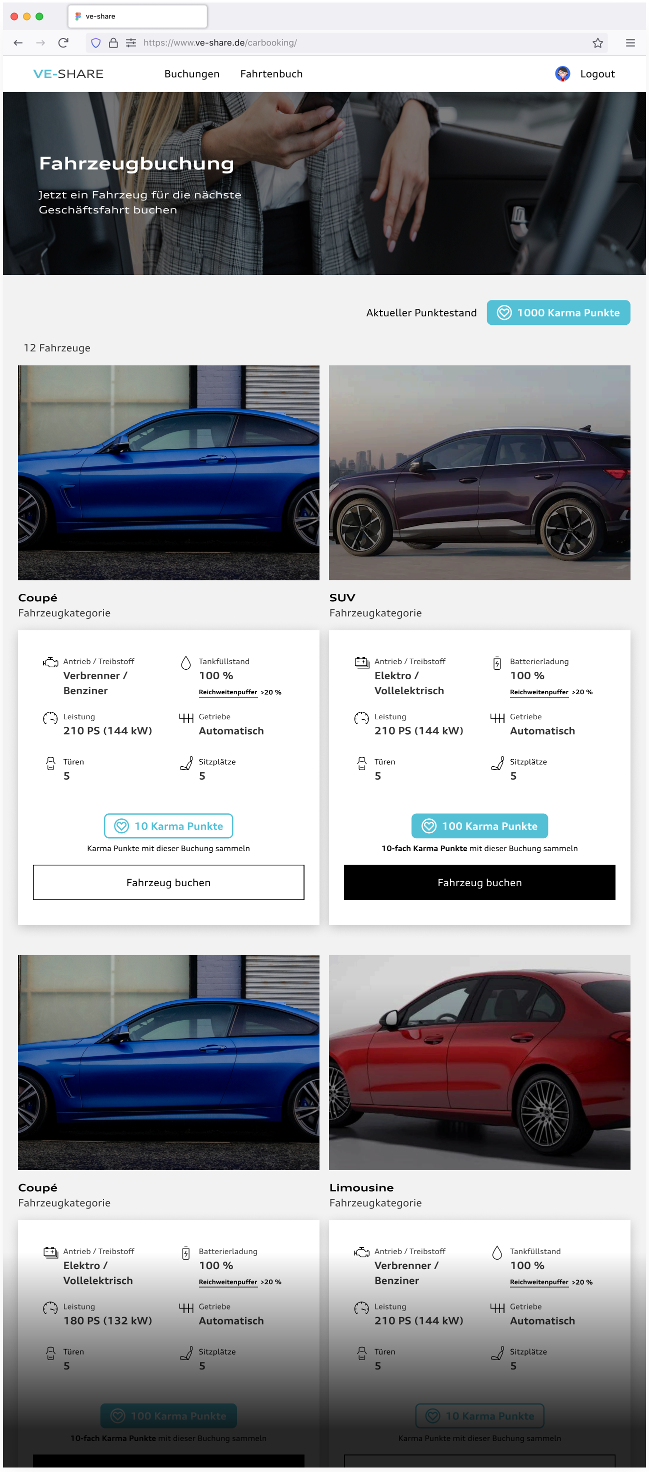


Note. This screen variant was presented to participants upon confirming their previous car selection.

Excerpt of the Car Booking Process of the Treatment Group

Figure G4

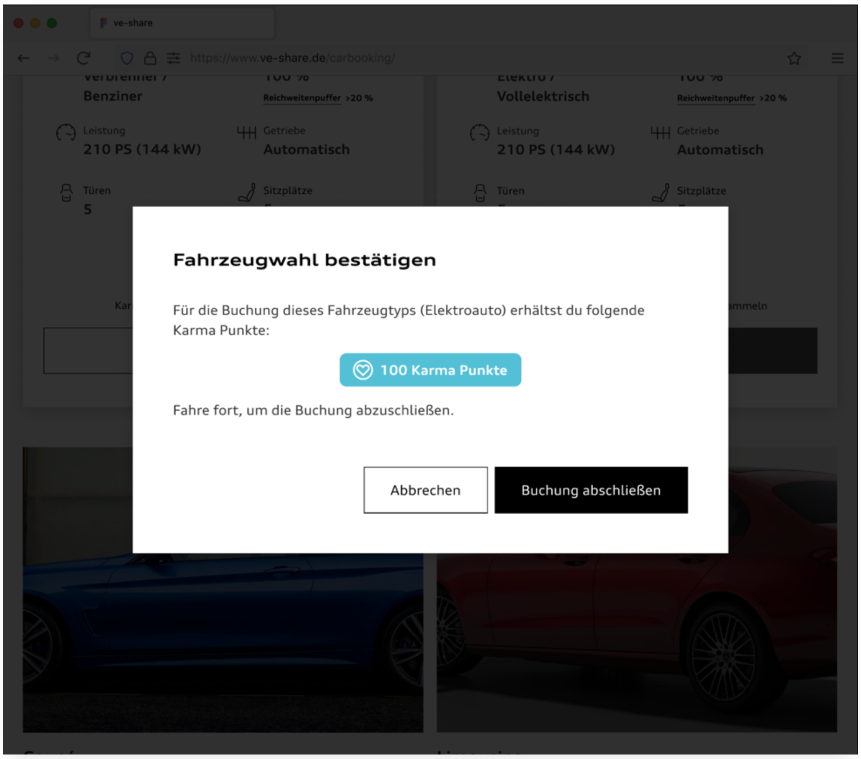
Car Selection Page Displayed to Participants in the High-Benefit Condition



Note. This screen provides a truncated view of the car selection page, presenting the car fleet. The number of gamification points linked to the car choice varies based on the car type.

Figure G5

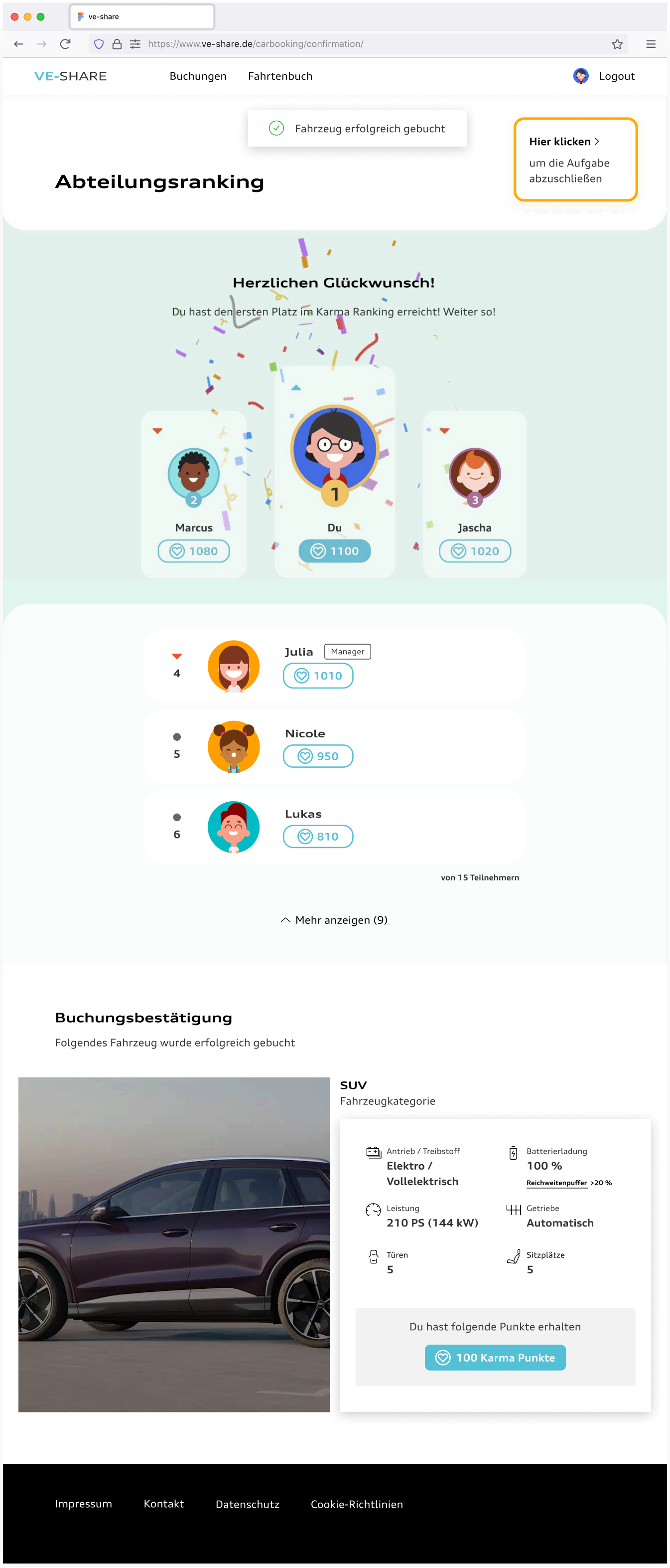
Confirmation of Car Selection Displayed to Participants in the High-Benefit Condition (BEV)



Note. This screen was presented to participants upon selecting a BEV for their upcoming business trip. Participants were required to confirm their choice before finalising their booking. Additionally, the screen presents the projected number of gamification points to be awarded upon confirmation of the car choice.

Figure G6

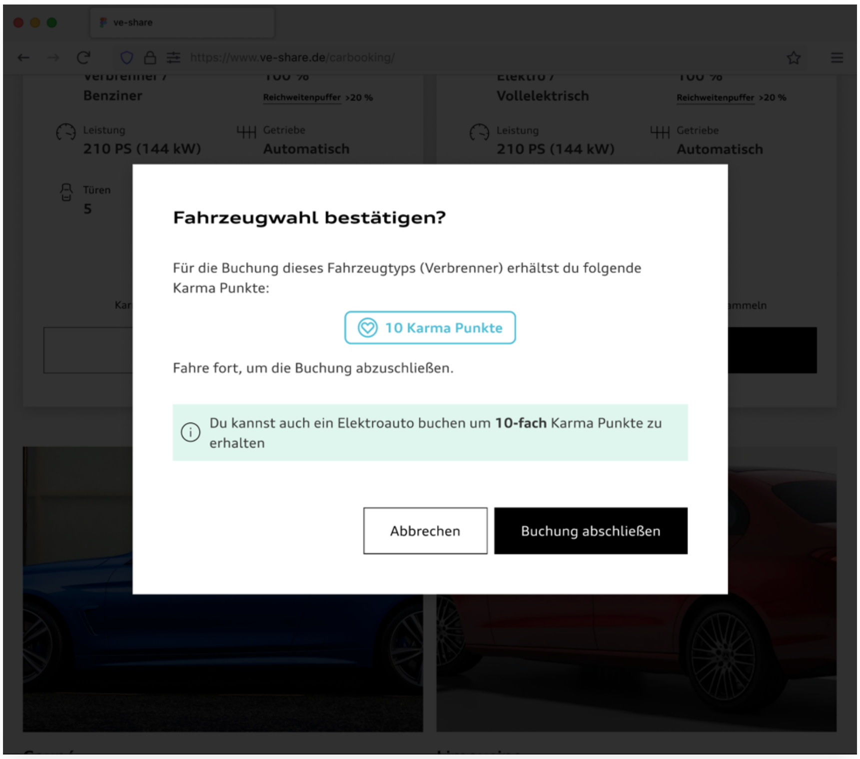
Car Booking Confirmation Displayed to Participants in the High-Benefit Condition (BEV)



Note. This screen variant was presented to participants upon confirming their previous BEV selection, featuring the updated leaderboard.

Figure G7

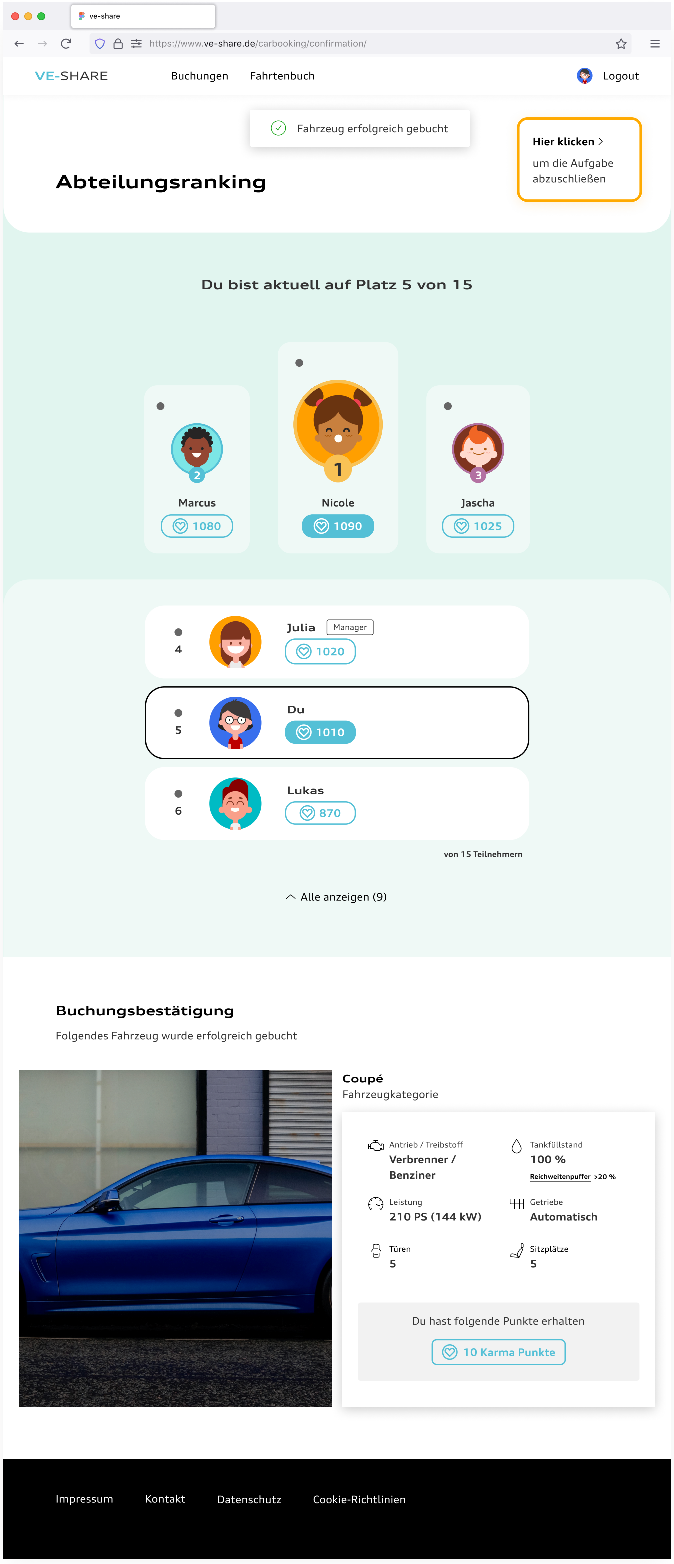
Confirmation of Car Selection Displayed to Participants in the High-Benefit Condition (ICEV)



Note. This screen was presented to participants upon selecting a conventional car for their upcoming business trip. Participants were required to confirm their choice before finalising their booking. Additionally, the screen presents the projected number of gamification points to be awarded upon confirmation of the car choice.

Figure G8

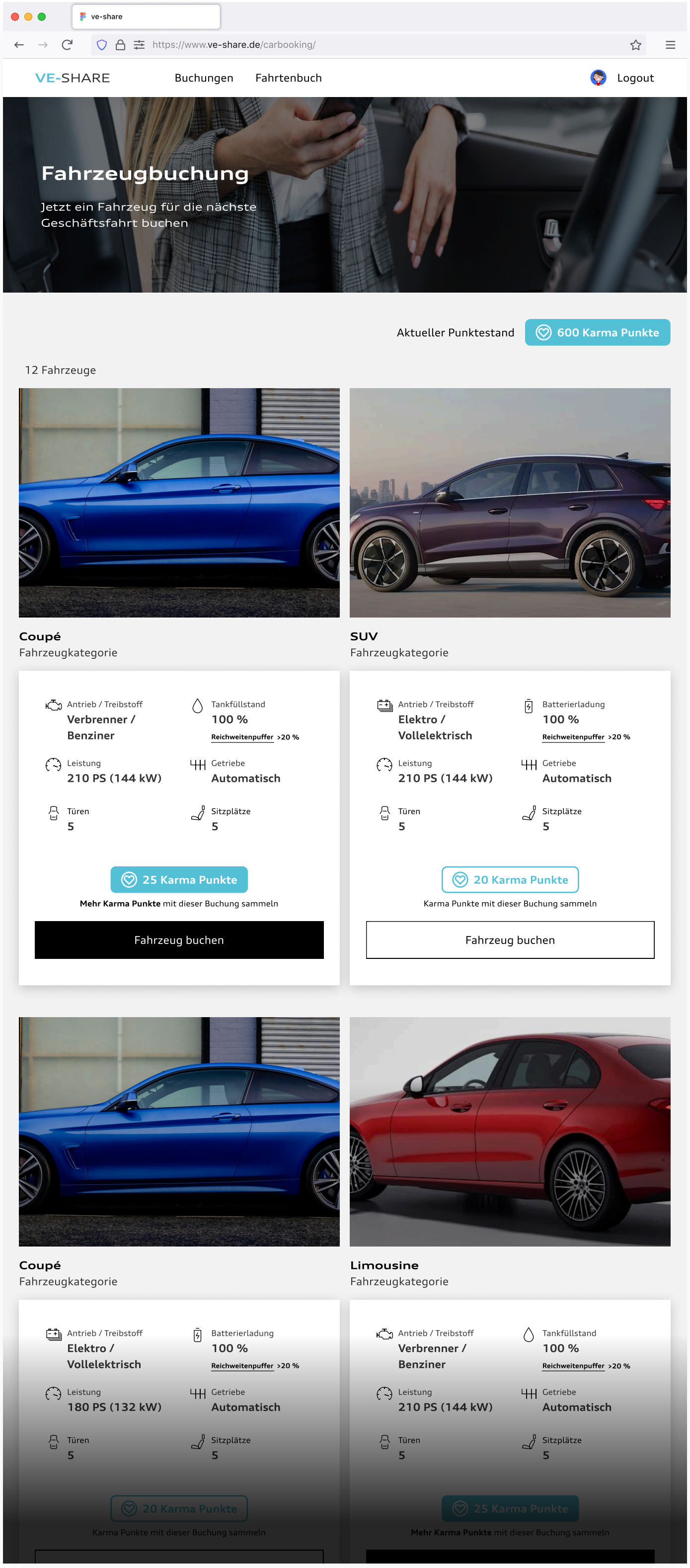
Car Booking Confirmation Displayed to Participants in the High-Benefit Condition (ICEV)



Note. This screen variant was presented to participants upon confirming their previous selection of a conventional car, featuring the updated leaderboard.

Figure G9

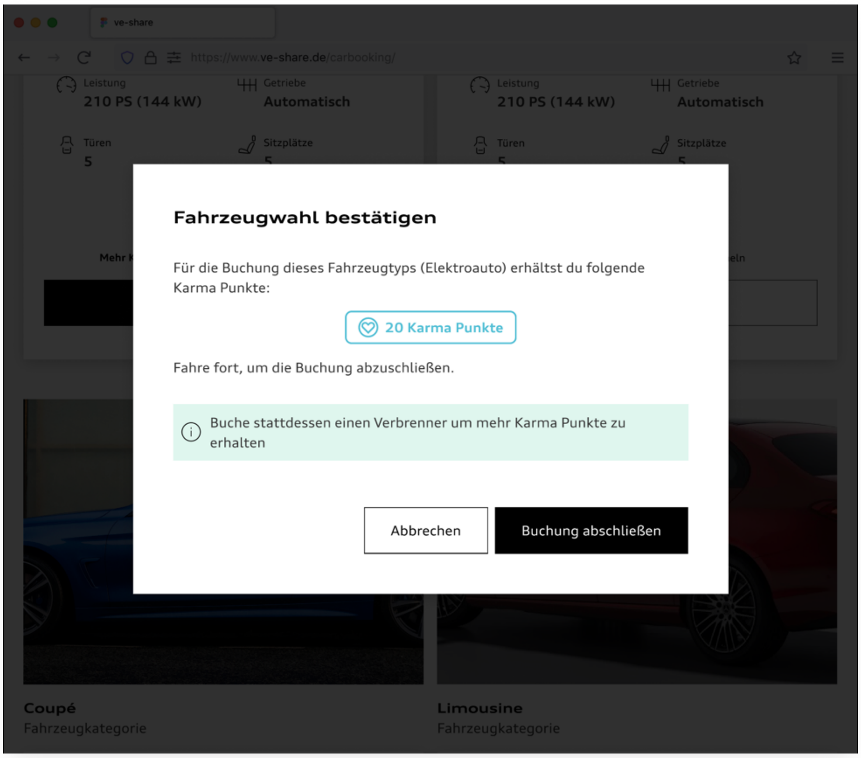
Car Selection Page Displayed to Participants in the Low-Benefit Condition



Note. This screen provides a truncated view of the car selection page, presenting the car fleet. The number of gamification points linked to the car choice varies based on the car type.

Figure G10

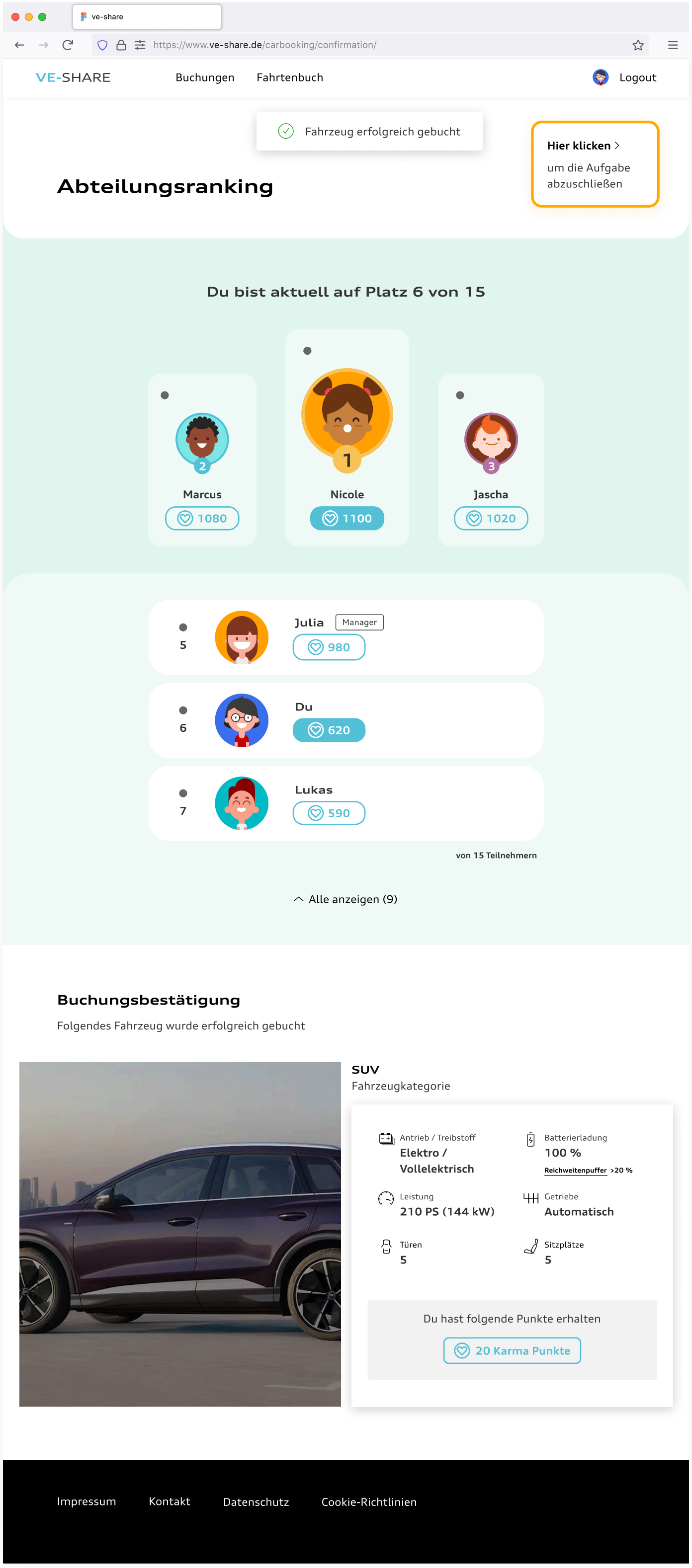
Confirmation of Car Selection Displayed to Participants in the Low-Benefit Condition (BEV)



Note. This screen was presented to participants upon selecting a BEV for their upcoming business trip. Participants were required to confirm their choice before finalising their booking. Additionally, the screen presents the projected number of gamification points to be awarded upon confirmation of the car choice.

Figure G11

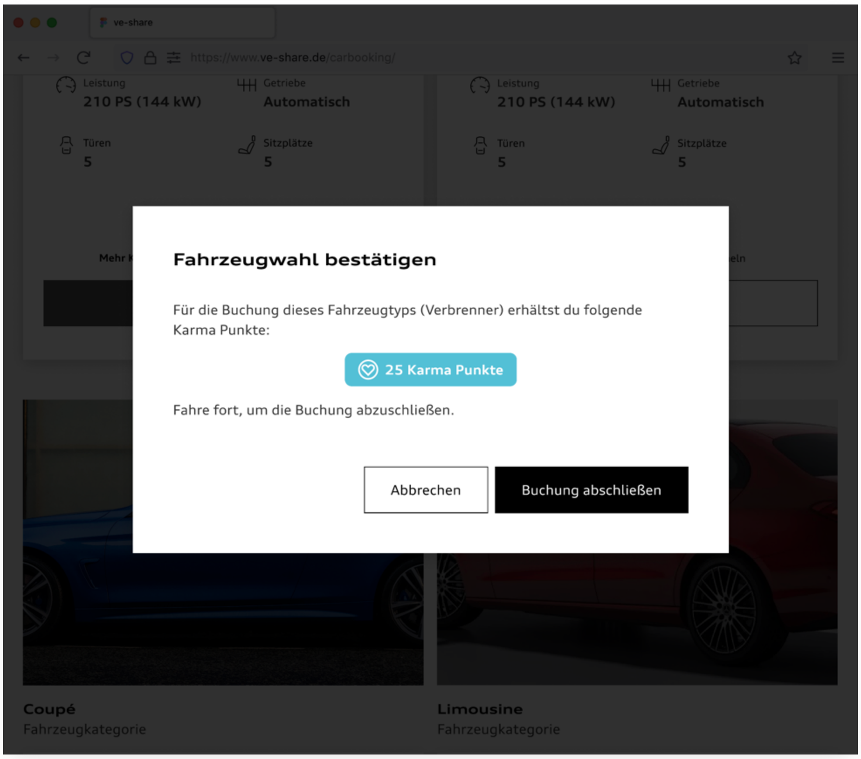
Car Booking Confirmation Displayed to Participants in the Low-Benefit Condition (BEV)



Note. This screen variant was presented to participants upon confirming their previous BEV selection, featuring the updated leaderboard.

Figure G12

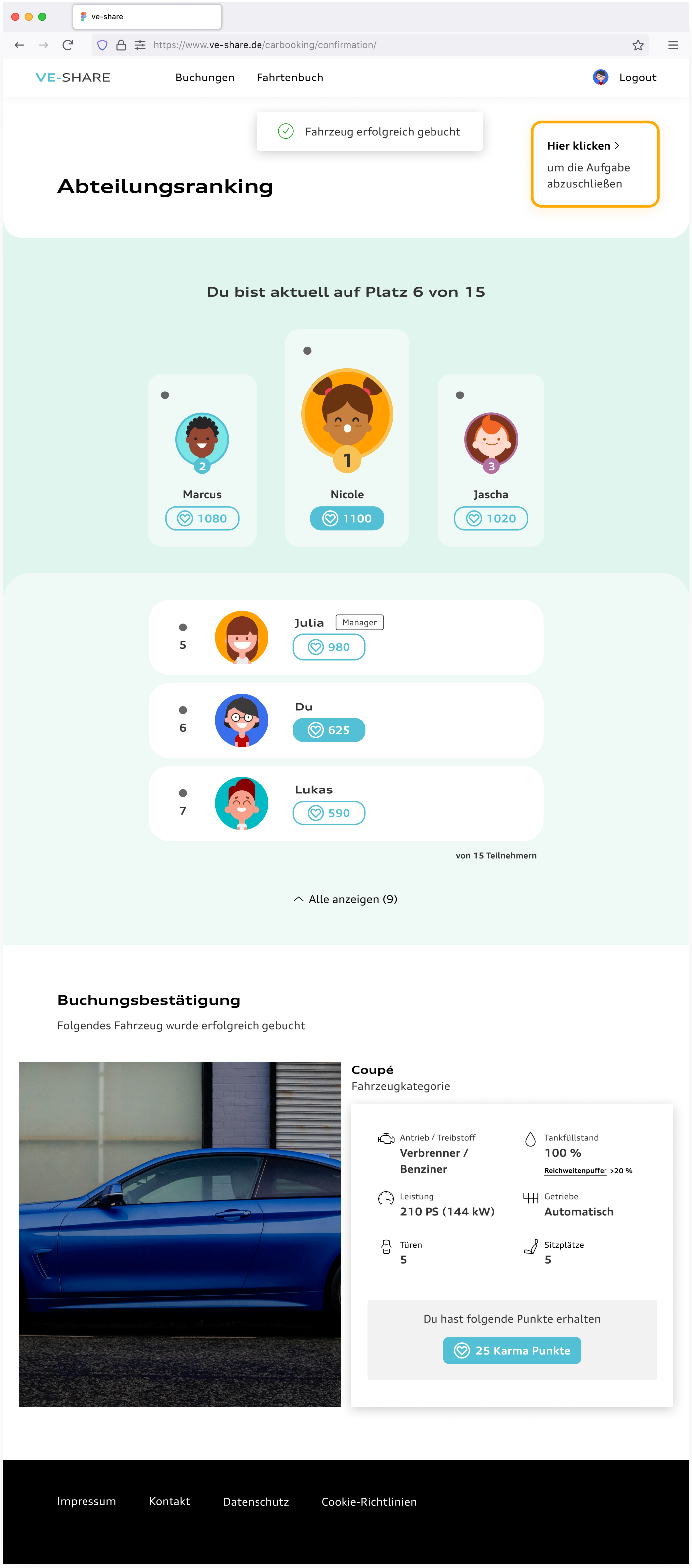
Confirmation of Car Selection Displayed to Participants in the Low-Benefit Condition (ICEV)



Note. This screen was presented to participants upon selecting a conventional car for their upcoming business trip. Participants were required to confirm their choice before finalising their booking. Additionally, the screen presents the projected number of gamification points to be awarded upon confirmation of the car choice.

Figure G13

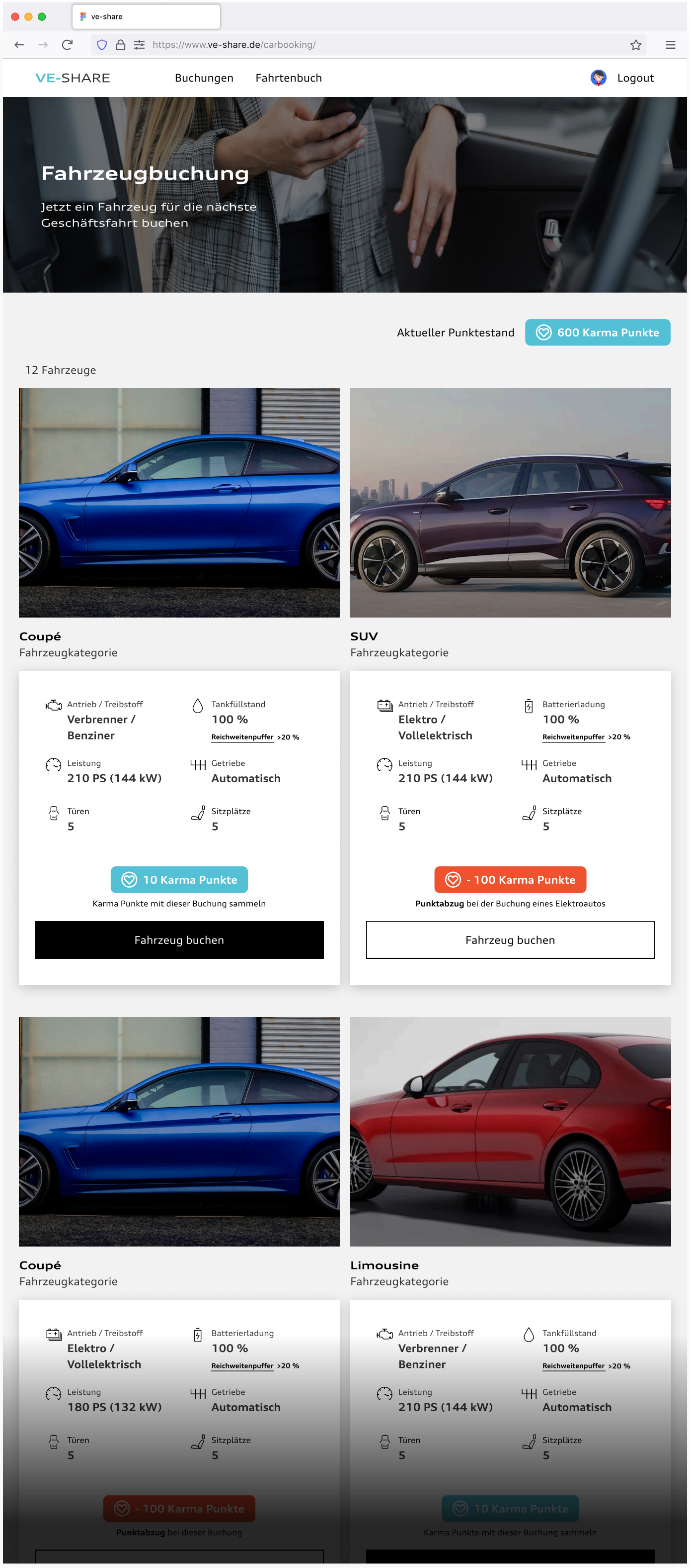
Car Booking Confirmation Displayed to Participants in the Low-Benefit Condition (ICEV)



Note. This screen variant was presented to participants upon confirming their previous selection of a conventional car, featuring the updated leaderboard.

Figure G14

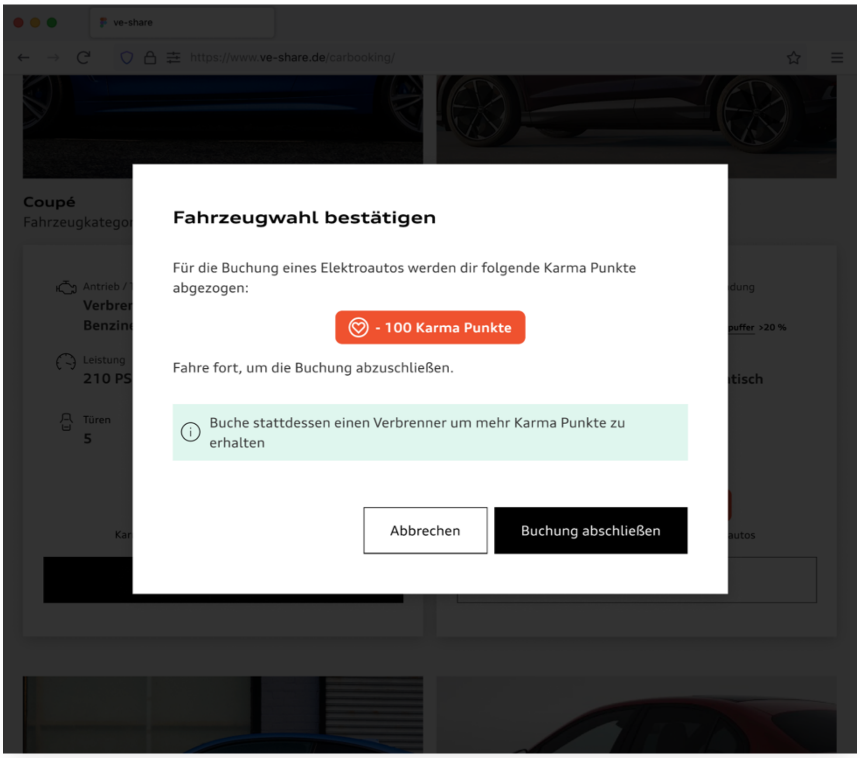
Car Selection Page Displayed to Participants in the High-Risk Condition



Note. This screen provides a truncated view of the car selection page, presenting the car fleet. The number of gamification points linked to the car choice varies based on the car type.

Figure G15

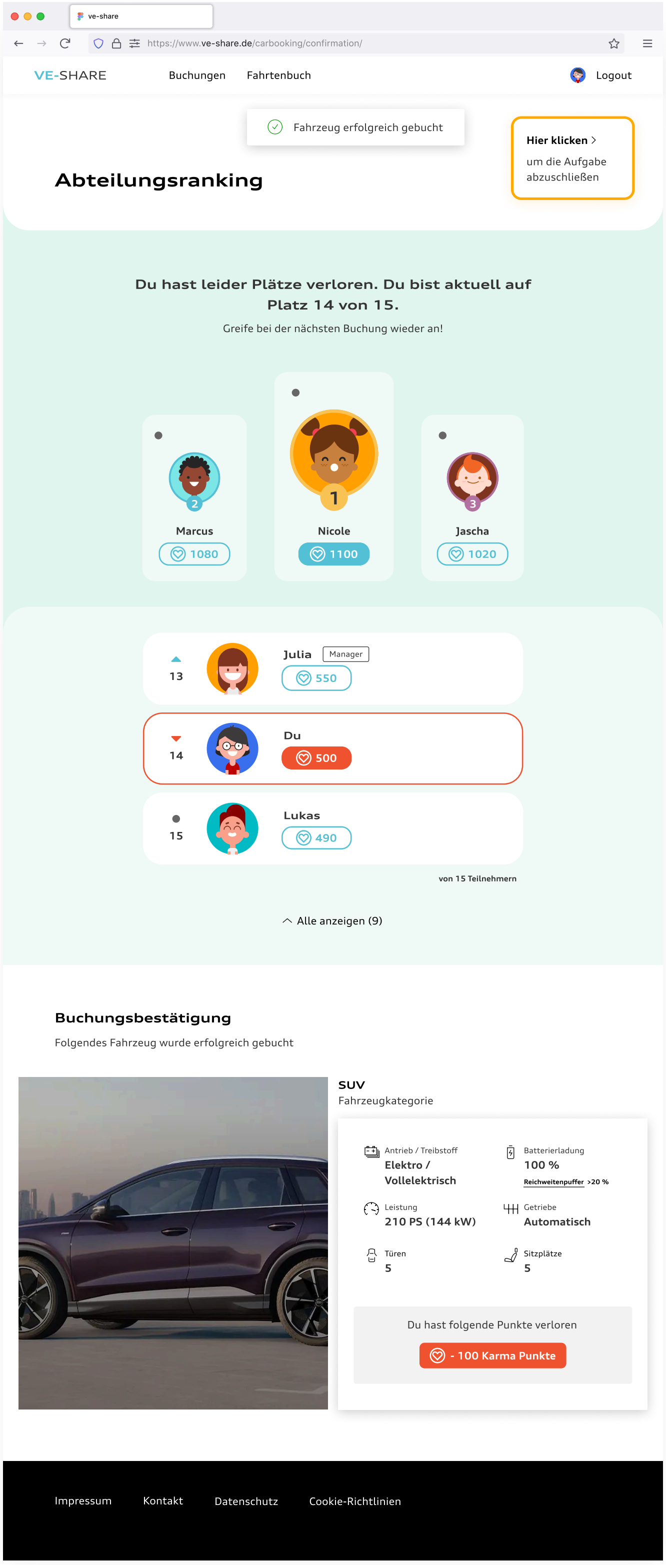
Confirmation of Car Selection Displayed to Participants in the High-Risk Condition (BEV)



Note. This screen was presented to participants upon selecting a BEV for their upcoming business trip. Participants were required to confirm their choice before finalising their booking. Additionally, the screen presents the projected number of gamification points to be awarded upon confirmation of the car choice.

Figure G16

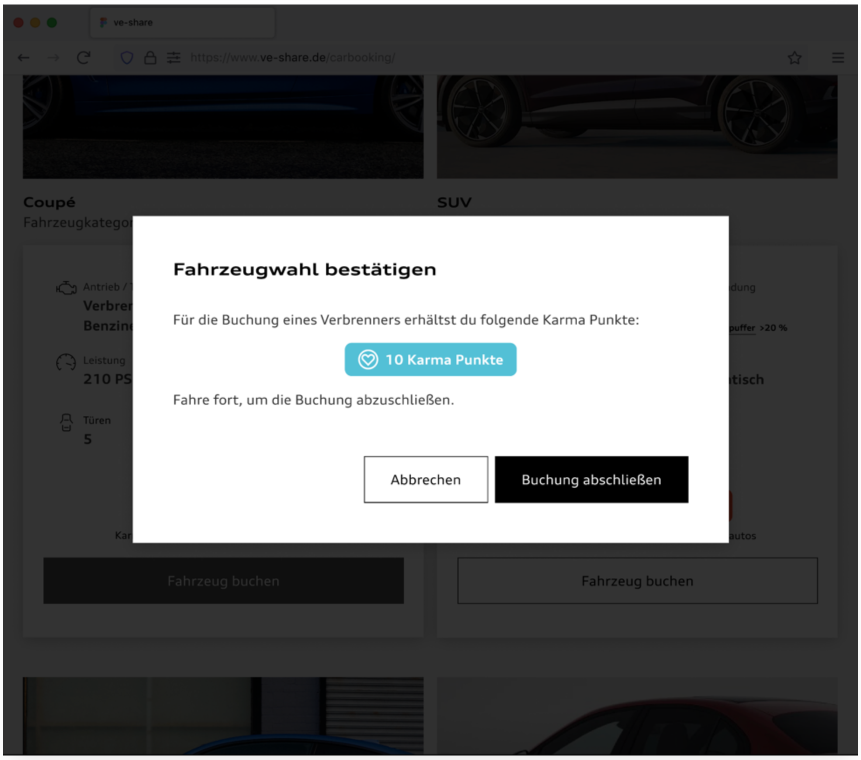
Car Booking Confirmation Displayed to Participants in the High-Risk Condition (BEV)



Note. This screen variant was presented to participants upon confirming their previous BEV selection, featuring the updated leaderboard.

Figure G17

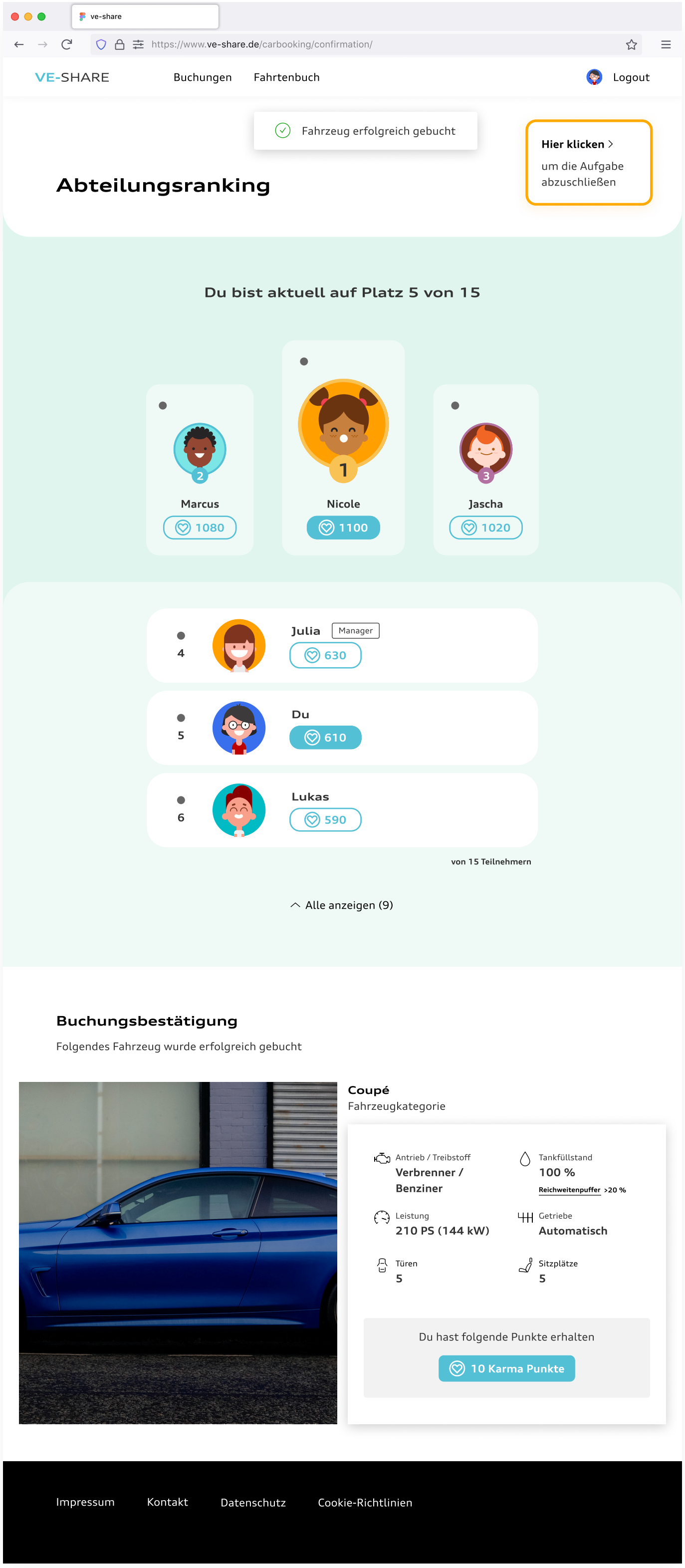
Confirmation of Car Selection Displayed to Participants in the High-Risk Condition (ICEV)



Note. This screen was presented to participants upon selecting a conventional car for their upcoming business trip. Participants were required to confirm their choice before finalising their booking. Additionally, the screen presents the projected number of gamification points to be awarded upon confirmation of the car choice.

Figure G18

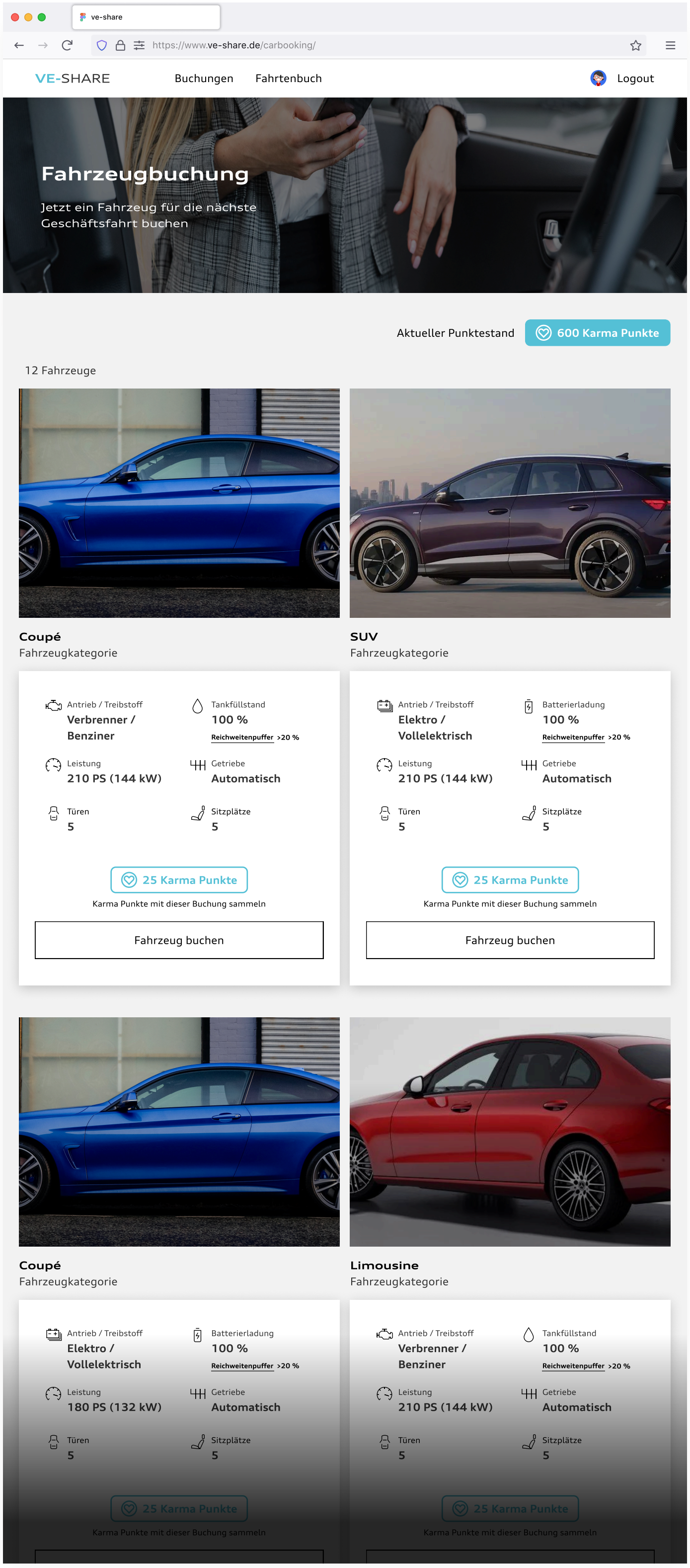
Car Booking Confirmation Displayed to Participants in the High-Risk Condition (ICEV)



Note. This screen variant was presented to participants upon confirming their previous selection of a conventional car, featuring the updated leaderboard.

Figure G19

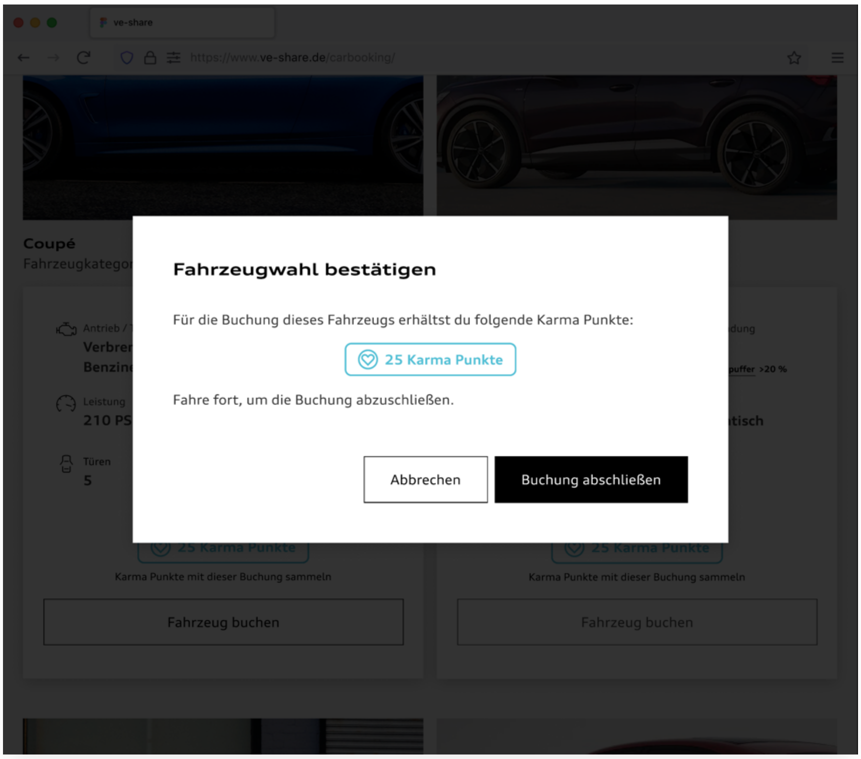
Car Selection Page Displayed to Participants in the Low-Risk Condition



Note. This screen provides a truncated view of the car selection page, presenting the car fleet. The displayed gamification points did not vary based on the selected car type.

Figure G20

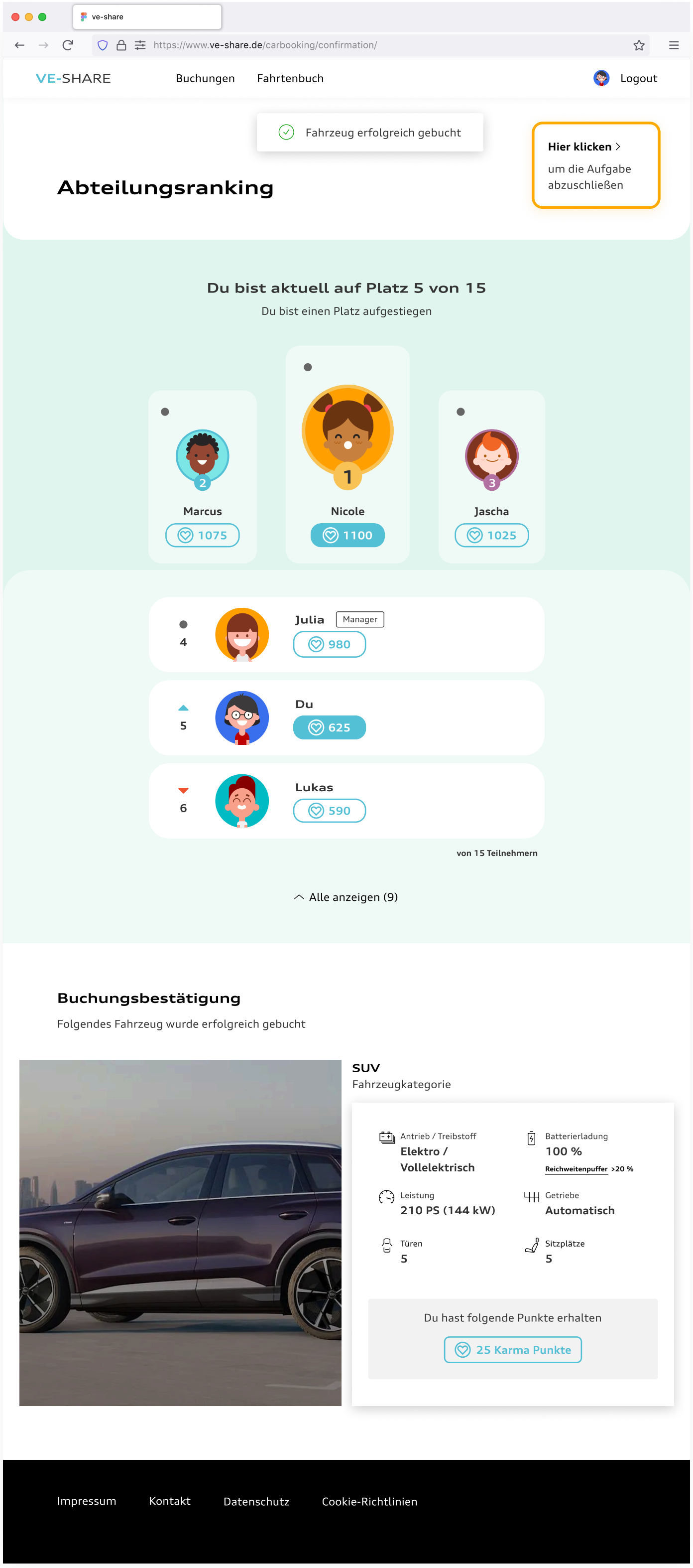
Confirmation of Car Selection Displayed to Participants in the Low-Risk Condition (BEV)



Note. This screen was presented to participants upon selecting a BEV for their upcoming business trip. Participants were required to confirm their choice before finalising their booking. Additionally, the screen presents the projected number of gamification points to be awarded upon confirmation of the car choice.

Figure G21

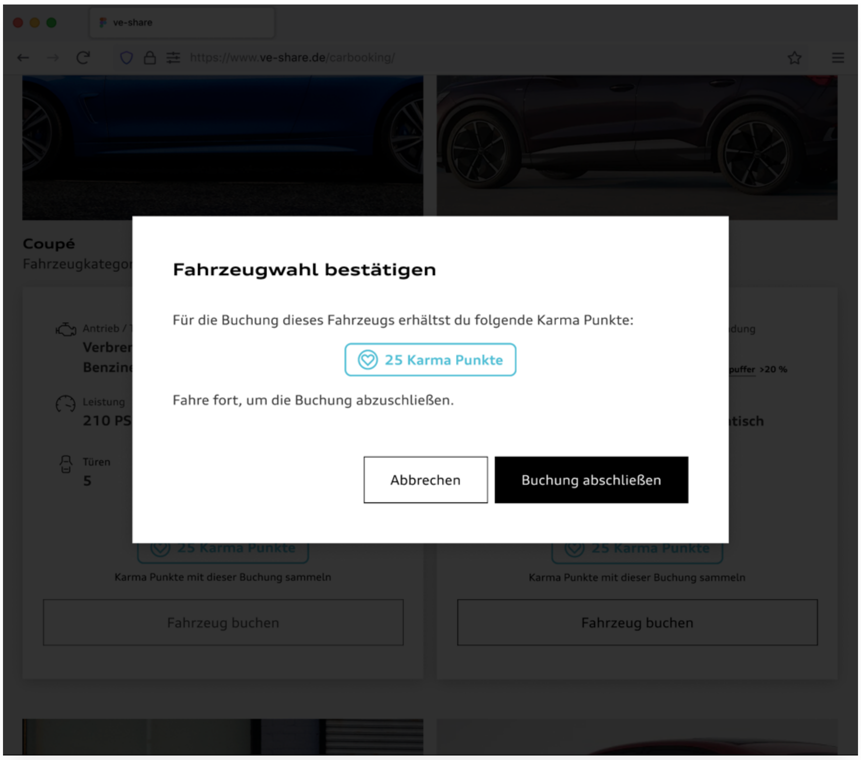
Car Booking Confirmation Displayed to Participants in the Low-Risk Condition (BEV)



Note. This screen variant was presented to participants upon confirming their previous BEV selection, featuring the updated leaderboard.

Figure G22

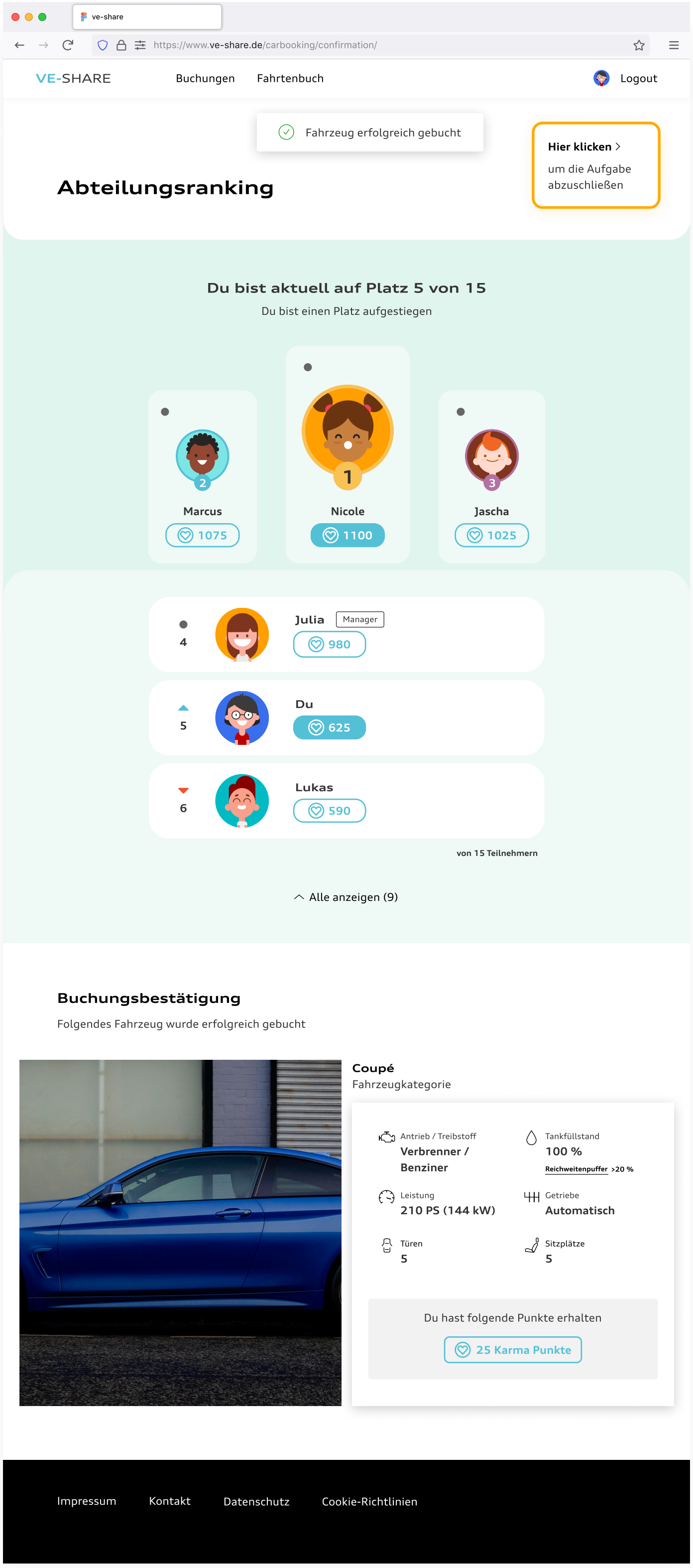
Confirmation of Car Selection Displayed to Participants in the Low-Risk Condition (ICEV)



Note. This screen was presented to participants upon selecting a conventional car for their upcoming business trip. Participants were required to confirm their choice before finalising their booking. Additionally, the screen presents the projected number of gamification points to be awarded upon confirmation of the car choice.

Figure G23

Car Booking Confirmation Displayed to Participants in the Low-Risk Condition (ICEV)



Note. This screen variant was presented to participants upon confirming their previous selection of a conventional car, featuring the updated leaderboard.