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MODERATING EFFECTS OF DATA PRIVACY RISKS ON THE TECHNOLOGY ACCEPTANCE OF CONNECTED CARS

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DISSERTATION WRITTEN UNDER THE SUPERVISION OF
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RESUMO

Título: Efeitos moderadores da privacidade de dados na aceitação tecnológica dos automóveis em rede

Autor: Julian Weller

Objectivo: Acelerada pela digitalização, a ligação entre humanos e máquinas cresceu exponencialmente nos últimos anos e a tendência continua a ganhar ímpeto. Os automóveis em rede [AR] seguem essa tendência de conectar objetos do quotidiano à Internet e, à medida que os veículos contemporâneos se tornam progressivamente mais digitais, os serviços afetos às funções de conectividade representam uma proposta de valor central nos modelos de negócio OEM. Contudo, enquanto as soluções de conectividade ampliam e melhoram as características funcionais de um veículo, a dependência de dados pessoais do utilizador promove a importância da privacidade dos mesmos. Esta tese visa examinar a função moderadora dos riscos da privacidade de dados no processo de adoção de funcionalidades dos AR. Com base no Modelo de Aceitação da Tecnologia (TAM) de Davis, é proposto um modelo de aceitação adaptado que considera os riscos associados à privacidade de dados nos AR.

Metodologia: Numa experiência de teste dividida, cerca de 440 participantes foram expostos a diferentes níveis de risco de privacidade de dados relacionado com AR tendo, posteriormente, sido requisitada a sua resposta a um questionário de aceitação. Regressão Linear Interativa revelou um efeito de moderação atenuante, estatisticamente significativo, da privacidade de dados na utilidade e facilidade de uso perceptível das funcionalidades dos AR, o que influencia a intenção de uso.

Resultados: Os resultados obtidos salientam a importância da privacidade de dados na adoção de funcionalidades dos AR contribuindo para a pesquisa existente salientando a relevância da combinação dos riscos da privacidade de dados com construções clássicas da TAM.

Palavras-chave: automóveis em rede, privacidade de dados, modelo de aceitação da tecnologia, utilidade, facilidade de uso

ABSTRACT

Title: Moderating effects of data privacy risks on the technology acceptance of connected cars

Author: Julian Weller

Purpose: Accelerated by the increasing digitalization, the connection of humans and machines has exponentially grown in recent years and the trend continues to gain momentum. Connected cars follow this course of connecting everyday objects to the internet and as contemporary vehicles are becoming more networked, services tailored around connectivity functions form a central value proposition of modern OEM business models. Yet, while connectivity features extend and improve a vehicle's functional portfolio, the dependency on personal user data fosters the relevance of informational privacy in vehicles. This thesis aims at examining the moderating role of data privacy risks in the adoption process of connected car features. Building on Davis' Technology Acceptance Model, an adapted acceptance framework which accounts for data privacy risks of connected car features is proposed.

Methodology: In a split-test experiment, 440 participants were exposed to different levels of connected car related data privacy risks and subsequently responded to an acceptance survey. Interaction based regression modelling revealed a statistically significant and practically meaningful attenuating moderation effect of data privacy risks on the perceived usefulness and perceived ease of use of connected car features, which in turn influenced usage intention.

Findings: The obtained results underscore the importance of data privacy for the adoption of connected car features and contribute to the existing research by showing the importance of combining data privacy risks of connected cars with classical TAM constructs.

Keywords: connected cars, data privacy, technology acceptance model, usefulness, ease of use

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LIST OF ABBREVIATIONS

AMT	Amazon Mechanical Turk
BI	Behavioral Intention
CASE	Connected Autonomous Shared Electrified
DoI	Diffusion of Innovation
HIT	Human Intelligence Tasks
IoT	Internet of Things
OEM	Original Equipment Manufacturer
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
TAM	Technology Acceptance Model

1 INTRODUCTION

1.1 Background

Over the past 50 years, automotive Original Equipment Manufacturers (OEMs) have pursued a relatively uniform business approach with regard to the development, production and sales of their vehicles and associated supplementary services (Ahuja et al., 2001). Thereby, the focus was on incremental improvements of established processes and technologies (Alam et al., 2015). Yet, in particular during the last decade, digital trends and technology enabled business transformations have significantly affected the competitive automotive landscape (Howard, 2005). In this new digital era, disruptive and networked innovation strategies are inevitable (Coppola et al., 2016). Particularly, the so-called CASE trends (Connected, Autonomous, Shared, Electrified) have comprehensively shaped the automotive landscape (Morris et al., 2018). Among the four automotive key trends, connected car technologies are the central component of data-based mobility concepts and the basis for two of the other CASE trends, namely shared mobility and autonomous driving (Bansal et al., 2016). Thereby, connected car technologies follow the trend of connecting everyday objects to the internet (Morris et al., 2018). Networked and digital communication-based technologies such as mobile devices, sensors, edge computing, IoT and digital applications are the technical basis for this type of connectivity (Coppola et al., 2016).

In this context, an increase in the usage of connected cars and the resulting opportunity to gather huge amounts of customer data enables OEMs to build a customer centric and individually tailored ecosystem for the distribution of digital services in cars (Nu et al., 2014). Growth drivers for OEMs will no longer be just based on the revenues accounted from the sales of cars, but rather on data-based and networked mobility solutions. In this context, sales potentials are rising to yet unforeseen revenues and profits, by means of newly created customer touchpoints throughout the automotive customer journey (Yasukawa et al., 2019). Due to this transformative business opportunity and the shaping influence on the complementary environment (e.g. insurance, entertainment, maintenance, or traffic coordination), Löffler et al. (2017) proclaim connected car concepts as the most relevant, central component to car manufacturers in the upcoming years. Supportive of Löffler's argumentation, McKinsey (2018) forecasts a value pool of 750 billion USD generated by new revenue streams and cost reductions from vehicle data by 2030.

However, to leverage the enormous business potential of connected car functionalities, OEMs need to ensure the acceleration of the mainstream adoption and commercialization of connected vehicles by generating further added value and network effects for customers (Nu et al., 2014). Yet, in order to facilitate new value propositions centered around digital information, OEMs rely on a constant high volume of not only technical driver data, but also sensitive private data about customer preferences generated within the connected ecosystem of a car (Martin et al., 2017). This prerequisite for the commercial breakthrough means that a critical mass of users, willing to share their data, is inevitable in order to be able to comprehensively leverage the potential of connectivity technologies and the respective service offerings (Morris et al., 2018). General Motors estimates that a connected car ecosystem will only be effective once 25% of the cars on the road are equipped with connected car technologies. According to their estimations, this number will not be achieved by 2025 if the adoption rate does not accelerate (Martin et al., 2018).

If OEMs fail to understand the factors preventing a fast commercial adoption and are thus not able to convince their customers of the value proposition of connected car features, they risk to miss out on the opportunities these innovations yield in terms of value capturing and creation. Thereby, OEMs could potentially lose ground to new market entrants and aftermarket service providers (Howard, 2005). At worst, they could find themselves typecast as legacy hardware manufacturers and locked out of the profitable service and software solution market, like many mobile phone and computer hardware manufacturers in recent years have been before them (Yasukawa et al., 2019).

1.2 Problem Statement

Although connected car functionalities already provide various comfort, efficiency and safety benefits to customers, there are still unexplained concerns around the customer's willingness to adopt connectivity innovations in cars (Coppola et al., 2016). As an extensive review of the existing literature has shown (see Chapter 2.3), these concerns often relate to data privacy and security domains of vehicular connectivity (Fagnant et al., 2015). Yet, a thorough analysis highlighting the actual impact of privacy concerns on the adoption behavior and ultimately the willingness to demand connected car innovations has not been conducted. Respectfully, this perspective provides a novel integration of research on technology acceptance within the wider context of connected cars and their perceived benefits and risks, as in more detail elaborated in the upcoming chapter.

The objective of this thesis is to identify how different levels of data privacy concerns have affected the previously relatively low usage rate of connected car technologies. Thereby, the research addresses the challenge of establishing a fast adoption process, by investigating if data privacy risks moderate the actual perceived usefulness and perceived ease of use of connected car technologies. Ultimately, it is examined how strong the behavioral intention to adopt is affected.

Accordingly, the research question of my thesis can be formulated as follows:

"Are data privacy risks moderating the effects of perceived usefulness and ease of use within the connected car adoption process?"

1.3 Relevance Statement

From an academic perspective, extensive research on connected car technologies and connected vehicle ecosystems exists. However, the focus of the present literature has been primarily on technological efficacies and secondarily on the impact of connected car technologies and related services on the overall business performance of OEMs (Lu et al. 2014). Yet, when it comes to adoption research of connected car technologies from a customer perspective, there are only few theoretical approaches, most of them failing to incorporate an exhaustive amount of factors relevant to the cognitive decision making process of consumers. Particularly, none of the models which have been proposed in the past (Chen et al., 2009; Howard, 2005; Kaur et al., 2018; Madigan et al., 2016 & Park et al., 2013), have incorporated data privacy-related factors, due to the fact that connected car features and their interrelation with privacy issues are very recent. Hence, this research fills a gap in the literature by investigating factors that detain the willingness of customers to demand connected car features, which is considered crucial for a fast establishment of a critical mass (Coppola et al., 2016). Thereby, the thesis project helps to understand the scenarios in which customers are most willing to adopt connected car functionalities and respectively how strong the opposed data privacy concerns act as an attenuating moderator. Hence, the thesis contributes to the existing adoption research by demonstrating the importance of combining perceived data privacy risks of connected cars with the respective perceived usefulness and ease of use.

In addition, a more practical goal of this thesis is to inform OEM managers, depending on the level and nature of data privacy risk, which cognitive behavioral intention dimension they should address when marketing their value proposition to specific customer groups and which security-related

investments they should pursue. In particular, I hope that based on the findings of this work managers are able to introduce connectivity functionalities more successfully by emphasizing different technological features to stimulate either a sense of usefulness or ease of use, depending on data privacy risks.

1.4 Thesis Structure

In order to answer the research question at hand I engage in different research phases, which combine multiple approaches. Firstly, an in-depth analysis and review of the existing literature on connected car technologies and their potential for OEMs, as well as their perceived value and risks from a customer perspective, is conducted. This first research phase lays the basis for the development of a conceptual research model, for the derivation of hypotheses and for the experimental set-up. The latter is outlined after putting the obtained findings into context of the technology acceptance model. An additional goal of the elaboration on the theoretical background is to understand the extent to which the technology adoption from a customer perspective has already been covered and discussed in prior research. This is necessary, in order to identify potential research gaps or weaknesses which can be filled (Zhang et al., 2012). Secondly, an elaboration of the decision-making process of customers for innovation adoptions by means of an extended and customized version of the Technology Acceptance Model (TAM) by Davis et al. (1989) is outlined and discussed. The chosen model, which is tailored to the adoption of innovations in the automotive sector, puts the preliminary findings from the literature review in perspective and clusters them with regard to the connected car adoption decision criteria. Based on the relevant adoption decision stage in the model, hypotheses are formulated, which aim at answering the research question. Thirdly, the derived hypotheses are quantitatively tested by means of a split-test controlled experiment and respective model-based statistical analyses. As a fourth step, the data analysis and results are presented. Based on the obtained results, academic and managerial implications are discussed, followed by a summary of the underlying research limitations and recommendations for future investigations.

2 THEORETICAL BACKGROUND

An important part of creating a strong theoretical framework involves dealing with discussions of scholars who have previously investigated the respective research topic (Sparrowe et al., 2011). By means of the theoretical background, I aim to focus on introducing the main customer centric automotive trends and shifts in user behavior, connected car definitions with respective functional specifications and associated risks with particular focus on data privacy. These elaborations will provide rationales for developing a conceptual research model and serve as a foundation for the experimental split-test methodology.

2.1 Introduction to Car Connectivity

In the past, automotive players were focusing on independent product development based on what they assumed was valued by customers (Ahuja et al., 2001). Yet, due to the increasing amount of new market participants, often stemming from different industries with a very strong customer focus of their business models (e.g. Car2Go, Tesla, Waymo), a sense of customer centric innovation urgency has overcome existing car manufacturers in recent years (Bansal et al., 2016). Those OEMs, which are slow to adjust, are suspended by competitors, which are ready to make a substantial transformation to their business model (Coppola et al., 2016).

While engine performance, premium quality or special design were important characteristics when making a purchase decision until a few years ago, the actual use of a car is becoming more important today (Ahuja et al., 2001). The car loses its meaning as a status symbol and is increasingly understood either as a pure mobility vehicle or as a smartphone like “ecosystem on wheels” (Terporten et al. 2012, p. 370). This change in customer value expectations is also reflected in the decreasing demand of material ownership in other areas of life, which is based on lower mandatory and acceptance values and stronger self-actualization values (Diez, 2006). These changing behaviors and values also affect brand and dealer loyalty in the automotive industry (Meffert et al., 2005). For OEMs, this creates the challenge of handling a decreasing emotional bond of customers with their cars or the OEM brand, which leads to an overall lower customer loyalty (Diez, 2018). As in recent years, customer loyalty has primarily been in the hands of contracted repair shops, connectivity concepts within cars are crucial for OEMs to change this dependency from their partners. Additionally, it is important for OEMs to strengthen their own direct customer contact as part of their relationship-marketing, which is primarily enabled by

connected car services (Meffert et al., 2005). Thus, in addition to the financial opportunities, connected car features enable OEMs to be in constant communication with their customers, which in turn is expected to lead to higher customer satisfaction and loyalty (Coppola et al., 2016).

As early as 2010, the Gartner research institute saw the networking of vehicles as the most significant transformation in over hundred years of automotive history. Thereby Gartner argued that connectivity and digital content will represent a new value proposition that goes beyond the customer's pure need for mobility (Coppola et al., 2016). In this capacity, connected cars features, which result from the interrelation of information technology and telecommunications components integrated into vehicle ecosystems, play a vital role. The term *connected car* is a collective term that covers the networking of vehicles, its systems and the associated ecosystems. "Connected cars have telematic components for data exchange with the ecosystem, which enables digital services that generate added value for drivers and owners in terms of safety, navigation, information, comfort and entertainment" (Bosler et al., 2017, p. 2). Characterized by an internet-based, multilateral or bilateral connection, connected car functionalities enable car systems to receive, send and share information (Nu et al., 2014). In addition, the associated wireless network functions make it possible to communicate with other vehicles, infrastructure or other devices both inside and outside the vehicle (Dahlman, 2013). By breaking down the different forms of vehicle connectivity into the categories ***Car-2-Web***, ***Car-2-Car*** and ***Car-2-Infrastructure,*** Löffler et al. (2017) highlights the different specifications for all three vehicle connectivity forms.

In the connectivity category ***Car-2-Web***, internet, social networks and entertainment technologies are part of the ecosystem of the automobile and its driver (Löffler et al., 2017). By means of this category, new personal exchange opportunities and business touchpoints are created, which lead to the transformation of revenue generation possibilities for a car. For example, the real time transmission of the maintenance status of vehicle components can drastically reduce the time, scope or costs of service appointments at maintenance garages (Kraan et al., 2014).

By contrast, ***Car-2-Car*** connectivity allows the recording and transfer of weather or road conditions to subsequent vehicles, the inter-vehicle transfer on local and temporary hazardous situations or the recording and communication of current traffic situations (Löffler et al. 2017). OEMs have the opportunity to provide such valuable information within their brand association (e.g. VW to

Porsche, Audi or Seat) and thus increase brand loyalty of drivers through an improved customer service (Schmidt et al., 2016).

The third category is ***Car-2-Infrastructure,*** which summarizes the connectivity of vehicles, drivers' devices, traffic systems or other external service providers. Car-2-Infrastructure for example contributes to the optimization of traffic flows via the connectivity traffic guidance systems (Löffler et al., 2017). In this context, intelligent traffic light assistants adapt to the actual traffic volume at intersections based on the input of navigation system's or GPS-based vehicle positioning services (Schmidt et al., 2016).

Essential technical prerequisites for the widespread use of connected car features are data-gathering sensors, standardized interfaces and protocols. Additional prerequisites include big data analytics platforms, permanent availability of real-time broadband and supporting mobile communication technologies (Dahlman et al. 2013 & Lee et al., 2016). Further details about technical prerequisites and general technical connected car architecture elaborations can be found in Appendix XI.

2.2 Functional Areas of Car Connectivity

The most relevant connected car features and respective service innovations are centered around seven functional areas, namely, safety, entertainment, vehicle management, mobility management, well-being, home integration and autonomous driving (Holland, 2019).

Safety

The primary intended goal of connected cars is to increase traffic safety, as the main cause of traffic accidents is human error (90% of accidents in 2014 were caused by humans). This risk can be significantly reduced with the help of highly developed driving assistant systems, which support the human driver in the actual driving task (Johanning et al., 2015). Further, the research of Copolla et al. (2016), Bosler et al. (2017) and Pilipovic et al. (2014) suggest the following functionalities as the most relevant connected car technologies regarding the reduction of safety and security issues on the road: breakdown call including transmission of vehicle data, automatic emergency calls (eCall), Car-2-Car communication to share information on upcoming danger points, notifications in case the parked vehicle is damaged or stolen, notifications in case the vehicle is leaving defined area-boundaries, notifications when speed limits are exceeded and alerts that detect and mitigate fatigue and other forms of individual failure.

Info- and Entertainment

The On-Board Unit (OBU) is the central operating and display unit of the infotainment system and is to be understood as the central interface between the vehicle and the passengers, which is why it is also referred to as the Human Machine Interface (Johanning et al., 2015). In this context, the research of Alam et al. (2015), Coppola et al. (2016), Bosler et al. (2017) and Luan et al. (2015) suggest the following functionalities as the most relevant connected car technologies and services in the info- and entertainment area: in-car messages, online search engine via the OBU, e-mail and calendar integration into the OBU, in-car integration of Microsoft Office, in-car music streaming (Tidal, Spotify, Internet Radio), in-car video streaming (Netflix, YouTube, Hulu), in-car gaming and in-car social networks (Facebook, Instagram, Twitter).

Vehicle Management

The research of Handel et al. (2014), Holland (2014) and Liu et al. (2013) suggest the following functionalities as the most relevant connected car technologies minimizing operating costs and increasing driving comfort: proactive maintenance management and remote diagnosis by OEMs, online appointments arrangeable via digital car communication portals, real time display of maintenance and service-related information, real time transmission of the maintenance status of crucial vehicle components, report on vehicle status regarding tank filling, tire pressure and oil status, personal driving statistics, support of adaptive insurance policies and on demand software upgrades purchasable via direct sales channel to OEM.

Mobility Management

The research of Coppola et al. (2016), Holland (2014) and Liu et al. (2013) suggest the following functionalities as the most relevant connected car technologies providing guidance on faster, economic and fuel-efficient routing: real-time information about traffic situations and road disabilities, real-time information about available parking spaces and respective price information, in-car Google street view integration, fleet management solutions for business customers, Uber integration for peer-to-peer services, footpath navigation from the car to the final destination, online based “point of interest” search in the infotainment system, predictive navigation with automatic suggestions for route guidance, electric toll fee collection via car integrated sensors and special route planning for electric cars with available charging points.

As the three functionality sub-categories autonomous driving, home integration and well-being are not a core construct of the conceptual research model and testing methodology developed in the following chapters, their elaborations can be found in Appendix XI.

2.3 Risks of Car Connectivity

While cars have traditionally been isolated from digital networks, the above described connectivity functionalities of cars have various touchpoints to the internet and other digital networks (Koscher, 2010). Thereby, the communication technologies of contemporary connected cars lead to various safety related risk potentialities and challenges for the development and protection of the entire vehicle electronics (McCluskey, 2017). The increasingly high degree of networking of electronic systems and the linking of information and entertainment systems with safety-critical systems in telematic units lead to considerable risks for passenger safety (Kleberger et al., 2011). Unlike conventional information and communication technologies, the security of in-vehicle networks has safety implications in addition to traditional security hazards, for example affecting confidentiality and integrity of passengers (Ring, 2015). In general terms, Schiffman et al. (2013) defined perceived risks as the uncertainty that customers might have, when the consequences of buying a product are not clearly predictable. Further, Schiffman et al. (2013) divided risks into data privacy risk, cyber security risk, functional risk, time dependent risk, social risk and psychological risk.

Data Privacy Risks

Martin et al. (2017) defined privacy concern as an individual’s awareness and evaluation of risks related to privacy violations. In the spectrum of connected cars, a major risk associated with connectivity functionalities is the loss of personal data without prior authorization and privacy invasions through third parties (McCluskey, 2017). The transmission of driving data to OEMs or other third parties is problematic from a data protection point of view if personal data is involved (Walter et al., 2020). This is the case if data contains individual information about personal or factual circumstances of a data subject and thus allows a conclusion to be drawn about the person concerned (Angst, 2009). Data that cannot be assigned to the data subject is anonymous and therefore not considered as personal data and uncritical in terms of data privacy (Martin et al., 2017). Yet, data protection issues become particularly critical when data from several sensors are combined and merged (sensor-data-fusion), which enables the framing of extensive user profiles on the basis of supposedly innocuous data. Thus, conclusions about driving behavior, lifestyle,

place of residence or personal interests can be drawn (Walter et al. 2020). For this reason, the collection, processing and use of personal data is only permitted under respective regional data protection laws (Angst, 2009). Yet, there is a risk for consumers that consent will be given prematurely or that the approval process is not fully self-determined (Martin et al., 2017). This could be for example the case, if consumers do not grasp the declaration of consent due to the lack of transparency or comprehensibility and therefore are not able to fully assess the scope of their decision. In addition, the disclosure of data points can also be triggered with controversy financial incentives, such as free service benefits or other cost advantages (Rushit et al., 2019). Examples of the latter are telematics and pay-as-you-drive tariffs for insurances, where drivers can save money if they document their driving behavior (Walter et al., 2020).

Cyber Security Risks

Beyond the data protection issues of connected car technologies, cyber security is also a huge challenge (Rushit et al., 2019). In 2015, a demonstrative use case of an US hacking team has already proved that it is possible to remotely control a vehicle via its connected networks, solely with the help of a laptop. Thereby, the researchers showcased the dangerous impact of vehicle related cybercrimes. Within the experiment, hackers were able to obtain complete control of the air conditioning system, music system, power transmission, instrument panel, brakes and the steering wheel (Greenberg, 2015).[1] Even more serious is the potential threat of cyber-attacks on Car-2-X communication systems, which offer attackers a platform to scale malicious code to multiple cars or fleets, as vehicles usually communicate via a trustworthy classified connection with each other. Thus, they are transparent for information from other vehicles and in case of cyber-attacks also to the malicious code from other vehicles (Hoppe, 2011). The rapid increase of successful demonstrative and experimental vehicle cyber-attacks have put attention on the yet lacking cyber-security measures implemented in connected cars (Koscher et al., 2010).

Further elaborations on cyber security risks as well as functional, time-dependent, social and psychological risks, which potentially could affect the decision-making process of buying a connected car, can be found in Appendix XI.

[1] Technically, hackers can use three different automotive components to take control of a vehicle wirelessly: internal components – electronic control unit with bus systems and connection gateways, external components – mobile devices which are connected to the components in the automobile and communication protocols – WiFi or Bluetooth (McCluskey, 2017).

3 DEVELOPMENT OF A CONCEPTUAL RESEARCH MODEL

The primary purpose of postulating the conceptual research model is to ground my hypotheses, by positioning them in relation to existing research and by relating the obtained theoretical insights to the innovation adoption process (Bono et al., 2011). By developing a logical argumentation, explaining why the hypotheses are related in the proposed fashion and by creating a sense of coherence in the relationships and mechanisms among the variables, the basis for the quantitative analyses is laid (Sparrowe et al., 2011).

3.1 Connected Car Technology Acceptance Model

In the existing literature, theories of adoption and diffusion form the basis of acceptance research, with adoption theory being the prerequisite for diffusion theory (Howard, 2005). An innovation must first be accepted by consumers (adoption) in order to expand in the market (diffusion) (Rogers, 1976). In this capacity, adoption theory describes the determination of factors that can lead to an adoption as well as a rejection of an innovation (Hoyer et al., 1990).

In the following, the factors which are determining the adoption willingness of connected car features are elaborated by emphasizing the underlying mechanisms and their impact on the adoption decision process. In addition to the factors which are directly influencing the behavioral intention towards the adoption decision, important moderating factors which are influencing the direct factors are discussed likewise (Andersson et al., 2014). In order to take all relevant dimensions into account, Rodgers' Diffusion of Innovation approach (DoI) and Davis' Technology Acceptance Model (TAM) are used as a reference (Davis, 1989 & Rogers, 2003). Both models are described in more detail in Appendix XI. To focus on the relevant connected car adoption decision mechanisms, only the relevant decision stage – *persuasion* – which is the stage where the adoption decision is formed, is considered in the following explorations, see *Figure 1* (Howard, 2005). In addition to the general decision factors from Rogers (2003) and Davis (1989), connected car-specific factors, which are relevant for the positioning of an adoption opinion, are put into context (Holland, 2019).

According to the existing literature, the most relevant dimensions for the *persuasion* stage of the adoption decision process are the properties of an innovation (Howard, 2005). Davis (1989) and Howard (2005) argued that the innovation properties influence the formation of a positive opinion towards an innovation. In context of the TAM innovation properties, ***Perceived Usefulness (PU)***

and ***Perceived Ease of Use (PEOU)*** are the two most relevant cognitive decision criteria to the connected car adoption decision process (Moore et al., 1991). Perceived Usefulness describes the degree to which an individual is convinced that the use of a certain innovation enhances the performance of a task. Perceived Ease of Use is defined as the amount of physical or mental effort an individual has to render in order to be able to use a certain innovation (Adams et al., 1992). The two decision criteria date back to the introduction of the Technology Acceptance Model first established by Davis (1986) and have ever since been used to explain the adoption process of technological innovations by means of their influence on the ***Behavioral Intention*** (BI) of individuals. Based on the Theory of Reasoned Action (TRA), the model suggests that the Behavioral Intention to use a technology is serving as proxy for the acceptance of the technological innovation (Ajzen et al., 1980).

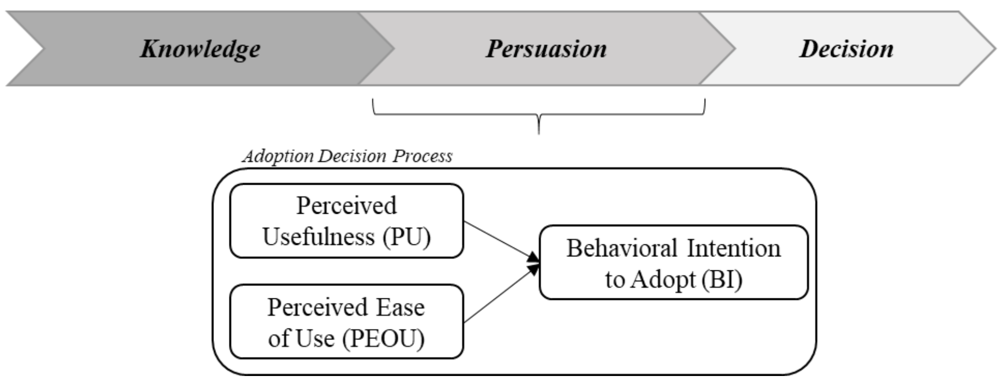

Figure 1: Adoption Decision Making Process

The DoI and respectively the TAM have been used as references for the conceptual model of my thesis, as the models are amongst the most cited and renowned models for technology adoption and have been tested to be reliable across different settings (Holland, 2019; Howard, 2005; Im et al., 2008 & Walter et al., 2020). In the context of connected car systems, the mechanisms behind the models have been used as a basis for models solving similar research questions, for example in the field of customer adoption of telematic systems in networked vehicle ecosystems (Chen et al., 2009) and in connected transportation infrastructure systems (Larue et al., 2015). Finally, as the decision criteria of the TAM are mainly used to explain adoption behavior in which individuals have had no or only limited time to use the innovations due to their novelty on the market (Adams et al., 1992), the application of the model seems to be appropriate for the connected car market, as

many connectivity features in cars have just recently become available or have not yet been launched by OEMs (Howard, 2005).

In the following, the relations and mechanisms of the underlying decision criteria of the referenced models are explained in order to derive hypotheses to the research question at hand.

3.1.1 Usefulness & Behavioral Intention to Adopt

As elaborated already above, Perceived Usefulness (in the following referred to as *Usefulness*) is defined as the degree to which a person is convinced that the use of a particular technology increases the performance in doing a task (Davis et al., 1989). People are generally attracted to positive use-performance relationships (Tornatzky et al., 1982) and strive to increase their individual performance and efficacy (Vroom, 1964). Usefulness thereby indicates whether customers are rewarded or punished by the technology adoption and thus represents a powerful determinant within the innovation adoption process (Adams et al., 1992). Accordingly, if a technological feature is increasing the benefit of an individual, the Behavioral Intention to Adopt (in the following referred to as *Behavioral Intention*) is positively affected and shifted towards the adoption of a technology (Davis et al., 1989). On the contrary, building on the expectancy model of Vroom (1964), a technological innovation which does not help people to perform a task in a better or more efficient way, is not received favorably and thus resulting in a rather negative Behavioral Intention being formed towards the adoption. In addition, previous findings of researchers in the domain of technology acceptance of automotive innovations suggest that Usefulness is the strongest determinant of Behavioral Intention (Howard, 2005 & Müller-Seitz et al., 2009).

In the particular case of connected cars, the main benefits expected by customers are centered around safety, entertainment, lean vehicle management and mobility efficiency (Coppola et al., 2016). If connected car features deliver a perceived improvement in one of these fields, Usefulness has a positive direct relationship with the Behavioral Intention to adopt these technological features (Davis, 1989 & Howard, 2005). A significant, positive relationship of Usefulness on Behavioral Intention to adopt technological innovations has been tested empirically by many researchers including Howard (2005), Chen et al. (2009), Khurram et al. (2016) and Holland (2019). The proven relation is taken as a baseline for further elaborations without the derivation of a Hypothesis

to be tested. Hence, the focus lies on identifying a novel part of research by investigating the moderating effects of risk determinants (Andersson et al., 2014).

3.1.2 Ease of Use & Behavioral Intention to Adopt

Next to the Usefulness of a technological innovation, the Perceived Ease of Use (in the following referred to as Ease of Use) is the second most important adoption decision criteria for automotive technology adoption research (Howard, 2005).

Ease of Use describes the extent of physical or mental effort that goes along with the use of a certain technology (Davis et al., 1989). With an increasing perceived complexity of technology-usage, the Behavioral Intention towards adopting a technological innovation decreases, as complexity of technological applications leads to counterintuitive handling and difficulties in performance and consequently increasing required mental effort (Tornatzky et al., 1982). Effort is a finite resource, individuals are able to dedicate to a limited amount of activities for which they are responsible (Radner et al., 1975). As humans strive to reduce mental effort, complex technological features, which require more mental effort than expected, diminish the benefit of a technology and thus lead to the formation of a negative Behavioral Intention towards the adoption of the technology (Tornatzky et al., 1982). On the contrary, a technological innovation which is perceived to be easier to use is more likely to be adopted by customers (Radner et al., 1975), as less mental effort must be applied.

Yet again, due to the various explorations by existing research and the empirical findings of a significant positive relationship of Ease of Use on the Behavioral Intention to adopt connected car features (Chen et al., 2009, Khurram et al., 2016), the relation is taken as a baseline for further elaborations (Andersson et al., 2014).

3.2 Moderating Role of Risk in the Technology Acceptance Model

A major criticism of acceptance research regarding the adoption decision process of Rogers (2003) and Davis (1989) lies in the rare observation of factors leading to the rejection of innovations (Königstorfer, 2008). In order to provide empirical validity to technology acceptance models, Venkatesh et al. (2003) compared and tested eight different technology acceptance models including Rogers' DoI Model. In this capacity, Venkatesh et al. (2003) found that although previous models in the automotive innovation adoption research explain much of the variance in the Behavioral Intention to adopt (about 40% with the two factors Usefulness and Ease of Use),

there is in particular one factor that is overlooked and has received inadequate attention, which is the perceived risk of an innovation. Additionally, Dabholkar et al. (2002) stated the importance of research around the effects of moderating variables within conceptual attitude models, which was adapted from King et al. (2006) in the context of technology acceptance research. The researchers identified in their meta-analysis considerable variability in the relation among TAM constructs, indicating that moderator variables concerned with perceived risk exist.

In the context of technology adoption, perceived risk is defined as the uncertainty of an outcome related to an adoption decision, affecting people's confidence in their resolution (Peter et al., 1967). Consumer behavior research in the field of innovation adoption involves dealing with risk inherently, as the performance of products which are new to consumers cannot be fully anticipated. Therefore, some consequences of product usage might be unpleasant or different than expected (Bauer, 1960). Hence, Bauer (1960) defined perceived risk as the combination of uncertainty and seriousness of a differently expected outcome. As most connected car features are new and unfamiliar to most users, there is an uncertain outcome attached to the usage of connectivity functionalities and accordingly the adoption decision process is influenced (Howard, 2005). In addition, Campbell et al. (2001) and Im et al. (2008) have both investigated the moderating effect of risk on Usefulness and Ease of Use regarding the adoption of innovations within the communication technology field. The researchers empirically found that perceived risks of an innovation moderates both, the effect of Usefulness and Ease of Use on the Behavioral Intention, and ultimately the adoption willingness of customers. Yet, Im et al. (2008) and Campbell et al. (2001) focused on a different set of technological innovations detached from the automotive industry and concentrated on risk dimensions specific to communication technologies. For this reason, the empirical elaborations of this thesis complement the existing literature as the emphasis lies on a different industry and risk domain.

In the upcoming paragraphs, the suggestions from Andersson et al. (2014) will be applied, as they outlined in their research on interaction effects that it is valuable to follow a certain structure when dealing with interaction effects. The researchers emphasized that the development of a conceptual model should follow a clear theoretical narrative. At first, the justification for elaborating on the specific risk domain (data privacy) should be described. Then, a detailed explanation of the general mechanisms behind the influence of perceived risks on the effect of Usefulness / Ease of Use on

the Behavioral Intention needs to be explained. Finally, the specific influence of the chosen risk domain (data privacy) on the effect of Usefulness / Ease of Use on the Behavioral Intention needs to be addressed. The proposed structure by Andersson et al. (2014) is applied in the following.

3.2.1 Relevance of Data Privacy Risk

As good functional and physical security levels have always been one of the dominant reasons for OEM and vehicle choice from a customer perspective, independent of the connectivity degree of a vehicle (Beirão et al., 2007), the elaborations of the risk dimensions *physical risk* and *functional risk* are inherent to the automotive adoption decision process. The latter have been studied both for connected and for non-connected cars. Thus, the impact of these two risk perceptions on the Usefulness and Ease of Use within the connected car adoption decision process are not specific to the technological innovation (Walter et al., 2020). Yet, due to the connectivity features and networked solutions heavily building on data, which itself is new to vehicle ecosystems and to adoption research among automotive innovations (Walter et at., 2018), it is important for OEMs to obtain information about the impact of Perceived Data and Informational Privacy Risks (in the following referred to as Data Privacy Risk). In this capacity, privacy concerns refer to a customer's care about his or her informational privacy (Malhotra et al., 2004) and comprise aspects of data collection, control and awareness (Martins et al., 2014). While there are numerous perceptions of privacy concerns like the following definition by Lanier et al. (2008, p. 5) "a concern for controlling the acquisition and subsequent use of information [. . .] about him or her", privacy concerns in the connected car field are defined as the "user's concerns about personal information disclosure during the interaction with a connected vehicular service" (Walter et al., 2020, p. 7). Various studies in similar settings, like the adoption of information systems (Malhotra et al., 2004) or the adoption of IoT devices (Khurram et al. 2016) have shown privacy concerns predict adoption behaviors (Malhotra et al., 2004). Consequently, if data privacy becomes important in connected cars, data privacy concerns are becoming a significant predictor of the adoption of connected car services as well (Martin et al., 2017).

3.2.2 Data Privacy Risk & Usefulness

General Mechanism of Risk on Usefulness

As perceived risks in consumer behavior lead to anxiety and psychological discomfort (Lanier et al., 2008), it is important to understand the process behind this behavioral reaction on Usefulness

and ultimately the Behavioral Intention to adopt an innovation. The underlying cost-benefit trade-off arises from the evaluation of a product as having desirable benefits (e.g. new safety features or enhanced driving experience) but at the same time potential costs (incalculable risks, e.g. software bugs or inaccurate positioning services). This trade-off ultimately leads to a devaluation of expected performance, as the benefits-costs ratio is uncertain (Kelman, 1981). When putting these elaborations into context of the direct relationship of Usefulness and the Behavioral Intention, it can be assumed that the implications of Perceived Risks directly interfere and reduce the impact of Usefulness on the Behavioral Intention. As Perceived Risks lead to the uncertainty about the nature and level of technology performance, the use-performance relationship is negatively affected (Bauer, 1960). Likewise, Im et al. (2008) and Campbell et al. (2001) found that for users, who perceived a higher risk in using a technological innovation, the Usefulness had a smaller effect on the adoption willingness than for those who perceived a lower risk.

Data Privacy Specific Effect of Risk on Usefulness

In order to derive data privacy specific risk hypotheses of the moderating impact on Usefulness it is critical to discuss and assess the nature of Data Privacy Risk with its underlying expected mechanism and influence on the connected car adoption decision process.

Most of the connected car features outlined in previous chapters are heavily depended on a continuous flow of data from the driver who is operating the car or data from the vehicle itself. Thus, only if customers are willing to share their data, they can fully benefit from the connectivity features. Yet, if there is a risk related to data privacy, customers who are risk-averse will devalue the affected features (Martin et al., 2007). Particularly, if data privacy issues arise related to at least one of Laimer's privacy concern levels (Laimer et al., 2008),[2] the actual performance expectancy of customers towards the connectivity functionalities is expected to be negatively influenced (Walter et al., 2018). Consequently, customers will not use these connectivity features and the performance-use relationship is attenuated (in more detailed described in Chapter 3.1.1).

Based on the connected car privacy concerns outlined in Chapter 2 and the mechanisms described in the previous chapters, the aforementioned attenuating effect of Perceived Risk on Usefulness is

[2] Level 1 – *Notification: Consumers* expect to be informed about the collection process and usage intention of their personal information by third parties. Level 2 – *Control*: Consumers expect to have control over the sharing of their personal information to third parties. Level 3 – *Security*: Consumers expect that the personal information and data they share to third parties, is stored securely.

also expected to be valid for data privacy specific risks. Hence, I hypothesize that high Data Privacy Risks attenuate the effect of Usefulness on the Behavioral Intention to adopt:

H1: High perceived Data Privacy Risks of connected car features attenuate the effect of perceived Usefulness on the Behavioral Intention towards adopting connected cars.

3.2.3 Data Privacy Risk & Ease of Use

General Mechanism of Risk on Ease of Use

Consumers perceive risk both consciously and unconsciously while evaluating products and underlying services for adoption (Egelhoff, 1991). Thereby, the existing literature on perceived risks in brand adoption states that higher perceived risks lead to an increased information seeking behavior of customers during the evaluation period of products, in order to minimize the uncertainty in their decision making (Peter et al., 1967). As the process of information seeking and information processing is demanding endeavors, the level of effort involved rises (Egelhoff, 1991). In addition, the more information and endeavors are needed to understand a product and to utilize its value, the more complex the overall familiarization and handling of the product functions become (Howard, 2005). As outlined in Chapter 3.1.2, Ease of Use is negatively affected by an increasing level of mental effort needed to familiarize with a product. Thus, a negative relation between Perceived Risks and Ease of Use is expected as a baseline relation (Peter et al., 1976).

Data Privacy Specific Effect of Risk on Ease of Use

When looking at the data privacy specific mechanisms of risk on Ease of Use, there are further factors to be considered as the specific risk dimension has a yet undiscussed potential moderating affect. This effect lies in the approval process of data sharing rights of consumers. In general, Phelps et al. (2000) found that individuals are more concerned about their informational privacy when their data is used without their prior authorization or without understanding the intended use of the personal data by third parties. Thereby, the main Data Privacy Risk lies in the hazard that consumers' consent to share data is given prematurely or that the approval process to share data in connected cars is not self-determined and in-transparent (Martin et al., 2017). In general, humans are less skeptical regarding potential data security and privacy issues when the used technology is generally easy to use with user-friendly features (Phelps et al., 2000). An intuitive interpretation of functionalities and their means for the technological process further reduces skepticism of

individuals regarding potential data privacy insecurities (Martin et al., 2017). Yet, with the rising number of connectivity features an increasing number of considerations if and at what point in time customers have to agree to the data sharing process arises. Consequently, more mental effort needs to be spent while using the connectivity features (Coppola et al., 2009). Based on these findings, it is expected that Data Privacy Risks attenuate the overall effect of Ease of Use on the Behavioral Intention to adopt. In addition, Coppola et al. (2016) emphasize in their research that customers perceive an increase in handling-complexity of cars with an increasing level of vehicle connectivity, as the number of system components and application interfaces rises. In turn, this requires again more mental effort to operate a connected car. Yet, as individuals strive to reduce the mental effort they have to spend while doing a task (Radner et al., 1975), technological features requiring additional consideration effort diminish the benefit of a technological feature. Thus, they are expected to lead to the aforementioned negative Behavioral Intention (Tornatzky et al., 1982). Hence, I hypothesize that high Data Privacy Risks attenuate the effect of Ease of Use on the Behavioral Intention to adopt connected car features:

H2: High perceived Data Privacy Risks of connected car features attenuate the effect of perceived Ease of Use on the Behavioral Intention towards adopting connected cars.

By connecting the literature and putting it into the context of the TAM adoption decision framework, the following conceptual research model is derived in order to answer the underlying research question.

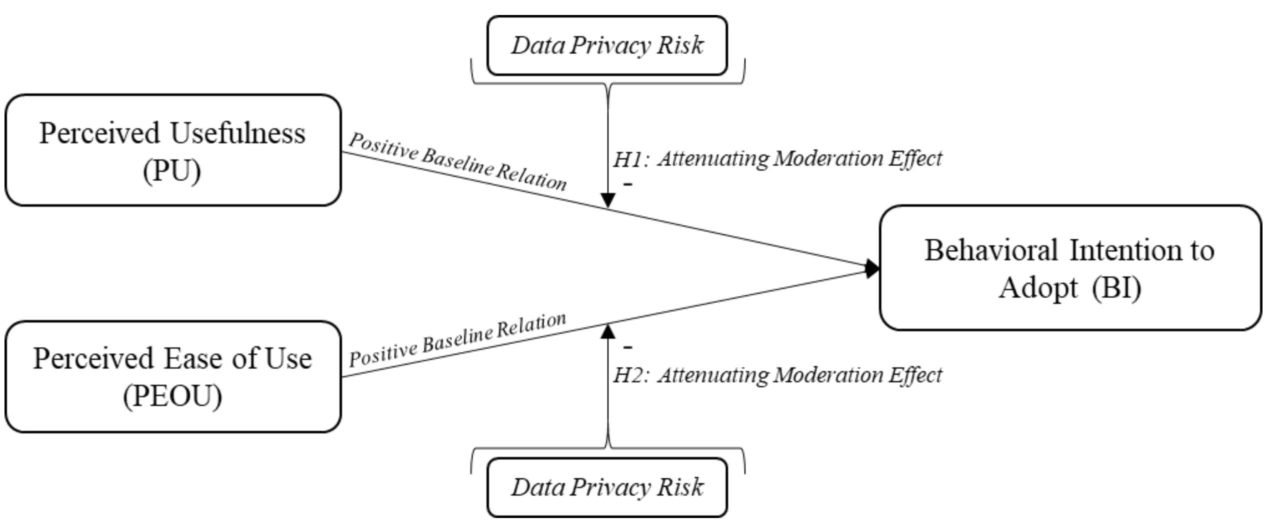

Figure 2: Conceptual Research Model Including Developed Hypotheses

4 METHODOLOGY AND DATA COLLECTION

The fourth chapter is dedicated to explaining the research methodology employed to test the previously developed hypotheses and ultimately to create the basis for answering the underlying research question. Thereby, the research strategy and design, the sample obtainment as well as the experimental procedure are outlined and their respective relevance for acquiring meaningful results are discussed. In addition, applicable measurements and scales to operationalize the relationship among the variables are addressed. As a final subject, the approach and the respective results of the performed pre-test are outlined.

4.1 Research Strategy and Design

4.1.1 Testing Strategy

In order to assess the moderating influence of different levels of Data Privacy Risks on the effect of Usefulness and Ease of Use on the Behavioral Intention to adopt connected car features and to test the respective hypotheses developed in the previous chapter, a multivariate between-subject split-test experiment, based on A/B/n testing methodology is employed (Kohavi et al. 2020). A/B/n tests, also referred to as online controlled experiments or control-treatment tests, are commonly used by technology companies to guide product development and data-driven decisions (e.g. Amazon, Facebook, Google, Microsoft, or Netflix). They have become the gold-standard for testing product development strategies by comparing two almost identical product versions with a deviation of solely one particular product feature (Kohavi et al., 2014 & Thomke, 2020).

Treatment Construct – Multivariate Manipulation

The multivariate treatment design is looking at two manipulated constructs, namely Data Privacy Risk and Usefulness (1st Treatment Construct) and respectively Data Privacy Risk and Ease of Use (2nd Treatment Construct), each with two stipulated variants. By manipulating the level of the two variables (high or low Data Privacy Risks and high or low Usefulness / Ease of Use) and controlling for other factors which potentially influence the impact of the independent variables, the relationship between the independent variables on the dependent variable (Behavioral Intention) can be determined. Additionally, it allows to identify the moderating effects of Data Privacy Risk (Bell et al., 2018). Respectively, four treatment conditions are used for the first TAM treatment construct (Data Privacy Risk and Usefulness) and in the same way, the experiment is replicated for the second TAM treatment construct (Data Privacy Risk and Ease of Use).

1st Treatment Construct – Usefulness	*2nd Treatment Construct –Ease of Use*
High Data Privacy Risk & High feature Usefulness	High Data Privacy Risk & High feature Ease of Use
Low Data Privacy Risk & High feature Usefulness	Low Data Privacy Risk & High feature Ease of Use
High Data Privacy Risk & Low feature Usefulness	High Data Privacy Risk & Low feature Ease of Use
Low Data Privacy Risk & Low feature Usefulness	Low Data Privacy Risk & Low feature Ease of Use

Table 1: Overview of Treatment Constructs

4.1.2 Target Population

The unit of analysis of the experiment is based on individual subjects as connected car adoption decisions are based on private individual decision criteria rather than on group or societal values and preferences (Bell et al., 2018).

In order to structure participant groups of academic research properly, participants engaging in an experiment-based study should possess characteristics found in the desired customer persona, respectively the people of the targeted customer group (Zhu et al., 2010). In addition, Kohavi et al. (2020) stated in his book on online controlled experiments that targeting a specific population requires that the experiment is only eligible for participants with particular characteristics. Common targeting attributes include geographic region, ethnicity, language, educational background or innovation type (Kohavi et al., 2020). Yet, as I want to capture the adoption willingness of a mainstream product, a car, and the respective influence of privacy risk factors from a mainstream commercialization standpoint, no specific technical requirements, experiences or backgrounds of participants are required. The only innovation specific parameters which are relevant in terms of participant characteristics are the possession of a driver's license and the frequent active use of a car (Howard, 2005). Additionally, as the underlying thesis and experiment is conducted in English, a further operational requirement is that the participants are fluent in English (Paolacci et al., 2010). As such, my experiment was restricted to participants from the United States of America. This also diminishes the presence of cultural differences regarding the conceptualization and perception of Data Privacy Risks and connected car features among the participants, which could influence the experiment results (Zhong et al., 2006). Further, as the existing literature on both data privacy and technology acceptance has been conducted mostly with samples from western populations with specific cultural perceptions and attitudes (Martin et al., 2017 & King et al., 2006), the underlying mechanisms and derived hypotheses of this thesis are

based on these western cultural values. This further strengthens the choice for the geographic target, the US population. The respective generalizability of the results to other markets is discussed in Chapter 4.1.4 and in the limitation section in Chapter 6.3.

4.1.3 Population Split

To control for extraneous factors and thus increase the research validity prior to the treatment, all participants were appointed to one of the four treatment conditions at random, by means of a between-subject design (Malhotra et al., 2017). In this context, the chosen between-subjects design enables to measure causal estimates by comparing the behavior intention of the potential connected car customers, who were placed in the different experiment conditions. Additionally, with the help of the A/B/n testing feature of Qualtrics, Sample Ratio Mismatches (SRM) can be automatically controlled for, as the different A/B settings are split at random to the participants by an exact 25/25/25/25 split ratio. Thereby, the randomization unit is the *consumer/customer,* which is the most common randomization unit in controlled experiments following the elaborations of Kohavi et al. (2020). To avoid further biases, no specific participant characteristics were triggering the distribution to treatment or control group. A detailed overview of the random sample split by means of the Qualtrics Survey Flow function can be found in Appendix II Experiment Flow.

4.1.4 Validity of Methodology

Internal Validity

Controlled experimental studies are a common method for testing relations and models in adoption research (Pinsonneault et al., 1993). Thereby, the researchers argued that experiments are particularly valuable for explanatory models where the effects need to be examined in natural settings and when the context of the research focus is set to innovations of the recent past (Pinsonneault et al., 1993). Survey based quantifications of data further add transparency and structure to research projects, particularly in terms of data collection (Malhotra et al., 2017). Validity of the test procedure is achieved, if the between subject split-test experiment is carried out parallel and with a random sample split, as elaborated in Chapter 4.1.3. The chosen approach diminishes the probability of spill-over effects and violations of the SUTVA condition (Stable Unit Treatment Value Assumption), which states that experiment units cannot interfere with one another (Kohavi et al., 2020). In comparison, within-subject experiment designs do not control for the

influence participants have on each other and thus, they could be biased in their experiment participation as a result of compiled experiences (Charness et al., 2012).

In addition, the collection of data on both the explanatory and explained variables from the identical respondents at one point in time raises common variance biases (CVB), as potentially false internal consistency is present in the obtained data (Chang et al., 2010). Yet, the chosen split-test experiment and the separation of the study into two distinct experimental units (1^{st} & 2^{nd} Treatment Construct) allows to overcome this kind of method biases. As the values for the independent variables (Usefulness, Ease of Use and Data Privacy Risk) are manipulated and only the data for the Behavioral Intention (dependent variable) is collected from the different treatment variants, the chosen A/B experimental set-up controls for this aspect of the CVB (Kohavi et al., 2020). Additional elaborations on CVB and validity among the measurement scales are discussed in Chapter 4.3.

As a final remark, Zhang et al. (2012) mentioned in their well-known work *Publishing in AMJ – Part 5: Crafting Methods and Results* that in the commonly revised literature, data for empirical studies is often obtained from archival sources. This is not always preferable, since the authors often do not have full access to all the details of the data collection procedures and cannot guarantee completeness, thus the results are frequently prone to selection biases (Zhang et al., 2012). By creating my own experiment with a respective survey questionnaire and conducting primary data collection, all details for the evaluation of my hypotheses are transparent and can be accounted for.

As such, the chosen experimental design is deemed to be appropriate, as it is frequently employed to test correlation patterns (Malholtra et al, 2017) and allows to establish causal relationships among the construct of different levels of treatment groups with a high probability and strong internal validity (Kohavi et al., 2017).

External Validity

External validity refers to the generalizability of the results obtained from the population at hand to other markets or populations (Mullinix et al., 2015). Generalizability of the experiment results is generally very good for controlled online experiments across populations with similar characteristics, for example results obtained from an US sample population can be well transferred to the entire US population (Hohnhold et al., 2015). However, according to Kohavi et al. (2020) generalizations across different populations with varying participant characteristics are generally

questionable in split-test experiments, as factors working for one sample may not work for another sample or an entire population. Yet, the solution usually is very simple, as the experiment should simply be re-run with the same set-up in different markets. Further Kohavi et al. (2020) exemplified that successful experiments conducted by tech companies in the United States are usually tested in other markets of interest instead of assuming that the results will generalize. Thus, as a limitation of this experiment, the generalizability is dependent on further studies in other markets, which is discussed in more detail in the limitation section in Chapter 6.3.

4.2 Data Collection

4.2.1 Sample Size

The sample size of my study was estimated based on the number of experimental conditions. In general, Van Voorhis et al. (2007) stated in their work "Quantitative Methods for Psychology" that at least 30 participants per experimental/treatment condition are recommended to detect significant findings when measuring group differences with t-tests or ANOVA. Given a large expected effect size, 30 participants per treatment condition should lead to approximately 80% statistical power (Voorhis et al., 2007), which is the lowest accepted power for ordinary studies, as suggested by Cohen (1988). To enhance experiment reliability and to further increase statistical power and the probability of detecting significant results (Rosenbaum, 2007), the number of participants per experimental/treatment condition was increased to a minimum of 50 participants per treatment condition (Kohavi et al., 2020). Thus, given the four treatment groups [2 (Usefulness / Ease of Use: high, low) x 2 (Data Privacy Risk: high, low)] in total 400 participant responses, 200 for each treatment construct (Risk & Usefulness and Risk & Ease of Use) needed to be acquired. In addition to this targeted participant number, an extra 10% were added to account for participants who fail to respond to attention checks correctly and to replace participants who would not meet the pre-set population characteristics. After cleaning the data (see Chapter 5.1), 403 of the 440 obtained responses were further considered for statistical analysis. For the first treatment construct 200 responses (Usefulness / Data Privacy) and for the second treatment construct 203 responses (Ease of Use / Data Privacy) were collected.

4.2.2 Distribution via Amazon Mechanical Turk

In recent years, various tools have been developed enabling researchers to distribute experiments via the internet and by doing so leverage the aforementioned advantages (Mason et al., 2012). The

tool chosen to distribute my experiment-based study is Amazon Mechanical Turk (AMT), which is Amazon's crowdsourcing platform introduced in 2005. Via AMT, researchers can post web-based tasks, referred to as Human Intelligence Tasks (HIT), which are completed by anonymous workers in exchange for a monetary reward. As AMT has been evaluated to be suitable particularly for conducting survey experiments (Buhrmester et al., 2011 & Mason et al., 2012) and has become extensively used throughout social sciences owning to its low cost, ease of application and context to produce more heterogeneous samples than subject pools of scholars (Berinsky et al. 2012 & Paolacci et al. 2010), this survey distribution approach was chosen for the purpose of answering the research question at hand. In addition, Buhrmester et al. (2011) stated that the data quality is comparatively independent of the compensation rate, which further contributes to the validity of the measure, elaborated in the previous sub-chapter.[3] Berinsky et al. (2012) further emphasized that the measurement data obtained via AMT is at least as robust as other common data collection methods and additionally he argued that the sample usually is more diverse from a demographic perspective, when comparing it to a sample obtained in a university laboratory set-up (Berinsky et al., 2012). Next to the aforementioned advantages, online controlled experiments via AMT also decrease the risk of researcher-bias, which is the manipulation of participants due to the physical administration by the researcher (Kraut et al., 2004).

To further enhance the quality of measurement, the study was limited to AMT participants with a HIT Approval Rate of above 95% and at least 1000 completed HITs (Buhrmester et al., 2011). For the technical realization of the experiment Qualtrics was chosen to host the study.

4.3 Procedure and Construct Measurement

The multivariate split-test experiment employed consisted of four sections: (1) Introduction to the Experiment, (2) Connected Car Explanation and Definition, (3) Random Condition Allocation of Participants to Treatments and (4) Screening Questions and Demographics.

(1) The experiment started with a brief introduction comprising relevant information about the study and the respective rules. Participants were also informed about the purpose of the experiment.

(2) When performing split-test controlled experiments, it must be ensured that besides the manipulated criterion the test groups are comparable, and that the test variants are exactly the same.

[3] Participants were awarded 0.35$ for conducting the study.

Thus, after the introductory section, all participants received the identical definition of connected cars. In addition, all participants received a very short definition of data privacy issues related to connected cars. All definitions were derived from the existing literature (see Chapter 2.1 and 2.2).

(3) Following these general definitions, participants were randomly assigned to one of the two treatment constructs (Data Privacy Risk & Usefulness or Data Privacy Risk & Ease of Use) and randomly assigned to one of the four treatment conditions.[4] Accordingly, all participants were given specific statements about how the aforementioned connected car features positively or negatively impact the Usefulness, Ease of Use and Data Privacy. Each of the treatment conditions for both treatment constructs can be found in Chapter 4.1.1.

As Khan (2011) mentioned in his research on validity in experiments, manipulation questions are a key assessment to ensure valid measurements. Thus, after being exposed to the treatment conditions, participants in each condition were asked to answer to a manipulation check question in order to assess whether they understood the treatment properly and are unconsciously aware that they are in the right treatment construct.

To further establish validity among the measurement scales and to reduce common variance biases,[5] the phrasing of the privacy risk levels, Usefulness and Ease of Use, have been leveraged from existing and proven research (Featherman, 2001; Koul et al.,2018; Walter et al., 2020).

Following the different treatment elaborations of the experiment, participants were asked about the main constructs of the conceptual research model, the Behavioral Intention to adopt. A single-item measurement approach was chosen, as various researchers have considered single measurement items to be suitable for experimental set-ups in adoption research (Bergkvist et al., 2007; Drolet et al., 2001 & Freed, 2013). Further elaborations on the choice of single-item measurements can be found in Chapter 5.3. As the experiment focused primarily on the querying of this measurement construct, participants were forced, by means of the Qualtrics Timing-Feature, to think at least four minutes about the treatment conditions they were confronted with, before answering to questions regarding their personal Behavioral Intention to adopt.

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[4] In general, any percentages of participants can be assigned to the treatment and control group, yet an equal split to the treatment groups provides the experiment the maximum statistical power (Kohavi et al., 2012).

[5] Podsakoff et al., (2003) state that CVB can be caused by survey formulations and are thus inherent to the actual wording of the experiment.

Again, the questionnaire and the measurement items were based on the existing literature and appropriately adopted to the connected car adoption research model. Items to measure Behavioral Intention were developed using the questionnaires from Davis (1989), Koul et al. (2018), Venkatesh et al. (2000) and Walter et al. (2020) about the origins of adoption. Each measurement item was thereby evaluated based on a seven-point Likert scale with anchors ranging from (1) strongly disagree to (7) strongly agree (Dawes, 2008). Likert-type scales facilitate statistically valuable results through the quantification of data and are at the same time simple to implement and easy to interpret (Albaum, 1997). As a quality criterion, in order to evaluate the presence of mind of participants, the survey further incorporated an attention dummy question which was not related to the content of the experiment.

(4) After the core constructs of the survey experiment were inquired, two screening questions were implemented to identify relevant participant characteristics by asking participants if they have a ***driver's license*** and how many ***years of driving experience*** they have. In addition, the following demographics have been incorporated in the questionnaire to control for possible effects on the conceptual research model: ***gender, age, education*** and ***income***. Thereby, I followed the elaborations of the Pew Research Center on questionnaire designs, which states that demographic questions should be asked near the end of a survey, unless the answers are necessary to determine qualification for the survey or for routing participants through certain sections of the experiment (Pew Research Center, 2019). Additionally, the ranges used to query the demographics have been previously tested and confirmed as valid from the existing literature (Hughes et al., 2016; Pew Research Center, 2019 & Qualtrics, 2020). The final version of the experiment set-up and the questionnaire can be found in Appendix I.

The variables used throughout the constructs of the experiment are summarized in *Table 2* below.

Abbreviations	**Variable Type**	**Scale**
Behavioral Intention to Adopt	*Dependent Variable*	*7-Point Likert measure for Behavioral Intention*
Perceived Usefulness	*Independent Variable*	*Dummy variable for high Usefulness*
Perceived Ease of Use	*Independent Variable*	*Dummy variable for high Ease of Use*
Data Privacy Risk	*Moderator*	*Dummy variable for high Data Privacy Risk*
Gender	*Control Variable*	*Dummy variable for male gender*
Age	*Control Variable*	*Age in years*
Education	*Control Variable*	*Dummy variable indicating educational level*
Income	*Control Variable*	*Yearly income in USD*
Years of Driving Experience	*Control Variable*	*Driving Experience in years*

Table 2: Overview of Measurement Constructs

The dependent variable or Overall Evaluation Criterion (OEC) is the quantitative measure of the experiment’s objective (Kohavi et al., 2012). In the specific case of the underlying research, the OEC is the Behavioral Intention to adopt connected car features. As elaborated in Chapter 3.2 on the conceptual research model, I expect an underlying relationship between the independent variables and a moderation effect of Data Privacy Risks on the Behavioral Intention. The Experimental Units (EU) are the controllable experimental variables (in this case also the independent variables), which are expected to influence the OEC (Kohavi et al., 2012). In the underlying thesis work, the variables Usefulness, Ease of Use and Data Privacy Risk, with their respective manipulated variants high and low, are considered as Experimental Unit.

4.4 Pre-Tests

Following the recommendations of Kohavi et al. (2012) to ensure sufficient robustness, working flow and formatting standards, a quality assurance procedure was conducted prior of running the actual experiment, by means of a pre-test with N = 32 participants from my personal and professional network (family, friends, fellow students and professional colleagues from PricewaterhouseCoopers). Thereby, participants were assigned to one of the eight treatment conditions of the two treatment constructs. After completing the experiment, all pre-test participants were informally and briefly interviewed about key aspects of possible improvement domains, typically assessed during the pre-test phase of split test experiments (Thomke, 2020). Following the recommendations of Thomke (2020) a particular focus of this pre-test procedure was laid on the following improvement domains: sufficient manipulation and understanding of measurement constructs (introduction of manipulation questions), required time for experiment sections (measurement of impinging and click velocity per experiment item), presentation of experiment illustrations (one vs. several pages of experiment elaborations), technical flow of experiment (survey completion rate and click time per item), simplicity of data obtainment via spreadsheet (mock generation of data output). Participants were asked to rate the appropriateness of these aspects after participating in the experiment. Based on the responses, slight adjustments were made to the experiment set-up. Respective pre-test results for the different domains can be found in Appendix III. The data of the pre-test was not included in the main experimental dataset.

5 RESULTS

Based on the collected data, all hypothesized direct and interaction effects were analyzed, subsequently leading to the acceptance or rejection of the respective hypotheses. Next to all relevant results, the statistical methods used to analyze the data are outlined and their appropriateness as well as their validity requirements and assumptions are discussed. In the first section, the characteristics of the participants are discussed. Thereafter, based on descriptive statistics, elaborations on measurement scale reliability and manipulation effectiveness of the respective treatment conditions are outlined. This led to an early indication of validity of the proposed conceptual framework and the experimental treatment. Subsequently, the hypotheses are tested using model-based evidences by means of t-test comparisons of treatment means and more sophisticated interaction regressions. In this capacity, RStudio (RStudio, 2016) was used to run the analyses of the obtained experimental data.

For the execution of the statistical analyses, following scientific standards in technology acceptance research (Howard, 2005 & Kohavi et al., 2020), a confidence level of 95% and a significance level of 5% was chosen, meaning that if there is indeed an effect, it is correctly inferred 95 out of 100 times. Thereby, the *p-values* will always be depicted in rounded form to the third decimal space. Further, at this point it is worthwhile elaborating on the goodness fit used for the upcoming analyses. As the R^2 does not consider the number of predictors in the model, the *Adjusted* R^2 is used, which measures the relative amount of variance in the dependent variable which is explained by the explanatory variables. The *Adjusted* R^2 can only attain values between 0 and 1, and solely increases in magnitude if added explanatory variables improve the model by more than what would be expected by chance (Chatterjee, 2013).

5.1 Preparation and Cleaning of Data

Before the obtained data was analyzed statistically, it had to be prepared and cleaned from invalid participant responses. The final Qualtrics output incorporated 556 responses, from which 116 had to be excluded, as the survey was not finalized (see Qualtrics screenshot in Appendix II). From a total of 440 responses (targeted number in Amazon mechanical Turk), 37 respondents had to be excluded. 10 of the 440 respondents answered twice to the experiment, which could be identified by means of comparing the respective IP-Addresses. In this case, the second response was removed from the dataset, as duplicates are not eligible to be accounted for in the analyses. 14 respondents

were excluded, as they failed to correctly respond to the attention check and thus are expected to have participated with a lack of focus (see Appendix I). Another 13 respondents were excluded, as they did not meet the target population characteristics, indicating that they do not have a driver's license or as they were not from the US (4 respondents were not from the US and 9 indicated that they do not have a driver's license). Target population requirements are described in more detail in Chapter 4.1.2. Yet, no data had to be removed when checking for univariate outliers using graphical plot analysis and z-scores (see Appendix IV). The absence of outliers in the core measurement constructs can be explained by the experimental use of Likert scales, which are by definition restricted to specific answers. In total, 403 participants (200 for the Usefulness treatment conditions and 203 for the Ease of use treatment conditions) formed the sample basis for the following statistical analysis.[6] As a final step, the skewedness of the distribution of the Behavioral Intention was checked. The histogram of the two treatment constructs showed that the Behavioral Intention (dependent variable) is well distributed and not extremely skewed into one direction (see Appendix IV). Therefore, it is not necessarily to apply a transformational logarithm, as it is better for any comparable model to keep the linear version of the dependent variable to ease interpretation and to be able to use the *Adjusted* R^2.

The original as well as the prepared data outputs are attached to this thesis in a separate file.

5.2 Sample Characterization

After the preparation and cleaning of the obtained experiment data, a total of 403 responses were taken into consideration for the analysis. Among these respondents, the gender is represented almost equally, as 41.4% of the respondents are female and 58.6% are male. As the experiment was limited to participants from the United States of America (see Chapter 4.1.2 on sample characterization), all responses are US citizens. As a further demographic variable, the yearly salary was clustered into three categories: low income (< 30,000$), medium income (30,000$ – 80,000$), and high income (>80,000$). In this context, 12.4% of the sample population can be categorized as participants with low income, 47.9% are considered to be medium income holders, and the remaining 39.70% are regarded to be high-income holders. Likewise, the age of participants was clustered into the following four categories: below 25 years of age (6.5%), between 25 and 45 years

[6] Additionally, the data obtained had to be converted to a csv. file in order to be readable for RStudio. In this capacity, the scales obtained by the Qualtrics experimental survey were for some items renamed and relabeled for a better and more lucid interpretation of RStudio results.

of age (64.3%), between 45 and 65 years of age (23.8%) and above 65 years of age (5.5%). In terms of education, 21.1% of participants do not hold more than a high school degree, 56.6% of participants hold a Bachelor's degree, 19.6% hold a Master' degree and 2.7% hold a PhD degree. Additionally, on average respondents indicated 20 years of driving experience. A more detailed sample description and descriptive statistics can be found in Appendix IV.

5.3 Scale Reliability

As a single-item measurement approach was chosen to evaluate the desired impact of my conceptual research model, there is no need to calculate the internal consistency by means of Cronbach's Alpha, as there have to be at least two items measuring the same output in order to apply checks for multi-item reliability (Bergkvist et al., 2007).[7] Nevertheless, it is important to qualitatively address the reliability of the chosen single-item measurement and outline justifications for why the reliability is expected to be at least as good as with multi-item measurements. Thereby, I want to reference particularly three researchers who have previously examined the appropriateness of single-items measures and have even stated that single-item measurements are better fitted for experimental set-ups in adoption research than multi-item measurements (Bergkvist et al., 2007; Drolet et al., 2001 & Freed, 2013).

Bergkvist et al. (2007) evaluated product features in an experiment-like study, where students were asked to rate the attractiveness of features of a particular product and give their opinion on their respective behavioral purchase intention. Thereby, the researchers found no difference in predictive capability between multi- and single-item measures, providing evidence for the lack of renunciation in measurement reliability. Hence, the approach used by the researchers is comparable to the one used in this thesis.

In addition, Drolet et al. (2001) found that experiment participants are prone to engage in "mindless response behavior" when multiple synonymous measurement items are used. Moreover, the researchers further emphasized that multi-items not only take more time, but also increase general response error. Building up on the research of Drolet et al (2001), Freed (2013) confirmed that single-item measurements suffice particularly if the constructs being measured are narrow or

[7] In general, to assess the reliability of multi-measurement items in experimental survey set-ups, Cronbach's Alpha is the main indicator of internal consistency. Thereby, the existing literature states that it is satisfactory when the Alpha coefficient of the Cronbach score, measured on a scale ranging from 0 to 1, is above $\alpha > 0.8$ and it is deemed excellent if $\alpha > 0.9$ (Gliem, 2003).

unambiguous to respondents. Thereby, he specifically highlighted the Usefulness of single-items when measuring subjective thoughts, such as future behaviors and personal adoption attitudes.

In addition, the specific item used in order to query the main experiment measurement of Behavioral Intention was tested and used multiple times in the existing literature for similar research set-ups (Davis, 1989; Koul et al., 2018; Venkatesh et al., 2000 & Walter et al., 2020) and thus seems to be appropriate to be leveraged for the purpose of my research.

5.4 Manipulation Checks

In order to assess the effectiveness of the treatments, manipulation questions were implemented in the experiment and were analyzed for each of the manipulation variants high/low Usefulness, high/low Ease of Use and high/low Data Privacy Risk. The detailed RStudio outputs of all manipulation check analyses and the respective results can be found in Appendix V.

Usefulness Manipulation Check

To test whether the Usefulness manipulation worked as intended, a one-way ANOVA was conducted by analyzing the *p-* and *F-values* with the Usefulness treatment condition as the independent variable and the result of the Usefulness manipulation check question as the dependent variable. As expected, respondents in the high Usefulness manipulation condition reported much higher levels of Usefulness, with a respective mean of $M_{HighUsefulness} = 5.84$ $(SD = 1.25)$ compared to the low Usefulness control condition with a respective mean value of $M_{LowUsefulness} = 3.49$ $(SD = 1.79)$. The ANOVA result further gave evidence that the difference in means between the two treatment groups is statistically highly significant: F (1, 198) = 114.8 with a *p-value* < 0.05 (p = 0.000). Thus, the Usefulness manipulation was deemed successful.

Ease of Use Manipulation Check

Next to the Usefulness manipulation check, a one-way ANOVA test was conducted to assess manipulation effectiveness of the Ease of Use treatment. Again, the independent variable was represented by the Ease of Use treatment condition and the result of the Ease of Use manipulation check question was serving as the dependent variable. Here again, there was a main effect of manipulation, such that respondents in the high Ease of Use manipulation condition reported higher levels of perceived Ease of Use ($M_{HighEaseOfUse} = 5.73$, $SD = 1.09$) compared to the low Ease of Use control condition ($M_{LowEaseOfUse} = 3.42$, $SD = 1.80$). Based on the ANOVA *p-* and *F-value*s, the

Ease of Use manipulation was deemed successful, as the difference in the means of the two groups is statistically significant, F (1, 201) = 122.9 with a *p-value* < 0.05 (p = 0.000).

Data Privacy Risk Manipulation Check

Likewise, for the manipulation of Data Privacy Risks, a final one-way ANOVA test was conducted, evaluating the manipulation efficacy. The independent variable was represented by the data privacy treatment condition and the result of the Data Privacy Risk manipulation check question was serving as the dependent variable. Again, there was a main effect of manipulation as the difference in the means of the two treatment groups is statistically highly significant, F (1, 401) = 73.76 with a *p-value* < 0.05 (p = 0.000). The respondents in the high Data Privacy Risk condition reported much higher levels of perceived Data Privacy Risks ($M_{HighRiskExposure}$ = 5.54, SD = 1.52) compared to the low Data Privacy Risk condition ($M_{LowRiskExposure}$ = 4.17, SD = 1.69). As such, also the third manipulation of the Data Privacy Risk treatment was deemed successful.

5.5 Hypotheses Testing

To answer the previously stated hypotheses and the research question, numerous inferential statistics were performed, to assess the relation among measurement and manipulation constructs by means of t-test comparisons and interaction regressions of the treatment constructs. To determine the model-based interaction effect, multiple linear regressions using the ordinary least squares (OLS) were performed to estimate the dependent variable. To calculate OLS, linear functions are placed in the space of the measured values and the residuals are calculated respectfully. The function with the lowest residual error sum is selected. Thus, the sum of the squared errors is minimized (Dougherty, 2007). In this context, the equations are solved by calculating the deviations from the mean by means of the product of independent and dependent variables for the respective coefficient by dividing the squared deviations of the independent variables. The result of this procedure expresses the proportion of the variance (measured as deviations from the mean) of the independent variable in the variance of the dependent variable (Zdaniuk, 2014). The coefficients of all variables in the model fully explain the variance of the independent variable in the optimal model (Dougherty, 2007). As OLS has previously been used to determine moderation effects in experiment-based split-test settings (Howard, 2005; Im et al., 2008 & Kohavi et al. 2020), the estimation method has been deemed appropriate for the purpose of the analyses.

5.5.1 Testing of Key Assumptions to Run ANOVA and Regression Analyses

Before presenting the detailed analyses results, the relevant pre-requisites to run these statistical models and analyses are evaluated by means of analyzing the underlying LRM assumptions (Poole et al., 1971).

Homogeneity of Variance

The assumption of homogeneity/homoscedasticity was assessed by firstly plotting the fitted values against the residuals, which can be seen in Appendix VI (Osborne et al., 2002). As the scatter variance of the plots were equally distributed (plotted values appeared randomly distributed with a mean equal to zero and no apparent curvature), the assumption seemed to be met for both treatment constructs, Usefulness and Ease of Use. In order to further confirm the assumption about homogeneity of variance, a Levene's test (Nordstokke et al., 2011) was conducted (see Appendix VI). The test results further supported the conclusion, as the significance level of the test for both treatment constructs was above $p = 0.05$ ($p_{PU} = 0.127$, $p_{PEOU} = 0.112$).

Normality

As a first indication to assess the assumption of normality, the Quantile-Quantile plot was visually inspected for both treatment constructs (see Appendix VII). The quantiles of the residuals were not strongly deviating from the theoretical quantiles, indicating that the normality assumption holds for both treatment constructs (Hayes, 2013). In order to statistically confirm normality, the assumption was further tested by conducting a Shapiro-Wilk test (Osborned et al., 2002). Yet, the results were not supporting the first impression retrieved from the visual plot analysis. Following the results of the Shapiro-Wilk test, the experiment data is not normally distributed as the significance values for both treatment constructs are below $p = 0.05$ ($p_{PU} = 0.005$, $p_{PEOU} = 0.010$ (see Appendix VII). However, given the indication of the Q-Q plots and the large sample size of my experiment (see Chapter 4.2.1), it is feasible to claim that central limit theorem holds (Shirota et al., 2014). Thus, regression/ANOVA can still be used to evaluate the hypotheses.

Independence of Sample

Independence of the sample was given, as all participants were randomly selected, the treatments were randomly distributed and all participants of the experiment were independent of each other and not able to influence each other's decision making (Osborned et al., 2002), which is in more detailed elaborated in the chapter on internal validity and SUTVA (Chapter 5.1.5.1).

5.5.2 H1: Moderating Effect of Data Privacy Risk on Usefulness

Evaluation of Direct TAM Base Line Relations by Means of a Bivariate T-Test

In order to investigate whether there is a moderating effect of Data Privacy Risk, it is first necessary to statistically evaluate the relation between Usefulness and the Behavioral Intention without considering the risk exposure of participants. In this capacity, a t-test was applied to analyze the significance in the different means between participants who were exposed to the high and low Usefulness experimental conditions (holding the level of risk exposure at a constant low level). T-tests observe the size of the difference between two means compared to their variance and are the most common statistical significance assessments in order to determine whether a difference between control and treatment constructs is real or just noise (Student, 1908).

The results (see Appendix VIII, *Table 18*) indicated, as zero was not included in the 95% confidence interval and the *p-value* ($p = 0.000$) was smaller than 1%, that H0 can be rejected. The difference was also shown in the output value of means, as the mean of the Behavioral Intention for high Usefulness exposure was $M_{HighUsefulness} = 6.08$ and for low Usefulness exposure $M_{LowUsefulness} = 3.00$ (all, given the *same low Data Privacy Risk* condition in both compared groups).

Thus, I can assume that there is a difference in the level of reported Behavioral Intention for the different level of Usefulness exposure, where participants with high Usefulness exposure are much more likely to form a positive Behavioral Intention to adopt connected car features (statistically significant and practically meaningful difference in means), confirming the stated relation of Usefulness and the Behavioral Intention to adopt, as outlined in Chapter 3.1.1.

Evaluation of Moderating Effect by Means of Two Bivariate T-Tests

In order to test if there is a difference in means for different level of Data Privacy Risk exposures, two t-tests were run to obtain a first indication of the Data Privacy Risk effect. The two risk treatment scenarios were compared for constant Usefulness scenarios.

<u>High Data Privacy Risk & High Usefulness vs. Low Data Privacy Risk & High Usefulness</u>

In order to test if there is a difference in means for different level of Data Privacy Risk exposures, two t-tests were run to obtain a first indication of the Data Privacy Risk effect. Thereby, the two risk treatment scenarios were compared for constant Usefulness scenarios.

The t-test results (see Appendix VIII, *Table 20*) indicated, as zero was not included in the 95% confidence interval and the *p-value* (*p* = 0.000) was smaller than 1%, that H0 can be rejected. The difference was also shown in the output value of means, as the mean of Behavioral Intention for high risk exposure was higher $M_{HighRisk} = 3.85$ than for low risk exposure $M_{LowRisk} = 6.08$ (all, given the *same high Usefulness* condition in both compared groups).

High Data Privacy Risk & Low Usefulness vs. Low Data Privacy Risk & Low Usefulness

Again, the t-test results (see Appendix VIII, *Table 21*) indicated, as zero was not included in the 95% confidence interval and the *p-value* (*p* = 0.0365) was smaller than 5%, that H0 can be rejected. The difference was also shown in the output value of means, as the mean of Behavioral Intention for high risk exposure was $M_{HighRisk} = 2.53$ and for low risk exposure $M_{LowRisk} = 3.00$ (all, given the *same low Usefulness* condition in both compared groups).

As expected, for both constant Usefulness conditions, at this stage it can be concluded that there is a statistically significant difference in the level of reported Behavioral Intention for the different level of risk exposure, where participants with a low risk exposure are more likely to form a positive Behavioral Intention, see *Table 3* below. This supports the mechanism stated in Chapter 3.2.2 that Data Privacy Risks can be considered as an attenuating factor on the Behavioral Intention to adopt.

	Low Risk	*High Risk*
Low Constant Usefulness	M = 3.00***	M = 2.53***
High Constant Usefulness	M = 6.08***	M = 3.85***

*p<0.1; **p<0.05; ***p<0.01

Table 3: T-Test Summary Usefulness

Evaluation of Moderating Effect by Means of Multivariate Regression Analysis

Yet, in order to determine model-based evidence on the moderating effect of Data Privacy Risk on the relation of Usefulness and the Behavioral Intention to adopt (Hypothesis 1), it is relevant to run regression analyses by means of interaction terms of the two categorical variables high/low risk (1st explanatory variable) and high/low Usefulness (2nd explanatory variable). The respective interaction regression in mathematical terms can be depicted as follows:

$$BI = \beta_0 + \beta_1 * High\ Usefulness + \beta_2 * HighRisk + \beta_3 * HighUsefulness * HighRisk + \mu$$

where $\beta_3 * HighUsefulness * HighRisk$ represents the actual interaction effect.

Before outlining the interaction regression results, a graphical analysis of the interrelation of the treatment constructs was deemed to be appropriate to have an indication of the treatment effect of Data Privacy Risk. When looking at the plot below (*Figure 3*), the blue dots indicate the level of the reported Behavioral Intention of participants exposed to the low Usefulness condition, whereas the yellow dots depict the responses of participants of the high Usefulness treatment (each dot represents one participant response). On the x-axis the level of risk exposure is depicted. Additionally, the fitted means for all treatment scenarios are indicated in the plot. Thereby, the means of the two Usefulness conditions of the two different risk exposure treatments are connected by a line, which enables to interpret the slope of the response-means with and without the risk treatment. In this context, it is visible that indeed a moderating effect seems to be present. More specifically, it can be seeen that participants who were exposed to the low Usefulness treatment, react less sensitive on the expousre of Data Privacy Risk as participants who have been exposued to the high Usefulness treatment. In the following, the regression results will give an exact overview of the actual moderating effect of Data Privacy Risk.

Plot of Treatment Effect: High Ease of Use & High Risk

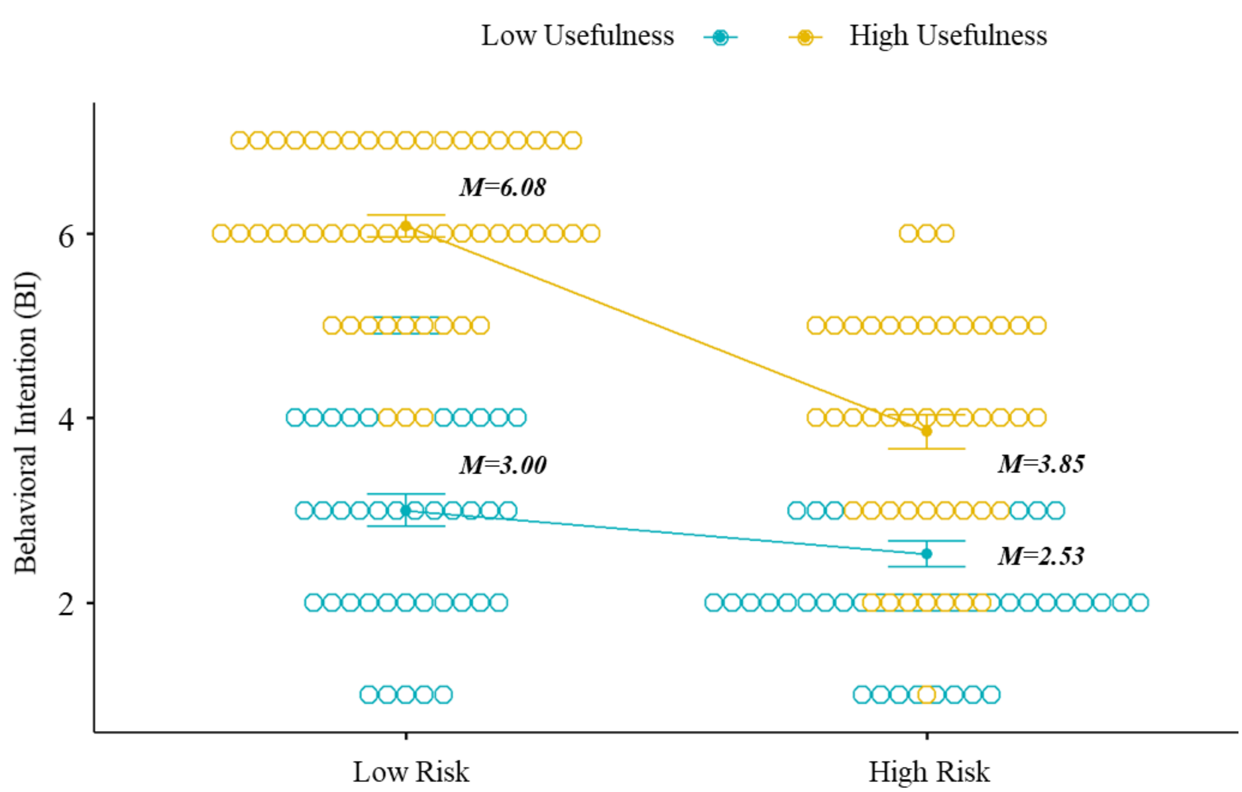

Figure 3: Treatment Effect Usefulness & Data Privacy Risk

For the following regression-based interaction interpretation, the results depicted in *Table 4* are relevant. Thereby, the chosen interaction model (Model 3: HU*HR) has a high power in predicting the effect of Usefulness and Data Privacy Risk on the Behavioral Intention (*Adjusted* R^2 = 0.627), as the model explains 62.7% of the variance in the reported Behavioral Intention. In addition, the interaction model is statistically highly significant for all outputted coefficients (all variable *p-values* < 0.01). On average, for participants who were in the high Usefulness condition, the exposure to Data Privacy Risks attenuates their reported level of the Behavioral Intention to adopt connected car features by -1.76 units (β_3= -1.755), as the coefficient of the interaction term (HighUsefulness*HighRisk, β_3=-1.755) shows how the effect of a high Usefulness exposure changes when participants were manipulated with the high Risk condition. Thus, their overall Behavioral Intention would only increase by 1.24 units (1.24=β_1+β_3=3.077-1.76) instead of 3.08 units, significantly different from zero at the 1% level. A detailed interpretation of all model coefficients can be found in Appendix VIII, *Table 22*.

Based on the results obtained from the interaction analysis, now with certainty, Hypothesis 1 can be confirmed: A statistically significant and practically meaningful attenuating effect of Data Privacy Risk (of about 1.8 units) on the relation of Usefulness and the Behavioral Intention to adopt exists, which is indicated by the coefficient value and significance level of $\beta_{3,}$ as elaborated above.

Interaction Regression of Moderating Effect of Data Privacy Risk on Usefulness

		BI *(Dependent Variable)*	
	HU *(Model 1)*	HU + HR *(Model 2)*	HU * HR *(Model 3)*
β_1 High Usefulness	2.295***	2.176***	3.077***
β_2 High Risk		-1.338***	-0.474**
β_3 High Usefulness*High Risk			-1.755***
β_0 Constant	2.735***	3.483***	3.000***
Observations	200	200	200
Adjusted R^2	0.420	0.562	0.622
Residual Std. Error	1.346 (df = 198)	1.171 (df = 197)	1.088 (df = 196)
F Statistic	145.326*** *(df = 1; 198)*	128.440*** *(df = 2; 197)*	109.973*** *(df = 3; 196)*
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4: OLS Linear Regression – Results of Usefulness & Data Privacy Risk Interaction

In addition, the interaction regression analysis also has been run with control variables. All obtained results hold in terms of significance levels, with slightly deviating coefficient values (β_1=3.22; β_2=0.39; β_3=1.94). From the control variables used, solely the variable *IncomeLow*, which includes all respondents with a yearly income below 30,000$, is statistically significant with a *p-value* smaller than 1% and a coefficient size of 0.658. This result indicates that people with less money were more likely to adopt connected car features, even when being exposed to data privacy risks. This rather unexpected result is further discussed in Chapter 6.3. The respective results of the interaction regression with control variables can be found in Appendix X *Table 27*.

5.5.3 H2: Moderating Effect of Data Privacy Risk on Ease of Use

Similar to the first treatment construct setting (Usefulness / Privacy Risk), all relevant graphical and statistical analyses were replicated for the second treatment construct – Ease of Use. All respective analyses and RStudio outputs can be comprehended in Appendix IX. Based on the results obtained, the direct effect of Ease of Use on the Behavioral Intention to adopt connected car features, by means of different levels of reported Behavioral Intention for the different levels of Ease of Use exposure was determined. Participants with a high Ease of Use exposure were much more likely to form a positive Behavioral Intention to adopt connected cars in comparison to participants exposed to the low Ease of Use condition ($M_{HighEaseOfUse}$ = 5.35, $M_{LowEaseOfUse}$ = 4.14). All results were statistically significant, *p-value* < 0.01, confirming the stated relation of Ease of Use and Behavioral Intention to adopt connected car features, as outlined in Chapter 3.1.2.

In line with the expectations, a statistically significant (*p-value* < 0.01) difference in the level of reported Behavioral Intention for the different levels of risk exposure was found for both constant Ease of Use conditions. Thereby, participants with a low risk exposure were much more likely to form a positive Behavioral Intention to adopt connected cars ($M_{HighRisk}$ = 3.71, $M_{LowRisk}$ = 5.35, all given the *same high Ease of Use* condition in both compared groups and $M_{HighRisk}$ = 3.48, $M_{LowRisk}$ = 4.14, all given the *same low Ease of Use* condition in both compared groups), see *Table 5* below.

	Low Risk	*High Risk*
Low Constant Ease of Use	M = 3.48***	M = 4.14***
High Constant Ease of Use	M = 3.71***	M = 5.35***

*p<0.1; **p<0.05; ***p<0.01

Table 5: T-Test Summary Ease of Use

To determine model-based evidence on the moderating effect of Data Privacy Risk on the relation of Ease of Use and the Behavioral Intention to adopt connected car features (Hypothesis 2), likewise to the first treatment construct, a respective interaction regression was run.

Before running the interaction regression, a graphical analysis was conducted. When looking at the interaction plot (*Figure 4*), which has the same set-up as the Usefulness treatment plot described in the previous chapter, it is visible that as well for Ease of Use a moderating effect seems to be present, indicated through the slope of the two fitted mean-lines. It is visible that participants who were exposed to low Ease of Use, react less sensitive on the exposure of Data Privacy Risk as participants in the high Ease of Use treatment. The slope difference for the risk treatment indicates that the interaction effect of risk is not as strong for the Ease of Use as for the Usefulness treatments, which suggests that the moderating effect is relative small.

Plot of Treatment Effect: High Ease of Use & High Risk

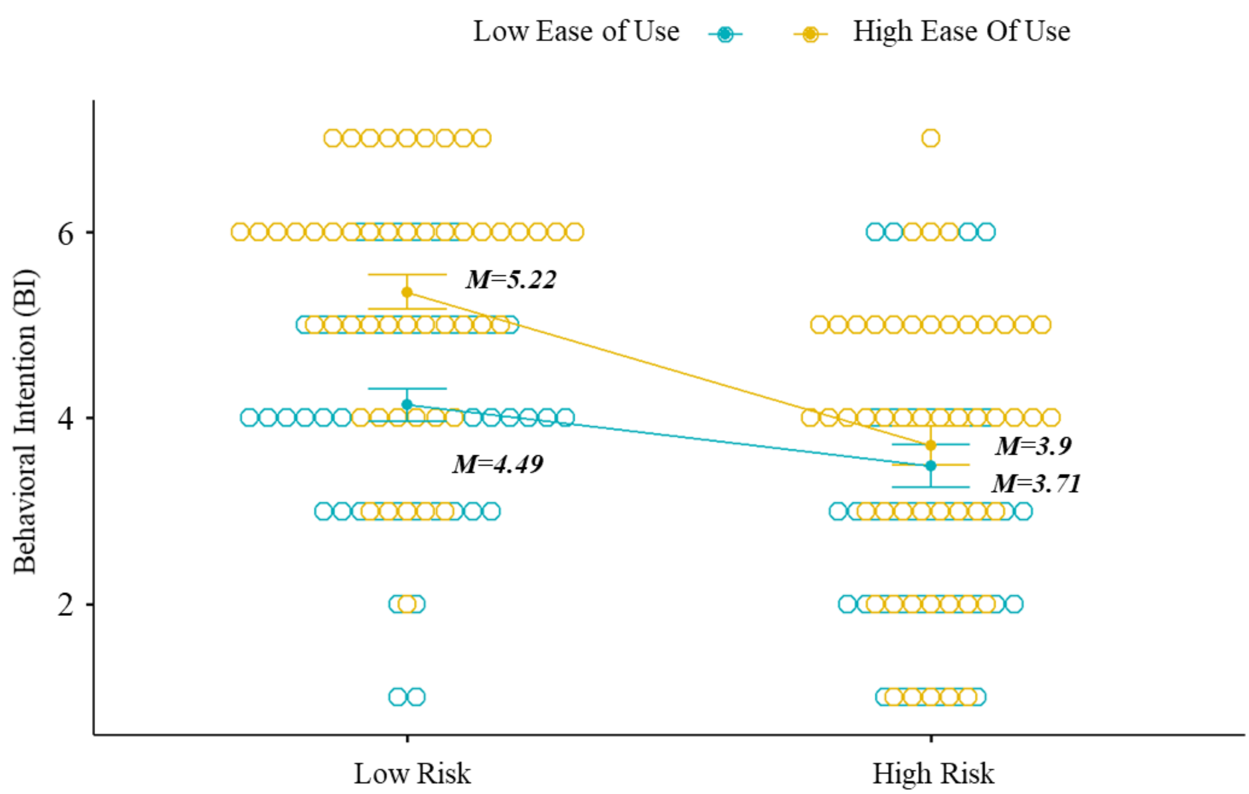

Figure 4: Treatment Effect Ease of Use & Data Privacy Risk

Additionally, the regression results outlined in *Table 6* will give an exact overview of the actual moderating effect of Data Privacy Risks. Thereby, the chosen interaction model (Model 3: HEOU*HR) has a relatively low power in predicting the effect of Ease of Use and Data Privacy Risk on The Behavioral Intention (*Adjusted* R^2 = 0.197), indicating that the model explains only 19.7% of the variance in Behavioral Intention. Nevertheless, the interaction model is for all outputted coefficients statistically highly significant (for all variables *p-values* < 0.01). On average, for participants who were in the high Ease of Use condition, the exposure to Data Privacy Risks attenuates their reported level of the Behavioral Intention to adopt connected car features by -0.99 units (β_3= 0.990). This is because the coefficient of the interaction term (HighEaseOfUse*HighRisk, β_3=0.990) shows how the effect of a high Ease of Use exposure changes when participants were manipulated with the high Risk condition. Thus, their overall Behavioral Intention would only increase by 0.23 (0.23=β_1+β_3=1.22-0.99) instead of 1.22, significantly different from zero at the 1% level. The detailed results of all model coefficients can be found in Appendix IX, *Table 25*.

Based on these results, Hypothesis 2 can be confirmed. A statistically significant and practically meaningful attenuating moderating effect of Data Privacy Risks (of about 1 units) on the relation of Ease of Use and the Behavioral Intention to adopt connected car features exists.

Interaction Regression of Moderating Effect of Data Privacy Risk on Ease of Use

		BI *(Dependent Variable)*	
	HEOU *(Model 1)*	HEOU + HR *(Model 2)*	HEOU * HR *(Model 3)*
β_1 High Ease of Use	0.718^{***}	0.723^{***}	1.216^{***}
β_2 High Risk		-1.155^{***}	-0.657^{**}
β_3 High Ease of Use*High Risk			-0.990^{***}
β_0 Constant	3.812^{***}	4.383^{***}	4.137^{***}
Observations	203	203	203
Adjusted R^2	0.047	0.176	0.197
Residual Std. Error	1.550 (df = 201)	1.441 (df = 200)	1.423 (df = 199)
F Statistic	10.877^{***} *(df = 1; 201)*	22.588^{***} *(df = 2; 200)*	17.493^{***} *(df = 3; 199)*
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 6: OLS Linear Regression – Results of Ease of Use & Data Privacy Risk Interaction

The interaction regression analysis has been run with control variables as well. Thereby, all obtained results hold in terms of significance levels, with slightly deviating coefficient values ($\beta_1 = 1.23$; $\beta_2 = 0.66$; $\beta_3 = 1.05$). From the control variables used, solely the variable *AgeVeryYoung*, which includes all respondents younger than 25 years of age, is statistically significant with a *p-value* smaller than 5% and a coefficient size of 0.96. This result indicates that particularly young people were more likely to adopt connected car features, even when being exposed to data privacy risks. The respective results can be found in Appendix X *Table 28*.

6 DISCUSSION AND CONCLUSION

This thesis ought to identify how Data Privacy Risks influence the effect of Usefulness and Ease of Use on the Behavioral Intention to adopt connected car features by means of a split-test experimental study. In this final chapter, the main findings are discussed with regards to the research question. Subsequently, managerial and academic implications are provided. Additionally, limitations of the conceptual research model, the experiment and the conducted analyses are pointed out and directions for future research are given.

6.1 Summary of Research Findings and Conclusions

As expected and outlined in Chapter 3.1.1 and Chapter 3.1.2, there is a statistically significant and also practically meaningful baseline effect of the two classical TAM constructs Usefulness and Ease of Use on the Behavioral Intention to adopt connected car features. The results indicate that the more Usefulness connected car features are perceived, the stronger the reported Behavioral Intention to adopt. Likewise, the Ease of Use of connected car features is a significant and meaningful predictor of the reported level of Behavioral Intention. At this point it is interesting to mention that there is a difference in effect size of the two TAM constructs and their explanatory magnitude of the Behavioral Intention, which was observable when comparing the plots of the interaction regressions in *Figure 3* and *Figure 4*. Independent of the Data Privacy Risk Exposure, the difference in effect size explaining the relations of Usefulness and Behavioral Intention and Ease of Use and Behavioral Intention is statistically significant and practically meaningful. For the low-risk treatment scenario, the difference in effect size of Usefulness and Ease of Use is about 2.3 units in explanatory magnitude, with Usefulness being a stronger predictor than Ease of Use. For the high-risk treatment scenario, the difference in effect size is only about 1.1 units in explanatory magnitude, yet again with Usefulness being the stronger predictor. The difference in the different effect size of the explanatory magnitude can be explained by the attenuating moderation effect of high-risk exposure, described in the upcoming paragraphs.

Based on the interaction regression, which was run as a more thorough method to understand the relation among the treatment constructs, both hypotheses H1 and H2 can be supported. Firstly, Hypothesis 1, which assumed an attenuating moderation effect of Data Privacy Risks on the effect of Usefulness, is statistically accepted due to the highly significant results. Also, its practical relevance can be underscored, as the moderation effect size of the interaction coefficients is very

high, particularly when comparing it to the effect size of the moderation of Data Privacy Risks in the second treatment construct (Ease of Use). The attenuating moderation effect of the previously described baseline relation of Usefulness and Behavioral Intention is decreased by 1.75 units due to the Data Privacy Risk exposure. When putting this result into context of both Usefulness conditions, the large effect becomes even more obvious. On average, for participants who were in the low Usefulness condition, the reported levels of Behavioral Intention decrease by approximately 0.5 units when being exposed to Data Privacy Risks. On the contrary, for participants who were in the high Usefulness condition, the increase in the reported Behavioral Intention due to the Usefulness treatment, decreases by approximately 1.7 units due to the Data Privacy Risk exposure. On average, participants, who agreed to the adoption of connected car features, would remain neutral towards the adoption of connectively features after being exposed to Data Privacy Risks. This means that they would neither agree nor disagree. Yet, it is important to emphasize that although there is a strong attenuating moderation effect, the level of reported Behavioral Intention of participants in the high Usefulness and high Data Privacy Risk condition is still higher than the level of reported Behavioral Intention of participants who were not exposed to Data Privacy Risks but were neither in the high Usefulness condition. This illustrates that the weight of the Data Privacy Risks needs to be considered when designing connected cars. Yet, the perceived benefits still outweigh the related Data Privacy Risks. An additional finding, which was rather unexpected, is that respondents with a low yearly income indicated a stronger willingness to adopt connected car features, even when being exposed to Data Privacy Risks. This is not in line with the expected mechanism that people with more financial possibilities are more likely to adopt automotive innovations. Usually, innovative technologies in the automotive sector are introduced using a top-down approach (Howard, 2005). This means that premium class vehicles are usually equipped with new technologies first, as the buyers in this segment have a high ability and willingness to pay a premium price and are very interested in owning new innovations in their vehicle as soon as they are ready for commercialization (Matheus, 2014). Yet, as the Willingness to Pay (WTP) has not been assessed by this study, which is in more detailed discussed in the following limitations chapter, the aforementioned low income finding needs to be treated respectfully.

Although for Hypothesis 2, which assumed an attenuating moderation effect of Data Privacy Risks on the effect of Ease of Use, the interaction regression results were as well statistically highly

significant, the practical attenuation implication was deemed not as strong as for the Usefulness scenario. On average, the attenuating moderation effect was about one unit, for participants who were in the high Ease of Use treatment condition and were exposed to Data Privacy Risks. This means that on average participants who responded that they agree to adopt connected car features, still reported that they would somewhat agree when being asked if they want to adopt connected car features after being confronted with Data Privacy Risks. A further finding to outline, is the impact of the covariate used to control for the age of participants. Thereby, the results indicate that particularly young people below the age of 25 years are more willing to adopt connected car features, even when being exposed with Data Privacy Risks. This is in line with the expected mechanism that younger people are generally more affine towards technological innovations and are additionally more willing to share their personal data in exchange for personalized experiences, even when being aware that third parties use their data (Yadin, 2012).

6.2 Academic and Managerial Relevance and Recommendations

From an academic view, a primary contribution of this thesis is the integration of informational privacy related factors with classical adoption theory in a vehicular context. By combining and interrelating the main TAM constructs of Usefulness and Ease of Use specifically with Data Privacy Risks in the connected automotive ecosystem, the findings of this thesis contribute to the current literature. The findings suggest that the classical TAM constructs remain the primary drivers of technology adoption of connected car related technologies. However, the results also demonstrate the importance of informational privacy and emphasize their relevance as a moderating factor in the Technology Acceptance Model of contemporary vehicular applications. Thus, the corresponding recommendation of an extension of the classical TAM constructs by means of data privacy aspects should serve as a basis for future research in the domain of technology acceptance.

Aside from its theoretical value, the results emphasize the importance of privacy-aware connected car designs for OEMs and complementors from a managerial perspective. The obtained findings provide practitioners a deeper awareness and understanding of how data privacy concerns affect customer acceptance of connected cars. By acknowledging the relevance of data privacy, car manufacturers should focus on designing connected car features which suit a customer's functional need of Usefulness and Ease of Use, while keeping informational data privacy preferences in mind.

Measures should be implemented, which improve the customer's control about personal data with the purpose of diminishing the perceived data privacy risks. In this capacity, OEM system architects have two contemporary measures for technology-related privacy protections at hand, namely, *privacy-by-default*[8] and *privacy-by-design*[9] (Lederman et al., 2016). Subsequently, by following at least one of these mechanisms, OEMs should be able to orchestrate organizational and technical efforts to ensure a privacy-preserving car environment for their customers (Coppola et al. 2009 & Martin et al., 2017). In this context, the underlying research results further enable OEM practitioners to develop various strategies in order to increase customer adoption rates by addressing different level of privacy concern. Thereby, the analyses results indicate that customers who have high privacy concern should be addressed by demonstrating high level of feature Usefulness to offset the data privacy risk concerns. This mechanism can be understood when looking at the results of the analyses in Chapter 5.5.2 and Chapter 5.5.3, as for participants who were exposed to high privacy risks, the Usefulness treatment had a much stronger effect on the overall behavioral intention to adopt, whereas Ease of Use did not. The respective most appreciated connected car features need to be the center of focus when promoting connected cars to these customers, improving their perceived Usefulness. On the contrary, for customers who have low data privacy concern, connected car features which drive them to perceive the features both useful and easy to use should be centered in the focus of communication and marketing campaigns, as both feature properties significantly affected the participant's willingness to adopt in the underlying experiment.

Overall, as the obtained results emphasize the importance of feature Usefulness and Ease of Use, the developed conceptual research model should further guide OEMs towards balancing the establishment of privacy-aware and functionally attractive connected car features. Thereby, potential customers of connected cars could be integrated into the early stages of R&D processes for the purpose of fostering more trust in connected technologies and to further enhance the reliability of public information (Ledermann et al., 2016). As Rohunen et al. (2018) pointed out in their research on data privacy concerns in the automotive sector, an effective part of a OEM's

[8] "Privacy by Default means that once a product or service has been released to the public, the strictest privacy settings should apply by default, without any manual input from the end user. In addition, any personal data provided by the user to enable a product's optimal use should only be kept for the amount of time necessary to provide the product or service" (Clearwater et al., 2018, p. 1 & ICS, 2018).
[9] "Privacy by Design states that any action a company undertakes that involves processing personal data must be done with data protection and privacy in mind at every step. This includes internal projects, product development, software development, IT systems, and much more. In practice, this means that any department that processes personal data, must ensure that privacy is built into a product during the whole life cycle of the product or process" (Clearwater et al., 2018, p. 1 & ICS, 2018).

public marketing strategy should include the transparent communication of the risk-benefit trade-off by informing customers about related technological risks of data disclosure, while highlighting the advantages of connected car features.

6.3 Limitations and Future Research

There are several limitations accompanying this research, which are outlined and discussed in the following sections. Additionally, derived from these limitations, suggestions for future research are pointed out.

Firstly, although the data obtainment via the crowdsourcing platform AMT is associated in various well cited papers with numerous advantages as mentioned in Chapter 4.2.2, the research setting also bears certain limitations (Paolacci et al., 2010). Particularly, the representativeness and external validity of the recruited sample population needs to be addressed. Thereby, external validity refers to the magnitude to which the experiment results can be generalized along different populations (Kohavi et al., 2020). By limiting my experiment to participants from the US (see Chapter 4.1.2) and thus to one country and cultural setting only, I aimed at controlling for cultural differences and deviating interpretations of data privacy risks and connected car features. Yet, this focus on the US population has its trade-offs (Zhong et al., 2006). The narrow focus on a specific population reduces the generalizability of the findings towards other populations and thus represents a hazard to the external validity (Kohavi et al., 2020). However, Kohavi et al. (2020) states that generalizations across populations are questionable as a rule. Yet, the researcher further emphasizes that particularly large tech companies, who often use online controlled experiments and split-test approaches, simply re-run successful experiments which were conducted in only one country in other markets, instead of assuming that the results will generalize (Kohavi et al., 2020).

In addition, the representativeness of the research results needs to be addressed, as the research setting might have led to self-selection biases. Self-selection bias occurs when participants self-select themselves into a certain experiment or survey, by means of expectations or certain influential past experiences they have collected regarding the particular file of interest (Heckman, 1979). Self-selection biases are inherent to the mechanism of AMT, as the survey participants can choose in which surveys they want to participate (Buhrmester et al., 2012). Additionally, AMT workers are offered a compensation for participating, thus the self-selection also leads to an exclusion of participants who evaluated the offered compensation as not sufficient, potentially

excluding a group of people with higher monetary standards, who could have reacted differently on the treatment constructs (Paolacci et al., 2010). As a recommendation, future research should not only repeat the study in different markets and cultural settings to generalize the results, but also with a more randomized distribution setting, thereby reducing self-selection biases.

Secondly, despite the fact that the manipulation scenarios of the treatment conditions Usefulness, Ease of Use and Data Privacy Risk were based on existing research within the domain of adoption research and mostly indigenous to the connected car environment, the manipulations could have been understood incorrectly, leading to response bias (Kohavi et al. 2020). Thereby, the experimental setting itself seems to be another limitation potentially decreasing external validity, as it is associated with a certain degree of self-relevance needed by participants to appraise the manipulations effectively (Mark et al., 1991). Participants might not have interpreted the manipulated scenarios as self-relevant enough, due to the fact of not being able to interrelate the consequences outlined in the survey to their real life.

Likewise, also the measurement of the dependent variable could be improved in future studies, as the current experiment set-up does not account for the actual willingness to pay (WTP) for connected car features. Respondents were not inquired to indicate their behavioral intention to buy products but were only asked if they generally would adopt them. Thus, the obtained results could suffer from hypothetical bias (Bobinac, 2019). There could be an over-value effect of the adoption willingness, as consumers are proven to be positively overconfident when being asked about their adoption behavior in experimental consumer research experiments which are detached from product prices (Hofstetter et al., 2020). This effect could also explain the unexpected finding that participants with a smaller yearly income are more willing to adopt connected car features, which is unusual for technological innovations in the automotive sector, as explained in the previous chapter.

Thus, I recommend that future research, if resources allow this kind of cumbersome setting, should use a real-life simulation of connected car features with respective functional advantages and disadvantages of Usefulness, Ease of Use and data privacy aspects, giving participants access to real connected cars before answering to the respective measurement items. In addition, the adoption willingness of participants should be measured by considering realistic price points for the respective connected car features (Bobinac, 2019). Furthermore, the chosen manipulation items are

based on the current state of connectivity advancements. Thus, going forward the manipulation items would need to be updated according to the current technological innovation when the experiment is re-run in different markets or when alternative distribution and model choices are being used.

Thirdly, the baseline adoption model chosen for the development of my conceptual research framework was Davis's Technology Acceptance Model. Thereby, the selection was motivated by the fact that TAM is one of the most frequently employed models in innovation adoption research (Howard, 2005) and has tested to be powerful for different research settings (Koul et al., 2017). Yet, as most other models in adoption research, the TAM constructs postulate an adoption decision-making process. Despite the fact that the output factor of the Behavioral Intention to adopt comprises an affectional assessment of the evaluated technology, they do not adequately portray affective constituents of the decision-making process. In this context, a different, more affect-aware adoption model might be Fazio's Motivation and Opportunity as Determinants approach (Fazio, 1990), which implies the information processing of individuals to be either elaborative or affective. Future research should accordingly try to reflect affective information processing more conspicuously in technology adoption models.

Finally, although the approach of the underlying research focuses on an experimental testing set-up with a random distribution, it focuses on a narrow one-tired research method. Yet, as no method can fully replicate the outcome of another method (Kohavi et al., 2020), using multiple scientific approaches can triangulate towards an even more precise measurement. By establishing a hierarchy of evidences through complementing methods such as surveys, focus groups and use experience research (UER), more robust results can be established (Lesorogol et al., 2005). Future research should leverage the advantages of combining multiple methods to engage in more extensive qualitative preparation of the experimental set-up by means of focus groups or interviews with experts and consumers (Kohavi et al, 2020).

6.4 Final Note

To conclude, I want to summarize the main outcomes of my research in the following paragraphs and provide my personal opinion on the key findings.

The underlying thesis provides a valid and novel modelling approach to study the adoption of connected car features by means of an extended version of the Technology Acceptance Model, interrelating the main adoption decision criteria Usefulness and Ease of Use with relevant Data Privacy Concerns. The Behavioral Intention to adopt was tested by means of a split-test experimental methodology, revealing that the connected car feature adoption is strongly attenuated by data privacy-related factors. As expected, the results indicate that the Usefulness of connectivity features remains the strongest predictor of usage adoption, followed by the second TAM construct, the intuitiveness and Ease of Use of the features. Yet, the interaction treatment and respective statistical analyses have provided valuable insights into the statistically significant and practically meaningful attenuating moderation effect of Data Privacy Risks, which also drive the affective assessment of connected car features. Ultimately, improving the customer's perceived informational privacy control, while reducing Data Privacy Risk perceptions, should enable OEMs to accelerate the adoption rate of connected cars and eventually establish a critical mass of connected vehicles on the road. This is necessary to leverage the potential network effect and according service revenue opportunities.

As a final word, I would like to mention that the research on consumer acceptance of connected cars, particularly with the interrelation of data privacy aspects is still in its infancy. As the connected vehicle ecosystem matures, new opportunities yet also challenges will arise. In this context, I hope that my explorations will help practitioners and academics to get a supportive overview of the proven mechanisms and interdependencies of connected vehicle features, their related data privacy aspects and ultimately the willingness of customers to adopt these technological novelties.

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8 APPENDIXES

Appendix I: Split-Test Experiment Set-Up

Introduction to the Experiment

Welcome and thank you for participating in this Study!
We are conducting an academic survey about connected cars, where we need to understand your personal opinion about respective features and data privacy aspects. It will take you no longer than 6 minutes to complete the entire task. Please answer as thorough and honest as possible.

Important Notes:
1. *As throughout the survey there will be randomly allocated attention checks, please read all instructions very carefully before answering to any question. Participants who fail to respond properly to the attention checks will not receive any compensation.*
2. *This survey can only be conducted once, duplicate responders will not receive any compensation.*
3. *Your participation is anonymous and the data collected will be used for academic purposes only.*
4. *If you have any questions, please e-mail: 152118214@alunos.lisboa.ucp.pt.*

Please consider the elaborations below very carefully.
As these are the only core questions of this study, it is important that you really think about the aspects outlined, before answering. Thus, you will have to spend **at least 4 minutes** *before being able to proceed to the next page.*

Thank you!

High Usefulness Manipulation

Connected Car Features
A connected car is a vehicle in which passengers can access, consume and share information with other cars, infrastructure or third parties, similar to the use of a smartphone.

In this capacity, test-drives have shown that users of connected cars:
- ***are significantly*** *safer while driving their car on the road*
- ***are able to majorly reduce*** *the maintenance effort and costs of their car*
- ***are able to noticeably enhance*** *their mobility efficiency and reduce their CO2 emissions*
- ***are able to noticeably enjoy*** *more of the info- and entertainment services in their car*

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Based on the results of the test drives, I believe that I would find connected car features useful for driving	○	○	○	○	○	○	○

Low Usefulness Manipulation

<u>Connected Car Features</u>
A connected car is a vehicle in which passengers can access, consume and share information with other cars, infrastructure or third parties, similar to the use of a smartphone.

Yet, test-drives have shown that users of connected cars:

- ***are insignificantly** safer while driving their car on the road*
- ***are only able to slightly reduce** the maintenance effort and costs of their car*
- ***are not able to enhance** their mobility efficiency and reduce their CO2 emissions*
- ***are only able to marginally enjoy** more of the info- and entertainment services in their car*

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Based on the results of the test drives, I believe that I would find connected car features <u>useful for driving</u>	○	○	○	○	○	○	○

High Ease of Use Manipulation

<u>Connected Car Features</u>
A connected car is a vehicle in which passengers can access, consume and share information with other cars, infrastructure or third parties, similar to the use of a smartphone.

In this capacity, test-drives have shown that users of connected cars:

- ***find it easy to learn** how to operate connected car features*
- ***perceive** that their interactions with connected car features are clear and understandable*
- ***are able to quickly** become skillful at using connected car features*
- ***perceive** that their interactions with connected car features do not require a lot of mental effort*

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Based on the results of the test drives, I believe that I would find connected car features <u>easy to use</u>	○	○	○	○	○	○	○

Low Ease of Use Manipulation

<u>Connected Car Features</u>
A connected car is a vehicle in which passengers can access, consume and share information with other cars, infrastructure or third parties, similar to the use of a smartphone.

Yet, test-drives have shown that users of connected cars:

- ***find it difficult to learn** how to operate connected car features*
- ***do not perceive** that their interactions with connected car features are clear and understandable*
- ***are only able to slowly** become skillful at using connected car features*
- ***perceive** that their interactions with connected car features require a lot of mental effort*

Based on the results of the test drives, I believe that I would find connected car features <u>easy to use</u>	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
	○	○	○	○	○	○	○

High Data Privacy Risk Manipulation

<u>Data Privacy of Connected Cars</u>
Next to the usability aspects, a potential risk associated with connected car features is the loss of personal data and privacy invasions through third parties.

Indeed, test drives have shown that users of connected cars:

- ***do not perceive** the approval process of sharing data intuitive and transparent*
- ***are not aware** how and for which purpose third parties are using their data*
- ***cannot be assured** that their personal data shared with third parties is stored securely*
- ***have to be aware** that extensive user profiles with information on their personal interests and behaviors are available to third parties*

Based on the results of the test drives, I believe that I would find connected car features <u>risky for my data privacy</u>	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
	○	○	○	○	○	○	○

Low Data Privacy Risk Manipulation

<u>Data Privacy of Connected Cars</u>
Next to the usability aspects, a potential risk associated with connected car features is the loss of personal data and privacy invasions through third parties.

Yet, test drives have shown that users of connected cars:

- ***perceive*** the approval process of sharing data intuitive and *transparent*
- ***are fully aware** how and for which purpose third parties are using their data*
- ***can be assured** that their personal data shared with third parties is stored securely*
- ***can be assured that no** user profiles with information on their interests and behaviors are available to third parties*

Based on the results of the test drives, I believe that I would find connected car features <u>risky for my data privacy</u>	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
	○	○	○	○	○	○	○

Attention Check

What is your most appreciated functional area of a connected car?

Due to the various different advantages connected cars yield, it is exciting to understand which are the features most appreciated by customers. Specifically, I am interested in knowing whether you take the time to read the instructions. In order to demonstrate that you have read the instructions, please ignore the items below. Instead simply write the word "next" in the empty (last) box below.

- Safety
- Mobility Management
- Autonomous Driving
- Entertainment
- Other

Demographics

Do you have a driver's license? Yes No

Do you own a car? Yes No

What is your gender? Male Female Other

How many years of driving experience do you approximately have?

In which country do you currently reside?

United States of America ▼

How old are you?

Under 18	35 - 44	65 - 74
18 - 24	45 - 54	75 - 84
25 - 34	55 - 64	85 or older

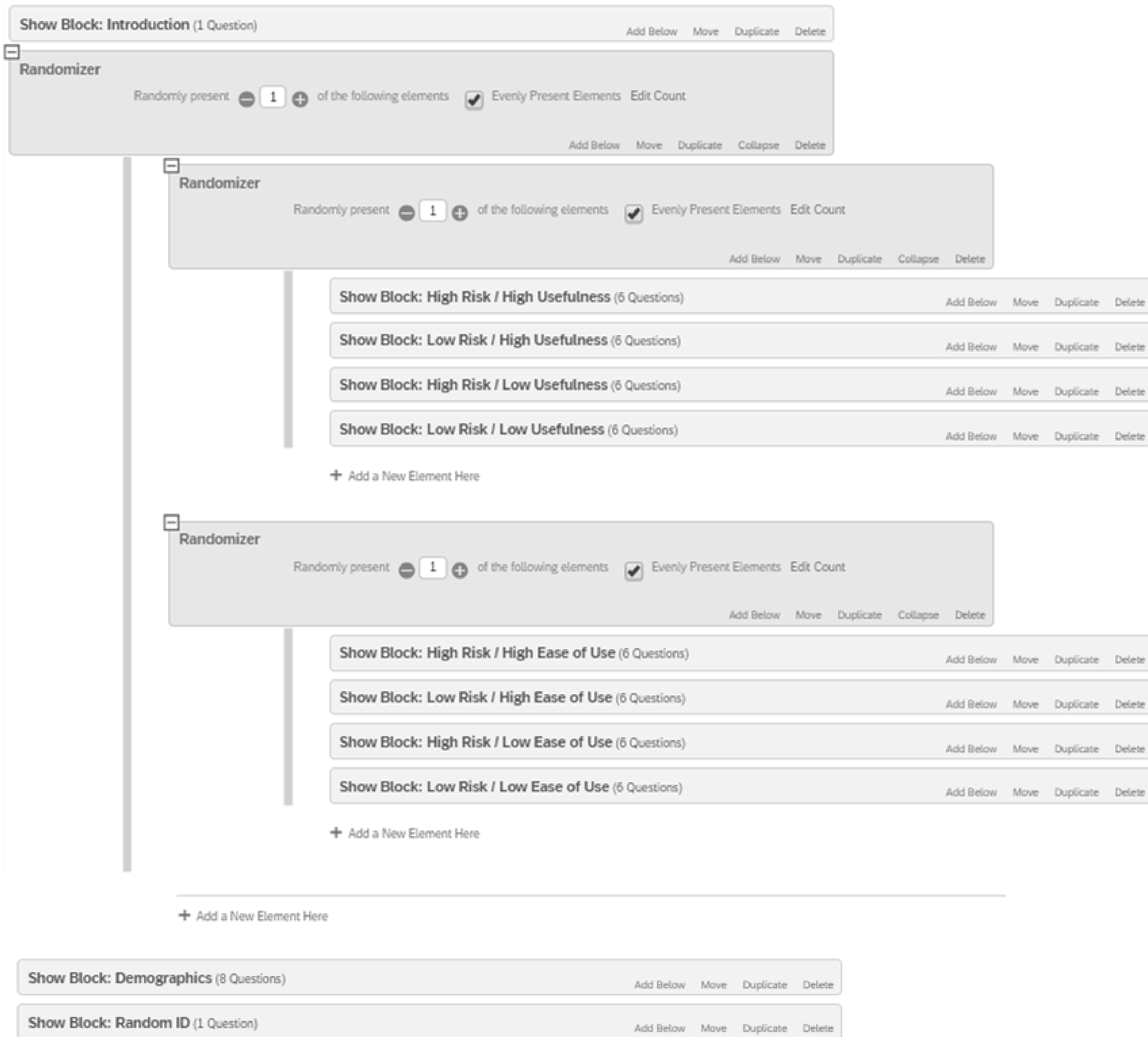
What is your level of education?

Less than high school	Bachelor graduate	PhD graduate
High school graduate	Master graduate	Other

What is your household income?

Less than $10,000	$30,000 - $39,999	$60,000 - $69,999	$90,000 - $99,999
$10,000 - $19,999	$40,000 - $49,999	$70,000 - $79,999	$100,000 - $149,999
$20,000 - $29,999	$50,000 - $59,999	$80,000 - $89,999	More than $150,000

Experiment Flow



Appendix II: Experiment Distribution

Figure 6: Amazon Mechanical Turk HIT Status Final

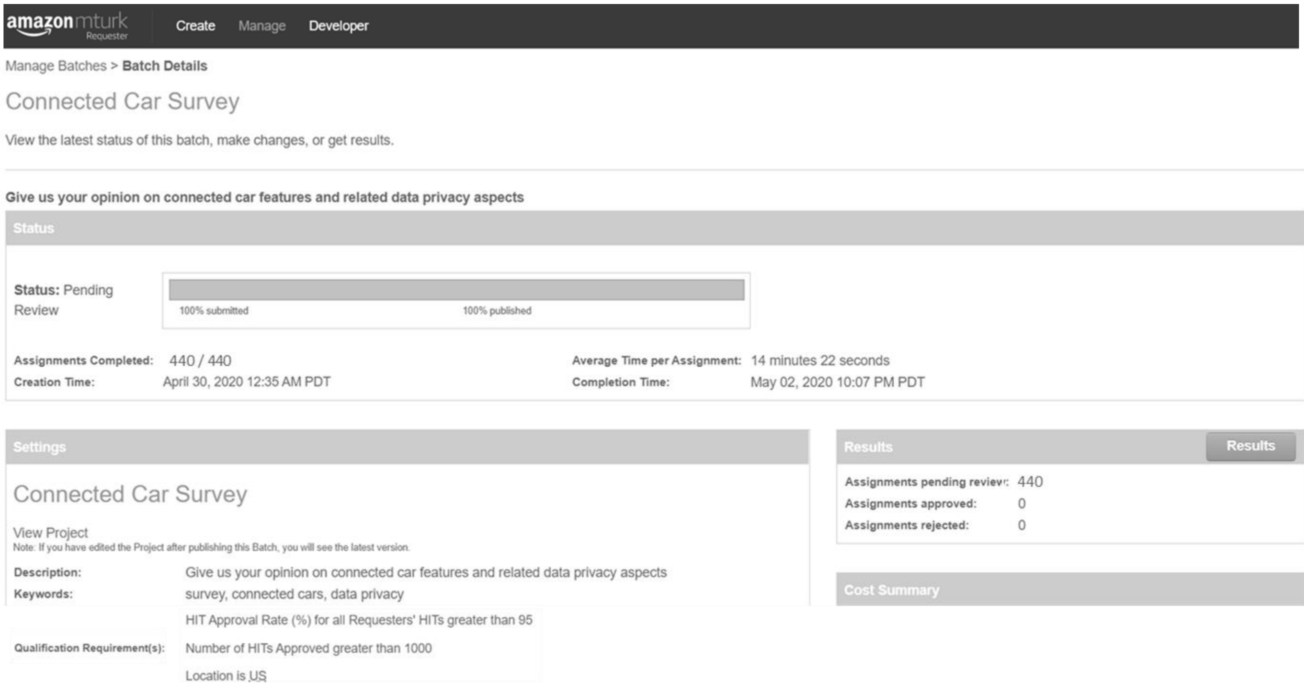
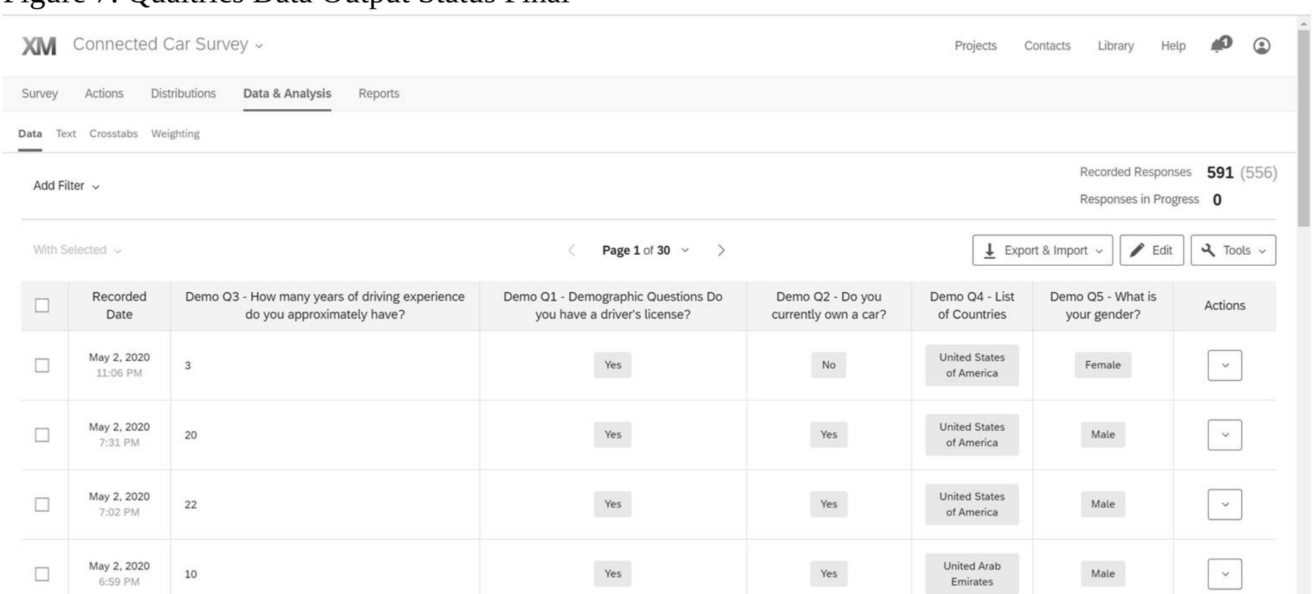


Figure 7: Qualtrics Data Output Status Final



Appendix III: Pre-Tests

Table 7: Pre-Test Output		*Participants*
# of Respondents		*N=32*
Timing of 4 minutes for main section	*Too Short*	2
	Just Right	25
	Too Long	5
Presentation of experiment illustrations	*All Elaborations on One Page*	26
	Elaborations Split to Several Pages	6
Manipulation	*Correct Usefulness*	32
	Incorrect Usefulness	0
	Correct Ease of Use	30
	Incorrect Ease of Use	2
	Correct Data Privacy Risk	29
	Incorrect Data Privacy Risk	3

Appendix IV: RStudio Output Sample Characterization

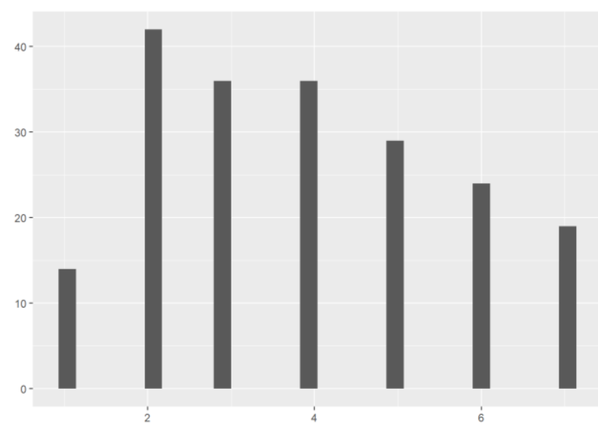
Table 8: Characterization of Sample

		Usefulness	*Ease of Use*	*Aggregated*
# of Respondents		*200*	*203*	*403*
Nationality	*US*	100%	100%	100%
Gender	*Female*	19.4%	22.1%	41.5%
	Male	30.3%	28.3%	58.5%
Age	*18-25*	3.2%	3.2%	6.4%
	25-45	31.3%	32.0%	63.3%
	45-65	12.4%	11.9%	24.4%
	>65	2.7	3.2%	5.9%
Car Usage	*Driver's License*	100 %	100%	100%
	Owns Car	46.7%	46.9%	93.6%
	Years of Driving Experience	18.8years	21.1years	19.9years
Education	*High School*	8.4%	12.7%	21.1%
	Bachelor	29.5%	27.1%	56.6%
	Master	10.2%	9.4%	19.6%
	PhD	1.5%	1.2%	2.7%
Income	*<30,000$*	8.9%	10.1%	19.0%
	30,000$-80,000$	20.8%	27.0%	47.8%
	>80,000$	19.9%	13.4%	33.2%

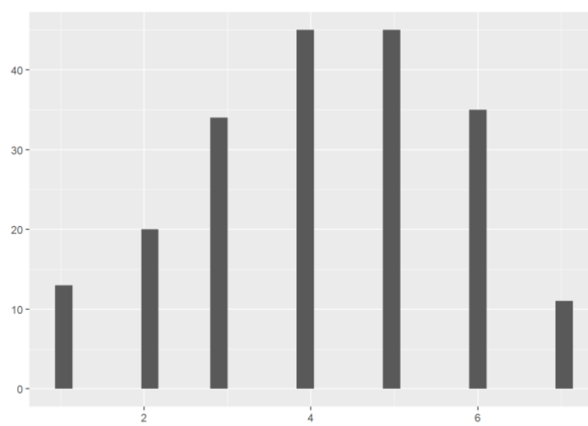
Table 9: Characterization of Treatment Constructs

		Mean of Reported Behavioral Intention to Adopt
High Usefulness	High Risk	3.848
Low Usefulness	High Risk	2.526
High Usefulness	Low Risk	6.077
Low Usefulness	Low Risk	3.000
High Ease of Use	High Risk	3.706
Low Ease of Use	High Risk	3.480
High Ease of Use	Low Risk	5.353
Low Ease of Use	Low Risk	4.137

Figure 8 & 9: Checking for Outliers and Skewedness via Distribution Plot



BI Usefulness



BI Ease of Use

Table 10: Checking for Outliers with Z-Scores

	Number of Rows with Conspicuous Z-Scores ±4
Usefulness	Empty data.table (0 rows) of 2 cols: BI, zscore
Ease of Use	Empty data.table (0 rows) of 2 cols: BI, zscore

Appendix V: RStudio Output Manipulation Checks

Table 11: ANOVA Usefulness Manipulation Check

	Degrees of Freedom	*Sum of Squares*	*Mean Square*	*F-Value*	*p-Value*
High Usefulness	1	275.20	275.2	114.75	0.000
Residual	198	474.88	2.4	-	-

Table 12: Descriptive Statistics Usefulness Manipulation Check

	N	*Mean*	*SD*	*Min*	*Median*	*Max*
High Usefulness	98	5.837	1.249	1	6	7
Low Usefulness	102	3.490	1.790	1	3	7

Table 13: ANOVA Ease of Use Manipulation Check

	Degrees of Freedom	*Sum of Squares*	*Mean Square*	*F-Value*	*p-Value*
High Ease of Use	1	270.70	270.7	122.9	0.000
Residual	201	442.80	2.2	-	-

Table 14: Descriptive Statistics Ease of Use Manipulation Check

	N	*Mean*	*SD*	*Min*	*Median*	*Max*
High Ease of Use	102	5.725	1.091	1	6	7
Low Ease of Use	101	3.416	1.796	1	3	7

Table 15: ANOVA Risk Manipulation Check

	Degrees of Freedom	*Sum of Squares*	*Mean Square*	*F-Value*	*p-Value*
High Risk	1	190	189.97	73.76	0.000
Residual	401	1033	2.58	-	-

Table 16: Descriptive Statistics Risk Manipulation Check

	N	*Mean*	*SD*	*Min*	*Median*	*Max*
High Risk	204	5.544	1.523	1	6	7
Low Risk	199	4.171	1.685	1	4	7

Appendix VI: RStudio Output LRM Assumptions for H1 - Usefulness

Graph 10 & 11: Plot of Fitted Values Against Residuals & Quantile-Quantile Plot

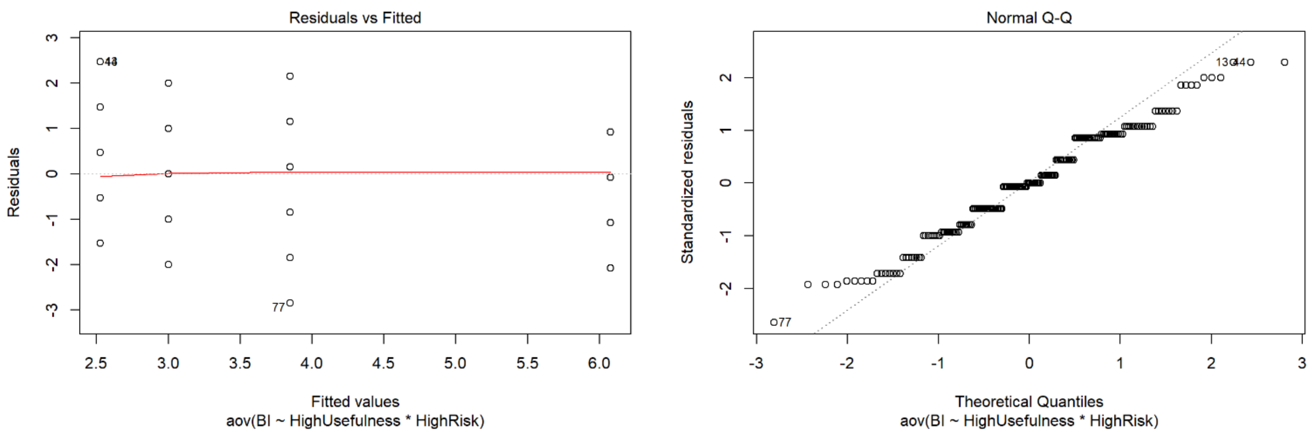


Table 17: Testing of ANOVA Assumptions Usefulness

Assumption Type	*Degrees of Freedom*	*F-Value*	*p-Value*
Homogeneity of Variance – Levene Test			***Fulfilled***
- *Usefulness Interaction*	3	F=1.92167	p=0.12736
- *Residuals*	196	-	-
Normality			***Fulfilled***
- Central Limit Theorem			n per cell > 30
- Shapiro-Wilk Test			p=0.00519
Independence of Sample			***Fulfilled***
- Random Sample	Randomly selected and independent of each other		

Appendix VII: RStudio Output LRM Assumptions for H2 – Ease of Use

Graph 12 & 13: Plot of Fitted Values Against Residuals & Quantile-Quantile Plot

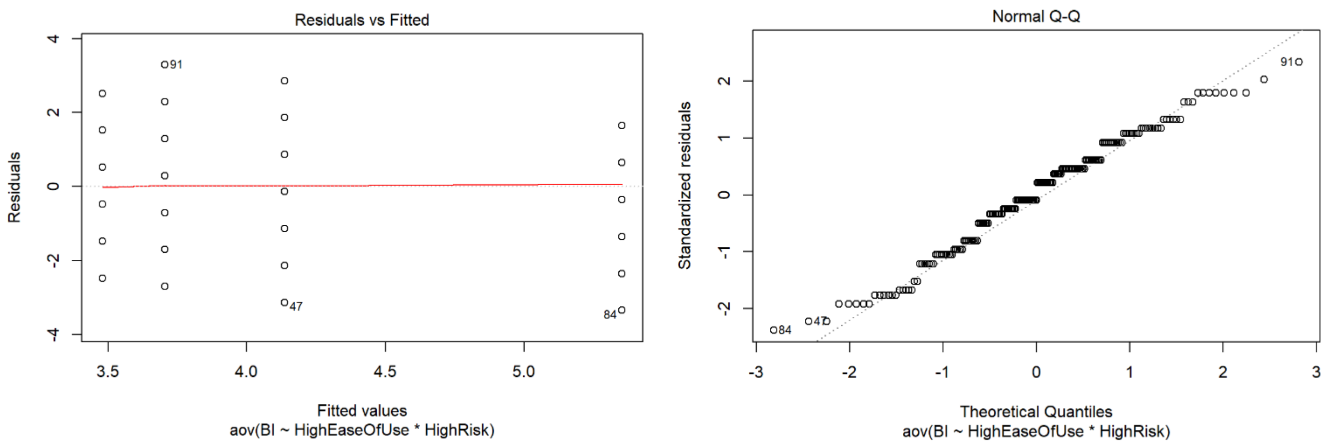


Table 18: Testing of ANOVA Assumptions Ease of Use

Assumption Type	*Degrees of Freedom*	*F-Value*	*p-Value*
Homogeneity of Variance – Levene Test			***Fulfilled***
- *Usefulness Interaction*	3	*F*=2.0206	*p*=0.1123
- *Residuals*	199	-	-
Normality			***Fulfilled***
- Central Limit Theorem			n per cell > 30
- Shapiro-Wilk Test			*p*=0.01013
Independence of Sample			***Fulfilled***
- Random Sample	Randomly selected and independent of each other		

Appendix VIII: RStudio Output for Hypotheses Testing – H1 Usefulness

Table 19: T-Test Results TAM Base Line Relation
Low Risk – Low Usefulness vs. Low Risk – High Usefulness

p-value	*0.00000000000000022*
95% confidence interval	*-3.500254 -2.653593*
t-statistics	*-14.461*
df	*81.124*
Mean LR-LU	*3.000000*
Mean LR-HU	*6.076923*

H0: There is no difference in the reported level of Behavioral Intention for participants who were exposed to different level of Usefulness
Ha: There is a difference in the reported level of Behavioral Intention for participants who were exposed to different level of Usefulness

Table 20: T-Test Results Moderation
High Risk – High Usefulness vs. Low Risk – High Usefulness

p-value	*0.0000000000000006405*
95% confidence interval	*-2.668510 -1.789684*
t-statistics	*-10.096*
df	*79.871*
Mean HR-HU	*3.847826*
Mean LR-HU	*6.076923*

H0: There is no difference in BI for participants who were exposed to different level of Data Privacy Risks in the same high Useful condition.
Ha: There is a difference in BI for participants who were exposed to different level of Data Privacy Risks in the same high Useful condition.

Table 21: T-Test Results Moderation
High Risk – Low Usefulness vs. Low Risk – Low Usefulness

p-value	*0.03653*
95% confidence interval	*-0.917019 -0.030350*
t-statistics	*-2.1228*
df	*89.658*
Mean HR-LU	*2.526316*
Mean LR-LU	*3.000000*

H0: There is no difference inf BI for participants who were exposed to different level of Data Privacy Risks in the same low Useful condition.
Ha: There is a difference in BI for participants who were exposed to different level of Data Privacy Risks in the same low Useful condition.

Table 22: OLS Linear Interaction Regression – Usefulness

	HU *(Model 1)*	HU + HR *(Model 2)*	HU * HR *(Model 3)*
β_1 High Usefulness	2.295^{***}	2.176^{***}	3.077^{***}
β_2 High Risk		-1.338^{***}	-0.474^{**}
β_3 High Usefulness*High Risk			-1.755^{***}
β_0 Constant	2.735^{***}	3.483^{***}	3.000^{***}
Observations	200	200	200
Adjusted R^2	0.420	0.562	0.622
Residual Std. Error	1.346 (df = 198)	1.171 (df = 197)	1.088 (df = 196)
F Statistic	145.326^{***} *(df = 1; 198)*	128.440^{***} *(df = 2; 197)*	109.973^{***} *(df = 3; 196)*
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

β_0= 3.00: On average, the reported level of Behavioral Intention of participants who were exposed with low Data Privacy Risk and low Usefulness treatment was exactly 3.00 (significantly different from zero at the 1% level), meaning that participants would somewhat disagree when being asked if they want to adopt connected cars.

β_1= 3.077: On average, the shift from low to high Usefulness exposure, keeping the Data Privacy Risk exposure constant at a low level, is associated with a 3.08 unit increase in the Behavioral Intention to adopt (significantly different from zero at the 1% level), meaning that participants would now agree when being asked if they want to adopt connected cars (3.00+3.08=6.08 BI out of 7).

β_2= -0.474: On average, the shift from low to high Data Privacy Risk exposure, keeping the Usefulness exposure constant at a low level, is associated with a 0.47 unit decrease in the Behavioral Intention to adopt (significantly different from zero at the 1% level), meaning that participants with high Data Privacy Risk exposure would now disagree when being asked if they want to adopt connected cars (3.00-0.47=2.53 BI out of 7).

β_3= -1.755: On average, for participants who were in the high Usefulness condition, the exposure to Data Privacy Risks attenuated their reported level of BI to adopt strongly by -1.755 units. Thus, their overall BI to adopt would only increase by 1.32 ($1.32=\beta_1+\beta_3=3.08-1.76$) instead of 3.08 (significantly different from zero at the 1% level), meaning that participants would neither agree nor disagree when being asked if they want to adopt connected cars (3.08+1.32=4.40 BI out of 7). Thus, participants would only report a slightly higher willingness to adopt than participants of the control group.

Appendix IX: RStudio Output for Hypotheses Testing – H2 Ease of Use

Table 23: T-Test Results TAM Base Line Relation
Low Risk – Low Ease of Use vs. Low Risk – High Ease of Use

p-value		*0.000005607*
95% confidence interval	*-1.718346*	*-0.713027*
t-statistics		*-4.7983*
df		*99.951*
Mean LR-LEOU		*4.137255*
Mean LR-HEOU		*5.352941*

H0: There is no difference in the reported level of Behavioral Intention for participants who were exposed to different level of Ease of Use
Ha: There is a difference in the reported level of Behavioral Intention for participants who were exposed to different level of Ease of Use

Table 24: T-Test Results Moderation
High Risk – High Ease of Use vs. Low Risk – High Ease of Use

p-value		*0.0000000383*
95% confidence interval	*-2.194745*	*-1.099373*
t-statistics		*-5.9678*
df		*98.112*
Mean HR-HEOU		*3.705882*
Mean LR-HEOU		*5.352941*

H0: There is no difference in BI for participants exposed to different level of Data Privacy Risks in the same high Ease of Use condition.
Ha: There is a difference in BI for participants exposed to different level of Data Privacy Risks in the same high Ease of Use condition.

Table 25: T-Test Results Moderation
High Risk – Low Ease of Use vs. Low Risk – Low Ease of Use

p-value		*0.02552*
95% confidence interval	*-1.232234*	*-0.082275*
t-statistics		*-2.2701*
df		*92.675*
Mean HR-LEOU		*3.480000*
Mean LR-LEOU		*4.137255*

H0: There is no difference inf BI for participants exposed to different level of Data Privacy Risks in the same low Ease of Use condition.
Ha: There is a difference in BI for participants exposed to different level of Data Privacy Risks in the same low Ease of Use condition.

Table 26: OLS Linear Interaction Regression – Ease of Use

	HEOU *(Model 1)*	HEOU + HR *(Model 2)*	HEOU * HR *(Model 3)*
β_1 High Ease of Use	0.718^{***}	0.723^{***}	1.216^{***}
β_2 High Risk		-1.155^{***}	-0.657^{**}
β_3 High Ease of Use*High Risk			-0.990^{***}
β_0 Constant	3.812^{***}	4.383^{***}	4.137^{***}
Observations	203	203	203
Adjusted R^2	0.047	0.176	0.197
Residual Std. Error	1.550 (df = 201)	1.441 (df = 200)	1.423 (df = 199)
F Statistic	10.877^{***} *(df = 1; 201)*	22.588^{***} *(df = 2; 200)*	109.973^{***} *(df = 3; 199)*
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

β_0= 4.137: On average, the reported level of Behavioral Intention of participants who were exposed with low Data Privacy Risk and low Ease of Use treatment was 4.14 (significantly different from zero at the 1% level), meaning that participants would neither agree nor disagree when being asked if they want to adopt connected cars.

β_1= 1.216: On average, the shift from low to high Ease of Use exposure, keeping the Data Privacy Risk exposure constant at a low level, is associated with a 1.22 unit increase in the Behavioral Intention to adopt (significantly different from zero at the 1% level), meaning that participants would now somewhat agree when being asked if they want to adopt connected cars (4.14+1.22=5.36 BI out of 7).

β_2= -0.657: On average, the shift from low to high Data Privacy Risk exposure, keeping the Ease of Use exposure constant at a low level, is associated with a 0.66 unit decrease in the Behavioral Intention to adopt (significantly different from zero at the 1% level), meaning that participants with high Data Privacy Risk exposure would now somewhat disagree when being asked if they want to adopt connected cars (4.14-0.66=3.48).

β_3= -0.99: On average, for participants who were in the high Ease of Use condition, the exposure to Data Privacy Risks attenuated their reported level of BI to adopt connected car features by -0.99 units. Thus, their overall BI to adopt would only increase by 0.23 (0.23=β_1+β_3=1.22-0.99) instead of 1.22 (significantly different from zero at the 1% level), meaning that participants would somewhat agree when being asked if they want to adopt connected cars (4.14+1.22=5.36 BI out of 7). Thus, participants would stay at the level of being indecisive, responding that they neither agree nor disagree when being asked if they want to adopt connected cars.

Appendix X: Interaction Regression with Control Variables

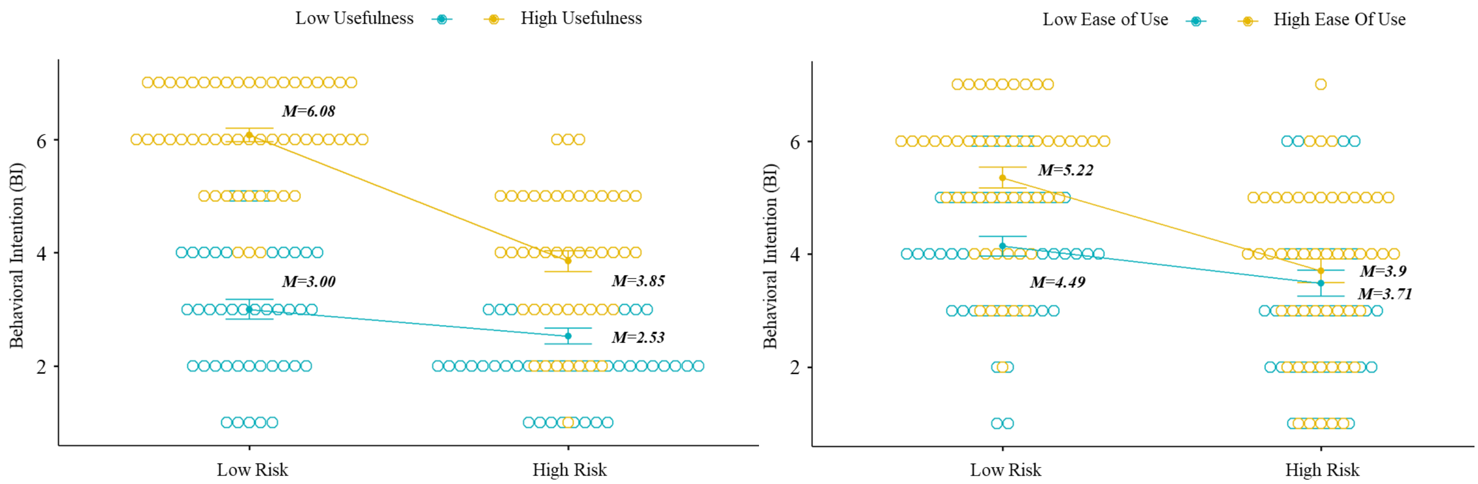
Table 27: OLS Linear Interaction Regression with Controls – Usefulness

	HU * HR	HU * HR + Controls
β_1 High Ease of Use	3.077***	3.223***
β_2 High Risk	-0.474**	-0.388*
β_3 Gender Male		-0.014
β_4 Own Car		-0.411
β_5 Income Low (<30k$)		-0.658***
β_6 Income Medium (30k$-80k$)		-0.392
β_7 Education		0.058
β_8 Age Very Old (>65)		-0.745
β_9 Age Very Young (<25)		0.368
β_{10} Age Young (25-45)		0.203
β_{11} High Ease of Use*High Risk	-1.755***	-0.1938***
β_0 Constant	3.000***	2.747***
Observations	200	200
Adjusted R^2	0.622	0.649
F Statistic	109.973*** *(df = 3; 196)*	34.451*** *(df = 11; 188)*
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 28: OLS Linear Interaction Regression with Controls – Ease of Use

	HEOU * HR	HEOU * HR + Controls
β_1 High Ease of Use	1.216***	1.225***
β_2 High Risk	-0.657**	-0.659**
β_3 Gender Male		0.332
β_4 Own Car		-0.226
β_5 Income Low (<30k$)		-0.213
β_6 Income Medium (30k$-80k$)		-0.295
β_7 Education		0.085
β_8 Age Very Old (>65)		-0.343
β_9 Age Very Young (<25)		0.958**
β_{10} Age Young (25-45)		0.332
β_{11} High Ease of Use*High Risk	-0.990***	-0.1049***
β_0 Constant	4.137***	3.870***
Observations	203	260
Adjusted R^2	0.197	0.218
F Statistic	17.493*** *(df = 3; 199)*	6.115*** *(df = 11; 191)*
Note:		*p<0.1; **p<0.05; ***p<0.01

Graph 14 & 15: Plot of Interaction Effects – Usefulness & Ease of Use



Appendix XI: Further Elaborations on Theoretical Background

Further Elaborations on Connected Cars Theory

The conceptual ambiguity of connected car features in particular with regard to the different advancement levels of existing technology advancements can be confusing when trying to make sense of the adoption willingness of connected cars features from a customer perspective. In this capacity, to ease the understanding of connected car technologies, McKinsey (2018) has developed a proposal for a "Connected Car Customer Experience (C3X) Framework", which is based on three years of research, 3,000 interviews with car buyers worldwide and more than 100 expert interviews (McKinsey, 2018). There framework thereby remembrance the five levels of autonomous driving (Kun et al., 2016).

- Level 1 - Basic Connectivity and Vehicle Monitoring: The driver can access basic information on driving behavior and check the technical status of the car.
- Level 2 - Individual Connectivity and Link to Drivers Digital Ecosystem: The driver has a personal profile to control digital services and platforms such as Android Auto or Apple CarPlay.
- Level 3 - Preference-Based Personalization: All occupants of the car have access to their personalized accounts (infotainment, advertising etc.) and targeted contextual advertising.

- Level 4 - Live Dialogue and Multisensory Interactions: All occupants can interact with the car in real time and receive active recommendations for offers tailored to them.
- Level 5 - Virtual Chauffeur and Intelligent Decision Making: The artificial intelligence anticipates the wishes of the occupants and does complex, not pre-programmed tasks.

Today, only about one out of five vehicles on the road are at or above level one of the C3X framework. Few vehicles in the premium segment, such as the Mercedes-Benz GLE, BMW 7, Audi Q7 and Tesla Model X, already meet the criteria for level two of the C3X framework, delivering a compelling in-vehicle connectivity experience to customers. However, currently no commercialized vehicle meets full level-three capabilities yet, though some models have some features in pilot stages. Yet again, this demonstrates the massive potential for advancements and highlights the importance of the adoption willingness of customers in order to build up a critical mass of connected cars on the road (McKinsey, 2018).

In the following, relevant literature findings are put into context of the DoI adoption decision process. For electric vehicles, which, like connected cars in general, rely on connectivity technology, OEMs already offer a comprehensive package of connectivity services. Today, there is a large dependency of electric vehicles on connectivity technologies in the vehicle due to the poorly developed charging infrastructure and the claim of electric vehicle owners to have installed the latest technological standards in their cars (Mahmud et al., 2018). In order to define the relevant hypotheses for the decision dimension of the personal and socio-economic dimension of the adoption decision process in the capacity of the DoI, a study by the Fraunhofer Institute is referenced below. This study shows that adopters of electric vehicles are usually men, predominantly from a technical professional environment, from suburbs or rural areas, often with a high level of education. The decision to buy from this group of adopters is mainly based on driving pleasure, individuality and environmentally friendly driving (Fraunhofer Institute, 2012). In accordance with the similarities in the adoption decision-making process of electric vehicles and connectivity functions of vehicles, as well as on the basis of the target group characteristics for vehicles from the premium car segment, comparable personality properties of the adopters of connected cars and the adopters of electric vehicles or vehicles from the premium class can be assumed (Singh et al., 2018). As a final personal characteristic, it is important to look at the technical efficacy of adopters. To use a technically complex innovation appropriately or to be able

to perceive the properties accordingly, end users must have a certain degree of technical knowledge (Rogers, 2003). Thereby, the literature assumes a positive connection between technical knowledge and the perception of technical innovations (Wu et al., 2005).

Further Elaborations on Connected Cars Functionalities and Risks

The research of Bosler (2017) and Coppola et al. (2016) suggests the following functionalities as the most relevant connected car technologies and services optimizing driver's physical well-being through manual process enhancements: general travel information, weather information, train and flight information, information about departure times taking into account the traffic situation via app, comparisons of local retailers with automatic reconciliation of individual grocery list, individualized discount offers from retailers based on location and preference of drivers, online-based intelligent voice control in the vehicle, remote programming of the charging process for electric cars, localization of the vehicle displaying the parking position, digital vehicle key via NFC smartphone functions and driver profile enabled individual car settings and configurations.The research of Bosler (2017) and Coppola et al. (2016) suggests the following functionalities as the most relevant connected car technologies and services linking vehicle to private households, offices, and other buildings: integration of smart home applications (Amazon Alexa, Google home), energy monitoring systems of home applications with heater adaptation possibilities, energy solution for charging possibilities of electric vehicle, ability to book remotely office space and meeting rooms, in-car parcel delivery via short-term access for mail carrier services like UPS or DHL granted via smart phone application. Autonomous cars may not only outperform the safety record of non-driverless cars but are also able to enhance the performance and efficiency of passengers (Lee et al., 2016). With autonomous cars commuting on their own, passengers will have a lot of free time which can be dedicated to productive outcomes, in particular on longer trips (Bansal et al., 2016). The research of Pilipovic et al. (2014) and Coppola et al. (2016) suggests the following functionalities as the most relevant connected car technologies and services: lane assistance, autonomous adaptive acceleration, Car-2-Car and Car-2-Infrastructure communication to locate other road participants, entertainment services like Netflix or gaming and office solutions as gap fillers for "free time" during autonomous ride.

An additional ***cyber security risk*** arises from Traffic Message Channels, which are radio channels for the distribution of traffic reports. With a TMC injection, attackers are able to simulate a radio

station and thereby send manipulated messages with false traffic reports to a driver or even a group of drivers and accordingly are able to navigate them in a certain way (Hoppe, 2011).

Apart from cyberattacks and data protection issues, connected cars can also be prone to ***functional risks*** inherent to the new technological features (Morris et al., 2018). Functional risk represents the insufficient power of an innovation compared to the expected performance by the customer, for example, insufficient protection of sensors, inaccurate safety-assistance systems or any other immature technical functionalities of connected cars, especially in the sub-area of assisted and autonomous driving (Löffler, 2017). Yet, to be able to take advantage of connected car technologies, the driver has to put a lot of trust in the technical features. In the case of automated driving, the occupants of vehicles entrust even their lives directly to the technology (Hoppe et al., 2011). As a failure of sensor technologies or a temporary malfunction can delay or hinder assistance systems, such as lane keeping or brake assistants, and thus cause harmful accidents, OEMs are developing safety measures and protection mechanisms to minimize the potential of non-plannable technological disorders (Ring, 2015).

Time dependent risk coheres with the effort the adopter must put into the research of the innovation. Since buying a vehicle is generally an extensive purchasing decision, customers usually spend a great deal of time in the information search process, which is considered to be a time dependent risk (Schiffman et al., 2013). Yet, Holland found during his research that there is no particular relation between the time dependent risks and willingness of customers to adopt connected cars, as the relation is not effected by connected car specific features and is inherent to the general buying decision of cars (Holland, 2019).

Social risk is the risk that the adoption of an innovation leads to a social devaluation of the adopter, whereas ***psychological risk*** lies in the possibility that the adoption of an innovation leads to damage of self-esteem of the adopter (Schiffman et al., 2013). However, connected cars are aimed at increasing traffic safety and traffic efficiency as well as at reducing emissions (Walter et al., 2020). On the contrary, the implementation of connected car technologies usually starts in the high-priced premium car segment, therefore, the acquisition or use of connected car features can even be considered as the attainment of a higher social status perception (Howard, 2005).

Further Elaborations on Technology Adoption Research

As the goal of this thesis is to explain the moderating effect of Data Privacy Risks on the adoption process of connected car features, the focus of this Appendix chapter is not on the diffusion process itself, but on the adoption process and the respective behavioral decision-making process.

When analyzing the adoption of innovations, a distinction can be made between the adoption of an innovation by individuals of a social system on the one hand and diffusion in the entire market on the other hand (Rogers, 1962). Since the underlying research focuses on the customer perspective of the adoption of connected cars and thus the adoption of an innovation by end users, the aggregated market perspective is not covered in the underlying thesis (Hoyer et al., 1990).

The behavioral analysis and conceptual framework of the adoption decision process of connected vehicle technologies, introduced in the following chapter, thereby represents the basis for the hypothesis development of my research. For a further elaboration on existing research, dealing with the analysis of connected car adoption.

When looking at the existing literature, only few approaches trying to explain the adoption of connected car features are worth mentioning. Van Rijnsoever et al. (2013) analyzed consumer preference for emerging technologies in the automotive sector using an ordinal logit model. However, his conducted research does not reflect key behavioral phenomena “as the structure of the logit model does not allow for the simultaneous choice of multiple technology options, and does not account for correlation of unobserved factors that affect multiple choice alternatives as well as heterogeneity in consumer preferences” (Van Rijnsoever et al., 2013). A second interesting research from Ewing et al. (2000) dealt with a multinomial logit model to assess consumer preferences for connected vehicular technologies. Ewing used the obtained estimation results to elaborate on the changes in consumer demand while controlling for changes in vehicle attributes, vehicle purchase price as well as government policies (Ewing et al., 2000). However, these studies are already outdated and cannot be taken as a measure to assess the current technological opportunities emerging from connected vehicle innovations. The latest research on the adoption of connected cars was conducted by Holland (2019). Holland introduced a modified version of the five-stage Diffusion of Innovation (DoI) adoption decision model originally developed by Rogers (1962), tailored to the adoption process of networked innovations in the automotive sector. During his research project, he modified the original DoI model and tested the newly added behavioral

dimensions by means of expert interviews with a diverse group of automotive experts (Holland, 2019). Yet, Holland's research only establishes a conceptual framework as a foundation for further research into the adoption of connected cars by end users and is limited to the fact that the framework is only based on the statements of experts and on existing knowledge of the adoption of innovations.

"Diffusion of innovation is the process by which an innovation is communicated through certain channels over time among the members of a social system. Given that decisions are not authoritative or collective, each member of the social system faces his or her own innovation decision" (Rogers, 2003). As part of this individual determination process, Rogers defined a complete decision framework for the adoption decisions of individuals and uses a multidimensional approach to explain the factors influencing the adoption choice. In order to properly understand the DoI adoption decision process, it is important to elaborate on the five stages which influence the adoption decision according to Rodgers.

- *Stage 1 – Knowledge/Awareness*
  "A person becomes aware of an innovation and has some idea of how it functions"
  Rogers calls the first stage, where a potential adopter perceives an innovation for the first time, the awareness / knowledge phase (Rogers, 1962). Information can be taken actively or passively and is guided by past experiences, needs, willingness to innovate, norms of the social system as well as socio-economic characteristics, personal characteristics and communication behavior (Rogers, 2003). At the same time, the consumer gathers knowledge of how this innovation can be used (Dickerson et al., 1983). In this capacity, Hoyer et al. (1990) define awareness as the simplest version of knowledge and acknowledgment of an innovation or a new service, followed by a complex cognitive structure based on previously gathered information. To conclude, a faster rate of adoption is expected if consumers have related knowledge and experiences with an innovation (Dickerson et al., 1983). Following the existing literature, the most relevant dimension is considered to be the personal and socio-economic characteristics of the adopter (Howard, 2005 & Holland, 2019), as these characteristics have a particular strong influence on the awareness towards an innovation (Howard, 2005). The relevant dimension criteria for the personal and socio-economic characteristics of an innovation in the knowledge stage are:

age, gender, education level and background, technical knowledge, salary, family status and place of residence (Holland, 2019 & Wu et al. 2005). To conclude the elaboration of criteria at the first stage of the decision process, Venkatesh et al. (2000) stated that various criteria (needs, willingness to innovate, norms of the social system, communication behavior) are only showing a significant effect in mandatory settings and are not significant in a voluntary context. Thus, in the following the four criteria are not further elaborated on, since the adoption decision of connected cars is majorly applicable to voluntary settings (private car-buying decision).

- *Stage 2 – Persuasion*

  "A person forms a favorable or unfavorable attitude toward the innovation"

  In the second stage, the potential adopter forms an attitude and Behavioral Intention towards the innovation (Rogers, 1962). Thereby, the characteristics of an innovation, namely the relative advantage / perceived Usefulness, complexity / perceived Ease of Use, compatibility, testability and observability, are the major determinants influencing the outcome of an end Behavioral Intention (Rogers, 2003). Moore et al. (1991) restudied the five attributes to build a measurement for the adopter's interaction with innovations and narrowed them down to the two most relevant dimensions: perceived Usefulness, perceived Ease of Use. Overall, the Behavioral Intention can be acceptance, resistance or postponement of the adoption decision (Dickerson et al., 1983). In the event of acceptance, the potential adopter is open to further information regarding the innovation (Homburg, 2012). Similar to the first stage of the decision process, Venkatesh et al. (2000) stated that several decision criteria (compatibility, testability, observability) are only showing a significant effect in mandatory settings and are not significant in a voluntary context. Thus, in the following the three criteria are not further elaborated on, since the adoption decision of connected cars is majorly applicable to voluntary settings (private car-buying decision).

- *Stage 3 – Decision*

  "A person engages in activities that lead to a choice to adopt or reject the innovation"

  In stage three, the potential adopter decides on the innovation (Rogers, 1962). With acceptance in pre-stage two, a decision for the innovation usually is made, which is then referred to as adoption. A possible decision against innovation leads to the rejection or postponement of adoption (Rogers, 1995). If the innovation is adopted, the innovation is

used in stage four. Stage four and stage five is in the capacity of my thesis not relevant, since the adoption decision has been made already in stage 3 (Rogers, 2003).

- *Stage 4 – Implementation*

  "A person puts an innovation into use"

  This stage implies the preparation for the acquisition of the innovation, the practical buying act and the actual use of the innovation (Rogers, 2003).

- *Stage 5 – Confirmation*

  "A person evaluates the results of an innovation decision already made"

  In the ultimate stage, adopters look for a confirmation of the adoption decision via various channels. Rogers (2003) refers to this level as the confirmation level.

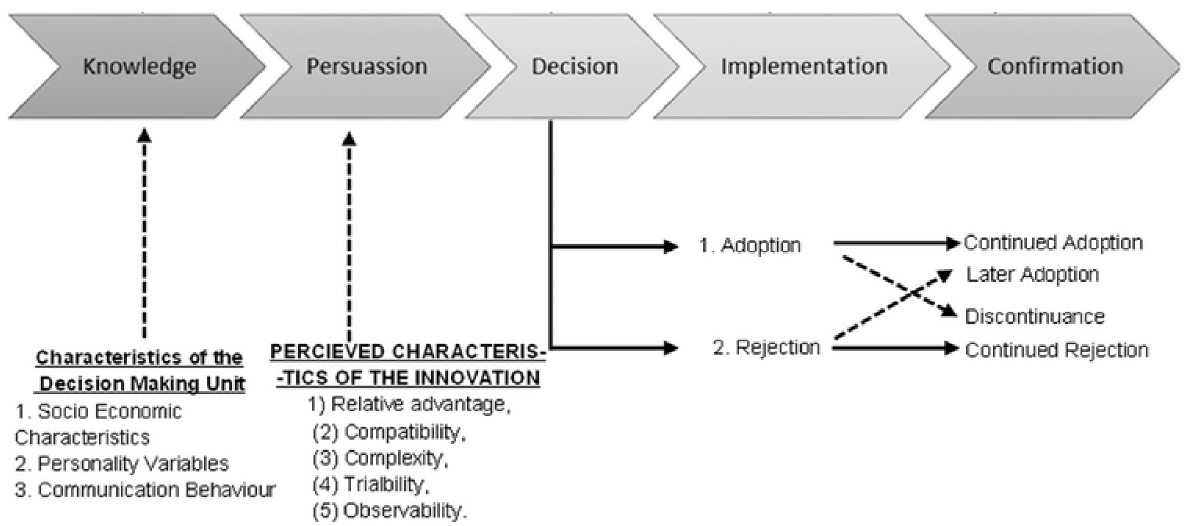


Figure 16: Adoption Decision Making Process