Universidade Católica Portuguesa

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Title:

Predicting consumers’ intention to purchase fully autonomous driving systems –

Which factors drive acceptance?

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Abstract

Title: Predicting consumers' intention to purchase fully autonomous driving systems – Which factors drive acceptance?

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This study aimed to find which factors influence consumers' intention to purchase a fully autonomous driving system in the future and which perceived product characteristics influence the purchase intention and how. Therefore, an extension of the acceptance model of Driver Assistant Systems by Arndt (2011) is presented. It integrates perceived product characteristics specific to autonomous driving technology, to investigate which factors determine the acceptance of fully autonomous driving systems. The proposed model was empirically tested based on primary data collected in Germany. Exploratory and confirmatory factor analyses were performed to assess the reliability and validity of the measurement model. Further, structural equation modeling was used to evaluate the causal relationships. The findings indicated that Attitude toward buying, Subjective Norm and the perceived product characteristics Efficiency, Trust in Safety and Eco-Friendliness significantly influenced individuals' behavioral intention to purchase driverless technology. The variables perceived Comfort, Image and Driving Enjoyment were not found to have a significant effect on behavioral intention. Attitude and Subjective Norm had the most significant influence. A somewhat surprising finding was that Subjective Norm not only had a direct effect on Behavioral Intention, as suggest by the theory of reasoned action and theory of planned behavior, but also on Attitude.

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Thank you,

Reiner Kelkel

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List of Abbreviations

ACC	adaptive cruise control
AVE	average variance extracted
CFA	confirmatory factor analysis
CFI	Comparative Fit Index
CR	Composite reliability
DARPA	Defense Advanced Research Projects Administration
DAS	driver assistant systems
EFA	explorative factor analysis
IHS	Information Handling Services
KMO	Kaiser-Meyer-Olkin
MADAS	Model of Acceptance of Driver Assistance Systems
NHTSA	National Highway Transport Safety Administration
OEMs	Original Equipment Manufacturers
PCA	principal component analysis
PLS	partial least square
SEM	structural equation modeling
TPB	theory of planned behavior
TRA	theory of reasoned action
V2I	vehicle-to-infrastructure
V2V	vehicle-to-vehicle
VFI	variable inflation factor

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1. Introduction

1.1 Relevance of the topic

During the last 30 years, the global car market has undergone significant changes in driver experience due to technological progress (Knight, 2012). Today, a typical middle-class car comes with standard features, such as power windows, automatic gearbox and electronic stability program (Handmer, 2014; Knight, 2012). High-end automobiles can be bought with intelligent features like automatic start-stop mechanism enhanced cruise control, active lane assistance and self-parking technology (Handmer, 2014; Knight 2014).

These innovations make driving more comfortable, but still require human interaction (Knight, 2012). However, todays' connected cars and increasing technological progress pave the way for fully autonomous vehicles (Handmer, 2014).

This master thesis adopts the definition from the National Highway Transport Safety Administration (NHTSA) for autonomous vehicles. According to the NHTSA (2013), driverless cars are defined as:

> *"[…] those in which operation of the vehicle occurs without direct driver input to control the steering, acceleration, and braking and are designed so that the driver is not expected to constantly monitor the roadway while operating in self-driving mode".*

Driver-less car technology today is very advanced and opens new possibilities for individuals, automotive companies but also for new market players

The most well-known OEMs of the automobile industry, as well as new companies, expect to sell limited self-driving cars, vehicles that allow drivers to hand over full control of all safety-critical functions under certain traffic or environmental conditions, before 2020 (IHS Automotive, 2014).

Furthermore, Information Handling Services (2014) (IHS) estimates that globally 230 thousand autonomous vehicles will be sold till 2025 and that this number will grow to 11.8 million cars in 2035.

Thus, if the assumption of autonomous driving technology comes true, it will have a strong effect on individual mobility. However, before driverless vehicles enter the market three main challenges relating to technology, legal and consumers lie ahead (IHS Automotive, 2014). Software reliability and cyber security must be guaranteed (Kelly & CNN, 2014), a legal framework for self-driving vehicles regarding insurance and liability has to be established (Kelly & CNN, 2014) and consumers must be convinced to accept driverless vehicles (IHS Automotive, 2014).

Consumers may question, whether driverless driving features will offer an overall better option than driving themselves. Taking into account that failure of consumer acceptance entails considerable costs to companies (Chiesa & Frattini, 2011). It is essential for organizations to understand under which circumstances customers accept autonomous cars. Acceptance and future use of new technologies are frequently subject to tradeoffs between uncertain benefits and costs of adopting the new invention (Venkatesh, Morris, Davis, & Davis, 2003).

Several studies have researched the acceptance of driver assistant systems (DAS) (Adell, 2009; Arndt, 2004; Arndt & Engeln, 2008; Huth & Gelau, 2013). However, so far no studies have explored users' acceptance of fully autonomous driving systems.

1.2 Objective and plan of action

This research aims to find which factors influence consumers' intention to purchase a fully autonomous driving system in the future and which perceived product characteristics influence the purchase intention and how.

The objective of this thesis is to answer the following questions:

(1) Which product characteristics of driverless technology influence consumers purchase intention?
(2) How strong are effects of perceived product characteristics on purchase intention?
(3) Are they positively or negatively related to purchase intention?

To answer the research questions, the model of acceptance of driver assistant system (Arndt, 2011) is adapted to ensure fit with the context of driverless cars. Further, a quantitative online survey is conducted to empirically investigate the topic. The determinants of purchase intention of a fully autonomous driving system are analyzed using structural equation modeling (SEM).

The dissertation proceeds as follows: In chapter 2, the background, expected functions, assumed benefits and drawbacks as well as the current state of autonomous driving technology is summarized. This is followed by a literature review of the fundamental theoretical models and the model of acceptance of driver assistant systems by Arndt (2011). In the first part of chapter 4 the research model is presented and hypotheses are derived. In the second part, the methodology is outlined. Chapter 5 presents the analysis of the collected data. This is followed by the presentation of the relevant findings. In section 7 a discussion about the survey results is provided. Moreover, limitations and implications for further research are emphasized. Subsequently, a conclusion summarizes the key aspects of this thesis and provides practical implications.

2. State of the art on fully autonomous driving technology

This chapter reviews the current state of the art of autonomous car technology, possible benefits, as well as challenges, and drawbacks from the technology.

The dream of autonomous vehicles is as old as the early 1930 when driverless vehicles and taxis have been improving the lives of millions in science fiction books (Weber, 2014). However, rather than revolutionary, progress was only incremental till the beginning of this century (Weber, 2014). For the first time in 2005, several driverless vehicles were able to cross a 150 miles long track in California's Mojave Desert in the Defense Advanced Research Projects Administration (DARPA) challenge (Fagnant & Kockelman, 2013; Weber, 2014). Furthermore, in 2007 six teams completed the Urban Challenge, which required to deal with moving and fixed obstacles and to obey traffic rules in order to simulate realistic everyday traffic scenarios (Fagnant & Kockelman, 2013). Since then, most of the OEMs, including BMW, Audi, GM, Nissan, Volkswagen, Mercedes-Benz began to accelerate research & development in driverless cars (Fagnant & Kockelman, 2013).

Autonomous vehicle technology is defined as electronic systems that complement todays cars to control its driving without the need of a human driver (IHS Automotive, 2014).

In NHTSA's statement of policy on automated vehicles, different levels of vehicle automation are defined as shown in table 2-1.

Table 2-1: Definitions of vehicle autonomy. Source: NHTSA (2013).

Level	Autonomy
0	No Automation. The driver is in complete and sole control of the vehicle controls (brake, steering, throttle, and motive power) at all times
1	Autonomy of one or more primary control functions. E.g. the vehicle assists automatically with pre-charged braking to enable driver to stop faster than possible by acting alone.
2	Autonomy of at least two primary control functions designed to work in unison to relieve the driver of control of these functions. E.g. the combined function of active cruise control and lane centering.
3	Limited Self-Driving Automation: Vehicles at this level of automation enable the driver to cede full control of all safety-critical functions under certain traffic or environmental conditions and in those conditions to rely heavily on the vehicle to monitor for changes in those conditions requiring transition back to driver control. The driver is expected to be available for occasional control, but with sufficiently comfortable transition time.
4	Full Self-Driving Automation: The vehicle is designed to perform all safety-critical driving functions and monitor roadway conditions for an entire trip. It is designed so that the driver will provide only destination or navigation input. The driver is not expected to be available for control at any time during the trip. This includes both occupied and unoccupied vehicles.

Currently, autonomous vehicles are already allowed to be tested on public roads in the four states Michigan, Florida, Nevada and California of the United States of America (and the government in the United Kingdom (has ruled to allow testing from 1st January 2015 (BBC News, 2014).

The requirements for a driverless car are straight forward. It has to be able to drive from its current location to a defined target and obey all traffic rules, including the reading and understanding of all necessary road signs and signals, during the journey (IHS Automotive, 2014).

Even though the companies' driverless car systems' show differences in design to fulfill these requirements, they usually consist of lasers, cameras, GPS, radar, processors and complex software systems (Knight, 2012) which are illustrated in figure 2-1.

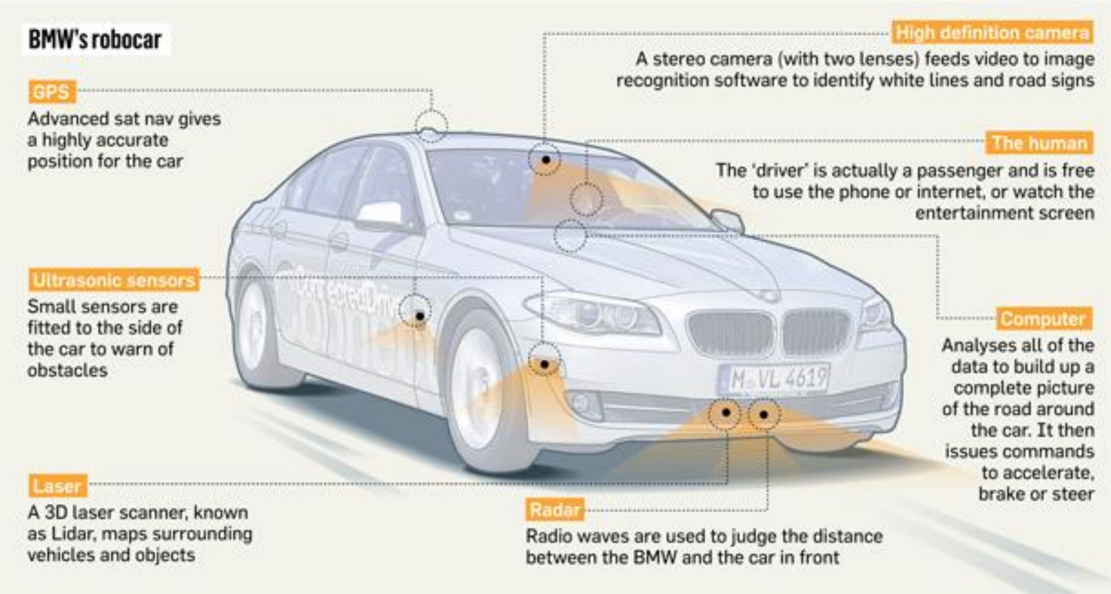


Figure 2-1: Technology and components that enable driver-less car technology. Source: Kiconco (2014).

The technology that enables autonomous driving can be described in three steps:

<u>First step:</u> the vehicle identifies its own position by GPS and perceives its environment, using cameras, lasers and radars to identify obstacles e.g. other vehicles, pedestrians, bikers or constructions sites on the road and also identifies the distance from these (IHS Automotive, 2014; Knight, 2012).

Figure 2-2: The sensors and camera recognize objects on the streets such as road signs, other vehicles, pedestrians and cyclists. Source: Urmson (2014)

<u>Second step:</u> the software and processors have to accumulate and process the input data to make sense of it (Knight, 2012).

Third step: the system reacts and adapts the movement of the vehicle in real time (Knight, 2012).

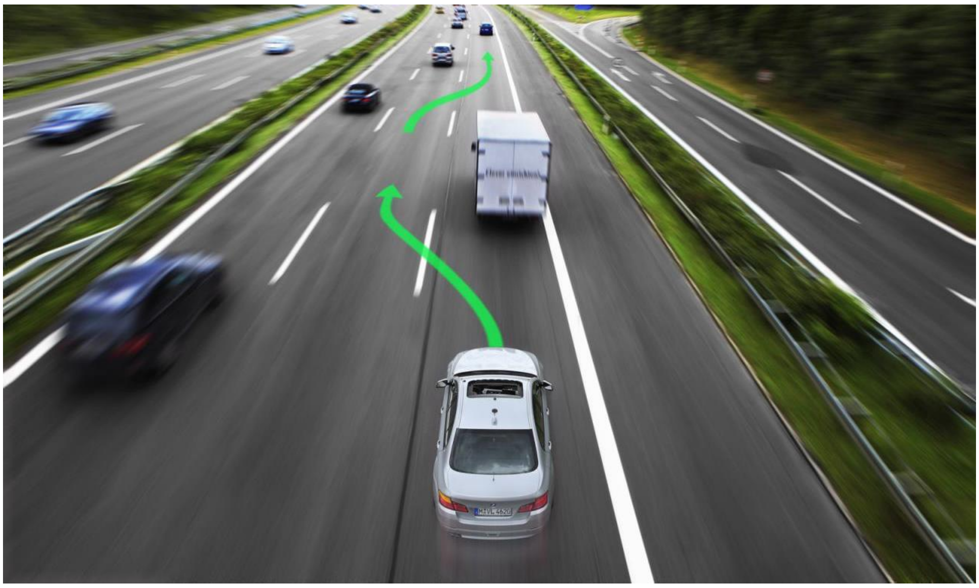


Figure 2-3: The system reacts and alternates its movement. Source: Tutu (2011).

Figure 2-4 illustrates how experts believe autonomous vehicle technology will evolve from the sum of the listed driver assistance systems. The horizontal axis describes the approximated entrance time of the technology and the vertical axis shows the corresponding autonomy level according to the definitions of NHTSA (2013).

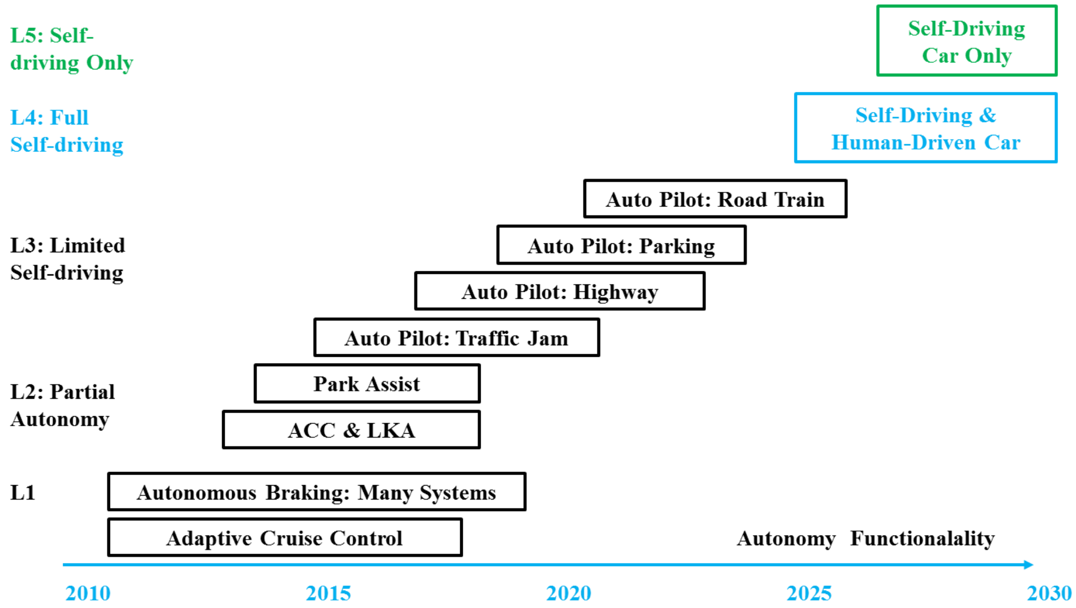


Figure 2-4: Expected development of autonomous technologies and level of autonomy over time. Source: IHS Automotive (2014).

It is expected that autonomous driving will be available from 2025 but first only in cars of the luxury segment and then slowly move down to mid- and low cost vehicles over the next decade (IHS Automotive, 2014).

2.1 Potential advantages and promises

2.1.1 Safety benefits

The NHTSA found that in 2008 human error accounted for 93 percent of car accidents in the U.S. (National Highway Traffic Safety Administration, 2008). Autonomous driving systems show a great potential to increase traffic safety, since they enable the driver to hand over all safety critical functions to the system, in situations of fatigue, sickness or when being distracted.

According to the World Health Organization, (World Health Organization, 2013) every year worldwide approximately 1.24 million people die and an additional 50 million people become injured in car accidents. Injuries from road accidents are number eight leading cause of death worldwide and for young people between 15 and 29 years old it is even the leading cause of death (European Commission, 2003; World Health Organization, 2009).

Several authors believe that the rate of accidents could be reduced close to zero percent for fully automated cars (Bickerstaffe, 2014; IHS Automotive, 2014; KPMG & CAR, 2012; Noor & Beiker, 2012).

2.1.2 Times savings

Automated cars have the ability to achieve time savings for passengers and other vehicles via several functions.

Automated vehicles are expected to be able to optimize their route choice according to up to date traffic information from other vehicles and thereby are expected to reach the desired destinations faster than human drivers (Fagnant & Kockelman, 2013).

The Federal Highway Administration (2005) found that one eight of congestion is attributable to road accidents. Reduced accident rates through automated vehicles will have an impact to reduce congestion and travel times for all participants (Anderson et al., 2014). Automobile manufacturers further develop cars, which enable vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication (Anderson et al., 2014;

Fagnant & Kockelman, 2013; KPMG & CAR, 2012). V2V enables vehicles to sense and anticipate the leading vehicles' decision to accelerate and brake (Anderson et al., 2014; KPMG & CAR, 2012) and thus declines. Traffic-destabilizing shockwave propagation can be achieved through more anticipatory speed adjustments when following others and when approach traffic lights (Fagnant & Kockelman, 2013). Likewise, autonomous vehicles are expected to be able to drive closer together and hence enable an increase in the utilization rate of current infrastructure (Fagnant & Kockelman, 2013; Tientrakool, Ho, & Maxemchuk, 2011). Tientrakool, Ho, & Maxemchuk (2011) posed if all vehicles would use adaptive cruise control (ACC) and sensors to automatically brake, the highway capacity would increase from 43 up to 273 percent and that speed of congested traffic may increase by 8 to 13 percent. Furthermore, V2I will enable autonomous cars to optimize adjustments in acceleration, speed and braking according to traffic information from traffic lights and other infrastructure (Anderson et al., 2014).

Autonomous vehicles are further designed with self-parking functionalities, which will evolve in two levels (Fagnant & Kockelman, 2014; IHS Automotive, 2014). The first level of self-parking is already commercially available and requires the driver to accelerate, speed and break manually, while the car takes over the steering into the gap (IHS Automotive, 2014). The second level, expected by 2018, will be an autopilot for finding a parking space and retrieving from it without interaction and without the presence of the driver (IHS Automotive, 2014). Shoup (2005) indicated that around 30 percent of traffic in business districts is caused by vehicles, trying to find a place to park near their occupants' desired destination. Drivers of autonomous vehicles can ask the vehicle to drop them off at destination and to find a parking place in a cheaper area. This saves the driver a significant amount of time and money (Fagnant & Kockelman, 2013; Ferreras, 2014; IHS Automotive, 2014; Knight, 2012; KPMG & CAR, 2012). Moreover, self-parking should reduce the number of minor damages caused by parking accidents.

Especially in rural areas, parents or friends spend a lot of time driving people around that are under current legislation unable to drive, e.g. elderly, young or sick people. Experts agree that the cost of time for these rides can be drastically reduced by transporting these groups of people in driverless cars (Fagnant & Kockelman, 2013; IHS Automotive, 2014; KPMG & CAR, 2012).

2.1.3 Fuel savings

Similarly to time savings, anticipatory driving from V2V and V2I communication enables fuel reduction (Fagnant & Kockelman, 2013). Atiyeh (2012) showed that fuel economy may increase by 23 to 39 percent through automated vehicles, ACC and V2V and V2I.

Additionally, the higher utilization of roads, autonomous vehicles ability' to travel closely together and reduction of air resistance of shared slipstreams will further result in fuel savings (Fagnant & Kockelman, 2013).

Lastly, several studies mention that increased fuel economy of automated vehicles may lessen environmental damage from reduced greenhouse emissions and lower air pollution and thus have a possibility to reduce social costs related to human health but also climate change (Anderson et al., 2014; Ferreras, 2014; KPMG & CAR, 2012).

2.1.4 Productivity

Autonomous technology enables passengers of driverless cars to involve themselves in different kinds of activities, such as working, watching movies, reading or even sleeping (Anderson et al., 2014; Fagnant & Kockelman, 2013; Kelly & CNN, 2014). Moreover, designers already imagine cars to be transformed into mobile offices for job categories like salespersons, which have to travel a lot (AG, 2014).

Finally, people have experienced situations in which they would like to meet friends or family, but eventually do not, because the use of public transport and/or driving themselves takes too much time and effort. With the possibility to do other things than driving, autonomous driving technology and its ability to reduce the opportunity cost of time, has a great potential to solve these issues (Fagnant & Kockelman, 2013; Kelly & CNN, 2014).

2.2 Effects on convenience and travel behaviour

2.2.1 Increased mobility for people unable or unwilling to drive

Automated vehicles will allow access to individual mobility for young, elderly, sick, or blind people that are currently not allowed to steer a car (Anderson et al., 2014). In Googles driverless car video "Self-Driving Car Test: Steve Mahan" a blind man is invited to go around town in one of their self-driving cars to run errands, such as buying tacos

(Google Inc., 2014). Other usage examples of self-driving cars are rides to hospital by sick people or just carrying the children to and from school.

Concluding, these groups of people can especially benefit from more independence, reduced social isolation and access to essential services (Ayodele & Ragland, 2003; Rosenbloom, 2001).

2.2.2 Efficiency – utilization of cars & cost savings

Shoup (2005) argued that the typical car sits idle in the parking spot around 95 percent of its lifetime. Researchers anticipate that private persons can reduce the number of cars they own since one automated car can drop of and pick up several family members during the day instead of a manual driven one being parked 23 hours out of every day (Fagnant & Kockelman, 2013, Ferreras, 2014).

As a solution to high vehicle cost and low utilization rate, consumers already engage in increased car sharing services. Therefore, experts anticipate this current trend in North America and Europe to strengthen with the emergence of autonomous cars and the possibility of lowering vehicle costs per person (Anderson et al., 2014; Butterman, 2013; Fagnant & Kockelman, 2013; KPMG & CAR, 2012)

2.2.3 Insurance charges

Experts believe that fully autonomous cars will have a large possibility to reduce individual car insurance costs (Anderson et al., 2014; KPMG & CAR, 2012). Car premiums are calculated based on driver and vehicle characteristics like age, number of accidents in the past, gender, engine size, etc.. New service models, such as “pay as you go and drive” are expected to enable drivers to save insurance costs, because insurance companies can offer different premiums for human driven and autonomous driven cars (KPMG & CAR, 2012). Thus, there is a high probability that insurance premiums for driverless cars will be lower due to the avoidance of human errors.

2.2.4 Trends

Knight (2012) argued that demographic change, ageing population with slower reflexes and worsening eyesight in Western societies increase the need for driverless cars to remain mobile and independent.

In contrast studies indicated that young people become less enthusiastic to drive and fewer young people gain a driver license (Davis & Dutzik, 2014; KPMG & CAR, 2012). Neff (2010) and Davis & Dutzik (2014) advocated that younger generations, growing up with social networks, game consoles and smart phones are less interested in cars, because they want to be constantly connected and perceive the act of driving rather as a distraction from being online. Davis & Dutzik (2014), KPMG & CAR (2012) and Fagnant & Kockelman (2014) posed that car ownership became less important to generation Y.

Additionally, KPMG & CAR (2012) found that even baby boomers owning premium cars would eagerly give up driving to work in exchange for a stress-free commute.

Moreover, especially in urban areas an increasing usage of car sharing is predicted because driverless cars can be ordered flexibly according to personal needs using telecommunication devices like smartphones (Fagnant & Kockelman, 2014; KPMG & CAR, 2012).

Concluding, experts anticipate that all three trends will support the acceptance of driverless vehicles. (Anderson et al., 2014; Butterman, 2013; Fagnant & Kockelman, 2013; KPMG & CAR, 2012).

2.3 Potential disadvantages

Autonomous driving technology does not only offer advantages, but also disadvantages. In case all mentioned benefits and trends prove true, they also point toward increasing vehicle miles with associated externalities of increasing absolute fuel consumption, congestion, suburban sprawl and higher demand for road capacity in total (Anderson et al., 2014; Fagnant & Kockelman, 2013; KPMG & CAR, 2012). Since many of the benefits depend on network effects, the adoption of autonomous cars, V2V and V2I communication, it is hard for experts to forecast the exact development.

Moreover, automated technologies are likely replace jobs related to driving, such as taxi and bus operators and delivery and professional driver jobs (Anderson et al., 2014; Fagnant & Kockelman, 2013; KPMG & CAR, 2012). In contrast, the new technology will also create a high amount of new jobs, however, it is questionable if a skill match exists for those people losing their occupation (Anderson et al., 2014).

Additional industries such as insurance companies, repair shops, doctors and lawyers will face strong changes in the economic environment as road accidents disappear (Fagnant & Kockelman, 2013).

2.4 Barriers

2.4.1 Software and hardware reliability

Today’s traffic situations are very complex because they involve many participants such as other vehicles, cyclist, pedestrians, animals but also physical obstacles like construction sites or lost objects on the Recognizing humans and other objects on the road is critical and difficult for computers, since they can appear in all sizes and may be standing, walking or even lying (Fagnant & Kockelman, 2013).

Especially urban traffic shows a high amount of complexity, which is yet not mastered by any of the current companies (Anderson et al., 2014). The software, operating these cars has to be completely reliable and will need extensive testing of all possible events (IHS Automotive, 2014).

Another issue mentioned by IHS Automotive (2014) is cyber security. Accordingly the industry will be constantly challenged to provide a secure system, which is able to detect and rectify intrusions into the vehicle’s operating system.

Additionally, the software reliability, poor weather conditions such as fog, snow, ice, rain and storms challenge the hardware, especially the sensors to safely operate self-driving vehicles (Anderson et al., 2014; Fagnant & Kockelman, 2013).

2.4.2 Customer acceptance

The acceptance of driverless technology by consumers ranks among the highest obstacles of driverless technology (Butterman, 2013). A lot of people really enjoy driving themselves and strongly identify themselves with cars (Butterman, 2013). Butterman argues that to give this freedom up is not appealing for them and will require a lot of effort to change their behavior and habits.

Furthermore, people have to trust the technology (IHS Automotive, 2014; KPMG & CAR, 2012). In a survey among 1,500 American, Australian and British drivers regarding limited and completely autonomous driving vehicles, approximately three-quarter of Americans and two-thirds of Australians and British are moderately and highly concerned about the performance of self-driving vehicles compared to human drivers (Schoettle & Sivak, 2014). Additionally, the survey results show that nearly two-third are strongly or moderately worried about the systems' and cars' security from hackers, a possible loss of privacy and data, the systems' performance in bad weather conditions and its interaction with other vehicles, bicyclists and pedestrians (Schoettle & Sivak, 2014).

2.4.3 Implementation of regulatory and legal framework

Finally, the availability or the lack of legislation will influence the speed at which automated cars are allowed to enter the market (IHS Automotive, 2014). Some states of the U. S., such as California and Nevada, already passed legislations permitting the operation of autonomous cars. However, the majority of states and especially no complete country in the world has passed any legislation yet (KPMG & CAR, 2012).

Furthermore, a legal framework regulating insurance and liabilities for self-driving cars is missing (IHS Automotive, 2014). There are still several open questions regarding the liability in accidents: "Who is liable if an automated car gets involved in an accident? - The passenger of the vehicle, the manufacturer or the company providing the operation system?" (KPMG & CAR, 2012). Since such potential complex liability issues have to be settled, legislation experts believe especially the implementation of a legal framework will slow down the growth of automated cars (IHS Automotive, 2014; Kelly & CNN, 2014; KPMG & CAR, 2012).

3 State of the art on acceptance and behavioural theory

At first, an introduction to the different definitions of acceptance and the term used for this research is given. Afterwards, the link between intention and behavior is explained. Moreover, the model of acceptance of DAS, the theory of reasoned action (TRA) and theory of planned behavior (TPB) are discussed.

3.1 What is acceptance

In the field of drivers' acceptance of support systems, it is close to impossible to find a standard definition of acceptance that fits all purposes and disciplines (Arndt & Engeln, 2008). Regan, Mitsopoulos, Haworth, & Young (2002) argued:

> *"While everyone seems to know what acceptability is, and all agree that acceptability is important, there is no consistency across studies as to what 'acceptability' is and how to measure it".*

A major problem of acceptance research in this field derives from the mixture of attitude and behavior aspects (Anstadt, 1994). Franken (2007) stated that the decision to accept a system is based on attitudinal acceptance from experience and emotions related to the system. Kollmann (1999) defined that acceptance goes beyond the affective and cognitive attitude formation, and intention to act. Additionally, he posed that acceptance manifests in the specific acquisition and usage of a product. Similarly, Arndt (2004) affirmed in the context of DAS that the acceptance of DAS has to connect the affective and cognitive assessment with the actual adoption and use of the system. Likewise, (Adell, 2009) defined acceptance of DAS as:

> *"the degree to which an individual intends to use a system and, when available, to incorporate the system in his/her driving."*

Based on the discussion of the term acceptance and the unavailability of driverless car technology, the definition for this research is built on intention and not actual behavior.

3.2 From intention to behavior

Behavioral intention is an indicator of a person's readiness to perform a given behavior and is considered to be the direct antecedent of behavior (Ajzen, 1991). Wicker (1969) revealed that studies using intention to predict behavior had a rather low and nonsignificant intention-behavior relationship. Conversely, Ajzen (1991) found the intention-behavior relationship to be positive and significant, if research is well established.

Intention is a weak predictor of behavior, if the target behavior is formulated vaguely, if attitude and intention after being measured change, and if the timespan between the measurement of intention and the behavior is very long (Ajzen, 2005). To reliably predict behavior from intention, the target behavior, the situation, in which the behavior should be performed, and the time aspect has to be formulated specifically (Ajzen, 1991).

Intention as a predictor of behavior is not limited to behavior changing studies, but is widely used in acceptance of information technology research, product development, and medical research (e.g. Davis, Bagozzi, & Warshaw, 1989; Venkatesh et al., 2003).

3.3 Fundamental theoretical models

This research is based on the revised "*Modell der Akzeptanz von Fahrerassistenzsystemen*" (Arndt & Engeln, 2008). An English title for the theory is not available; therefore the proposed translation "Model of Acceptance of Driver Assistance Systems" (MADAS) will be used for better understanding for the rest of the study.

Since the MADAS is based on the theory of reasoned action and the theory of planned behavior, both theories are reviewed before proceeding to MADAS.

3.3.1 Theories of reasoned action and of planned behavior

The TRA by Fishbein & Ajzen (1975) is one of the most fundamental and influential theories to predict human behavior (Venkatesh et al., 2003). It states that an individual's behavioral intention depends on the person's attitude toward behavior and the surrounding subjective norms toward the behavior (Fishbein & Ajzen, 1975). The behavioral intention then directly influences people's behavior.

The TPB is an extension of the TRA to help explain how people's behavior can be changed (Ajzen, 1991). Both are illustrated in figure 3-1.

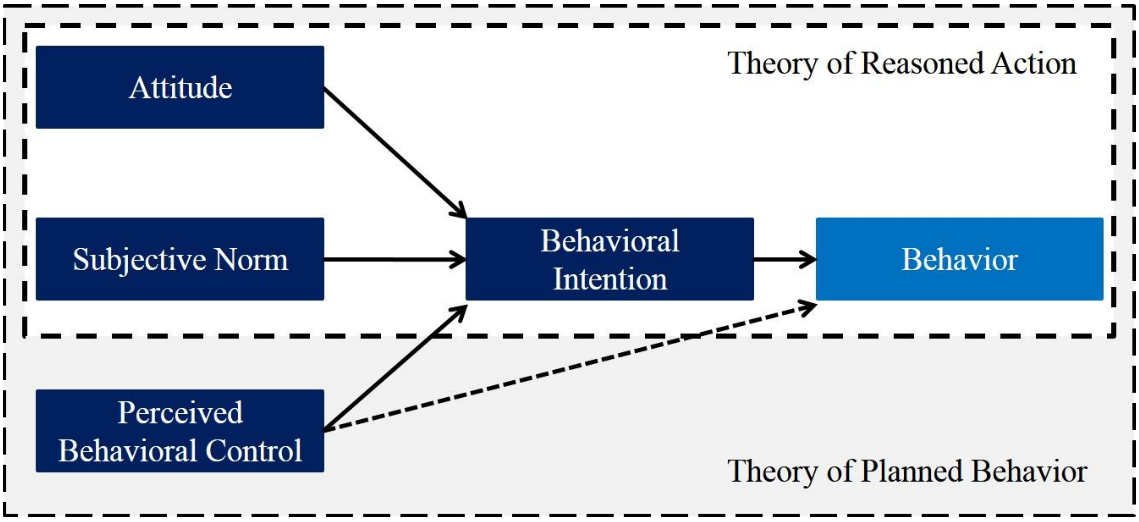


Figure 3-1: Theory of reasoned action and theory of planned behavior. Source: Adapted from Madden, Ellen, & Ajzen (1992).

Ajzen (1991) included the variable Perceived Behavioral Control into TRA to account for non-voluntary behaviors. The formed TPB suggests that Behavioral Intentions and Behavior are guided by Attitude toward Behavior, Subjective Norm and by Perceived Behavioral Control (Ajzen, 1991).

Attitude toward Behavior is an individual's evaluation of positive and negative consequences that are perceived results from performing the target behavior (Fishbein & Ajzen 1975). *Subjective Norm* describes a person's perception whether people, who are important to him/her, think that he/she should or should not perform the behavior under consideration (Fishbein & Ajzen 1975). *Perceived Behavioral Control*, is a persons' evaluation with which expected easiness or difficulty the behavior will be performed (Ajzen, 1991). The *Behavioral Intention* measures a person's relative strength of intention to perform the behavior in question (Fishbein & Ajzen, 1975). Finally, *Behavior* is the observable outcome in response to a given situation and target (Fishbein & Ajzen, 1975).

3.3.2 Model of Acceptance of Driver Assistance Systems

The MADAS is based on the *theory of planned behavior* and the *acceptance model of road pricing measures* by Schlag (1997). Firstly, Arndt & Engeln (2008) designed the model to explain the acceptance of DAS, where acceptance is being defined as the actual purchase and use of the systems. Secondly, it is used to identify and analyze barriers and incentives to buy these systems before they are introduced to the market (Arndt & Engeln, 2008).

The MADAS is shown in figure 3-2.

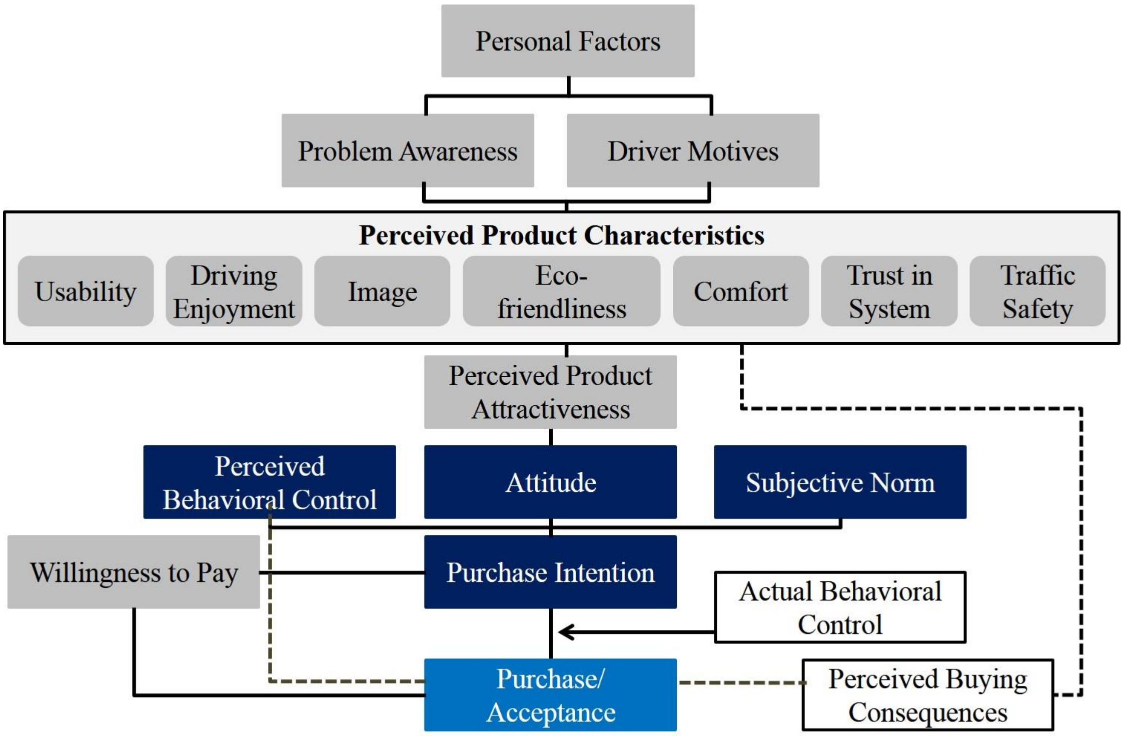


Figure 3-2: Model of Acceptance of Driver Assistance Systems. Source: Arndt, Engeln, & Vratil, (2008).

The acceptance of a DAS is predicted using the variables of the TPB, and includes external variables (perceived product features) to obtain detailed reasons for the acceptance or rejection of DAS.

Purchase Intention to buy driverless driving technology is defined as the degree to which an individual believes that one will acquire a fully autonomous driving system in the future. *Attitude toward Buying* includes the consequences that potential customers expect from the purchase and the value they attach to these expectations (Arndt & Engeln, 2008).

Subjective Norm is an individual's belief that reference persons or groups have regarding the acceptance of the system in question (Arndt & Engeln, 2008).

Perceived Behavioral Control is defined as the expected ease or difficulty to actually purchase the DAS, which is assumed to depend on an individual's belief about own abilities, resources and situational factors (Arndt & Engeln, 2008).

The *Perceived Product Characteristics* identify and measure the direction and strength of whether users approve or reject some characteristics (Arndt & Engeln, 2008). They proposed that a DAS can contribute to *comfort while driving, traffic safety, eco-*

friendliness, *driving enjoyment* and *driver image*. Additionally, this construct measures the consumer's *trust in the system* and the *usability* of it.

Arndt (2011) revised the MADAS, after performing a two-step structural equation model analysis on it in her doctoral thesis. Figure 3-3 illustrates the revised model.

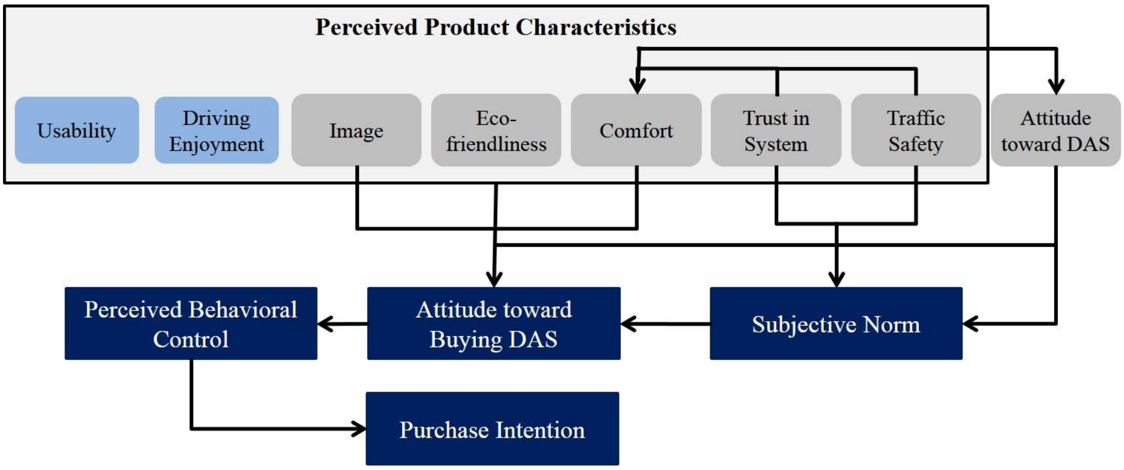


Figure 3-3: Revised Model of Acceptance of Driver Assistance Systems. Source: Arndt (2011).

Arndt (2011) tested the model for a navigation system and found that all effects from Perceived Product Characteristics were completely mediated by the variables of the TPB on Purchase Intention. In contrast to TPB, Subjective Norm did not have a direct impact on Intention but on Attitude toward Buying the DAS. Additionally, Attitude toward Buying the DAS was found to directly influence Perceived Behavioral Control besides directly influencing Purchase Intention (Arndt, 2011). The causal effects of Usability and Driving Enjoyment could not be assessed since they caused a negative covariance matrix (Arndt, 2011).

4 Research methodology

In the beginning of this section, the research model to explore the acceptance of driverless car technology is presented and the hypotheses to be tested, are developed. Afterwards the method and measures used to gather, process and analyze the data, are described. The chapter finishes with an overview on descriptive statistics of the survey.

4.1 Research model

The research model, illustrated in figure 4-1 is based on the MADAS (Arndt, Engeln, & Vratil, 2008), and adapted to the acceptance of fully autonomous driving systems for cars.

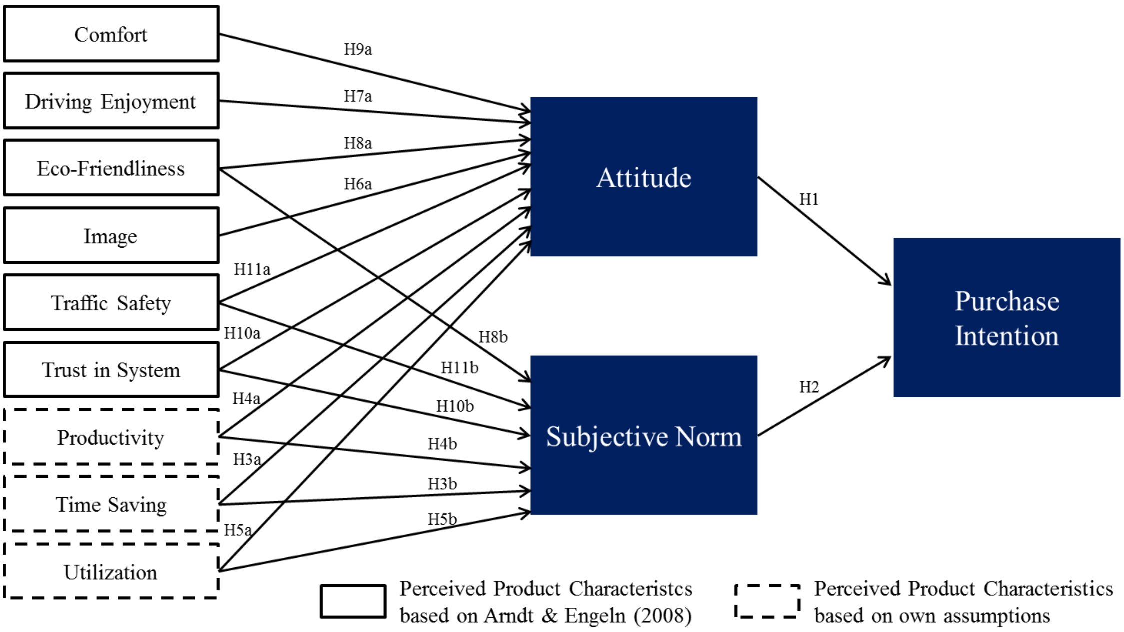


Figure 4-1: Research model including hypothesized direct effects. Source: Own illustration.

The model hypothesizes that Perceived Product Characteristics are expected to influence Subjective Norm and Attitude. Potential consumers' Purchase Intention is proposed to be determined by his/her Attitude and by Subjective Norm. Attitude and Subjective Norm are expected to mediate all effects from Perceived Product Characteristics on Purchase Intention.

Purchase Intention to buy driverless driving technology is defined as the degree to which an individual believes that one will acquire a fully autonomous driving system in the future.

Attitude, equivalent to Attitude toward Behavior by Fishbein & Ajzen (1975), is the product of the consequences that potential customers expect from the purchase of a fully autonomous driving system and the value they attach to these expectations (Arndt & Engeln, 2008).

S*ubjective Norm* is an individual’s belief that reference persons or groups have regarding the acceptance of the system in question (Arndt & Engeln, 2008).

Perceived Product Characteristics identify whether the users approve or reject some characteristics. They measure the perceived impact of DAS on *Comfort while driving, Traffic Safety, Eco-Friendliness, Driving Enjoyment, Driver Image* and consumer’s *Trust in the System* (Arndt & Engeln, 2008). To fit the model to driverless systems, the perceived characteristics *Productivity, Efficiency,* and *Time Saving,* derived from fully autonomous driving literature (see chapter 2), are added as possible predictors of intention. Moreover, *Usability* was removed from the model.

The construct of Perceived Product Characteristics helps to answer the first, second and third objective of this research: (1) Which product characteristics of driverless technology influence the consumers’ purchase intention? (2) How strong is the influence of perceived product characteristics on purchase intention? (3) Are the influences positively or negatively related?

The variables *Attitude* towards buying and *Subjective Norm* of the TRA, are mediators. Mediators describe a causal chains of causation and help to identify a more accurate explanation for the relationships between independent and dependent variables (Hair, Black, Babin, & Anderson, 2010). In this research model, they are necessary to answer the fourth objective: (4) Why do the perceived product characteristics affect purchase intention?

4.2 Theoretical reasoning and hypothesis development

In chapter 3.2 empirical findings regarding the positive relationship between behavioral intention and behavior have already been discussed. (Ajzen, 1991) found if a person has a strong behavioral intention, the probability is high that the person will perform the behavior. In context of this study, purchase intention means that the person has the objective to buy a fully autonomous driving system and based on past findings, predicts actual purchase in the future.

4.2.1 Effects of behavioral variables

Attitude consists of an emotional evaluation toward the behavior and an cognitive evaluation of the expected consequences of the behavior (Arndt, 2011). Arndt (2011); König (2005) and identified Attitude to be the strongest predictor, explaining between 69 and 74 percent of the variance in Purchase Intention of DAS. In line with this, it is proposed:

H1: Attitude has a positive direct effect on Purchase Intention.

Subjective Norm is determined by the perceived expectations of people, who are important to the user and the strength of motivation to comply with their expectations Due to the high price value of a car purchase and different needs of users in a household, potential buyers take into account the opinion of others in their purchase decision (Davis, 1976). Further, while only a part of the benefits are accumulated by the buyer of the vehicle, the majority of benefits accrues to other vehicles, bicyclists, pedestrians and the environment in the form of positive externalities (Anderson et al., 2014; Fagnant & Kockelman 2013). Both, opinion of important others and the wider society, are expected to cause a positive relationship between Subjective Norm and Purchase Intention.

H2: Subjective Norm has a positive direct effect on Purchase Intention.

4.2.2 Effects of perceived product characteristics on acceptance

Empirical studies have shown that consumers' evaluation of product functions impact the acceptance of DAS (Arndt, 2004; Arndt, 2011; Huth & Gelau, 2013; König, 2005, Van der Laan, 1998). Since fully autonomous driving systems are made up of the sum of several DAS, perceived product characteristics are hypothesized to impact the Purchase Intention of these systems in the future.

Usability (often termed Perceived Easiness to Use) has shown to be an important predictor of use in several acceptance studies (Davis, 1985; Davis et al., 1989; Venkatesh, Thong, & Xu, 2012). However, currently only assumptions are available on how driverless technology will be controlled in the future, e.g. via voice control or smartphone (KPMG & CAR, 2012). Without the possibility of interacting with a prototype or viewing a presentation on how the systems will be operated, reliable results when asking individuals regarding their perceived usability of a driverless system are not expected. Thus, it was decided to remove it from the model. Nevertheless, once the operation of the systems is known, it is recommended to include this variable in future acceptance studies related to driverless driving technology.

Perceived Time Saving measures the degree to which an individual believes that using the system will help to save time. The use of fully autonomous driving technology is expected to decrease traveling time through optimized routing, anticipative driving and efficient use of lanes (Anderson et al., 2014; Fagnant & Kockelman, 2013; KPMG & CAR, 2012). Shoup (2006) observed that around 30 percent of traffic in business districts is caused by vehicles trying to find a place to park. The system's self-driving and self-parking function is expected to enable drivers to send the vehicle to find a parking and park on its own (Fagnant & Kockelman, 2013; Ferreras, 2014; IHS Automotive, 2014; Knight, 2012; KPMG & CAR, 2012). Moreover, fully autonomous driving systems enable individual mobility for people that are unfit or unable (e.g. elderly, young or physically handicapped) to drive (Fagnant & Kockelman, 2013; KPMG & CAR, 2012). With this the time spent driving family members or friends around that are unable to drive, can be reduced, because they can use a car with a driverless system themselves. In conclusion it is hypothesized:

H3a: Time Saving has a positive direct effect on Attitude.

H3b: Time Saving has a positive direct effect on Subjective Norm.

H3c: Time Saving has a positive indirect effect on Purchase Intention.

Perceived Productivity assesses the degree to which consumers associate that the use of the system supports them to increase their ability to achieve more things that are important to them. The technology enables passengers to involve themselves in all kind of different activities such as working, watching movies, reading or even sleeping (Anderson et al., 2014; Fagnant & Kockelman, 2013; Kelly & CNN, 2014) while driving. Thus, the opportunity cost of time for owners of the technology is reduced (Fagnant & Kockelman, 2013; Kelly & CNN, 2014). Moreover, people encounter situations where they would like to go to places, meet family or friends but driving there and back by car is too much effort and public transport can be inconvenient and costly. Since driverless driving enables to reach places without engaging in tiring drives and without compromising on convenience or flexibility it is expected to increase the time and amount for activities with family and friends. Therefore, it is hypothesized:

H4a: Productivity has a positive direct effect on Attitude.

H4b: Productivity has a positive direct effect on Subjective Norm.

H4c: Productivity has a positive indirect effect on Purchase Intention.

Perceived Utilization measures the degree to which an individual believes that purchasing the system will enable a higher usage of a car. According to Shoup (2005) the typical car sits idly in the parking spot around 95 percent of its lifetime. Cars with fully automotive driving systems enable to use a car more often and thereby increase possible utilization (Fagnant & Kockelman, 2014; Ferreras, 2014; KPMG & CAR, 2012). Since one automated car can drop of and pick up several household members during the day instead of a manual driven car sitting idly on the parking spot while being at work (Fagnant & Kockelman, 2014) a positive relationship between Utilization and Attitude, Subjective Norm and Purchase Intention is hypothesized.

H5a: Utilization has a positive direct effect on Attitude.

H5b: Utilization has a positive direct effect on Subjective Norm.

H5c: Utilization has a positive indirect effect on Purchase Intention.

Perceived Image measures the effect of the system's use on driver image and acceptance of the technology (Arndt, 2011). Cars and new technologies, are often used to express or improve ones' status (Arndt, 2011). Yet, the use of driverless technology could also have a negative effect, since the technology could convey that its users are bad drivers. Nevertheless, as benefits of driverless driving technology accrue to the owner and to other traffic participants, household members and environment (Fagnant & Kockelman, 2013), it is expected that buying a driverless system is viewed as beneficial and desirable by society. Since the effect of Image considers what other people think about the purchase, Image is hypothesized to have a positive effect on Subjective Norm and Purchase Intention.

H6a: Image has a positive direct effect on Subjective Norm.

H6c: Image has a positive indirect effect on Purchase Intention.

Perceived Driving Enjoyment measures the degree to which an individual perceives that a driverless system positively influences driving enjoyment (Arndt, 2011). Arndt (2011) argued that acceptance is negatively influenced by driving systems that reduce driving enjoyment or increase boredom while driving. The impact of fully driverless technology on driving enjoyment is however unclear, since it depends on whether people enjoy the act of driving more than doing something else, e.g. reading a book, working or socializing. Nevertheless, as people can decide when to drive themselves and when to use the system to engage in another activity, a positive relationship between Driving Enjoyment and Attitude and Purchase Intention is hypothesized.

H7a: Driving Enjoyment has a positive direct effect on Attitude.

H7b: Driving Enjoyment has a positive indirect effect on Purchase Intention.

Perceived Eco-Friendliness is the degree to which a person associates that the system reduces the environmental impact of driving (Arndt, 2011). Through anticipative driving, efficient routing and higher usability of the car, autonomous driving systems are expected to use fuel more efficiently and to be more environmentally friendly (Fagnant & Kockelman, 2014; KPMG & CAR, 2012). Over the last decade, social responsible consumption and demand for sustainable products has been increasing (Webb, Mohr, & Harris, 2008). Studies found that consumers' intention to buy environmentally friendly products were affected by environmental consciousness, social norms and the pressure to conform to it. Additionally, consumers were found to purchase green products to improve their self-image (Kaiser, Wolfing & Fuhrer, 1999; Kim & Chung, 2011; Park & Sohn, 2012). Since fully autonomous driving systems are expected to have a positive impact on the environment, and taking into consideration findings from conscious consumer studies, a direct effect on Subjective Norm, Attitude and Purchase Intention is hypothesized:

H8a: Eco-Friendliness has a positive direct effect on Attitude.

H8b: Eco-Friendliness has a positive direct effect on Subjective Norm.

H8c: Eco-Friendliness has a positive indirect effect on Purchase Intention.

Perceived Comfort deals with the degree to which an individual believes that the system impacts the comfort of driving in a car (Arndt, 2011). Driver system relieving the driver from stressful situations have a positive effect on acceptance (Arndt, 2011). Again, the possibility to hand over control to the system at any time and to avoid driving in stressful traffic situation, e.g. during rush hours, or when being tired, is expected to positively influence acceptance of the technology (KPMG & CAR, 2012). Consequently, Comfort is expected to positively influence Attitude and Purchase Intention.

H9a: Comfort has a positive direct effect on Attitude.

H9b: Comfort has a positive indirect effect on Purchase Intention.

Perceived Trust identifies the effect of trust on acceptance of the system (Arndt, 2011). A fully autonomous driving system performs all functions of controlling the vehicle (IHS Automotive, 2014). Therefore, it is expected that only people that have trust in the system will value the product and form a Purchase Intention, since a malfunction of the system could lead to injury or death. Additionally, other researchers posed trust to be an important determinant of acceptance (e.g. Abe & Richardson, 2006; Arndt, 2011; Kassner & Vollrath, 2006). Moreover, Arndt (2011) found a positive relationship between Trust and Subjective Norm. Consequently, it is hypothesized:

H10a: Trust has a positive direct effect on Attitude.

H10b: Trust has a positive direct effect on Subjective Norm.

H10c: Trust has a positive indirect effect on Purchase Intention.

Perceived Traffic Safety measures the degree to which consumers perceive that fully autonomous driving technology improves traffic safety (Arndt, 2011). Unlike humans, computers do not get distracted or tired in traffic (Fagnant & Kockelman, 2013; KPMG & CAR, 2012) and hence, automated vehicles have an enormous potential to reduce traffic accidents related to human error (Anderson et al., 2014; Bickerstaffe, 2014; Butterman, 2013; Fagnant & Kockelman, 2013; Hayes, 2011; IHS Automotive, 2014; KPMG & CAR, 2012). Since drivers have the motive to reach their destination safely and most drivers have encountered precarious situations while driving, such a system would have been beneficial. A direct effect of Traffic Safety on Attitude is postulated. Moreover, a direct effect on Subjective Norm is expected, since researchers have found that the purchase of safety systems if often motivated by the pressure to comply with the expectations of others (Arndt, 2011; Schade & Schlag, 2003). The following is hypothesized:

H11a: Traffic Safety has a positive direct effect on Attitude.

H11b: Traffic Safety has a positive direct effect on Subjective Norm.

H11c: Traffic Safety has a positive indirect effect on Purchase Intention.

4.3 Measurement

In the field of acceptance of DAS studies, no general tool is available to validly and reliably measure the various constructs affecting it (Adell, 2009; Arndt, 2011; Regan et al., 2002). Nevertheless, there is consensus that quantitative questionnaires are the most suitable method to assess acceptance and underlying constructs (e.g. Beier, Boemak, & Renner, 2001; Van der Laan, 1998). Similarly, the acceptance of IT, which is the most mature field in acceptance studies is mainly measured using quantitative questionnaires (e.g. Davis, 1989; Gefen, Karahanna, & Straub, 2003; Venkatesh et al., 2012).

Accordingly, the underlying study draws on a quantitative questionnaire and mostly uses items and scales, which have been tested previously. Since the former questionnaire was in German, an English translation is presented while the German one is available in the Appendix A. The questionnaire items and their sources are shown in table 4-1.

The variables of Perceived Product Characteristics, Subjective Norm and Purchase Intention were measured on a 5-point Likert scale from (1) “Strongly Disagree” to (5) “Strongly Agree” with (3) “Neither Agree nor Disagree” in the middle. Attitude toward buying a fully autonomous driving system is measured using a semantic differential with 5 points drawn from Ajzen & Fishbein (2002).

Table 4-1: Translated questionnaire items. Source: Own illustration.

Construct	**Item**	**Source**
Which characteristics do driverless/autonomous car systems have? *Please evaluate the different properties of the system.*		
Traffic Safety	TraSaf1: The system improves road safety. TraSaf2: The system helps to reduce the risk of accidents	Arndt (2011)
Image	Image1: The system harms the image of the owner. Image2: It would be embarrassing for me to use the system in front of my colleagues. Image3: The system will be used by people that do not feel safe driving themselves.	Arndt (2011)
Driving Enjoyment	DE1: The system makes driving boring. DE2: The system increases driving enjoyment.	Arndt (2011)
Trust	Trust1: I trust that the system performs in my interest. Trust2: I do not trust the system.	Arndt (2011) Own item
Comfort	Comf1: The system allows the driver to physically relax while driving. Comf2: The system increases the stress level of the driver.	Arndt (2011)
Eco-Friendliness	EcoF1: The system supports environmental friendly driving. EcoF2: The system would help me to save fuel.	Arndt (2011)
Productivity	Prod1: The system would increase my chances of achieving things that are important to me. Prod2: The system would help me accomplish things more quickly.	Venkatesh et al. (2003) Own Item
Time Saving	TimeSav1: The system would help to decrease traveling time to my destinations. TimeSav2: The system would help me to save time.	Own item Own item
Utilization	Utilization1: The system enables to share a car more efficiently with others. Utilization2: The system enables a better/more efficient usage of the car.	Own item
Would you buy a car with a fully autonomous driving system? *I find buying a car with autonomous driving technology....*		
Attitude	Bad – Good Useless – Useful Unpleasant – Pleasant Unimportant – Important Harmful – Beneficial	Ajzen & Fishbein (2002)
What do you believe other people think about fully autonomous driving systems?		
Subjective Norm	SN1: I can imagine that my friends will buy a car with such a system. SN2: My friends would encourage me to buy a driverless system. SN3: My family would appreciate, if I would have such a system in my car. SN4: Others would find it good if I had a driverless system.	König (2005) Arndt (2004a) Arndt (2004a) Meyer (2002)
Would you buy a car with a fully autonomous driving system?		
Purchase Intention	PI1: I would like to have this system in my car. PI2: I will consider buying a car with such a system. PI3: Once the technology is available, I plan to buy a car with a driverless system.	Meyer (2002) Arndt (2011) Arndt (2011)

4.4 Data collection procedure and sample

The initial survey was pretested among 10 people in order to avoid vagueness in the questionnaire that could impact validity and reliability of the research. After ambiguous items were corrected, the survey was conducted online from 15.11. – 27.11.2014 using the Qualtrics survey software and distributed via social networks and e-mails.

As the topic of the survey was expected to be rather new to the survey participants, an introduction to driverless technology was provided before the survey started, which can be found in the Appendix B.

The survey proceeded as illustrated in figure 4-2.

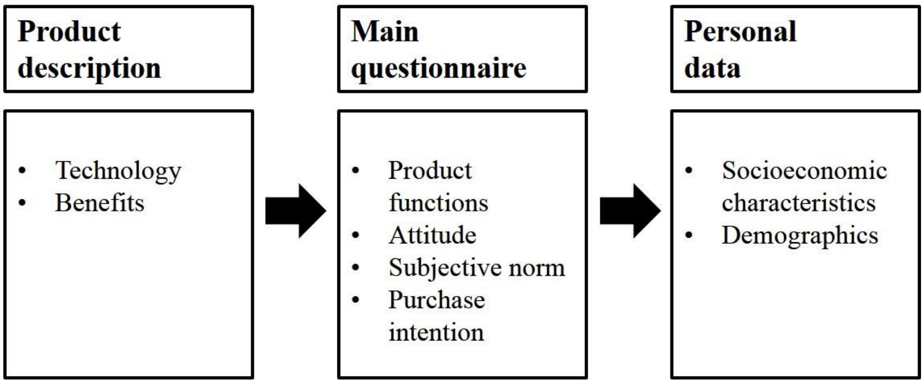


Figure 4-2: Process of survey. Source: Own illustration.

4.5 Method

As recommended by Arndt (2011), the research model was evaluated using structural equation modeling (SEM) via the software program AMOS. SEM allows to specify and operationalize hypothesis more precisely than multivariate regression, reveals relationships that have not been hypothesized and can be used for exploratory and confirmatory studies (Bagozzi & Yi, 2012). Further, SEM enables to examine complex relationships between latent variables simultaneously, to account for measurement errors and to calculate direct, indirect and total effects between variables (Jöreskog & Sörbom, 1982). Following the recommendation by Anderson & Gerbing (1988), the measurement and structural model were estimated separately. Reliability and validity of data obtained and theorized constructs were tested by exploratory factor analysis (EFA). EFA revealed that several of the constructs should be combined, due to high correlations between them. Therefore, a revised model was developed during the analysis part. The revised measurement model was tested for reliability and validity by confirmatory factor analysis (CFA). After the measurement model has been validated, the structural model was developed and hypothesized relationships were tested.

Prior to the analysis, the items TraSaf2, DE1, Comf2, Image1, Image2, Image3 and Trust2 were transformed to measure the same direction as the other items belonging to the same construct.

4.6 Descriptive statistics

Table 4-2 illustrates the demographic data of the sample. The sample of 115 participants consisted of 53 females (46 percent) and 62 males (54 percent).

Table 4-2: Descriptive statistics based on the survey. Source: Own survey and analysis.

	Frequency	Percent (%)	Cumulative
Total Sample	115	100,0	100,0
Gender			
Female	62	53,9	53,9
Male	53	46,1	100,0
Age			
16-24	21	18,3	18,3
25-34	59	51,3	69,6
35-44	11	9,6	79,1
45-54	10	8,7	87,8
55-64	7	6,1	93,9
65-74	7	6,1	100,0
Driven kilometers over the last year			
no km	4	3,5	3,5
below 5,000 km	36	31,3	34,8
5,001-10,000 km	28	24,3	59,1
10,001-15,000 km	23	20,0	79,1
15,001-20,000 km	13	11,3	90,4
more than 20,001 km	11	9,6	100,0
Net household income			
below € 500	3	2,6	2,6
€ 500 to € 1,000	12	10,4	13,0
€ 1,001 to € 2,000	19	16,5	29,6
€ 2,001 to € 3,000	20	17,4	47,0
€ 3,001 to € 4,000	18	15,7	62,6
€ 4,001 to € 5,000	13	11,3	73,9
above € 5,000	13	11,3	85,2
Unknown	17	14,8	100,0

5 Analysis

In this chapter, the survey results are presented and analyzed.

5.1 Data screening

5.1.1 Univariate

The online survey was completed by 123 German respondents. Thereof, three responses were deleted because of missing data. Since all variables were measured on a Likert scale, extreme outliers did not exist. Nevertheless, five additional responses were deleted due to unengaged answering (standard deviation < 0.5), as recommended by Gaskin (2012a), leaving 115 valid responses.

Since all variables were measured on 5-point Likert scales, it is adequate to assess univariate normality using kurtosis (Gaskin, 2012a). All variables showed univariate normality within the threshold of ±3.0 standard errors of kurtosis (Bollen, 1989), thus no lack of sufficient variance was detected.

5.1.2 Multivariate (tested after revised model)

Linearity was tested by curve estimation regression for all relationships in the model. It determined that all direct effects were sufficiently linear (all p-values<0.005) to be tested in SEM.

Multicollinearity was assessed calculating the Variable Inflation Factor (VFI) for all independent variables simultaneously. All of the VIFs had an acceptable level below 5.0 indicating that the variables were distinct (Hair, Ringle, & Sarstedt, 2011).

5.2 Measurement Model

5.2.1 Exploratory Factor Analysis

Several items have been newly developed for this research and the items drawn and adapted from other research have never been used in the context of fully autonomous driving systems. To investigate if variables loaded as expected, were sufficiently correlated within one factor and whether criteria of validity and reliability were met, explorative factor analysis (EFA) using principal component analysis (PCA) with varimax rotation was conducted. The Kaiser-Meyer-Olkin (KMO) measure and the Bartlett’s test assess whether the variables are adequate for an EFA (Janssen & Laatz,

2013) and communalities measure whether an item correlates with all other items. KMO values >0.8, a significant Bartlett's test and communalities higher than 5, indicate a good adequacy (Janssen & Laatz, 2013).

The KMO measure of 0.851, a significant (p=0.000) Bartlett test and all items except *Image1, Prod1 and TimeSav1* showing higher communalities than 0.5, indicated that the variables were sufficiently correlated and suitable for a factor analysis (Hair, Tatham, Anderson, & Black, 1998; Tabachnick & Fidell, 2007).

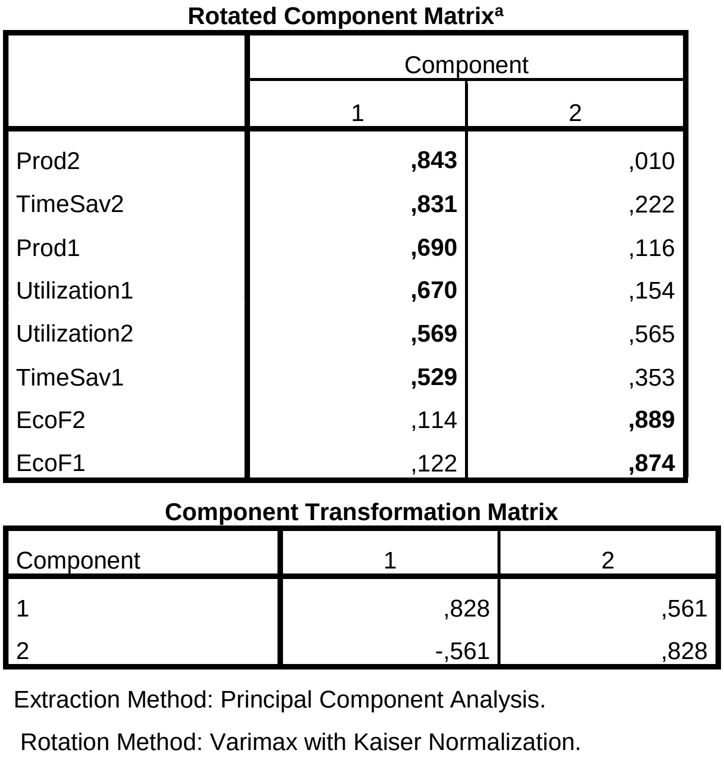
Based on Kaiser-criterion the rotated-component-matrix identified a 7-factor model, explaining 67.64 percent of total variance and did not support the theoretical model with 11 factors. The detailed results of the EFA can be found in Appendix C.

The EFA revealed that the items belonging to *Image*, *Subjective Norm*, *Driving Enjoyment*, *Comfort* and *Attitude* loaded as expected on a distinctive factor. However, EFA also reported that the three new constructs *Utilization*, *Time Saving* and *Productivity* loaded on the same factor as *Eco-Friendliness* and that *Trust* and *Traffic Safety* loaded on one factor.

As part of analyzing an EFA, Fabrigar & Wegener (2012) and Hair et al. (1998) stress the importance to balance parsimony (a model consisting of very few factors) and plausibility (ensuring that an appropriate number of factors are in the model to sufficiently account for correlations among variables), when deciding how many factors to be included. Moreover, Gaskin (2012b), Hair et al. (1998) and Janssen & Laatz (2013) recommended, if a theory has been established before doing an EFA, one should not blindly believe the EFA results, but should try to retain as much theoretical considerations as possible while still gaining valid results. Further, when considering the EFA solutions, one should check whether the items that load on the same factor are similar in nature (face validity) and make sense (Gaskin, 2012b).

The wording of the constructs *Utilization*, T*ime Saving* and P*roductivity* are all related to either time saving, accomplishing things in less time or better usage efficiency and can be considered to have a similar context. However, the items for E*co-Friendliness* ask whether fuel could be saved or environmental driving is supported, which is different in nature. Therefore, a second factor analysis with only these eight items was conducted. As table 5-1 shows, based on eigenvalue>1, two factors, with one factor consisting of all six items of *Productivity*, *Time Saving* and *Utilization* and a second factor consisting of the two *Eco-Friendliness* items were extracted, which are sufficiently uncorrelated (0.561). Based on this finding, it was decided to include the eight items into the models as two separate variables. One latent variable consisting of *Utilization*, T*ime Saving* and *Productivity* named “Efficiency” and the two items belonging to Eco-Friendliness have been retained under the same variable name, “Eco-Friendliness”.

Table 5-1: Rotated Component Matrix and Component Transformation Matrix. Source: Own survey and analysis.



Rotated Component Matrix[a]

	Component	
	1	2
Prod2	**,843**	,010
TimeSav2	**,831**	,222
Prod1	**,690**	,116
Utilization1	**,670**	,154
Utilization2	**,569**	,565
TimeSav1	**,529**	,353
EcoF2	,114	**,889**
EcoF1	,122	**,874**

Component Transformation Matrix

Component	1	2
1	,828	,561
2	-,561	,828

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

Likewise, a separate PCA for the items of *Trust* and *Traffic Safety was conducted*, which showed to load on two distinctive factors in past research but loaded on the same factor in the underlying EFA. However, as table 5-2 indicates, it was not possible to separate those items. A possible explanation for the strong correlation of these items could be that trust in a fully autonomous driving system is directly related with perceived traffic safety. If people do not consider the system safe they will not trust it. Vice versa it can be expected that people, who do not trust the system, will not consider it to improve traffic safety. Therefore, the variables should be kept as one variable named “Trust in Safety”, despite the findings of Arndt (2011), which found the items should load on different constructs.

Table 5-2: Component Matrix. Source: Own survey and analysis.

Component Matrix^a

	Component
	1
TraSaf1	,849
Trust2	,824
Trust1	,808
TraSaf2	,790

Extraction Method: Principal Component Analysis.

a. 1 component extracted

Since all other items loaded as proposed in the theoretical model, the revised model is shown in figure 5-1. As a result, the hypotheses H3a - H3c, H4a - H4c, H5a - H5c, H10a - H10c and H11a - H11c cannot be tested anymore. However, two new hypotheses are formed for the new factor “Efficiency” and “Trust in Safety”.

H12a: Efficiency has a positive direct effect on Attitude.

H12b: Efficiency has a positive direct effect on Subjective Norm.

H12c: Efficiency has a positive indirect effect on Purchase Intention.

H13a: Trust in Safety has a positive direct effect on Attitude.

H13b: Trust in Safety has a positive direct effect on Subjective Norm.

H13c: Trust in Safety has a positive indirect effect on Purchase Intention.

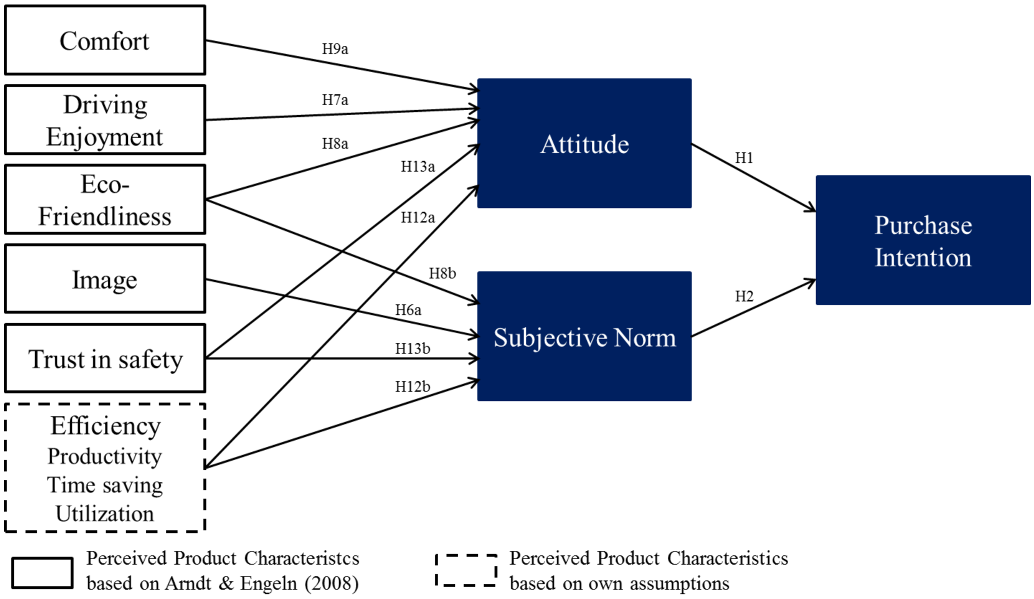


Figure 5-1: Revised research model. Source: Own illustration.

Reliability, meaning how dependable a set of items will consistently load on the same factor (Gaskin, 2012b) for the variables of the revised research model, was calculated using Cronbach's alpha and are shown in table 5-3.

Table 5-3: Construct reliability of the revised research model. Source: Own survey and analysis.

Variable Label	**Number of items**	**Cronbach's alpha**
Comfort	2	0.719
Driving Enjoyment	2	0.622
Eco-friendliness	2	0.793
Image	3	0.552
Trust and Safety	4	0.830
Efficiency	6	0.821
Attitude	5	0.91
Subjective Norm	4	0.84

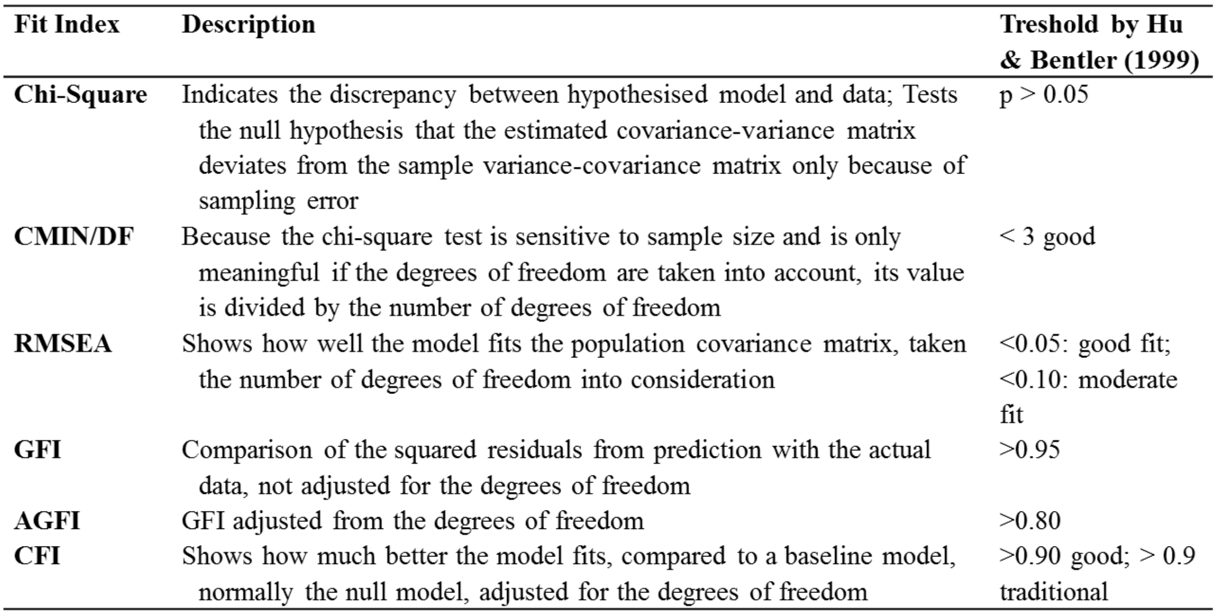
5.2.2 Confirmatory Factor Analysis

After the EFA, a CFA was conducted to test measurement model for validity and reliability.

Goodness of fit

Model fit analysis is used to assess how well the proposed model fits the data (Hair et al., 1998) and is the basis for accepting or rejecting a model. Measurement model validity is subject to an acceptable level of goodness of fit for the measurement model and construct validity (Hair et al., 2010). A description of the model fit indices for assessment of the measurement and structural model and recommended threshold by Hu & Bentler (1999) are shown table 5-4.

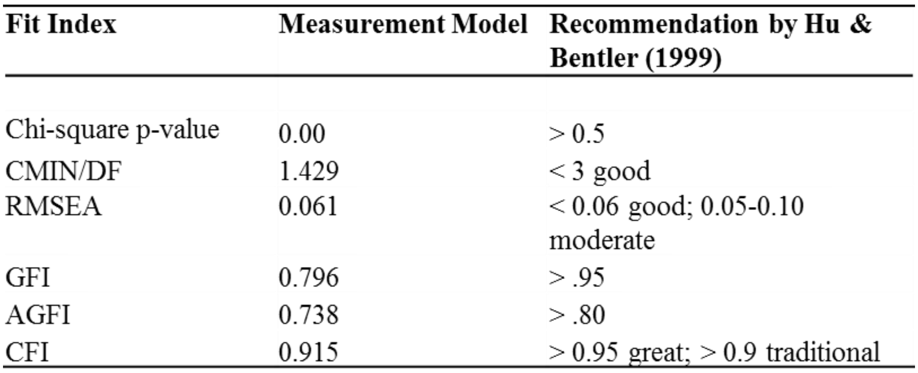
Table 5-4: Goodness of fit indices and recommended thresholds. Source: Vieira (2011).



Fit Index	Description	Treshold by Hu & Bentler (1999)
Chi-Square	Indicates the discrepancy between hypothesised model and data; Tests the null hypothesis that the estimated covariance-variance matrix deviates from the sample variance-covariance matrix only because of sampling error	p > 0.05
CMIN/DF	Because the chi-square test is sensitive to sample size and is only meaningful if the degrees of freedom are taken into account, its value is divided by the number of degrees of freedom	< 3 good
RMSEA	Shows how well the model fits the population covariance matrix, taken the number of degrees of freedom into consideration	<0.05: good fit; <0.10: moderate fit
GFI	Comparison of the squared residuals from prediction with the actual data, not adjusted for the degrees of freedom	>0.95
AGFI	GFI adjusted from the degrees of freedom	>0.80
CFI	Shows how much better the model fits, compared to a baseline model, normally the null model, adjusted for the degrees of freedom	>0.90 good; > 0.9 traditional

In order to improve the model fit, the error terms between Image1 and Image3, TimeSav2 and Prod 2, SN2 and SN4 and TraSaf1 and TraSaf2 are covaried. The goodness of fit values for the model are illustrated in table 5-5. Only CMIN/DF, CFI and RMSEA show sufficient values.

Table 5-5: Research model fit indices and recommended values. Source: Hu & Bentler (1999).



Fit Index	Measurement Model	Recommendation by Hu & Bentler (1999)
Chi-square p-value	0.00	> 0.5
CMIN/DF	1.429	< 3 good
RMSEA	0.061	< 0.06 good; 0.05-0.10 moderate
GFI	0.796	> .95
AGFI	0.738	> .80
CFI	0.915	> 0.95 great; > 0.9 traditional

Validity and Reliability

Convergent validity measures if the indicators load high on their hypothesized factors and do not load high on other factors (Bagozzi & Yi, 2012; Hair et al., 2010) and is calculated using the average variance extracted (AVE). A AVE of greater than 0.50 indicates high validity of the construct and the individual variable (Anderson & Gerbing, 1988; Bagozzi, Yi, & Phillips, 1991; Hair et al., 1998). For Image (0.362), Efficiency (0.420) and Driving Enjoyment (0.455) convergent validity issues were observed while, the other factors' AVE were above 0.50. AVE computations are illustrated in table 5-6.

Discriminant validity, measures whether a construct is really different from others (Fornell & Larcker, 1981; Hair et al., 2010). Constructs demonstrate discriminant validity when the square root of their AVE (value on diagonal on matrix below) is higher than any inter-factor correlations (Hair et al., 2010). Table 5-6 presents the outcome of the discriminant analysis and illustrates discriminant validity issues for Image with square root of AVE (0.602) < correlation between Image and Attitude (0.623) and Subjective Norm's square root of AVE (0.726) < correlation between Subjective Norm and Attitude (0.786). All other constructs had adequate discriminant validity.

Composite reliability (CR) measures the internal consistency of a measure and should be above 0.70 to be reliable (Fornell & Larcker, 1981; Hair et al., 2010). Table 5-6 shows the computed CRs' for every factor. For all factors CR was higher than 0.70, indicating reliability in the factors except for Image (0.624) and Driving Enjoyment (0.625), which displayed internal reliability issues in the factors.

Table 5-6: Validity and reliability measures for hypothesized constructs. Source: Own survey and analysis.

	CR	AVE	Image	Attitude	Efficiency	Safety	SN	DE	Comfort	EcoFriend
Image	**0.624**	**0.362**	**0.602**							
Attitude	0.913	0.679	0.623	0.824						
Efficiency	0.811	**0.420**	0.551	0.632	0.648					
Safety	0.806	0.520	0.56	0.696	0.432	0.721				
SN	0.816	0.527	0.571	0.786	0.583	0.605	**0.726**			
DE	**0.625**	**0.455**	0.588	0.565	0.533	0.521	0.472	0.675		
Comfort	0.736	0.588	0.473	0.564	0.555	0.513	0.507	0.568	0.766	
EcoFriend	0.794	0.659	0,269	0,283	0,566	0,313	0,201	0,212	0,051	0,812001

SN=Subjective Norm; DE=Driving Enjoyment; EcoFriend=Eco-Friendliness; Safety=Trust in Safety

Even though issues related to convergent and discriminant validity and reliability are evident, it was decided to keep all constructs and items in the model. Image and Driving Enjoyment are kept, since their respective items have been tested in past research and showed to be reliable and valid. Even though Efficiency is internally not especially strong (AVE=0.420), this shortcoming is considered admissible, since it is still a reliable (CR=0.811) and distinct construct within the model measuring three different perceived product characteristics (Time Saving, Productivity and Utilization).

5.3 Structural model

After the measurement model has been validated, the hypothesized relationships are tested using SEM in AMOS. The path model was created using composite variables from latent variables based on factor scores in AMOS.

The revised model did not demonstrate a good fit with the underlying data structure. Only CFI (0.947) achieved an adequate value. Modification indices revealed an insufficient model fit due to a wrong specification of Subjective Norm in the model. Subjective Norm was indicated to influence Attitude, which seems logical since it means that individuals take into account the opinion of other people when forming an attitude. Therefore, a regression line from Subjective Norm to Attitude has been included in the model.

The comparison of model fit indices is illustrated in Table 5-7. The model after the fitting indicates a good model fit.

Table 5-7: Model indices before and after fitting. Source: Hu & Bentler (1999).

	Changes	**Chi-square p-value for the model**	**CMIN/DF**	**RMSEA**	**GFI**	**AGFI**	**CFI**
Recommended values*		> 0.5	< 3 good	< 0.06 good; < .05-0.10 moderate	> .95	> .80	> 0.95 great
Revised model	-	0.00	4.727	0.134	0.927	0.673	0.958
Revised and refitted model	Including regression line from Subjective Norm to Attitude	0.641	0.774	0.000	0.987	0.934	1

6 Findings

Figure 6-1 displays the final structural model including the path from Subjective Norm to Attitude, significant and insignificant structural relationships, standardized regression weights and the predictive power (variance explained) of Attitude, Subjective Norm and Purchase Intention. The model explains 67 percent of the variance in Purchase Intention, 82 percent variance in Attitude and 68 percent of the variance in Subjective Norm.

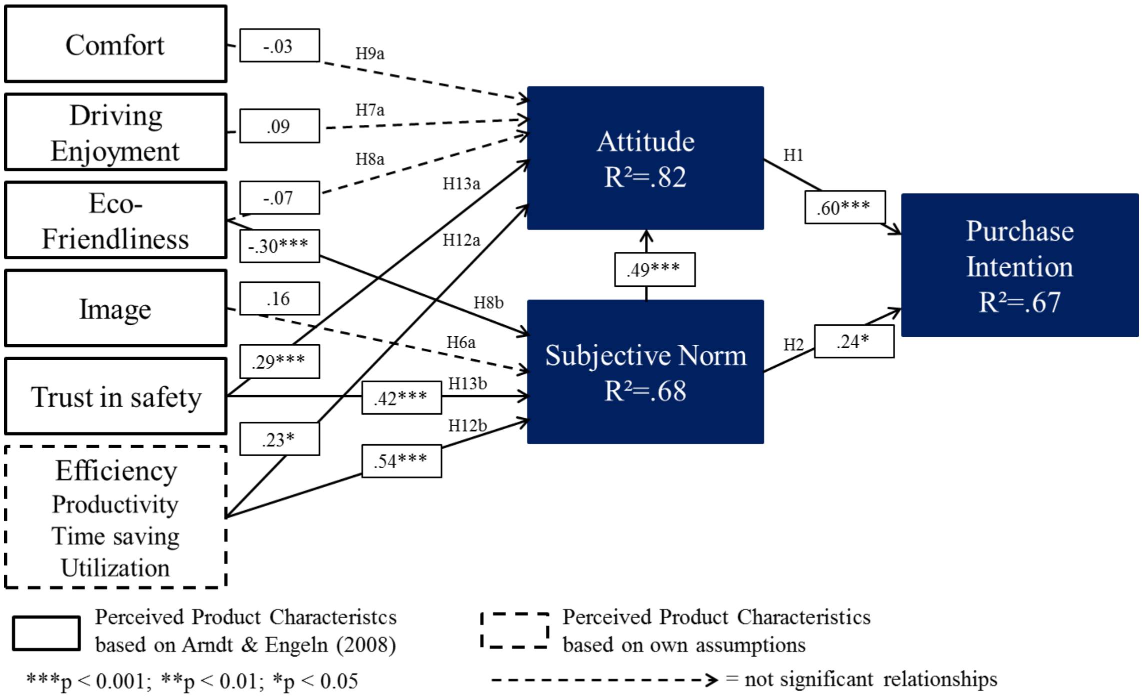


Figure 6-1 Direct effects of revised and fitted SEM. Source: Own survey and analysis.

As shown in Figure 6-1, and as postulated by the research model, Attitude and Subjective Norm have been found to be the only variables with a direct effect on Purchase Intention. The significant path from Subjective Norm to Attitude, meaning that Attitude mediates effects from Subjective Norm on Purchase Intention was not hypothesized but was found to be highly significant.

The path analysis confirmed the positive and significant direct effects from Attitude (0.604**) and Subjective Norm (0.236*) on Purchase Intention, supporting H1 and H2 and mean that Attitude and Subjective Norm are important determinants of Purchase Intention. Hypothesis H12a and H13a were also supported, since Efficiency (0.234*) and Trust in Safety (0.291***) indicated a significant positive direct effect on Attitude. Likewise, Trust in Safety (0.415***) and Efficiency (0.541***) also had a positive direct effect on Subjective Norm, confirming H12b and H13b. H8b, had to be rejected even though Eco-Friendliness (-0.296***) had a significant direct effect on Subjective Norm, the effect was not hypothesized to be negative. H7a, H8a and H9a had to be rejected since Comfort (-0.030), Driving Enjoyment (0.086) and Eco-Friendliness (-0.072) did not show a positive direct effect on Attitude. Further, Image (0.155) was not found to have a significant effect on Subjective Norm leading to a rejection of H6a.

Table 6-1 shows the strength and direction of the standardized direct, indirect and total effects of the SEM. 2,000 bias-corrected bootstrapping resamples with a confidence level of 95 was used to assess direct and indirect effects.

Table 6-1: Estimation results of the revised and refitted research model. Source: Own survey and analysis.

Structural Model Results: Revised and refitted model			
DV: Purchase Intention	**Standardized direct effects**	**Standardized indirect effects**	**Standardized total effects**
R²	0.67		
Efficiency		0.428**	0.428**
Trust in Safety		0.395**	0.395**
Image		0.082	0.082
Eco-Friendliness		-0.200**	-0.200**
Driving Enjoyment		0.052	0.052
Comfort		-0.018	-0.018
Attitude	0.604***		0.604**
Subjective Norm	0.236*	0.294***	0.529**
DV: Attitude	**Standardized direct effects**	**Standardized indirect effects**	**Standardized total effects**
R²	0.82		
Efficiency	0.234*	0.263**	0.497**
Trust in Safety	0.291***	0.202**	0.493**
Image		0.076	0.076
Eco-Friendliness	-0.072	-0.144**	-0.216*
Driving Enjoyment	0.086		0.086
Comfort	-0.030		-0.030
Subjective Norm	0.487***		0.487**
DV: Subjective Norm	**Standardized direct effects**	**Standardized indirect effects**	**Standardized total effects**
R²	0.68		
Efficiency	0.541***		
Trust in Safety	0.415***		
Image	0.155		
Eco-Friendliness	-0.296***		
DV: Purchase Intention	**Standardized direct effects**	**Standardized indirect effects**	**Standardized total effects**
R²	0.66		
Attitude	0.603***		0.603
Subjective Norm	0.236*	0.520**	0.756

***p < 0.001; **p < 0.01; *p < 0.05

The standardized total effects on Purchase Intention indicate the total impact of all variables in the model. Efficiency (0.428**) and Trust in Safety (0.395**) had a significant, positive total impact on Purchase Intention, confirming H12c and H13c. H8c had to be rejected since Eco-Friendliness (-0.200**) had a significant negative effect on Purchase Intention, which was hypothesized to be positive. Further, Image (0.082), Driving Enjoyment (0.052) and Comfort (-0.018) did not have a significant indirect effect on Purchase Intention and therefore H6c, H7c and H9c had to be rejected.

Additionally, Attitude (0.604**) has been found to be the variable with the strongest total effect on Purchase Intention, followed by Subjective Norm (0.529**), Efficiency (0.428**), Trust in Safety (0.395**) and Eco-Friendliness (-0.200**).

Moreover, as indicated by Table 6-2, Attitude and Subjective Norm alone have been found to explain 66 percent of variance in Purchase Intention.

Further, analyzing direct effects of Efficiency, Trust in Safety and Eco-Friendliness on Attitude and Subjective Norm and their indirect effects on Purchase Intention, Attitude and Subjective Norm together have been found to fully mediate the effects of Efficiency, Trust in Safety and Eco-Friendliness on Purchase Intention.

Table 6-2 displays the summary of the hypothesis, tested during the analysis.

Table 6-2: Hypothesis Summary Table. Source: Own analysis and data.

Hypothesis	**Path coefficient and significance**	**Supported**
H1: Attitude positively affects Purchase Intention.	0.604***	Yes
H2: Subjective Norm positively influences Purchase Intention.	0.236*	Yes
H3a: Time Saving has a positive direct effect on Attitude.	-	-
H3b: Time Saving has a positive direct effect on Subjective Norm.	-	-
H3c: Time Saving has a positive indirect effect on Purchase Intention.	-	-
H4a: Productivity has a positive direct effect on Attitude.	-	-
H4b: Productivity has a positive direct effect on Subjective Norm.	-	-
H4c: Productivity has a positive indirect effect on Purchase Intention.	-	-
H5a: Utilization has a positive effect on Attitude.	-	-
H5b: Utilization has a positive effect on Subjective Norm.	-	-
H5c: Utilization has a positive indirect effect on Purchase Intention.	-	-
H6a: Image has a positive direct effect on Subjective Norm.	0.155 (n.s.)	No
H6c: Image has a positive indirect effect on Purchase Intention.	0.082 (n.s.)	No
H7a: Driving Enjoyment has a positive direct effect on Attitude.	0.086 (n.s.)	No
H7b: Driving Enjoyment has a positive indirect effect on Purchase Intention.	0.052 (n.s.)	No
H8a: Eco-Friendliness has a positive direct effect on Attitude.	-0.072 (n.s.)	No
H8b: Eco-Friendliness has a positive direct effect on Subjective Norm.	-0.296***	No
H8c: Eco-Friendliness has a positive indirect effect on Purchase Intention.	-0.200**	No
H9a: Comfort has a positive direct effect on Attitude.	-0.030 (n.s.)	No
H9b: Comfort has a positive indirect effect on Purchase Intention.	-0.018 (n.s.)	No
H10a: Trust has a positive direct effect on Attitude.	-	-
H10b: Trust has a positive direct effect on Subjective Norm.	-	-
H10c: Trust has a positive indirect effect on Purchase Intention.	-	-
H11a: Traffic Safety has a positive direct effect on Attitude.	-	-
H11b: Traffic Safety has a positive direct effect on Subjective Norm.	-	-
H11c: Traffic Safety has a positive indirect effect on Purchase Intention.	-	-
H12a: Efficiency has a positive direct effect on Attitude.	0.234*	Yes
H12b: Efficiency has a positive direct effect on Subjective Norm.	0.541***	Yes
H12c: Efficiency has a positive indirect effect on Purchase Intention.	0.428**	Yes
H13a: Trust in Safety has a positive direct effect on Attitude.	0.291***	Yes
H13b: Trust in Safety has a positive direct effect on Subjective Norm.	0.415***	Yes
H13c: Trust in Safety has a positive indirect effect on Purchase Intention.	0.395**	Yes

***p < 0.001; **p < 0.01; *p < 0.05; (n.s.) = not significant

7 Discussion

The following chapter discusses the empirical results of the thesis. Subsequently, limitations and implications for further research are provided.

7.1 Critical reflection on research results

The findings provide empirical support for some of the relationships originally proposed by Arndt (2011) and contribute to acceptance studies in the field of DAS studies. With an explanatory power of 67 percent, the model contributes to the understanding of which factors are important and how they influence purchase intention of driverless driving technology and thus contribute to theoretical and practical understanding.

Hypothesis 1, postulating a positive direct effect of Attitude on Purchase Intention, was supported and indicated that peoples' Purchase Intention is positively influenced by an individual's evaluation of the consequences of buying the product and that an increase in Attitude leads to an increase in Purchase Intention. Hypothesis 2, stating that Subjective Norm has a positive direct effect on Purchase Intention, has also been supported, meaning that besides an individual's attitude, social normative pressure to use the system and the perception that important others view the use of the system as positive, influence the Purchase Intention. Further to the hypothesized direct effect of Subjective Norm on Attitude, the SEM also revealed a causal path from Subjective Norm to Attitude, meaning that Attitude mediates effects of Subjective Norm on Purchase Intention. However, since Subjective Norm still has a direct effect on Purchase Intention, Attitude only partially mediates the effects and thus, Subjective Norm should stay in the model to increase explanatory power. This direct effect on Attitude could be explained by the fact that the purchase of a car has a high price value and is one of the most expensive investments people make. In order to avoid bad investment, they take into account the opinion of others, when forming an attitude towards buying. Moreover, buying a car is often a household decision, which is not decided by a single person but rather by several household members.

The finding that none of the perceived product characteristic had a significant direct effect on Purchase Intention indicates that the variables Attitude and Subjective Norm are sufficient to predict Purchase Intention, if one is not interested in the effects of product characteristics. This is reflected by the variance in Purchase Intention explained, since

Attitude and Subjective Norm alone explain 66 percent, only 1 percent less than the whole model.

Hypothesis 6a-c, which proposed a positive effect of Image on Subjective Norm and Purchase Intention, had to be rejected since Image did not show a significant effect on both. The technology is still several years away and more than 50 percent of the sample has only heard a few times of it (see descriptive statistics in chapter 4.6). Therefore, it is possible that only a few people have discussed the technology with their friends and peers. Most of them, however, have not formed an opinion on the subject yet. Consequently, if one does not have an opinion whether the purchase will impact their image as a driver, the impact on image is not a critical factor that is taken into account when forming a purchasing intention.

Driving Enjoyment did also not show a significant influence on Attitude and Purchase Intention. Likewise to Image, this could be because people did not have a chance to interact with the technology. Thus, they could not yet evaluate whether the technology actually increases or decreases the pleasure of driving car. In contrast to H9a and H9b, Comfort did also not have a significant effect on Attitude and Purchase Intention.

Arndt & Engeln (2008) and Arndt (2011) found that depending on the purpose of the DAS, not all perceived product characteristics have always a significant impact on Purchase Intention (e.g. Eco-Friendliness did not have a significant effect on the intention to purchase an automatic windscreen wiper). Therefore, it is possible that Driving Enjoyment and Comfort in fact do not significantly influence acceptance. In support of this argument it has to be mentioned that 69 percent of the study sample was below 34 years old. Thus, it is possible, that these individuals are more price consciousness and less comfort-focused and hence allocate more importance to gains in efficiency and safety, while an increase in comfort is a nice-to-have side effect. One additional explanation could be that due to the low awareness of the sample of the technology, people are not yet aware of all the benefits the system offers and therefore these characteristics do not have an influence yet.

Hypothesis 8a, which proposed a positive direct relationship between Eco-Friendliness and Attitude, was not supported. Also H8b and H8c, which hypothesized a positive effect of Eco-Friendliness on Subjective Norm and Purchase Intention, were found to be wrong.

In contrast to the hypotheses, the effect on Subjective Norm and Purchase Intention was found to be negative, which means that the more eco-friendly the system becomes, the lower the purchase intention is. These negative relationships seem somewhat unreasonable since other studies have found a positive relationship between eco-friendly products and Purchase Intention (Kaiser, Wolfing & Fuhrer, 1999; Kim & Chung, 2011; Park & Sohn, 2012). A possible explanation could be that people expect the system to become more expensive, the more environmental friendly it is. According to the supply and demand concept, a higher purchase price leads to less demand. Thus people might assume that an increase in eco-friendliness will lead to an increase in the prices. Consequently, a higher price makes eco-friendly products less attractive and thus could explain the negative effect of eco-friendliness on Subjective Normand Purchase Intention.

The hypotheses H12a-c, which hypothesized that Efficiency has a positive direct effect on Attitude and Subjective Norm and a positive indirect effect on Purchase Intention, have been supported by the results. Moreover, Efficiency has also shown to have the strongest impact of all perceived product characteristics on Purchase Intention. Consequently, this characteristic is the most influential one when forming a Purchase Intention.

Similarly to Efficiency, Trust in Safety, which was hypothesized to positively directly influence Attitude and Subjective Norm and indirectly Purchase Intention, has been found to confirm all three hypotheses. The strong positive effect of Trust in Safety implicates that a change in the value of this characteristic has a strong impact on Purchase Intention.

7.2 Limitations

Among limitations, the generalizability of these findings has to be mentioned. The study was only conducted in Germany and therefore the findings may not apply to other countries. Further, the survey was only conducted online and thus the results are not representative of the whole German population.

The revised model was largely confirmed and achieved a good model fit, however this could be specific to the sample of this study and does not necessarily imply a good structure of the model. Moreover, during the development of the measurement model, issues related to convergent and discriminant validity as well as reliability were encountered, which were reflected in only a moderate model fit and further questions the results.

The small sample size (N=115) has to be mentioned as a limitation. According to Baumgartner and Homburg (1996) the sample size should be at least five times bigger than the free parameters, to achieve trustworthy parameter estimates. This study only achieved a 4:1 ratio.

Since it is not clear when driverless driving systems will be available for purchase, the situation and specific time in which the purchase should be performed could not be specified as recommended by Ajzen (2005). Thus, the reliability to predict the actual purchase of a fully autonomous driving system from intention is questionable.

Moreover, since the technology was not available at the time of the study a product description of fully autonomous driving systems was given to read before people would answer the survey. Therefore, the results of the survey might be biased due to the product description by the author.

7.3 Implications for further research

Based on already mentioned limitations, several implications for further research are given. Future studies should rely on a bigger sample size and should enable consumers to interact with a prototype of the system and to ask questions related to the use of the product before answering the questionnaire. This would enable to include the constructs “usability” or “perceived easiness to use” into the model, which have been found to be a strong predictor in Information System studies. In order to achieve all this, offline surveys are recommended, which should enable to achieve a more representative sample and with this a better generalizability of the findings. In addition, future research should use longitudinal data instead of only cross-sectional data to actually prove the theorized relationships, rather than to solely infer those.

While it was beyond the scope of this study, future research should also try to analyze how demographic factors (age, gender, income etc.) moderate or influence the acceptance of driverless driving technologies.

Additionally, the purchase of a car and with this the decision to add a fully autonomous driving system often depends on several people in a household. Therefore, an investigation of the acceptance using theories such as the adoption of technology in households (Brown & Venkatesh, 2005) may allow for deeper insights into factors that influence purchase intention and actual purchase of driverless systems.

8 Conclusion

This study aimed to explore which factors influence the intention to purchase a fully autonomous driving system in the future. Moreover, it questioned which perceived product characteristics influence purchase intention and how they do this. For this purpose, the model proposed by Arndt (2011) to predict the acceptance of Driver Assistance Systems was modified and used.

The empirical findings showed that Attitude towards buying the system had the strongest positive effect on the intention to purchase a fully autonomous driving system, followed by Subjective Norm. Additionally, among the perceived product characteristics, Efficiency had the strongest positive effect on Purchase Intention, followed by Trust in Safety, which also had a positive effect. Eco-Friendliness was found to influence Purchase Intention, however, it showed to have a negative effect on Purchase Intention. Perceived Image, Driving Enjoyment and Comfort were found to not have an effect on Purchase Intention at all.

To give managerial implications, this master thesis aimed to reveal a more accurate explanation on why perceived product characteristics affect Purchase Intention. An analysis of the causal relationship between the variables revealed that Attitude towards buying is affected by Efficiency, Trust in Safety and Subjective Norm. Thus, Efficiency, Trust in Safety and Subjective Norm influence the Purchase Intention through an individual’s Attitude towards buying. Moreover, Subjective Norm is influenced by Efficiency, Trust in Safety and Eco-Friendliness meaning that their effect on Purchase Intention is mediated by Subjective Norm.

Consequently, in order to increase the Attitude of people to buy a fully autonomous driving system in the future, OEMs should increase the value of the product characteristics that consumers take into account when forming a purchasing intention. As shown, the perceived efficiency and safety benefits offered by driverless driving systems have the strongest impact and thus marketers should exploit this lever and focus to increase the value of these functions to achieve a high purchase intention. Thus, marketing campaigns should focus on promoting the characteristics of Efficiency and increase Trust and Safety. Campaigns could for example focus on the benefits from the technology that family members could be picked up by the autonomous car, while the actual owner is at work. Another possibility would be to highlight the improved safety aspects through this technology. Since Subjective Norm had the second biggest standardized effect on Purchase Intention and also a strong impact on Attitude, public campaigns that promote “driverless driving to be safer than manual driving” are not only expected to increase the awareness of people but also expected to increase social pressure to use this technology. Autonomous driving brings along a lot of benefits for the user and the whole society therefore, changing social norms similar to “anti-smoking” or “don’t drink and drive yourself” campaigns are expected to have a strong impact on people’s intention to buy the technology through social pressures.

Appendix

A) German Questionnaire Items

Table A-1: German Questionnaire Items Source: Own survey.

Construct	Item	Source
Welche Eigenschaften hat selbstfahrende Fahrzeugtechnologiie? *Bitte bewerten Sie die verschiedenen Eigenschaften des Systems.*		
Traffic Safety	TraSaf1: Das System erhöht die Verkehrssicherheit. TraSaf2: Das System trägt dazu bei, das Unfallrisiko zu senken.	Arndt (2011)
Image	Image1: Das System schadet dem Image des Fahrers. Image2: Es wäre mir vor meinen Kollegen peinlich, das System zu benutzen. Image3: Das System wird von Personen genutzt, die sich beim Fahren nicht sicher fühlen.	Arndt (2011)
Driving Enjoyment	DE1: Das System würde das Autofahren langweilig machen. DE2: Das System erhöht den Fahrgenuss.	Arndt (2011)
Trust	Trust1: Ich vertraue darauf, dass dieses System in meinem Interesse handelt. Trust2: Ich vertraue diesem System nicht.	Arndt (2011) Own item
Comfort	Comf1: Das System fördert die körperliche Entspannung beim Fahren. Comf2: Das System erhöht den Stress für den Fahrer.	Arndt (2011)
Eco-Friendliness	EcoF1: Das System unterstützt eine umweltfreundliche Fahrweise. EcoF2: Das System würde mir helfen Kraftstoff zu sparen.	Arndt (2011)
Productivity	Prod1: Das System erhöht die Chance Dinge zu erreichen/erledigen, die mir wichtig sind. Prod2: Das System würde mir helfen Dinge schneller zu erledigen.	Venkatesh et al. (2003) Own item
Time Saving	TimeSav1: Das System würde mir helfen meine Reisedauer zu verkürzen. TimeSav2: Das System würde mir helfen Zeit zu sparen.	Own item Own item
Utilization	Utilization1: Das System ermöglicht ein Auto besser mit anderen Personen zu teilen. Utilization2: Das System ermöglicht eine bessere/effizientere Nutzung des Autos.	Own item
Würden Sie ein Auto mit vollautonomer Fahrzeugtechnologie kaufen? *Ich finde den Kauf eines Autos mit autonomer Fahrtechnologie…*		
Attitude	schlecht – gut nutzlos – nützlich unangenehm – angenehm unwichtig – wichtig nachteilig – vorteilhaft	Ajzen & Fishbein (2002)
Was glauben Sie, würden andere Personen über fahrerlose Fahrzeugsysteme sagen?		
Subjective Norm	SN1: Ich kann mir vorstellen, dass sich meine Freunde ein Auto mit solch einem System kaufen werden. SN2: Meine Familie würde es begrüßen, wenn ich diese Technologie in meinem Auto hätte. SN3: Andere würden es gut finden, wenn ich ein fahrerloses System hätte. SN4: Meine Freunde würden mich darin bestärken, mir diese Technologie zu kaufen.	König (2005) Arndt (2004a) Arndt (2004a) Meyer (2002)
Würden Sie ein Auto mit vollautonomer Fahrzeugtechnologie kaufen?		
Purchase Intention	PI1: Ich würde dieses System gerne in meinem Auto besitzen. PI2: Ich werde den Kauf eines Autos mit solch einem System in Betracht ziehen. PI3: Sobald diese Technologie verfügbar ist, plane ich ein Auto mit fahrerlosem System zu kaufen.	Meyer (2002) Arndt (2011) Arndt (2011)

B) Questionnaire product description

Nun folgt eine Einführung zum fahrerlosen/autonomen Autofahren.

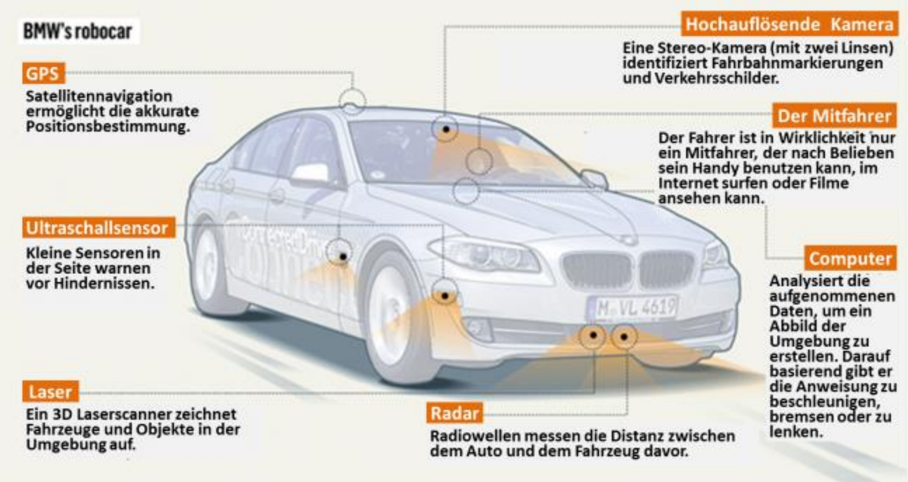
Heutige Fahrerassistenzsysteme, wie das *Antiblockiersystem (ABS)*, *Elektronisches Stabilitätsprogramm (ESP)*, *Spurassistent* und *automatisiertes Bremsen*, tragen zu erhöhter Verkehrssicherheit bei. Komfortsysteme, wie der *Abstandsregeltempomat* gestalten das Autofahren komfortabler.

Es wird erwartet, dass im Laufe der nächsten Jahre weitere Assistenzsysteme, wie Autopiloten für Stau und Autobahnen, kommerziell verfügbar sind. In Kombination werden solche Fahrerassistentsysteme zu Systemen führen, die ununterbrochenes, fahrerloses/autonomes Autofahren ermöglichen.

Voll autonom fahrende Fahrzeuge übernehmen alle sicherheitskritischen Fahrfunktionen, das Fahren, Steuern, Einparken und die Fahrbahnüberwachung für die gesamte Fahrt, ohne den Einfluss/Eingriff eines menschlichen Fahrers zu benötigen. Der Fahrer gibt lediglich das Reiseziel an. Diese fahrerlosen Systeme sollen es ermöglichen besetzte und unbesetzte Fahrzeuge zu kontrollieren.

Ein autonomes Fahrzeug zu benutzen, kann mit einem Taxi verglichen werden, in das man einsteigt und dem Fahrer das Ziel angibt. Der Unterschied ist, dass man im eigenen Auto fährt, das von einem technologischen System kontrolliert wird.

Dieses Bild zeigt exemplarisch die Technologie und Bauteile, die es Autos ermöglichen, ohne Fahrer zu fahren.



GPS
Satellitennavigation ermöglicht die akkurate Positionsbestimmung.

Hochauflösende Kamera
Eine Stereo-Kamera (mit zwei Linsen) identifiziert Fahrbahnmarkierungen und Verkehrsschilder.

Der Mitfahrer
Der Fahrer ist in Wirklichkeit nur ein Mitfahrer, der nach Belieben sein Handy benutzen kann, im Internet surfen oder Filme ansehen kann.

Ultraschallsensor
Kleine Sensoren in der Seite warnen vor Hindernissen.

Computer
Analysiert die aufgenommenen Daten, um ein Abbild der Umgebung zu erstellen. Darauf basierend gibt er die Anweisung zu beschleunigen, bremsen oder zu lenken.

Laser
Ein 3D Laserscanner zeichnet Fahrzeuge und Objekte in der Umgebung auf.

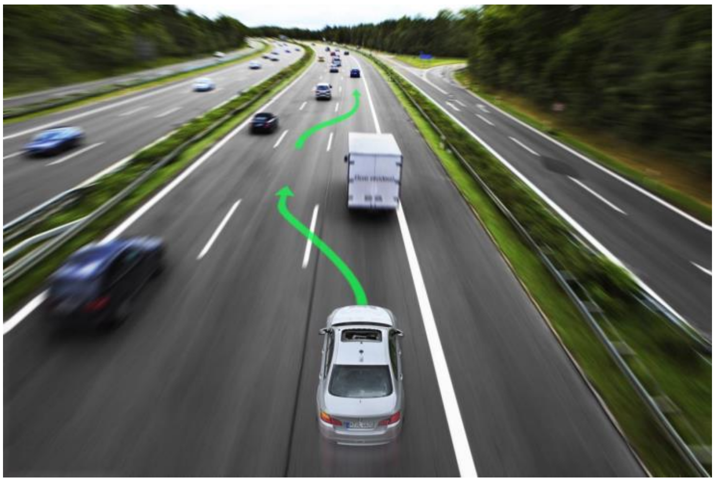
Radar
Radiowellen messen die Distanz zwischen dem Auto und dem Fahrzeug davor.

Die Technologie, die autonomes Fahren ermöglicht, kann in drei Schritten erklärt werden.

<u>1. Schritt:</u> Das Fahrzeug bestimmt seine eigene Position mit dem Satellitensystem GPS und nimmt seine Umgebung mit Kameras, Lasern und Radar wahr, um Hindernisse auf der Fahrbahn, wie zum Beispiel andere Fahrzeuge, Fußgänger oder Fahrradfahrer, zu identifizieren und deren Abstand zu messen.

2. Schritt: Die Computer- und Softwaresysteme sammeln und verarbeiten die erfassten Daten, um deren Bedeutung zu verstehen und Handlungsmaßnahmen einzuleiten.

3. Schritt: Das System reagiert und passt die Fahrzeugbewegung in Echtzeit an.



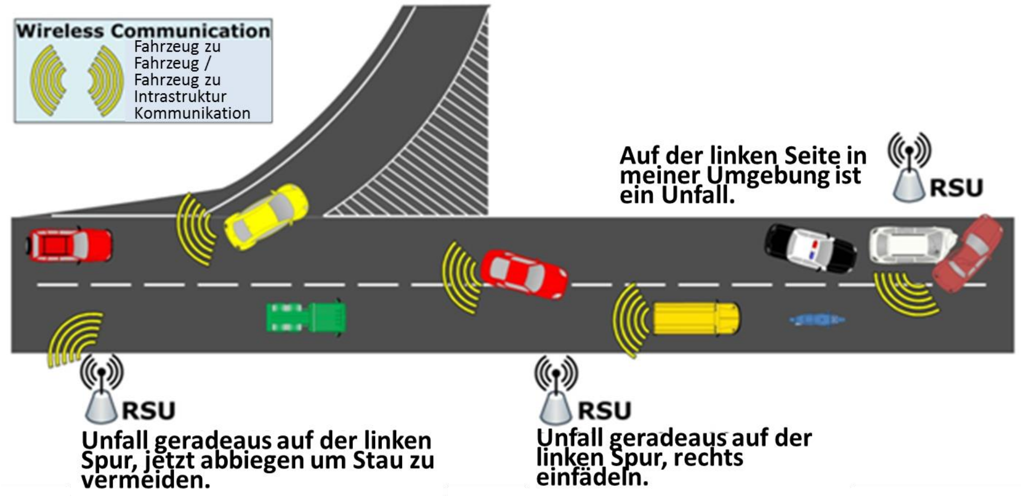
Fahrerlose Systeme erweitern die Beschäftigungsmöglichkeiten während der Fahrt sowie die Nutzungsmöglichkeiten des Autos.

Anstelle das Auto selbst zu steuern kann der/die FahrerIn sich anderweitig beschäftigen, z. B. mit lesen, Filme schauen, im Internet surfen, arbeiten, sich entspannen oder schlafen.

Autonomes Fahren soll auch individuelle Mobilität für Personen, die fahruntauglich (krank, körperlich beeinträchtigt, blind, unter Einfluss von Medikamenten oder Alkohol stehen) oder zu jung zum Selbstfahren sind, ermöglichen.

Es wird davon ausgegangen, dass Autos nach Bedarf per Mobiltelefon oder Computer gesteuert werden können. Sie könnten sich z. B. zur Arbeit fahren lassen und das Auto danach anweisen, sich selbst einen Parkplatz zu suchen oder zurück nach Hause zu fahren, um anderen Personen zur Verfügung zu stehen. Die Fernsteuerung und das Fahren ohne Personen ermöglichen damit eine bessere Nutzung des Autos für mehr Personen.

Außerdem wird erwartet, dass autonome Fahrzeuge aufgrund von Echtzeitinformationen, durch die Kommunikation von Fahrzeugen untereinander und mit der Infrastruktur, schneller ans Ziel kommen. Darüber hinaus ermöglicht optimiertes Beschleunigen und Bremsen auch mit weniger Kraftstoff eine umweltfreundlichere Fahrweise.



Schließlich werden diese Systeme zur Fahrsicherheit beitragen, da Computer schneller reagieren und sich nicht vom Verkehr abwenden. Menschliche Fehler aufgrund von Ablenkung, z. B. durch Mitfahrer, andere Fahrer, Handys oder Stimmungsschwankungen, wie Müdigkeit, Langeweile oder Trunkenheit, können somit verringert werden.

C) Exploratory Factor Analysis Results

Table C-1: KMO and Bartlett's Test. Source: Own survey and analysis.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,851
Bartlett's Test of Sphericity	Approx. Chi-Square	1807,680
	df	378
	Sig.	,000

Table C-2: Communalities. Source: Own survey and analysis.

Communalities

	Initial	Extraction
Attitude1	1,000	,803
Attitude2	1,000	,770
Attitude3	1,000	,794
Attitude4	1,000	,720
Attitude5	1,000	,750
Comf1	1,000	,751
Comf2	1,000	,692
DE1	1,000	,569
DE2	1,000	,608
EcoF1	1,000	,665
EcoF2	1,000	,713
Image1	1,000	,367
Image2	1,000	,733
Image3	1,000	,644
Prod1	1,000	,455
Prod2	1,000	,722
TraSaf1	1,000	,718
TraSaf2	1,000	,726
TimeSav1	1,000	,411
TimeSav2	1,000	,730
Trust1	1,000	,714
Trust2	1,000	,658
Utilization1	1,000	,626
Utilization2	1,000	,666
SN1	1,000	,685

SN2	1,000	,802
SN3	1,000	,714
SN4	1,000	,736

Table C-3: Total Variance Explained. Source: Own survey and analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	9,717	34,702	34,702	9,717	34,702	34,702	4,227	15,095	15,095
2	2,287	8,168	42,870	2,287	8,168	42,870	3,615	12,912	28,006
3	1,966	7,022	49,892	1,966	7,022	49,892	2,805	10,018	38,024
4	1,490	5,320	55,212	1,490	5,320	55,212	2,621	9,361	47,385
5	1,258	4,494	59,706	1,258	4,494	59,706	2,189	7,819	55,204
6	1,199	4,282	63,988	1,199	4,282	63,988	1,887	6,738	61,942
7	1,024	3,659	67,647	1,024	3,659	67,647	1,598	5,706	67,647
8	,994	3,551	71,198						
9	,944	3,373	74,571						
10	,812	2,899	77,470						
11	,720	2,573	80,043						
12	,668	2,386	82,429						
13	,621	2,216	84,645						
14	,573	2,046	86,691						
15	,491	1,752	88,443						
16	,464	1,656	90,099						
17	,416	1,484	91,583						
18	,328	1,172	92,755						
19	,302	1,080	93,835						
20	,299	1,067	94,902						
21	,243	,869	95,771						
22	,238	,848	96,619						
23	,209	,745	97,364						
24	,195	,695	98,059						
25	,179	,638	98,697						
26	,132	,473	99,170						
27	,121	,432	99,602						
28	,111	,398	100,000						

Extraction Method: Principal Component Analysis.

Table C-4: Rotated Component Matrix. Source: Own survey and analysis.

Rotated Component Matrix^a

	Component						
	1	2	3	4	5	6	7
Attitude1	**,754**	,208	,237	,170	,262	,182	,070
Attitude2	**,717**	,336	,070	,183	,006	,189	,264
Attitude3	**,803**	,059	,153	,215	,242	,134	,007
Attitude4	**,703**	,137	,044	,375	,066	,009	,245
Attitude5	**,751**	,252	,270	,141	,107	,089	,101
Comf1	,163	,154	,223	,141	,367	**,704**	,019
Comf2	,184	,023	,307	,202	-,014	**,706**	,152
DE1	,185	-,001	,048	,123	**,690**	,103	,176
DE2	,119	,197	,139	,122	**,716**	,035	,085
EcoF1	,076	**,634**	,389	-,083	,055	-,300	,082
EcoF2	-,009	**,688**	,360	-,004	-,101	-,308	,071
Image1	,296	,202	,037	-,058	,269	,070	**,396**
Image2	,311	,121	,071	,052	,123	,235	**,737**
Image3	-,008	,028	,200	,305	,139	-,099	**,694**
Prod1	,291	**,504**	-,073	,186	,272	,049	,012
Prod2	,188	**,517**	-,090	,031	,449	,427	,163
TraSaf1	,114	,218	**,784**	,116	,043	,132	,098
TraSaf2	,105	,133	**,809**	,095	-,042	,159	,079
TimeSav1	,233	**,547**	,155	,130	,107	,071	,005
TimeSav2	,096	**,688**	-,032	,144	,371	,202	,218
Trust1	,479	,043	**,568**	,144	,365	,044	,067
Trust2	,392	,001	**,633**	,149	,255	,082	,096
Utilization1	,223	**,617**	-,142	,132	-,002	,379	-,117
Utilization2	,127	**,742**	,187	,153	-,020	,147	,140
SN1	,240	,143	,113	**,679**	-,140	,255	,220
SN2	,219	,086	,105	**,799**	,273	,108	,100
SN3	,557	,174	,151	**,590**	,017	,030	,047
SN4	,267	,176	,138	**,726**	,285	,072	,022

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 10 iterations.

Table C-5: Component Transformation Matrix. Source: Own survey and analysis.

Component Transformation Matrix

Component	1	2	3	4	5	6	7
1	,581	,430	,340	,383	,311	,250	,239
2	-,317	,864	,038	-,346	-,059	-,163	-,036
3	-,039	-,171	,887	-,106	-,292	-,293	-,003
4	-,358	-,173	,251	-,396	,654	,401	,185
5	-,452	,091	,139	,428	-,379	,651	-,134
6	-,455	-,005	-,039	,513	,177	-,425	,562
7	,146	-,033	-,109	-,346	-,460	,245	,757

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

Assertation

I ensure that I wrote this thesis without the help of others and without the use of other sources than mentioned. This thesis has never been submitted in the same or substantially similar version to any other examinations office. All explanations that I have been adopted literally or analogously are marked as such.

Aschaffenburg, January 4th 2014

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