The Adoption of Smart Systems

Influencing Factors of the Intention to Use and Actual Use

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List of Abbreviations

A	Attitude
ACC	Adaptive Cruise Control
AD	Autonomous Driving
AV	Autonomous Vehicle
Corr.	Correlation
DLC	Direct Load Control
DR	Demand Response
DSI	Demand Side Integration
DSM	Demand Side Management
EC	European Commission
EEG	Erneuerbare-Energien-Gesetz
EU	European Union
H	Hypothesis
I	Intention to Use
IoT	Internet of Things
IPA	Intelligent Personal Assistant
IT	Information Technology
LISREL	Linear Structural Relations
LS	Load Shifting
MD	Manual Driving
MW	Megawatt
NHTSA	National Highway Traffic Safety Administration
NLP	Natural Language Processing
ns	not significant
PA	Perceived Advantages
PC	Perceived Control
PD	Perceived Disadvantages
PLS	Partial Least Squares
QR-Code	Quick Response Code
RFID	Radio Frequency Identification
RQ	Research Question
SAE	Society of Automotive Engineers
SEM	Structural Equation Model
SN	Subjective Norm

T/TP	Trust in Product (Smart System)
TAM	Technology Acceptance Model
TM	Trust in Manufacturer
TPB	Theory of Planned Behavior
WTP	Willingness to Pay

List of Symbols

A	Attribute
AVE	Average Variance Extracted
f^2	Effect Size
i	Indicator
K	Class
Q^2	Stone-Geisser's Q^2
R^2	Coefficient of Determination
$SE(\beta)$	Standard Error of Regression Coefficient
$Sig.\ (p)$	p-value
t	t-statistic
VIF	Variance Inflation Factor
X	Independent Variable
Y	Dependent Variable
β	Regression Coefficient

1 Introduction

Our everyday life is more and more pervaded by technology, which, partly automatically, takes over tasks and supports everyday life. Smartphones recognize appointments from incoming e-mails and automatically enter them into calendars, cars automatically keep their lanes, or the navigation device suggests an alternative route based on the traffic situation. All these examples are smart systems. They are often understood as assistants who support the user in certain tasks (Lanting and Lionetto, 2015, p. 2). Smart systems come in many different appearances. Their area of application is diverse and includes manufacturing, energy, security, communications, entertainment and more (Lanting and Lionetto, 2015, p. 3). They offer a wider range of functions than former assisting systems (Lanting and Lionetto, 2015, p. 2) and thus increase the productivity of the user on the one hand and his safety on the other (Lee and See, 2004, p. 50). Productivity increases due to the (sub-) tasks that smart systems relieve the user of. This allows users of smart systems to delegate tasks to smart systems and focus on other tasks instead. The fact that the security of the user increases by using a smart system is based on the assumption that smart systems make fewer mistakes than humans (Parasuraman and Riley, 1997, p. 235). In addition, smart systems always make rational decisions and do not make wrong decisions based on emotions.

Even if smart systems nowadays meet with great interest, the concept and the term „smart systems“ have existed since 1989 (Ahmad, 1989; Riley, 1989; Rogers, 1989). However, it can be observed that smart systems have only recently become increasingly popular (Harbor Research, 2019). Digitalization is the driving factor behind this development. Technical innovations and increasing connectivity are contributing to the fact that the previously analogue transmission of information is increasingly taking place via digital channels. In concrete terms, this applies not only to the procurement of information, but also to communication and transactions. Letters became e-mails, remittances became online transfers and the most popular encyclopaedias are no longer printed, but distributed digitally (McCarthy, 2012). But not only existing processes and instances were digitalized. The new concept of the Internet of Things (IoT) has developed as part of the digitalization. The Internet of Things first describes the digital representation of physical objects and states, e.g. using RFID tags or sensors (Atzori, Iera and Morabito, 2010, p. 2787). Thus, objects from the physical world become available and analysable in the digital world. Tracking and tracing is often cited as an example of application (Chiuchisan, Costin and Geman, 2014, p. 532; Gnimpieba *et al.*, 2015; Kiritsis, 2011, p. 483). Packages are given a barcode or QR code, which is scanned at all stages of the delivery process. The delivery process can thus be tracked digitally. But the IoT goes even further. In addition to the pure representation of objects in the digital world, these objects can also be able to communicate with each other

(Miorandi *et al.*, 2012, p. 1497) like smart systems, which can communicate with each other (European Commission, 2007, p. 32; Lanting and Lionetto, 2015, p. 3). For example, a Smartwatch communicates the vital data of the user to the corresponding smartphone for evaluation. These phenomena supported the development of smart systems. The list of available smart systems is already very long and the market share of smart products is growing steadily. Lee and See (2004, p. 50) also predict great potential for the future use of smart systems in other areas.

1.1 Smart Systems

Even though smart systems are becoming increasingly popular, there is no consensus, particularly in practice, on the definition of a smart system. Backlund (2000, p. 448) describes a system as a set of at least two elements. These elements must be directly or indirectly connected to each other so that no subgroups of elements exist. According to this definition, a smart system consists of several elements that are connected to each other. The first definition of smart systems named built in or intrinsic sensor(s), actuator(s) and control mechanism(s) as the elements of a smart system (Ahmad, 1989). Chan *et al.* (2012, p. 137) and Stagl, Konrad and Michelmann (2018, p. 3) define that smart systems using functions that can be grouped under three elements: Data Acquisition, Data Processing and Actuating. These elements of smart systems are passed through successively. Further, Ahmad (1989) and Akhras (2000, p. 25) view automation as an essential characteristic of smart systems.

1.1.1 Data Acquisition Element

Via the Data Acquisition Element smart systems are able to detect changes in their environment and provide feedback in a variety of ways (Varadan and Varadan, 2000, p. 953). The environment of a smart system is defined by all information that can be captured. This also includes the user, who is therefore not part of the smart system. From this environment the smart system receives a stimulus (e.g. an impulse or an instruction) and into this environment the smart system sends its response (Ahmad, 1989). For capturing the stimuli of its environment, smart systems are equipped with one or more sensors (Ahmad, 1989), for example microphones (Akhras, 2000, p. 29). A possible stimulus can be an instruction from the user, but a stimulus can also be autonomously interrogated by the system and does not necessarily have to be actively introduced into the system by the user. The data acquisition element converts the stimuli into digitally usable data. By capturing the stimulus via the sensor(s) and converting it, the Data Acquisition Element provides input data for the subsequent Data Processing Element.

1.1.2 Data Processing Element

What Ahmad (1989) describes as control mechanisms forms the Data Processing Element between sensors and actuators (Akhras, 2000, p. 29). Even if all smart systems have the Data Acquisition Element, Data Processing Element and Actuating Element, these elements do not automatically make a system smart. A distinction can be made between smart systems and purely reactive systems. (European Technology Platform on Smart Systems Integration, no date). If one looks at the literature on smart systems, it becomes clear that the design of the Data Processing Element makes a system smart in the first place (Akhras, 2000, p. 29). Akhras (2000, p. 29) uses the analogy of the nervous system for smart systems and concretizes that the Data Processing Element is the brain of the system and makes the system smart. The Data Processing Element of a smart system is thus attributed a certain "mental power". Also Verberne, Ham and Midden (2012, p. 799) describe smart systems as intelligent automation technology. This intelligent automation technology „[…] undertakes significant cognitive processing on behalf of the user […]“ (Salomon, Perkins and Globerson, 1991, p. 2). The cognitive processing power of the smart system stems from their ability to analyse data and take decisions (Akhras, 2000, p. 29). These decisions concern the way a task is handled and are necessary to achieve the goal (efficiently). Therefore, the criterion for a system to be smart is the decision-making competence in the Data Processing Element. Since decisions are only necessary if there are different options, complex situations with different action alternatives (solution space) are characteristic for the area of application of smart systems. In its operation the smart system first evaluates all action alternatives. For this, additional data beside the stimulus data may be used. These additional information can be gathered by additional sensors, the Internet or from an intrinsic database containing data from previous operations of the smart system. The independent determination of the additional information happens so that the user does not have to enter this information into the system and thus experiences a more comfortable usage of the system. It is also possible that the user does not have access to all necessary information. On the basis of the additional information, an evaluation of the alternative courses of action takes place. Based on this evaluation, the smart system reduces the alternatives for action. It is also possible for the smart system to suggest a selection of action alternatives to the user. A reduction to just one alternative is therefore not necessary. This reduction of alternatives represents the decision the smart system takes. In order to distinguish smart systems from reactive systems, one example for each is described below.

If one considers an autonomous vehicle as an example of a **smart system**, the user's target input results in many different decision situations for the system. In every decision situation, the system must decide which operation to perform, such as braking, accelerating or steering. The user's input of objectives results in a solution space with many different alternatives as to how the system achieves the objective. On the basis of sensors and real-time traffic data, the vehicle evaluates the various alternatives and ultimately decides on an alternative course of action.

An example of a **reactive system** is an air conditioning system. The user specifies the desired room temperature. The system uses sensors to determine the current temperature. In the Data Processing Element, an adjustment of target temperature and actual temperature is carried out within a logic, which results in either "heating", "cooling" or "doing nothing". If the room temperature is below the desired temperature, the logic outputs "heating". Thus the solution space consists of only one alternative (one permissible solution), namely "heating". In reactive systems, the predefined logic makes it clear how the problem is to be solved. Reactive systems only execute instructions and do not make independent decisions. In order for the use of reactive systems to make sense, either only one alternative action should be available or the existing alternatives should be equivalent. The fact that reactive systems are not able to evaluate and reduce alternative courses of action, does not make them worse systems than smart systems, but it becomes clear that the evaluation and reduction of action alternatives in the application areas of reactive systems is not necessary at all.

1.1.3 Actuating Element

As a result, the Data Processing Element sends the decision to the Actuating Element. The Actuating Element is the last element of a smart system which is processed when the system receives a stimulus. Its task is the execution of decisions made in the Data Processing Element (Ahmad, 1989). For this, actuators are used (Akhras, 2000, p. 29). Actuators can respond to the environment in different ways. Therefore, Akhras (2000, p. 28) list *"optical, magnetic, thermal, mechanical [...][,] chemical [...][and] electrical"* Actuators. Examples for these actuators are speaker or displays. The following diagram shows the elements of smart systems whose interfaces with the environment.

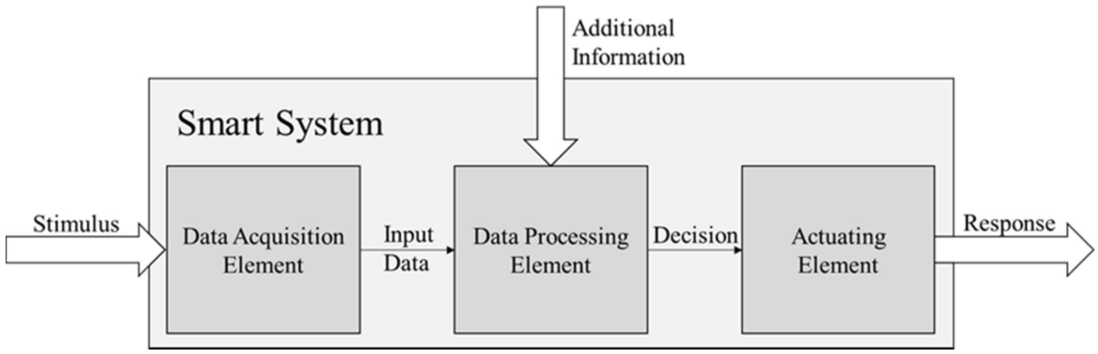

Figure 1: Elements of Smart Systems

1.1.4 Automation

The extent to which the smart system supports the user can vary. The level of support can be described as the degree of automation. Automation means that processes are executed without the control of the user (Muir, 1994, p. 1905). Since smart systems take over at least a part of the decisions for the user, smart systems are always automated to a certain extent. Therefore, smart systems are also understood as intelligent automated technologies (Verberne, Ham and Midden, 2012, p. 799). Automation generally describes *"technology that actively selects data, transforms information, makes decisions, or controls processes"* (Lee and See, 2004, p. 50). Automation in relation to smart systems is often understood as the autonomy with which the system makes decisions and implements them (Parasuraman, Sheridan and Wickens, 2000; Riley, 1989; Sheridan and Verplank, 1978). This can occur to varying degrees in smart systems. Verberne, Ham and Midden (2012, p. 800) argued that the user of the smart system does not necessarily give complete control over a decision to the system. Takeover of control is more of a continuum (McDaniel, 1988; Riley, 1989, p. 126). Thus, Sheridan and Verplank (1978, p. 168) define 10 levels of automation.

Table 1:Levels of Automation (Sheridan and Verplank, 1978, p. 168)

Levels of Automation	Description
1	Human does the whole task.
2	Computer helps determining the options.
3	Computer helps determining the options and recommends one option.
4	Computer selects option; Human may or may not do it.
5	Computer selects option and takes action if the human approves.
6	Computer selects option and gives human enough time to intervene before the computer takes action.
7	Computer does the whole task and informs the human afterwards.
8	Computer does the whole task and informs the human only if asked.
9	Computer does the whole task and informs the human only if the computer decides to.
10	Computer does the whole task autonomously.

Verberne, Ham and Midden (2012, p. 800) note that these different levels of automation can be distinguished by the information the system provides to the user and the degree to which the actions are performed independently. The automation levels can be further summarized in:

- Smart system reduces action alternatives (Level 2 & 3)
- Smart System selects one action alternative (Level 4 - 6). Before the execution the user has a possibility to intervene.
- Smart System selects and executes one option (Level 7 - 10). It is not intended that the user intervenes in the execution.

The first level from Sheridan and Verplank (1978, p. 168) does not represent any automation. Therefore, this level is not relevant in terms of smart systems.

1.2 Research Questions

The use of smart systems can bring various advantages. The advantages are based on the automation and decision-making competence of the smart system (e.g. Alam, Reaz and Ali, 2012, p. 1191; Augusto and Nugent, 2006, p. 1; Lanting and Lionetto, 2015, p. 2). Automation describes the (partial) takeover of tasks by the smart system (Verberne, Ham and Midden, 2012, p. 800). It is possible to take over only certain sub-tasks or the whole task (Sheridan and Verplank, 1978, p. 168). By executing tasks via a machine, sources of error such as the subjective assessment or emotions of the user are excluded (Parasuraman and Riley, 1997, p. 235). As a result, calculations that are performed automatically by the system tend to have fewer errors than calculations that are performed by the user himself (Parasuraman and Riley, 1997, p. 235). This may increase the security of the user (Gold *et al.*, 2015, p. 3026) and may even bring economic benefits (Parasuraman, Sheridan and Wickens, 2000, p. 286). However, calculations performed by the smart system are not only more reliable. A smart system can also perform calculations faster than the user (Parasuraman and Riley, 1997, p. 232) and thus give the user time for other things and also generate economic advantages (Parasuraman and Riley, 1997, p. 234). Last but not least, the smart system relieves the user by taking over decisions and tasks, and thus promises a gain in comfort (Gold *et al.*, 2015, p. 3026).

The examples above make it clear that smart systems can make everyday tasks easier for their users by taking on (sub-)tasks. However, smart systems do not only have advantages (Mert, Suschek-Berger and Tritthart, 2008, p. 31). The price for comfort and security is the disclosure of information to the smart system or the operator of the system (Mert, Suschek-Berger and Tritthart, 2008, p. 35; Rauschnabel and K. Ro, 2016, p. 130; Shin, Park and Lee, 2018, p. 247). The data provided does not even have to contain personal information. But through the combination with other (also non-personal) data, these can allow conclusions to be drawn about the respective user and ultimately become personal information (Kulk and van Loenen, 2012, p. 201). For example, in 2006 AOL published 650,000 anonymous search queries for scientific analysis. Journalists of the New York Times were able to identify an elderly lady by this anonymised data (Barbaro and Zeller, 2006). Further examples can be found in Narayanan (2006), Simpson (2011) and Golle (2006). In addition to the disclosure of information, the delivery of control is also a potential disadvantage of smart systems (Mert, Suschek-Berger and Tritthart, 2008, p. 32). The delivery of control is particularly critical when the smart system has a malfunction (e.g. Brooker, 2008). Even if these malfunctions should only be the exception (Parasuraman and Riley, 1997, p. 235), errors can occur in any element of a smart system and in any data transfer (Parasuraman and Riley, 1997, p. 238 et sqq.). Data may be damaged during transfer between elements, or calculation steps in an element may be performed incorrectly. Therefore, a situation arises characterised by uncertainty and risk (Verberne, Ham and Midden, 2012, p. 807). In addition to the disclosure of information and possible malfunctions, smart systems can have other disadvantages, which vary from system to system. For example, it can be disadvantageous that some types of intelligent personal assistants, such as the Amazon Echo, can only be controlled via speech and sometimes only have speech output. So people can have problems talking to a machine (Noyes, 2001, p. 504). System-specific disadvantages will be discussed in more detail in the following chapters.

Advantages and disadvantages have an influence on the adoption of smart systems by the user (Chen, Xu and Arpan, 2017; Featherman and Pavlou, 2003; Loh and Venkatraman, 1995; Park, Kim and Kim, 2014; Venkatesh, Morris and Davis, 2003, p. 447). Due to the various advantages and disadvantages mentioned above, it is not clear whether users would adopt a smart system or not. The different weighting of advantages and disadvantages between the users may lead to different results regarding the adoption.

Whether smart systems are adopted can be of central importance (e.g. Kowalczuk, 2018, p. 419). For example, for manufacturers of these smart systems or companies who would like to employ smart systems (Payre, Cestac and Delhomme, 2014, p. 253). Of particular interest is what influences the adoption of smart systems (Arts, Frambach and Bijmolt, 2011, p. 134). Once the influences on adoption have been identified, smart systems can be adapted so that adoption by the user is more likely. It is quite conceivable that potential users may be deterred by the disadvantages of a smart system or may not consider the system's features to be advantageous (Mert, Suschek-Berger and Tritthart, 2008, p. 31). But it is not always clear why a (potential) user exactly does not adopt a smart system (Shabanpour *et al.*, 2018, p. 464). However, the reasons for adopting or refusing smart systems can be very revealing.

If the reasons for the adoption are known, smart systems can be better adapted to the requirements of the users (Davis, 1986, p. 2). It is possible to uncover false expectations about the smart system (Nees, 2016, p. 1449) and incorrect operation by the user (Parasuraman and Riley, 1997, p. 238), but also which functions are not needed at all and which even reduce the willingness to adopt smart systems (Easwara Moorthy and Vu, 2015). Companies can incorporate this knowledge into their communication with customers and into the development of smart systems (Payre, Cestac and Delhomme, 2014, p. 253). This allows users to derive more benefit from the adoption of the smart system but also allows manufacturers to successfully sell their products (Davis, 1986, p. 2). These reasons are called factors throughout this thesis. The research question of this thesis thus arises as follows:

RQ: Which factors influence the adoption of smart systems?

In order to answer this research question, it is first necessary to clarify how adoption is to be measured and which factors may influence the adoption. First, the measurement of adoption will be addressed and afterwards which factors are influencing it.

1.2.1 Adoption

Before understanding how adoption is measured, it is necessary to clarify what is meant by adoption in the context of smart systems. Smart systems can generally be considered as technological innovations (Akhras, 2000, p. 25). Thus the use of the concept of adoption from the field of technological innovations can be used. It has already been examined by several authors what motivates people to adopt technological innovations (e.g. Ahn, Ryu and Han, 2004; Arndt, Engeln and Vratil, 2008; Benbasat and Wang, 2005). These works are mostly based on the works of (Rogers, 2003) or (Davis, 1989).

Rogers (2003, p. 176) described the decision-making process a person goes through until an innovation is adopted. This often used (Karahanna, Straub and Chervany, 1999, p. 185) innovation-decision-process is divided into the following steps (Rogers, 2003, p. 176 et sqq.):

1. Knowledge of the innovation
2. Attitude towards this innovation
3. Decision to adopt or reject the innovation
4. Use of the innovation
5. Confirmation

In the first stage, the potential user receives the first information about the innovation, while in the second stage an attitude towards this innovation is formed. Stage three describes the decision to adopt an innovation and stage four the realisation of this decision. In step five, the user searches for a confirmation for the use of the innovation and, eventually, ends the use of the innovation if he does not get it. Thus the adoption of an innovation corresponds to the acquisition or use of this innovation (Rogers, 2003, p. 180).

Davis (1986) investigated the acceptance of information systems. He distinguishes acceptance into the stages attitude towards using the information system, behavioural intention to use the information system and the actual system use (Davis, 1986, p. 25 et sqq.). Thereby he identifies adoption with actual system use (Davis, 1989, p. 322). However, Davis also notes that all three levels are suitable for examining adoption, but with different accuracies (Davis, 1986, p. 39). These preliminary stages of adoption can also be found in the innovation-decision-process of Rogers (2003) in stages 2 to 4 (Arts, Frambach and Bijmolt, 2011, p. 135).

Thus, this thesis defines adoption not only as actual use of the smart system, but includes also the attitude towards using the smart system and behavioural intention to use the smart system. All three stages have their justification for existence. Davis (1986, p. 38) describes that the acceptance (and thus also the adoption) of information systems that are not available cannot be measured by actual use. To this end, he proposes to use intention to use as a measure. Davis also describes that in situations in which the respondent could not form an intention regarding the adoption of the information system, the attitude is an adequate estimator for the actual use (Davis, 1986, p. 39). With each stage (from attitude to actual use), the accuracy of predictions increases. Thus, studies about adoption based on actual use are more accurate than studies based on attitude (Abraham *et al.*, 1999, p. 2607; Davis, 1986, p. 39). Thus, the aim should be to measure the actual use as far as possible in order to obtain as valid statements as possible on the adoption of smart systems. However, this is not possible with every smart system. The measurement of these three quantities differs. While actual use is measured directly via observations, attitude and intention to use, as latent variables, can just be measured indirectly, e.g. via questionnaires. Because smart systems are partly highly automated technical innovations, not all smart systems are always available on the market or may be too expensive to investigate the actual use of these systems under controlled conditions. In these cases, measuring adoption by intention to adopt is a cheap (van Ittersum and Feinberg, 2010, p. 808) and adequate alternative (Armstrong, Morwitz and Kumar, 2000, p. 394; Arts, Frambach and Bijmolt, 2011, p. 134; Infosino, 1986, p. 381; Jamieson and Bass, 1989, p. 344; Silk and Urban, 1978; Urban and Katz, 1983). The intention to use an innovation has many times been proven to be a very good predictor of its usage (Armitage and Conner, 2001, p. 482 et sqq.; Venkatesh, Morris and Davis, 2003,

p. 427; Vijayasarathy, 2004, p. 748). The intention even represents an often used proxy for actual use in practice (Jamieson and Bass, 1989, p. 336; Sun and Morwitz, 2010, p. 356). Thus, the choice of the measure of adoption depends on which smart system is being studied. The smart systems to be examined in this thesis, and thus also the measures of adoption, were selected on the basis of the influencing factors on adoption to be examined.

1.2.2 Influencing Factors

Since smart systems can be very diverse (Akhras, 2000, p. 25), there are also various factors influencing adoption (Arts, Frambach and Bijmolt, 2011, p. 135). In the literature, the degree of automation (e.g. Gold *et al.*, 2015; Muir, 1994; Riley, 1989, p. 124) and the risk associated with the use of technology (Hubert *et al.*, 2018, p. 186; Riley, 1989, p. 128) are often cited as the most important factors influencing adoption. For this reason, this thesis places automation and risk at the centre of the investigation besides several other influencing factors of the adoption of smart systems. In the following, automation will be described first as an influencing factor and then risk.

1.2.2.1 Degree of Automation as Influencing Factor

Automation has already been described as an important characteristic of smart systems (Ahmad, 1989; Akhras, 2000, p. 25). Not only is automation an important element of smart systems, but automation is also an important factor influencing the adoption of smart systems (Riley, 1989, p. 124). Thus, automation is in the focus of many studies (Gold *et al.*, 2015; Parasuraman and Riley, 1997; e.g. Parasuraman, Sheridan and Wickens, 2000). The automation is advantageous for the user in three respects and therefore may increase the probability of adoption. Automation can influence adoption by increasing the comfort of the user, reducing errors (Gold *et al.*, 2015, p. 3026) or creating economic advantages (Parasuraman, Sheridan and Wickens, 2000, p. 286). The degree of automation of a smart system is a driver for the user's comfort. The higher the degree of automation of a smart system, the more tasks the user is relieved of (Parasuraman, Sheridan and Wickens, 2000, p. 286). While lowly automated systems only provide decision support for the user, highly automated systems even take over the execution of the action and may not even inform the user anymore (Sheridan and Verplank, 1978, p. 168). The increase in comfort is achieved so that the workload on the user is reduced and he can concentrate on other things (Parasuraman and Riley, 1997, p. 234). Another advantage of automation is the reduction of errors. Parasuraman and Riley (1997, p. 235) explained that the main reason for the introduction of automation is the reduction of errors by the operator as a fundamental reason. For instance, calculations by computer are usually more accurate and contain fewer errors than calculations by humans. Also, when decisions are made by a smart system, subjective impressions may be excluded, which makes the decision of the smart system more reliable. However, a smart system can also perform certain operations and calculations faster than a human being. This also results in economic advantages through automation (Parasuraman, Sheridan and Wickens, 2000, p. 286). The automatic route adjustment of a navigation device due to traffic situations, for example, reduces the workload on the user. The driver does not need to get the current traffic information and also to evaluate and select the different routes to the destination (solution space). This automation increases the user's comfort while driving and even increases the efficiency with which the task is performed. The number of errors is also reduced because the smart system can perform route evaluation calculations faster and more accurately than the user.

Besides the advantages that can increase adoption, automation also has disadvantages that can reduce the willingness to adopt, which can be aggregated under the delivery of control. With increasing automation, more and more control over the execution of the task is transferred to the smart system (Parasuraman, Sheridan and Wickens, 2000, p. 286). The delivery of control is particularly critical when the smart system has a malfunction. Even if these malfunctions should only be the exception, a situation arises characterised by uncertainty and risk (Verberne, Ham and Midden, 2012, p. 807). Thus, automation influences adoption in a positive as well as in a negative way and as a result it is not clear how increasing automation will influence adoption among users.

In addition to the direct influence on adoption, automation can also have an indirect influence on adoption. The effect of other influencing factors on adoption can be strengthened or weakened by the increasing degree of automation (Rovira, McGarry and Parasuraman, 2007, p. 84; Visser and Parasuraman, 2011, p. 224). Therefore, the perception of advantages and disadvantages of smart systems can change due to the degree of automation (Hoff and Bashir, 2015, p. 424). Advantages can be enhanced by automation, as the user has to do less and less to experience the benefits of the smart system (Parasuraman, Sheridan and Wickens, 2000, p. 286). However, disadvantages can also be perceived more negatively due to increasing automation, as the user has less and less control over the execution of the task (Hoff and Bashir, 2015, p. 424).

Automation also has an impact on trust, which is often mentioned in the literature as a factor influencing the adoption of technologies (Lee and Moray, 1992, p. 1243; Muir, 1987, p. 534, 1994, p. 1905; Parasuraman and Riley, 1997, p. 236). As already described, with increasing automation, more and more control is transferred to the system. This loss of control can lead to a feeling of surrender of the user (Weyer, 1997, p. 246). Since the user is less and less involved in the execution of the task with increasing automation, the user has to trust more and more in the correct execution of the task by the smart system (Hoff and Bashir, 2015, p. 424). Depending on the degree of automation, a different degree of trust in the smart system is required to use it (Muir, 1994, p. 1905). However, automation also creates trust in the smart system through the error reduction (Hoff and Bashir, 2015, p. 424). Most automated systems also work reliably and have failures only in exceptional cases. Therefore, these automations are mostly trusted (Parasuraman and Riley, 1997, p. 238). This trust can lead to an overreliance and thus to a misuse and disuse of the smart system (Parasuraman and Riley, 1997, p. 238).

To measure the influence of the degree of automation on the adoption of smart systems, several smart systems with different degrees of automation have to be investigated. Measuring adoption on the basis of usage is difficult, particularly with highly automated smart systems, since smart systems with a high degree of automation are potentially too expensive for experiments or not available at all. An example is autonomous cars. It is not possible to examine the entire spectrum of automation within an experiment in order to find out whether an individual is willing to adopt in the sense of actual use. Therefore, adoption has to be measured either by the intention to use or the attitude towards using the smart system. Since measuring the adoption by the intention to use is more reliable than the attitude towards using them (Davis, 1986, p. 39), the intention to use a smart system should be investigated. For this reason, the initial research question can be specified and the following research question develops:

RQ1: How does the degree of automation influences the intention to use a smart system?

1.2.2.2 Risk as Influencing Factor

Besides the degree of automation, the adoption of automated smart systems is also dependent on the risk associated with the use of smart systems (Parasuraman and Riley, 1997, p. 238; Riley, 1989, p. 128). Of the different risk views in the literature, risk in the narrower sense is considered in this work (Kless, 1998, p. 93; Rücker, 1999, p. 30; Siepermann, 2008, p. 11). Risk in the narrower sense is based on the assumption that a risk causes always something negative and has no positive deviation from a planned value. A distinction is made between two risk perceptions: the cause-related risk perception and the effect-related risk perception. The cause-related perception considers the reasons for a deviation from an intended result, whereas the effect-related perception of risk considers the consequences of a risk (Siepermann, 2008, p. 11 et sqq.). A similar segmentation was also examined by Kaplan and

Garrick (1981, p. 12) who described that risk consists of uncertainty and damage. Due to the logical separation of these two perceptions, their influence on adoption should also be examined separately.

The **effect-related perception** of risk defines risk as the potential damage which arises by the use of a smart system (Jenni, 1952, p. 19). Possible damages caused by the use of smart systems can be the reduction of wealth (Nicklisch, 1912, p. 161) or required additional expenses (Leitner, 1915, p. 8), which may arise, for example, from ordering a wrong product or a product that is too expensive. However, the failure of a service can also be considered damage (Bader and Seidel, 2002, p. 8; Hax, 1949, p. 15; Lisowsky, 1947, p. 98; Oberparleiter, 1930, p. 99) if, for example, the smart system does not execute the instructions at all. In the worst case, the use of a smart system can harm people, for example if an autonomous car malfunctions.

The potential damage is measured as the difference between the planned outcome and the actual outcome (Eucken, 1965, p. 139; Hax, 1949, p. 15). It depends on the area of application of the smart system and can thus vary from system to system. Among other influences, Riley (1989, p. 127) showed that the risk in the particular situation is decisive as to whether an automated system is adopted or not. The risk is therefore dependent on the particular task or situation in which the smart system is used. Tasks or situations in which greater damage is caused by malfunctions of the smart system have a greater risk than situations or tasks in which a malfunction causes no damage at all (Jenni, 1952, p. 19). Intelligent personal assistants (IPA) could suggest wrong product for purchase or unauthorized persons could order products through the IPA (Liptak, 2017). This could result in financial damage. Autonomous cars, for instance, could perceive their surroundings incorrectly and therefore cause accidents (e.g. Davies, 2017). The size of the potential damage can hinder users from using a smart system (e.g. Dowling and Staelin, 1994; Featherman and Pavlou, 2003).

In areas where there is a high risk in terms of damage due to malfunction of the smart system, a faultless functioning of the smart system is essential for these systems to be used (e.g. Gold *et al.*, 2015, p. 3030). This requirement leads to the development of complex smart systems (Hubert *et al.*, 2018, p. 181; Weyer, 1997, p. 241). In order to avoid errors, smart systems in high-risk areas use the latest technology (Furgale *et al.*, 2013, p. 809) and algorithms (e.g. Huang and Ren, 1999), and may even have redundant sensors (Wei *et al.*, 2013, p. 770). This also makes the systems very expensive. In addition, very high risk only occurs in certain applications, such as autonomous driving (Liu, Yang and Xu, 2018, p. 326). These situations are difficult to represent in a controlled manner within an experiment. Therefore, it is also not possible to examine the entire spectrum of effect-related risk within an experiment in order to find out whether an individual is willing to adopt in the sense of actual use.

Analogous to the degree of automation, the influence of the effect-related risk on the adoption of smart systems will not be measured by the actual use, but by the intention to use. Thus, the following research question arises for the effect-related risk:

RQ2.1: How does the effect-related risk influences the intention to use a smart system?

The **cause-related perception** of risk defines the reasons for possible negative consequences as risk (Siepermann, 2008, p. 11). The risk of a smart system can be based on the one hand on a potential malfunction or wrong decision of the smart system (decision-related perception of risk, see Philipp, 1967, p. 13; Wittmann, 2013, p. 189), but on the other hand also on an uncertain information situation of the smart system (information-related perception of risk, see Imboden, 1983, p. 47 et sqq.). Risks according to cause-related perception can to some extent be quantified by probabilities. However, this is not possible in all cases because either not all information is available for calculation or the person confronted with the risk is not able to calculate this probability (Siepermann, 2008, p. 12).

With regard to the decision-related perception of risk, malfunction can occur in any element of a smart system and in any data transfer. Data can be damaged during transfer between elements, or calculation steps in an element can be performed incorrectly. This would correspond to a failure of the decision-making instance (Philipp, 1967, p. 17). With regard to the information-oriented view of risk another type of malfunction can be caused by wrong, incorrect or incomplete information. For this reason the output of the smart system may be also incorrect (Siepermann, 2008, p. 12). If the information is not characterised by uncertainty, the willingness of users to adopt smart systems may increase. Also if the probability of a malfunction of the decision-making instance is low, this can increase the trust in the smart system and thus also the adoption willingness of the user.

To test this influence of the decision-related risk in an experiment, the output of the smart system can be manipulated and for testing the influence of information-related risk, simply the uncertainty of the situations where the smart system is used has to differ. Therefore, it is possible to examine the influence of the cause-related risk on the adoption of smart systems by using one smart system and manipulate the output and differentiate the uncertainty of the situation. By this, the whole spectrum of cause-related risk can be covered by just one smart system, which does not have to be very complex. Thus, the last research question arises:

RQ2.2: How does the cause-related risk influences the use of a smart system?

1.3 Literature Review

The aim of this thesis is to investigate the influencing factors on the adoption of smart systems and particularly the degree of automation and risk. Studies on the adoption of smart systems and their influencing factors exist in large quantities. But most of the studies do not consider the adoption of smart systems as a whole, but of individual smart systems. These include, for example, studies on smart homes (Jin Noh and Seong Kim, 2010; Wang, McGill and Klobas, 2018), intelligent personal assistants (Han and Yang, 2018; Orehovački, Etinger and Babić, 2019), autonomous vehicles (Hartwich *et al.*, 2018; Hutchins and Hook, 2017), smart meter and home appliances (Kranz, Gallenkamp and Picot, 2010; Mert, Suschek-Berger and Tritthart, 2008), smart wearables (Kim and Shin, 2015; Yang *et al.*, 2016) or expert systems (Anthony, Wood and Holmes, 2007; Madni, 1988).

Due to the diversity of smart systems, the factors influencing adoption of the above studies are manifold. Concerning one of the central influencing factors, all the above studies considered smart systems only in a certain degree of automation. However, the studies show deficits in the investigation of the degree of automation and risk as an influence on adoption, so that only limited conclusions can be drawn. With regard to the influence of the degree of automation on the adoption of smart systems, however, studies exist that at least underline the importance of automation for the adoption of smart systems.

Nordhoff, van Arem and Happee (2016) focused their work on creating a concept for explaining, predicting and improving the acceptance of driverless vehicles. The authors carried out a meta-study, which compiled the results of 45 research studies on autonomous vehicles. A central hypothesis put forward by the researchers is that the degree of automation correlates negatively with acceptance. This is underlined by several authors in various empirical studies. Kyriakidis, Happee and Winter (2015) investigated public opinion on automated driving. To this end, 5,000 people from 109 countries were interviewed. The respondents were asked to answer a questionnaire with 63 questions about their acceptability, concerns and willingness to pay for different degrees of automation. The questionnaire was published on the platform Crowdflower.com and the participation was paid with 0.30$. Regarding the influence of the degree of automation on adoption, the authors found that the willingness to pay for highly automated vehicles is lower than for low automated vehicles. In an online survey, Schoettle and Sivak (2015) asked 505 US citizens about their preferred degree of automation for vehicles. In the results, respondents did not prefer automation (43.8%), some still preferred semi-automated vehicles (40.6%), and only a few preferred fully automated vehicles (15.6%). Brookhuis and Waard (2006) came to a different conclusion. They examined the consequences of automating a vehicle on the acceptance and behaviour of the driver. The simulated vehicle on which the study took place has several control options. The driver can use the vehicle like a bus (manual), a tram (semi-automatic) or a subway (full-automatic). The drivers were then supposed to drive a 9 km test track, which was modelled after a track near the city of Eindhoven. The drivers had to drive manual first, but could then decide whether they wanted to switch to semi-automatic or full-automatic. On average, 55% of the test persons decided to continue driving in full-automatic mode. This shows that full-automatic vehicles are preferred in this area.

Two studies also proved that the influence of the degree of automation does not necessarily have to be linearly correlated with adoption. Rödel *et al.* (2014) also investigated the influence of the degree of automation on acceptance. Scenarios were developed to describe the different degrees of automation. 336 test persons were confronted with 5 scenarios in an online survey and subsequently asked about their acceptance. As a result, a negative correlation between degree of automation and acceptance was documented. However, this is not linear, since the second automation level has a higher acceptance than the first. Verberne, Ham and Midden (2012) investigated the influence of trust and automation levels on the acceptance of smart systems. Relevant for this work are particularly the findings regarding the influence of the automation level on the acceptance of a smart system. In the study, 57 persons participated in an experiment in which the test persons were to assess three driver assistance systems. The driver assistance systems were presented to the test persons in the form of a written description of the systems. The first driver assistance system (ACC_{info}) only informed the driver how to react (automation levels 1 – 4 (Sheridan and Verplank, 1978, p. 168)). The second system ($ACC_{info+action}$) takes over these tasks and informs the driver about the completion of the task (automation levels 5 – 7 (Sheridan and Verplank, 1978, p. 169)). The last system (ACC_{action}) also took control of the vehicle, but no longer informed the driver about his actions (automation levels 8 – 10 (Sheridan and Verplank, 1978, p. 170)). In order to measure whether the test persons accepted the ACC system, a questionnaire had to be completed. Significance tests were then used to determine whether the acceptance of the ACC was dependent on the automation level. The result showed that there was no linear correlation between automation level, as defined by Sheridan and Verplank (1978, p. 168), and acceptance. Thus, $ACC_{info+action}$ achieved the most acceptance. It could be proven that this system is accepted significantly more than ACC_{action}. No significant differences in acceptance could be measured between ACC_{info} and $ACC_{info+action}$, or between ACC_{info} and ACC_{action}.

The influence of the degree of automation on the adoption of smart systems was therefore only dealt with to a limited extent in the literature, since the studies concentrate only on autonomous vehicles as smart systems. The results of these studies are also partly contradictory. The second influencing factor to be examined in this paper is the risk associated with the use of smart systems. For this purpose the cause-related risk and the effect-related risk are considered. Liu, Yang and Xu (2018) investigated the public acceptance of fully automatic cars as well as the influence of social trust, risks and benefits on acceptance. The 441 respondents were addressed personally. The questionnaire consisted of 5 demographic questions and 22 questions on the constructs social trust, perceived benefit, perceived risk, general acceptance, behavioural intention. The risks examined included both cause-related and effect-related risks. All risks were summarized in the perceived risk construct. The risk has negative effects on general acceptance and willingness to pay, but there is no significant influence on behavioural intention. Yang *et al.* (2016) addressed the acceptance of wearable devices. The authors define wearable devices as devices that are integrated into clothing or can be attached to clothing. Smartwatches are also referred to as wearable devices. The model for measuring acceptance includes both the influence of cause-related risk (performance risk) and the influence of effect-related risk (financial risk) on the perceived value, which in turn should have an influence on the intention to use the wearable device. Both the performance risk and the financial risk have a weakly significant negative influence on the perceived value of the smart wearable. The influence of the measured benefits is therefore stronger than the risks. It was also shown that risks only play a role for potential users, but not for people who already use a wearable device. Performance risk (cause-related risk) had a somewhat greater influence than financial risk (effect-related risk). Hulse, Xie and Galea (2018) considered the perception of autonomous vehicles. Not only was the perspective of the drivers of autonomous vehicles of interest, but also the perspective of pedestrians. 925 respondents were asked about their perception and acceptance of autonomous cars via an online questionnaire. The perception of the autonomous vehicle was compared with other vehicles. Overall, the risk (cause-related and effect-related) was perceived as low. In the comparison between a manually controlled car and an autonomous car, the respondents stated that the situation was more risky for the passenger than for the pedestrian. Autonomous cars were also considered to be more risky than self-steering trains. Men considered autonomous cars to be less risky and accepted them more readily than women. Hubert *et al.* (2018) examined, among other things, the influence of effect-related risk (privacy risk, security risk, time risk) and cause-related risk (performance risk) on the adoption of smart homes. The model was based on a total of three basic models: Technology Acceptance Model, Innovation Diffusion Theory, Perceived Risk Theory. To test the hypotheses, 409 persons were interviewed. The risk construct, which includes the effect-related and cause-related risk, helped to explain the variance of the model. Security risk was identified as the strongest predictor for the risk construct. The risk had a strong indirect negative effect on the intention to use the smart home. Han and Yang (2018) took the parasocial relationship perspective in investigating the adoption of intelligent personal assistants. The aim was to explain how the parasocial relationship influences the adoption and continuous use of an intelligent personal assistant. In this context, they also investigated the indirect influence of effect-related risk (privacy/security risk) on adoption. A negative influence of the risk on the parasocial relationship between users and intelligent personal assistants was postulated. The questionnaire was published on Amazon Mechanical Turk and answered by 304 persons. It turned out that the negative influence of the risk on the parasocial relationship is highly significant.

Another publication looked at both the automation and the risk in investigating the factors influencing the adoption of a smart system. In this study by Yang, Lee and Zo (2017), the acceptance of smart home services was examined on the basis of the Theory of Planned Behaviour. The considered risk is the effect-related risk (privacy/security risk and physical risk). While a negative influence of risk on attitude was postulated, it was assumed that automation has a positive influence on attitude. The result for the effect-related risk is ambivalent. The postulated influence of physical risk on attitude could not be confirmed, but the security/privacy risk has a weakly significant negative influence on attitude. Furthermore, no influence of automation on attitude could be observed.

Although the publications presented here show that risk and automation have some influence on the adoption of smart systems, it is not considered whether this influence changes if the respective influencing factor varies. This thesis tries to make general statements about the influence of the degree of automation and risk on the adoption of smart systems by considering several smart systems and thus to go beyond individual considerations of smart systems. Therefore, each study of a smart system is preceded by an additional literature review of the respective smart system.

1.4 Structure of the Thesis

The remainder of this thesis is structured as follows. To answer the research questions, the thesis is divided into two sections. The first section examines the influence of the degree of automation and the effect-related risk on the acceptance of smart systems (RQ1 & RQ2.1). The second section is devoted to the question of how cause-related risk influences the use of smart systems (RQ2.2). The table below gives an overview of the structure of the research questions between the two sections.

Table 2: Section Structure of the Thesis

<table>
<tr><th colspan="2">Factors</th><th>Measurement of Adoption</th><th>Research Question</th><th>Section</th></tr>
<tr><td colspan="2">Automation</td><td>Intention to Use</td><td>RQ1</td><td>Section I</td></tr>
<tr><td rowspan="2">Risk</td><td>Effect-related</td><td>Intention to Use</td><td>RQ2.1</td><td>Section I</td></tr>
<tr><td>Cause-related</td><td>Actual Use</td><td>RQ2.2</td><td>Section II</td></tr>
</table>

The sections are each based on three scientific papers. Table 3 shows the titles and publication status of the underlying papers.

Section I examines the influence of effect-related risk and the degree of automation on the intention to use three smart systems. These smart systems can be distinguished by their degree of automation and the extent of possible damage a malfunction would cause. The first model (Survey A) focuses on intelligent personal assistants (*"The Acceptance of Intelligent Personal Assistants").* These assistants are usually speakers with microphones (Kowalczuk, 2018, p. 418). These assistants can play music or control the light via voice control (Lopatovska *et al.*, 2018, 2). But these assistants can also be used to obtain information (decision support) (Hoy, 2018, p. 81). The second smart system considered (Survey B) is externally controlled household appliances (*"Turn it on!-User Acceptance of Direct Load Control and Load Shifting of Home Appliances"*). These household appliances are, for example, washing machines, dryers, dishwashers or refrigerators and can be controlled for smoothing the load curve (Finn, O'Connell and Fitzpatrick, 2013, p. 684). Thus, the user simply specifies a time window for execution and the smart system coordinates and schedules the execution within this time frame. In the third smart system (Survey C), the acceptance of autonomous vehicles is investigated (*"Where can I Take you? - The Drivers of Autonomous Driving Adoption").* Only fully automated vehicles are considered. The user simply specifies a target and hands over complete control to the vehicle (NHTSA, 2016). All of these three models are structural equation models. The underlying hypotheses were tested by means of surveys.

Section II deals with the drivers of using a smart system in situations with different degrees of cause-related risk. A dedicated smart system was created for this purpose. This smart system is a decision support system, which should give the user support in decision situations in the form of recommendations for action. In order to acquire a sufficiently large number of volunteers, the study was enriched with gamification elements, where test persons should try to perform as well as possible in a simple digital card game. For the player decision support was offered. In order to investigate the actual use of smart systems, the conditions under which a test person follows the decision support of the smart system were then investigated. The evaluation was carried out with the help of a decision tree (*"What Drives Decision Makers to Follow or Ignore Forecasting Tools-A Game Based Analysis")* and linear regressions (*"The Effect of Uncertainty and Quality Perception on the Usage of Forecasting Tools–A Game Based Analysis"* and *"What Drives Decision Makers to Follow or Ignore Forecasting Tools-A Game Based Analysis"*).

Finally, the results of both sections are compiled, limitations of the work are discussed and future starting points are pointed out.

Table 3: Underlying Papers

Title	**Publishing Status**	**Authors**
The Acceptance of Intelligent Personal Assistants	Working Paper	Lackes, Siepermann, Vetter
Turn it on!-User Acceptance of Direct Load Control and Load Shifting of Home Appliances	Published in the Proceedings of the European Conference on Information Systems 2018 (Jourqual 3: **B**).	Lackes, Siepermann, Vetter
Where can I Take you? - The Drivers of Autonomous Driving Adoption	Under first revision for the European Conference on Information Systems 2019 (Jourqual 3: **B**).	Lackes, Siepermann, Vetter
The Effect of Uncertainty and Quality Perception on the Usage of Forecasting Tools–A Game Based Analysis	Published in Lecture Notes in Computer Science (Jourqual 3: **C**).	Lackes, Siepermann, Vetter
What Drives Decision Makers to Follow or Ignore Forecasting Tools-A Game Based Analysis	Published in the Proceedings of the 51st Hawaii International Conference on System Sciences 2018 (Jourqual 3: **C**).	Vetter, Siepermann, Lackes
What Drives Decision Makers to Follow or Ignore Forecasting Tools-A Game Based Analysis	Accepted for publication in the Journal of Business Research (Jourqual 3: **B**).	Lackes, Siepermann, Vetter

This thesis is a paper-based work. Some passages of the papers on which this thesis is based have been taken over, while other passages have been changed. The changes are intended to make the paper easier to read and understand. The contents of the publications have remained the same and have been supplemented by a framework dedicated to the research question of this work.

Section I

Determining Factors of the Intention to Use Smart Systems

2 Section I: Determining Factors of the Intention to Use Smart Systems

In section I the two research questions RQ1 and RQ2.1 will be answered. RQ1 raises the question of the influence of the degree of automation on the intention to use smart systems and RQ2.1 of the influence of the degree of effect-related risk on the intention to use smart systems. First, possible influencing factors on the intention to use will be identified for a basic research model. Intention to use is a latent variable. A direct measurement is therefore not possible. The literature relies on measurement via indicators for latent variables. The potential influencing factors and their presumed impact on the intention to use were thus modelled in a structural equation model, taking into account established models. The hypotheses established in the model were then tested by means of surveys. The basic research model developed was varied to answer research questions RQ1 and RQ2.1 in order to examine the degree of automation and effect-related risk as an influencing factor. For this purpose, the basic research model was adapted and extended to three different types of smart systems. The three smart systems were chosen such that with each model the degree of automation and the effect-related risk increases. The smart systems covered are: intelligent personal assistants, direct load control and autonomous driving. The degree of automation indicates to what extent the smart system merely serves as a decision-making aid or even makes decisions for the user itself. The level of effect-related risk represents the possible damage the user experiences when the smart system malfunctions. The following paragraphs briefly explain the representatives, the degree of automation of the system, and the level of effect-related risk.

Intelligent personal assistants are devices that can perform certain tasks or provide information via voice control. Prominent examples of intelligent personal assistants or smart speakers are Amazon's Echo with Alexa, Google Home or Sonos One. With these devices it is possible to play music, do shopping, and much more. The user gives an instruction or a question to the intelligent personal assistant (IPA). Using the microphones (sensors), the IPA records the request and has it analysed. The IPA then uses this instruction to search for permissible solutions. If music should be played, all songs with a matching name are searched. If a product should be purchased, the IPA determines all products that match the request. These alternatives (songs with a matching name; products who match the request) correspond to the solution space. Using additional information, the IPA then reduces the solution space. The additional information is determined from databases on the Internet. For songs, for example, popularity is used to play the right song. For shopping, the user is offered the product that best matches his search query and the seller recommends. How the solution space is reduced depends on the design of the data processing element. The actuator of an IPA is the speaker and for some models a display. This actuator is used, for example, to play the particular song or offer the selected product to the user. If the user purchases via the IPA, he must always confirm the purchase of a product. It becomes apparent that the degree of automation varies depending on the task that the IPA has to perform. While playing music is executed completely independently, tasks that could directly incur costs for the user or harm the user are not performed automatically. In the case of a risky decision, such as the purchase of goods, it is still possible to make a different decision. This puts IPAs at automation level 5 according to Sheridan and Verplank (1978, p. 168). Even if orders via IPAs have to be confirmed, there are reports of incidents where an IPA received commands from unauthorized persons and unintentionally ordered things (Hackett, 2017). In these cases the unauthorised person not just placed the order but also confirmed it. Therefore, there is still a potential damage and therefore effect-related risk left by using an IPA. There may also be effect-related risks arising from the misuse of data that the IPA constantly collects.

Direct Load Control (DLC) is an instrument for load control of the consumer. There the consumption of electricity at the consumer is partly controlled by a smart control system. Here, externally controlled household appliances are regarded as concrete implementations of DLC. These devices should make it possible to adjust the load curve of the consumer in such a way that cost savings can be realized or more renewable energies can be used. However, a shift in the execution time of household appliances only makes sense for certain household appliances. These appliances include, for example, washing machines, refrigerators or dishwashers. For using this smart system, the consumer uses a user interface (sensor) to specify a period during which the device is ready for the DLC. The smart control system (Data Processing Element) not only has information about the time period in which the device should run, but also information about other users' time periods and also information about the market prices for energy (additional information). On the basis of this information, the system decides when which household appliance should run and automatically starts the household appliance at the determined time (actuator). In addition to the request that the household appliance should be controlled, the user must also specify the time frame as an additional condition. A malfunction of this smart system would be a control error of the household appliance. A control error would be that the household appliance does not work at all or the execution time of the household appliance is pushed into a time that is very expensive. These effects represent the effect-related risks of the DLC. The system makes the final decision as to when the appliance will work on its own, but the user still has enough time to intervene. This corresponds to an automation level of 6 according to Sheridan and Verplank (1978, p. 168).

Autonomous driving is distinguished between different levels of automation. In this example, only fully automated cars are examined. These cars take over all decisions and actions regarding the control of the car. The user simply enters the destination of his journey via a user interface (sensor) and leaves the rest of the journey to the vehicle. To reach the destination there are many different possibilities (solution space). This solution space is further reduced by the information of sensors that scan the surroundings of the car. The information provided by these sensors is intended to make the journey as smooth and accident-free as possible. Via an Internet connection, the car can obtain further information, e.g. on the traffic situation. Taking all this additional information into account, the car decides to execute one of the alternative solutions. Alternative solutions are, for example, braking, accelerating or steering, which are taken over by the respective actuators (brakes, engine, and steering wheel). The car does not inform the user of every decision it makes and can therefore be classified at Level 10 according to Sheridan and Verplank (1978, p. 168). The potential damage of autonomous cars can be very high. A malfunction of the system could have serious consequences. In addition to damage to other cars, damage to occupants and pedestrians could also result from a malfunction. Therefore, the effect-related risk of the use of autonomous cars is very high.

For each structural equation model of these three smart systems, adjustments had to be made. On the one hand, the questions were put into context and adapted for each smart system. The questionnaires used can be found in Appendices (p. 152.). Furthermore, the basic model was partially extended. The extensions are necessary in order to take system-specific properties into account for the analysis. The content of this section is based on the publications listed below.

Table 4: Publications Section I

Survey	Title	Publishing Status
A	*The Acceptance of Intelligent Personal Assistants*	Working Paper.
B	*Turn it on!-User Acceptance of Direct Load Control and Load Shifting of Home Appliances*	Published in the Proceedings of the European Conference on Information Systems 2018 (Jourqual 3: **B**).
C	*Where can I Take you? - The Drivers of Autonomous Driving Adoption*	Under first revision for the European Conference on Information Systems 2019 (Jourqual 3: **B**).

Section I is structured as follows. First, the basic research model is presented to investigate the influencing factors. Then the applied methodology and the evaluation procedure are explained. Subsequently, each of the smart systems mentioned is presented as an object of investigation and the specified models are derived. For each model a separate evaluation takes place. The research questions RQ1 and RQ2.1 are then answered in an interim conclusion.

2.1 Basic Research Model

A prerequisite for the success of new technologies like smart systems is the adoption of users. Since Davis (1986, p. 322) compares adoption with the acceptance, it is crucial that the majority of people accept this new technology. Acceptance is the willingness to positively approve someone or something, usually some kind of innovation like a new product or a new service. In general, there are three different kinds of acceptance that can be distinguished (Kjellén and Sklet, 1995, p. 218). The first kind of acceptance is a person's positive attitude towards an innovation. It refers to the mental preparedness of a person to use an innovation. If a person is not prepared, s/he will usually refrain from usage. A positive attitude secondly fosters the intention to use the innovation. The more a person wishes to use the innovation, the more likely s/he will do so. Finally, this wish results in the continuous usage of the innovation. Obviously, the third step of permanent acceptance can only take place if the person has already experienced the innovation (Wirtz, Mory and Ullrich, 2012, p. 650). Thus, the continuous usage of an innovation can only be predicted if the innovation is already available on the market.

To measure the acceptance of a new technology, several models exist of which the Technology Acceptance Model (TAM) of Davis (1986, 1989) and its successors like the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris and Davis, 2003) is among the most often used ones (Chau and Hu, 2002, p. 195 et sqq.). The reason is that the TAM, which is based on Ajzen's and Fishbein's Theory of Reasoned Action (Ajzen and Fishbein, 1980; Fishbein and Ajzen, 1975), usually shows very good results in explaining the factors that influence the acceptance and usage behaviour of people (Gentry and Calantone, 2002; Mathieson, 1991; Venkatesh and Davis, 2000). Therefore, it is often used to measure the acceptance of technical innovation (Chau and Hu, 2002, p. 195 et sqq.). But it should also be noted that it is also criticised for its simplicity (Lee, Kozar and Larsen, 2003, p. 766). However, as causal models should be kept simple and focused on the main questions to be investigated, the core constructs of the TAM are a good starting for the development of a suitable research model for examining the adoption of a smart systems.

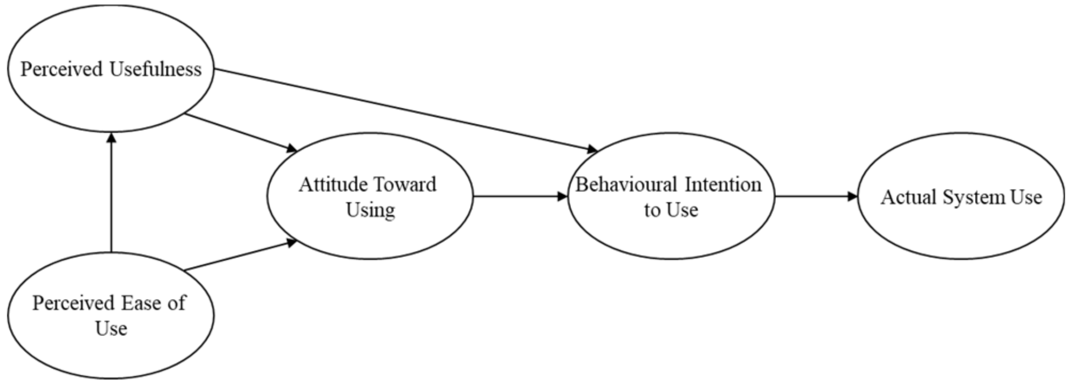

Figure 2: Technology Acceptance Model (Davis, 1986, 1989)

The TAM core states that the attitude towards an innovation (like a smart system) (1st kind) influences the behavioural intention to use it (2nd kind) that again has an impact on the actual use (3rd kind). For the investigations in this thesis, the third kind of acceptance is not being measured, because the considered technologies are still in their infancy and most people had no contact to these technologies. Hence, the use of continuous usage behaviour as a construct is resigned and the model is restricted to the first two kinds of acceptance, namely the attitude towards the technology and the intention to use it. This is hardly a limitation as the intention to use an innovation has been proven many times to be a very good predictor of its usage (Armitage and Conner, 2001, p. 482 et sqq.; Venkatesh, Morris and Davis, 2003, p. 427; Vijayasarathy, 2004, p. 748). As a result, it can be hypothesised in accordance to TAM:

H1: A positive attitude towards the smart system positively influences the intention to use it.

Several factors influence the attitude towards a smart system. In the first place, the attitude is shaped by the positive characteristics of the smart system and how people assess them (Davis, 1986, p. 67, 1989, p. 335). TAM postulates that the usability (ease of use) of an innovation (like a smart system is) influences the way how users perceive its usefulness. Perceived ease of use and usefulness in turn both have an impact on the users' attitude towards the innovation (Davis, 1986, p. 67, 1989, p. 335; Venkatesh and Davis, 2000, p. 195 et sqq.). Usefulness depicts the characteristics of the innovation and how advantageous people perceive them (Venkatesh, Morris and Davis, 2003, p. 447). Perceived ease of use measures the usability of the innovation, i.e. how it is to use it (Venkatesh, Ramesh and Massey, 2003, p. 54). Nowadays, the usability is a prerequisite for the economic success of an innovation (Venkatesh, Ramesh and Massey, 2003, p. 54). If the usability is low, an innovation will hardly be used (Venkatesh, Ramesh and Massey, 2003, p. 55) so that it serves as a kind of hygiene factor (Herzberg, 1968). In addition, assessing the usability of an innovation that cannot be tested by people is quite difficult and may distort the results of the investigation. Therefore, it is resigned to measure the perceived ease of use. However, even if consumers have no experience with a smart system, its usefulness can be judged on the basis of expected advantages and disadvantages, which can be assessed as they can be described easily. Therefore, it is hypothesised concerning the perceived advantages:

H2a: The perceived advantages positively influence the attitude towards the smart system.

H2b: The perceived advantages positively influence the intention to use the smart system.

In contrast to other papers, this research model consists not of separate constructs for each benefit but uses them as measures for the now formative construct perceived advantages. The main advantage is that respondents are not asked several times for the same aspect so that the resulting questionnaire can be kept short. The disadvantages are modelled in the same way. While TAM and its successor models focus on a system's benefits and the environmental conditions for its use (Davis, 1986, 1989; Venkatesh and Davis, 2000; Venkatesh, Morris and Davis, 2003), several extensions have proven the importance of perceived disadvantages and risks on attitude an intention to use an innovation like a smart system (Chen, Xu and Arpan, 2017; Featherman and Pavlou, 2003; Loh and Venkatraman, 1995; Park, Kim and Kim, 2014). Hence, it is not only the perceived usefulness of the innovation in terms of its advantages measured but also the disadvantages in terms of potential threats and personal confinements. As a result, it is hypothesised:

H3a: The perceived disadvantages negatively influence the attitude towards a smart system.

H3b: The perceived disadvantages negatively influence the intention to use a smart system.

Trust is an important antecedent for the interaction of people and therefore for the behaviour of a person towards another person or an artefact (Gefen, Karahanna and Straub, 2003, p. 60; Reichheld and Schefter, 2000, p. 108). It is a multidimensional concept (Mayer, Davis and Schoorman, 1995; McKnight, Choudhury and Kacmar, 2002b, p. 297; Rousseau *et al.*, 1998) and an important antecedent for interactions of people (Gefen, Karahanna and Straub, 2003, p. 60; Reichheld and Schefter, 2000, p. 108). Menon *et al.* (1999, p. 554) regard trust as the belief of the trusting person in attributes of the trustee while Fung and Lee (1999, p. 518) understand trust as the trustor's willingness to believe the trustee. In other words, trust is *"the willingness of a party to be vulnerable to the action of another party [...] irrespective of the ability to monitor or control the other party"* (Mayer, Davis and Schoorman, 1995, p. 712). Thus, trust exhibits two facets: The involved parties and the control mechanisms (Tan and Thoen, 2000b). In general, two parties are involved: The trustor and the trustee (Chopra and Wallace, 2003, 5 et sqq.; Krasnova *et al.*, 2010, p. 114 et sqq.; Tan and Thoen, 2000b, p. 850). It is conceivable that the mistrust of people against a smart system or their manufacturer reduces people's attitude towards this innovation. Hence, the following hypothesis can be derived:

H4a: Trust in the innovation positively influences the attitude towards the smart system.

In addition, trust is proven to influence the perceived risks (Krasnova *et al.*, 2010, p. 125 et sqq.) here the perceived disadvantages, and the perceived usefulness (Chen, Xu and Arpan, 2017, p. 99; Park, Kim and Kim, 2014, p. 217), here the perceived advantages. Therefore, it is hypothesised:

H4b: Trust in the smart system positively influences the perceived advantages of the smart system.

H4c: Trust in the smart system negatively influences the perceived disadvantages of the smart system.

The resulting research model is depicted in Figure 3.

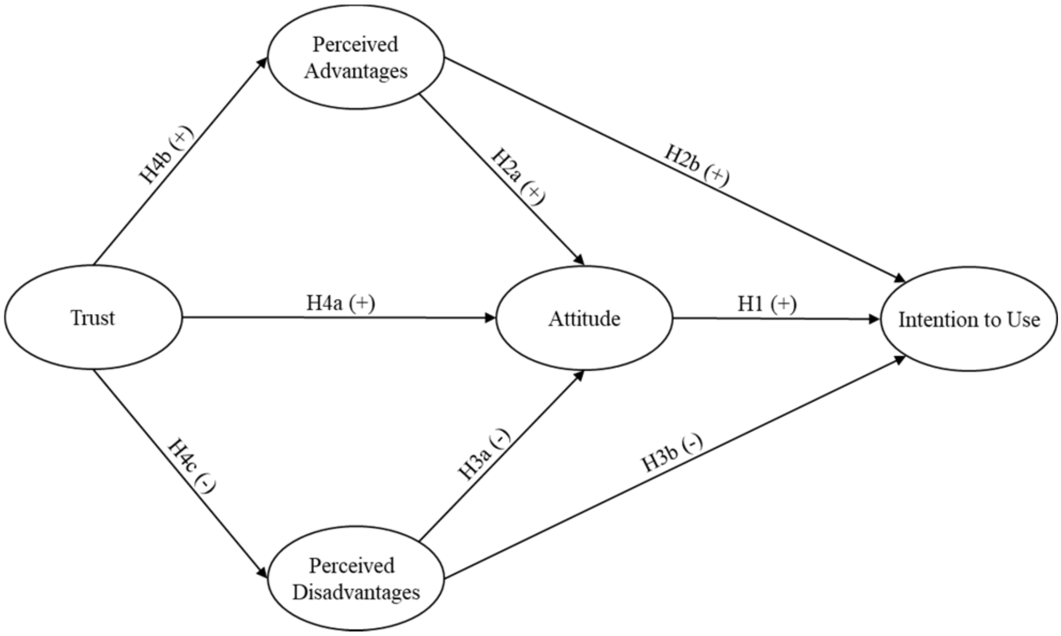

Figure 3: Basic Structural Equation Model

2.2 Methodology

Due to the fact that our theoretically developed structural equation model (SEM) consists of reflective as well as formative constructs (Hair *et al.*, 2016; Jarvis, MacKenzie and Podsakoff, 2003, p. 201), the software SmartPLS 2.0 (Ringle, Wende and Will, 2005) and SmartPLS 3.0 (Ringle, Wende and Becker, 2015) was used for the analysis of the collected data and the SEM. SmartPLS is based on the partial least squares algorithm (PLS). In contrast to covariance-based software as LISREL it is suitable to evaluate reflective as well as formative constructs (Gefen, Straub and Boudreau, 2000, p. 10; Weiber and Mühlhaus, 2014, p. 74). Furthermore, PLS does not restrict the sample size and does not pretend any distributional assumption (Cassel, Hackl and Westlund, 1999, p. 436; Chin, Marcolin and Newsted, 2003, p. 197). For the analysis of the model with SmartPLS, this thesis follows the guideline of Hair *et al.* (2014, p. 14) among others (Haenlein and Kaplan, 2004, p. 290; Henseler, Ringle and Sinkovics, 2009, p. 306; Huber *et al.*, 2007, p. 6). In addition to the PLS algorithm a Bootstrapping is used for the determination of the significance of weights, loadings and path coefficients, with case wise replacement and 5000 subsamples (Hair *et al.*, 2014, p. 51; Hair, Ringle and Sarstedt, 2011, p. 145; Sarstedt *et al.*, 2014, p. 109). For testing the model on multicollinearity SPSS is used to conduct a regression analysis.

2.3 Analysis

The structure of the analysis is based on the guidelines of Hair *et al.* (2014, p. 14). Accordingly, first the analysis of the measurement is explained and afterwards the analysis of the structural model.

Measurement Model

Two kinds of measurement models can be distinguished (Jarvis, MacKenzie and Podsakoff, 2003, p. 203): reflective and formative measurement models. In reflective constructs, the associated indicators are characterisations of the construct, whereas formative constructs are built from their indicators. In contrast to reflective constructs, the complete formative construct changes as an indicator changes (Bollen and Lennox, 1991; Jarvis, MacKenzie and Podsakoff, 2003). The evaluation of both measurement models differs due to the aforementioned properties. Therefore, in the following, the evaluation is carried out first for reflective and then for formative constructs.

For reflective constructs, the indicator reliability, the convergence criterion, the discriminant validity, and the predictive validity have to be considered (Chin, 1998b, p. 320 et sqq.; Hair *et al.*, 2014, p. 96 et sqq.; Hair, Ringle and Sarstedt, 2011, p. 145; Hair, Sarstedt and Pieper *et al.*, 2012, p. 328; Henseler, Ringle and Sinkovics, 2009, p. 298). The indicator reliability is composed of the loading and the t-statistic. The loading of an indicator depicts the relationship between the indicator and its construct, and should be greater than 0.7 (Chin, 1998a, p. 8; Hair *et al.*, 2014, p. 157). The t-statistic demonstrates the significance level of an indicator (Huber *et al.*, 2007, p. 45). For a level of 10%, the t-statistic has to exceed the threshold of 1.65, for 5% of 1.96 and for 1% of 2.57 (Hair *et al.*, 2014, p. 157 et sqq.). Indicators which do not meet these or the following criteria must be eliminated from the model.

For fulfilling the convergence criterion, three measures have to be checked: the average variance extracted (AVE), the composite reliability, and the Cronbach's alpha (Chin, 1998a, p. 5; Huber *et al.*, 2007, p. 12; Weiber and Mühlhaus, 2014, p. 263). The AVE of a reflective construct has to explain, on average, "more than a half of the variance of its indicators" (Hair *et al.*, 2014, p. 103). Therefore, it has to exceed the value of 0.5 (Fornell and Larcker, 1981, p. 45 et sqq.). The composite reliability of a construct indicates how accurately the indicators measure the construct and must exceed the limit of 0.7 (Hair *et al.*, 2014, p. 105; Hair, Ringle and Sarstedt, 2011, p. 145; Huber *et al.*, 2007, p. 45; Nunnally, Bernstein and Berge, 1994). Cronbach's alpha reflects the internal consistency of a construct (Cronbach, 1951, p. 300; Hair *et al.*, 2014, p. 103; Nunnally, Bernstein and Berge, 1994, p. 251) and is required to exceed the threshold of 0.7 (Hair *et al.*, 2006, p. 102 claims a limit of 0.6; Nunnally, Bernstein and Berge, 1994).

The discriminant validity indicates if constructs are sufficiently different. It covers the Fornell-Larcker criterion and the cross loadings. The Fornell-Larcker criterion is met if the AVE of a reflective construct is beyond all its squared correlations with the other constructs (Chin, 1998b, p. 321; Fornell and Larcker, 1981, p. 46; Hair *et al.*, 2014, p. 105). Concerning the cross loadings, the loadings of a construct's indicators must be higher on the construct itself than on any other construct of the SEM (Hair *et al.*, 2016, p. 115).

The predictive validity of a reflective construct shows if the data points of the construct's indicators are well predicted. It is covered by Stone-Geisser's Q^2 (1-SSE/SSO Communality) that has to exceed the threshold of zero (Chin, 1998b, p. 318).

For the assessment of formative constructs, the significance of the indicators, the discriminant validity, and the test on multicollinearity have to be considered. To analyse the significance of the indicators, the weights have to be greater than 0.1 (Chin, 1998b, p. 324 et sqq.; Huber *et al.*, 2007, p. 45) or smaller than -0.1 (Sarstedt *et al.*, 2014, p. 109). At the same time the t-statistics have to comply with the same constraints as reflective constructs (10%: 1.65, 5%: 1.96, 1%: 2.57). Concerning the discriminant validity, the correlation between a formative construct and all other constructs of the model is investigated. The threshold for this criterion is 0.9 (Huber *et al.*, 2007, p. 45).

To ensure that the analysis leads to reliable results and that the influence of the individual indicators is distinguishable, multicollinearity between indicators of formative constructs is not permitted (Diamantopoulos, Riefler and Roth, 2008, p. 1212; Diamantopoulos and Winklhofer, 2001, p. 272 et sqq.; Henseler, Ringle and Sinkovics, 2009, p. 303; Weiber and Mühlhaus, 2014, p. 207). For this, the variance inflation factor (VIF) for all indicators i, with $VIF_i = 1/(1 - {R_i}^2)$, (Sarstedt *et al.*, 2014, p. 109) should not exceed the given threshold of 5 (Hair *et al.*, 2014, p. 125; Hair, Ringle and Sarstedt, 2011, p. 145 et sqq.). In addition, to ensure that there is no distortion of the weights because of undetected multicollinearity of formative constructs, by means of VIF_i, the condition indices are required to be below 30 (Hair *et al.*, 2014, p. 125; Hair, Sarstedt and Ringle *et al.*, 2012, p. 430; Henseler, Ringle and Sinkovics, 2009, p. 303).

Because formative constructs are built by their indicators, indicators that do not meet these criteria, except for multicollinearity, cannot be eliminated. Otherwise, the elimination of an indicator would cause a change of the statistical values and the theoretical meaning of the belonging construct (Bollen and Lennox, 1991, p. 306; Jarvis, MacKenzie and Podsakoff, 2003, p. 201).

Structural Model

The evaluation of the structural model concerns the assessment of the constructs and the paths between them, i.e. the hypotheses. The explanatory power of the model is described by the coefficient of determination R^2 that results from a regression analysis. It is said to be 'substantial' if $R^2 \geq 0.67$, 'moderate' if $R^2 \geq 0.33$, and 'weak' if $R^2 \geq 0.19$ (Chin, 1998b, p. 323). To ensure reliable results for the structural model, multicollinearity between the constructs is not allowed (Hair *et al.*, 2006, p. 227; Hair, Sarstedt and Ringle *et al.*, 2012, p. 430; Huber *et al.*, 2007, p. 109). The calculation and thresholds are the same as described in the previous section. For the assessment of the hypotheses, the path coefficients and the t-statistics have to be examined. The path coefficient must be greater than 0.1 or lower than -0.1 (Chin, 1998a, p. 13 claims a limit of 0.2; Lohmöller, 1989, p. 60; Sarstedt *et al.*, 2014, p. 109; Weiber and Mühlhaus, 2014, p. 261). The significance level of a path is determined by the t-statistic. The same thresholds apply as for the significance of indicators (10%: 1.65, 5%: 1.96, 1%: 2.57).

2.3.1 Three Empirical Studies on the Intention to Use Smart Systems

This chapter contains three empirical studies on the intention to use smart systems. The studies are ordered by their degree of automation and possible amount of damage if the system malfunctions. First in survey A, the intention to use of intelligent personal assistants is in the focus. In survey B demand side management as a smart system is investigated. The last study (survey C) contains a highly automated smart systems namely an autonomous vehicle.

2.3.1.1 Survey A: Intelligent Personal Assistants

The popularity of intelligent personal assistants (IPA) has increased dramatically since 2015 (Forrester Research, 2017) and will continue to increase in the future. Gartner (2016) forecast that 3.3% of households worldwide will have at least one IPA in their household. Transparency Market Research (2016) expects an annual market growth of IPAs of 32.8% from 2016 to 2024. Examples of these smart systems are Google Home, Amazon Echo with Alexa, Apple's Siri or Microsoft's Cortana. This is software that is usually implemented in a device that has a loudspeaker and microphones. IPAs are therefore often called smart speakers. Before IPAs were implemented in smart speakers, some were already integrated on smartphones (e.g. Siri).

The functionality of IPAs ranges from simple daily functions to complex tasks. The simple functions include saving reminders, ordering products or obtaining information. The rather complex functions of IPAs include integration into the smart home, i.e. communication with other electronic devices (Augusto and Nugent, 2006, p. 3). The functional scope of IPAs is constantly growing, as everyone is able to program additional functions for the IPA via software development kits. Therefore, IPAs differ in their functional scope, but the ability to understand what the user wants and to put information into context is the same for all IPAs (Reis *et al.*, 2017, p. 600 et sqq.). An IPA assists the user in technical, social and administrative respects (Riccardi, 2014, p. 54 et sqq.; Saad *et al.*, 2017, p. 12518; Santos *et al.*, 2016, p. 194). Thus the IPA can take over the control of other devices of the smart home (technically), serve as a conversation partner for amusement (socially), or manage appointments and compile information (administratively).

IPAs are controlled via voice. Many IPAs therefore have several microphones with which they can continuously listen to their environment. In order for the IPA to perform a task, the user must say a code word. The IPA then attempts to execute all voice commands after the code word. The acoustic signals given by the user after the code word are recorded by the IPA and sent to a server via the Internet. This server has the ability to analyse audio files using Natural Language Processing (NLP). Thus the audio file is converted into a string and evaluated with the help of text mining methods. By this, the demands of the user can be unveiled. The server then creates the answer of the IPA. The answer of the IPA can either consist of the output of information or of the execution of tasks such as buying something or controlling another device. In addition to the analysis of pure language, approaches are developed that can also recognize emotions based on the user's facial expressions (Knight, 2016) or monitor the user's vital signs automatically and continuously. However, this study will focus exclusively on voice-controlled IPAs.

One aim of voice control is to make IPAs more humane. In this way, the user can ask the IPA questions just like a normal person. Further developments of IPAs are increasingly trying to imitate human response behaviour, for example IPAs which can tell jokes. The quality of the NLP is also rising steadily and conversation with an IPA comes very close to conversation with a real person (Han and Yang, 2018, p. 624). IPAs can now even answer follow-up questions. These are questions that refer to a previous question. Through the human-like communication, the conversation with the IPA should also become socially more pleasant (Han and Yang, 2018, p. 624) and the user should thus build up an emotional connection to the IPA (Han and Yang, 2018, p. 621). Hence, IPAs are often referred to as "digital buddies" (Han and Yang, 2018, p. 622). Once the user has established a binding, he also uses the IPA more often (Han and Yang, 2018, p. 624).

In addition to the functions and applications of IPAs listed here, there are also disadvantages regarding the use of IPAs. For example, in a morning show at the CW6 station in San Diego, a reporter triggered mass orders for dollhouses. The reporter interviewed a girl named Alexa. At the end of the interview, the reporter said *"I love the little girl, saying 'Alexa ordered me a dollhouse,'"*. As a result the Amazon Echos of the viewer then ordered dollhouses (Liptak, 2017). This example is part of a series of incidents where IPAs acted on instructions of unauthorized people. But the biggest disadvantages concern privacy and data security. For example, the IPA receives all talks in its surrounding via its microphones. Even if the IPA only responds to questions and instructions after the code word, it still analyses every conversation in its environment. By using IPAs, the user's data is stored centrally. Therefore, the misuse of theft of this data is another risk and disadvantage of using IPAs.

Due to the advantages and disadvantages presented, the acceptance of intelligent personal assistants is not guaranteed. Whether a person would like to use an IPA is unclear. In order to clarify this, the factors influencing the acceptance of IPAs should be determined and their influence measured. The following research question is to be answered in this way.

RQ1.1: Which factors drive the acceptance of intelligent personal assistants?

Literature Review

Han and Yang (2018) examined factors influencing the continuous adoption and use of IPAs. They designed a structural equation model (SEM) based on the Para-Social-Relationship Theory. The aim of the study was to investigate whether there is a social relationship between the IPA and the user and whether this relationship influences satisfaction with the IPA. A total of 304 participants were interviewed. As a result, Han and Yang showed that security/privacy risk and interpersonal attraction (task attraction, social attraction and physical attraction) have a significant influence on para-social-relationship, which in turn, in addition to task attraction, was influential in satisfaction. Finally, there was a significant positive correlation between satisfaction with IPA and intention to use IPA. Kowalczuk (2018) investigated the behavioural intention to use smart speaker via an SEM. For the development of the SEM he analysed 2,186 customer reviews and 899 tweets and combined these results with models from the literature. The resulting model was tested by interviewing 293 people in an online survey. The influence of risk and perceived enjoyment on behavioural intention to use smart speakers could be confirmed next to the influence of perceived usefulness and perceived ease of use. The influence of technology optimism, system diversity and system quality on perceived usefulness was also confirmed. The perceived enjoyment had the strongest influence on the behavioural intention to use smart speaker. Orehovački, Etinger and Babić (2019) examined the antecedents of adoption of an IPA in an educational setting. The Google Assistant was used as a representative for this. After using the IPA, the indicators for the constructs effectiveness, controllability, reliability, accuracy, ease of use, usefulness, satisfaction, and loyalty were measured using a questionnaire. A total of 309 students were interviewed. Whether the IPA is perceived as an advantageous application depends on whether it improves the participants' performance, helps the user to process a task in a particular way and is perceived as easy to communicate with. If students see the benefits of using IPA, they are likely to use it continuously. Siddike and Kohda (2018) developed a framework of trust determinants to examine the use of IPAs more closely. Through an extensive literature review they found out that reliability, attractiveness and emotional attachments are important factors influencing the trustworthiness of IPAs. They also found that innovativeness moderates the intention to use IPAs.

Studies on IPAs as a combination of loudspeaker and speech assistant are scarce (Orehovački, Etinger and Babić, 2019, p. 76), but there are further studies dedicated to the acceptance of IPAs in mobile devices. For example, IPAs were already used on smartphones before smart speakers were ready for the market. Sano, Kaji and Sassano (2016) investigated the continuous use of IPAs such as Siri on mobile devices. For this purpose they developed a prospective user engagement prediction model. The authors define engagement as whether a user likes IPA and whether he wants to use it continuously. For this purpose, large-scale user logs of 348,295 users of an IPA were analysed. Through the analysis of usage patterns, 338 attributes were identified as influences on engagement. The attributes were categorized into utterance frequency features, response frequency features and time interval features. Jiang *et al.* (2015) investigated the quality of IPAs such as Siri or Cortana on mobile devices. The aim was to develop a method for the automatic evaluation of user satisfaction. A total of 60 participants of a local IT-company took part in the study. The participants had to submit standardised requests to the assistant. The results showed that the quality of speech recognition and intent classification influences the user experience. Jiang *et al.* were able to successfully evaluate the quality of IPAs as well as speech recognition and intent classification. Kiseleva *et al.* (2016) also examined IPAs on mobile devices. They observed the factors influencing satisfaction with the IPA in various scenarios. These scenarios were controlling a device, web search, and structured search dialog. Satisfaction with the IPA differed between the different scenarios. The task completion and the amount of effort spent were identified as factors influencing satisfaction. Another important factor is the ability of the IPA to understand the context of the conversation.

Model Adjustments and Specification of the Indicators

For the construct *Perceived Advantages* in the context of intelligent personal assistants the following indicators were used. The main advantage of IPAs is their simple voice-controlled user interface (indicator PA1) that makes the interaction with the underlying system extremely easy (Hoy, 2018, p. 81 et sqq.). In addition, the usability of a system is nowadays a prerequisite for success (Venkatesh, Ramesh and Massey, 2003, p. 54). It serves as a hygiene factor without which it a system will not be accepted by users (Herzberg et al., 1967). Therefore, it can be resigned to explicitly measure the ease of use as a single construct. Instead, this thesis investigates the advantages of IPAs further. IPAs serve different purposes. They remind people of appointments (López, Quesada and Guerrero, 2018, p. 243) or things to do (PA3) (Hoy, 2018, p. 83). They make enquiries in the Internet (Reis *et al.*, 2017, p. 594), they report the weather forecast (PA2) (Han and Yang, 2018, p. 620), they can make bookings and place orders (PA4) (Yang and Lee, 2018, p. 666). They can help to writes memos (Reis *et al.*, 2017, p. 595) and control different other devices in the household like light, TV, radio, heating etc. (PA5) (Han and Yang, 2018, p. 620). Therefore, it can be hypothesised:

H2a: The perceived advantages positively influence the attitude towards the IPA.

H2b: The perceived advantages positively influence the intention to use the IPA.

Furthermore, the following indicators for perceived disadvantages were used. Besides a general aversion against talking with a machine (indicator PD3) (Noyes, 2001, p. 504) and the fear that the IPA does not do what it should (PD2) (Orehovački, Etinger and Babić, 2019, p. 85), the data security risk may play an important role. The continuous recording of all conversations by the IPA may be seen as disadvantageous (PD5). The protection of this data is therefore very important (PD1). In addition, the data can be used to save detailed user profiles (PD6) making users and their behaviour transparent to the service provider (PD4) (Han and Yang, 2018, p. 627). A misuse of the data and the profiles may harm attitude towards IPAs. Therefore, it can be hypothesised:

H3a: The perceived disadvantages negatively influence the attitude towards the IPA.

H3b: The perceived disadvantages negatively influence the intention to use the IPA.

In the case of IPAs, the trustor is the user of an IPA. Concerning the trustee, two different parties can be distinguished: The IPA itself and the manufacturer who runs the IPA's services on his servers. The user interacts with the IPA. He confides in the functions of the IPA and its reliability to do what it is intended to do. This is to some extent a technical perspective concerning the capability and performance of the IPA. However, the user also has to trust the manufacturer as all the data that is collected during the interaction with the IPA is sent to the manufacturer, analysed and stored on the vendor's server. Thus, the user has to believe in the benevolence of the manufacturer (McKnight, Choudhury and Kacmar, 2002a, p. 337). Without that belief, the user will hardly trust the IPA and regard the IPA as useful. Therefore, trusts influences how benefits (Chen, Xu and Arpan, 2017; Park, Kim and Kim, 2014) and risks (Krasnova *et al.*, 2010) are perceived. As a result, it can be hypothesised for trust in the IPA:

H4a: The trust in the IPA positively influences the user's attitude towards the IPA.

H4b: The trust in the IPA positively influences the perceived advantages.

H4c: The greater the trust in the IPA is, the less severe are the disadvantages perceived. (The trust in the IPA negatively influences the perceived disadvantages.)

Further it can be hypothesised for the trust in the manufacturer:

H4d: The trust in the manufacturer positively influences the perceived advantages.

H4e: The greater the trust in the vendor is, the less severe are the disadvantages perceived. (The trust in the vendor negatively influences the perceived disadvantages.)

H4f: The trust in the manufacturer positively influences the user's attitude towards the IPA.

H4g: The trust in the manufacturer positively influences the user's trust in the IPA.

The resulting specified research model is depicted in Figure 4.

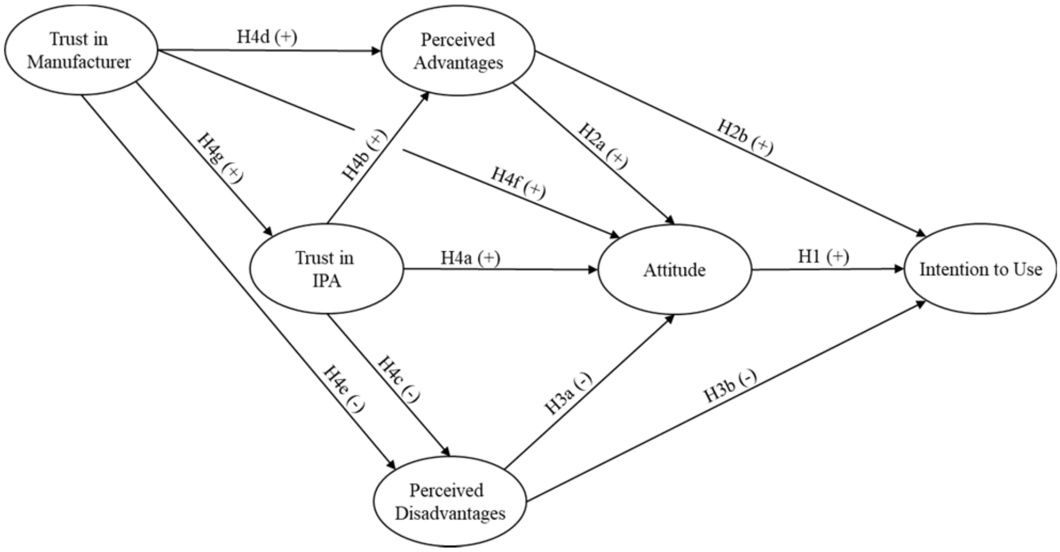

Figure 4: IPA Research Model

Analysis

To answer the research question, a questionnaire with 31 questions was designed for the presented SEM. The survey took place in November 2018. Not every question of the questionnaire had to be answered. Questions could also be skipped. The questionnaire included a further 5 questions in addition to the 26 indicator questions. 213 persons took part in the online survey. 84 responses had to be eliminated as they had more than 15% missing values.

The remaining 129 respondents were 51.41% female. 70.63% have already used an IPA, but only 33.57% have their own IPA. 5.52% of respondents were younger than 20 years, 55.86% between 20 and 29 years, 12.41% between 30 and 39 years, 25.52% between 40 and 79 years and 0.69% older than 80 years. In terms of monthly net income, 27.78% earned less than 500€, 32.54% between 500€ and 1,500€, 24.6% between 1,500€ and 3,000€, 10.32% between 3,000€ and 4,000€, and 4.76% more than 4,000€.

Measurement Model

In the model, reflective and formative constructs can be differentiated according to Jarvis, MacKenzie and Podsakoff (2003, p. 201). First, the reflective constructs are to be examined. The reflective constructs include *Intention to Use*, *Attitude*, *Trust in IPA* and *Trust in Manufacturer*. The indicator reliability is below the 1% significance level for all reflective constructs (see Table 5). The convergence criterion is also met, since the AVE for each construct is greater than 0.5, the composite reliability is above 0.7, and Cronbach's alpha is above the critical value of 0.7. With regard to discriminant validity, Table 7 shows that the highest correlation from *Intention to Use*, *Attitude*, *Trust in IPA* and *Trust in Manufacturer* to other constructs is below the root of the respective AVE. Thus, the Fornell-Larcker criterion is fulfilled. Table 8 documents the cross loadings. It can be seen that all loadings of the indicators are highest in the corresponding construct. Thus, the reflective constructs differ sufficiently from each other. Since the Stone-Geisser´s Q^2 is greater than 0 for each reflective construct, predictive validity is given (see Figure 5). Thus a prediction of the constructs by their indicators is obtained.

Table 5: IPA Results

Construct	Indicator	**loadings** / weights		**AVE** / VIF	Composite Reliability	Cronbach's Alpha
Intention to Use (reflective)	I1	**0,919**	***	**0,733**	0,916	0,877
	I2	**0,807**	***			
	I3	**0,917**	***			
	I4	**0,771**	***			
Attitude (reflective)	A1	**0,872**	***	**0.810**	0,928	0,883
	A2	**0,909**	***			
	A3	**0,919**	***			
Perceived Advantages (formative)	PA1	0,003	ns	2,742		
	PA2	0,305	***	2,634		
	PA3	0,253	*	2,486		
	PA4	0,301	**	1,771		
	PA5	0,344	***	2,241		
Perceived Disadvantages (formative)	PD1	0,306	**	1,393		
	PD2	0,086	ns	1,943		
	PD3	0,514	***	1,758		
	PD4	0,139	ns	2,261		
	PD5	0.040	ns	1,576		
	PD6	0,364	***	1,244		
Trust in IPA (reflective)	TI1	**0,803**	***	**0,647**	0.880	0,822
	TI2	**0,821**	***			
	TI3	**0,818**	***			
	TI4	**0,775**	***			
Trust in Manufacturer (reflective)	TM1	**0,865**	***	**0.669**	0.890	0,837
	TM2	**0,783**	***			
	TM3	**0,824**	***			
	TM4	**0,797**	***			

*Significance of indicators; ns=not significant; *p<0.10; **p<0.05; ***p<0.01*

Table 6: IPA Shares of Answers IPA

Construct	Indicator	Share of Answers 1	2	3	4	5
Intention to Use	I1	45.0%	30.0%	13.3%	9.2%	2.5%
	I2	36.0%	24.0%	10.7%	7.3%	22.0%
	I3	60.0%	24.2%	9.2%	5.0%	1.7%
	I4	63.6%	16.5%	11.6%	4.1%	4.1%
Attitude	A1	7.1%	11.2%	15.9%	32.4%	33.5%
	A2	7.1%	16.0%	24.9%	33.7%	18.3%
	A3	8.3%	16.7%	20.8%	31.0%	23.2%
Perceived Advantages	PA1	7.0%	7.0%	8.9%	35.7%	41.4%
	PA2	3.8%	6.4%	14.6%	33.8%	41.4%
	PA3	7.1%	6.4%	14.1%	35.9%	36.5%
	PA4	35.3%	30.8%	14.1%	12.8%	7.1%
	PA5	16.1%	12.3%	11.6%	25.8%	34.2%
Perceived Disadvantages	PD1	2.0%	10.7%	25.3%	31.3%	30.7%
	PD2	1.3%	15.7%	13.1%	34.6%	35.3%
	PD3	31.2%	14.3%	20.1%	18.8%	15.6%
	PD4	5.3%	15.1%	17.1%	30.3%	32.2%
	PD5	4.6%	16.6%	7.3%	34.4%	37.1%
	PD6	0.7%	6.5%	24.6%	31.9%	36.2%
Trust in IPA	TI1	13.3%	25.9%	41.5%	15.6%	3.7%
	TI2	15.8%	28.6%	43.6%	9.0%	3.0%
	TI3	17.8%	32.6%	37.8%	10.4%	1.5%
	TI4	11.2%	20.9%	26.1%	26.1%	15.7%
Trust in Manufacturer	TM1	13.6%	17.9%	48.6%	14.3%	5.7%
	TM2	14.3%	27.1%	41.4%	16.5%	0.8%
	TM3	14.7%	33.3%	24.6%	18.8%	5.8%
	TM4	23.0%	40.7%	29.6%	6.7%	0.0%

Table 7: IPA Fornell-Larcker Criterion

Construct	Highest Correlation to other Constructs	$\sqrt{AVE}$
Intention to Use	0.636	0.856
Attitude	0.806	0.900
Trust in IPA	0.604	0.804
Trust in Manufacturer	0.604	0.818

The analysis of the formative constructs shows that a few indicators of different constructs are not significant as either their p-value or their weight is below the required threshold (see Table 5). In more detail, regarding the construct *Perceived Advantages* one (PA1) of five indicators has an insufficient weight. The weight of two (PD2 and PD5) of six indicators of the construct *Perceived Disadvantages* are also too low. All these indicators with insufficient weight (PA1, PD2 and PD5) are non-significant as well. In addition to these indicators, one more indicator (PD4) of the construct *Perceived Disadvantages* is not significant. Except for one indicator (PA3) with a significance level of 10% and two indicators (PA4 and PD1) with significance level of 5%, all other indicators are significant at the 1%-level. As there is no indication for multicollinearity (for all indicators $VIF < 5$ and $condition\ index < 30$) and therefore all indicators are sufficiently different and independent, no indicator must be dropped. Also, the discriminant validity is given for the formative constructs as the highest latent variable correlation that occurs between *Perceived Advantages* and *Attitude* is 0.806 and therefore beyond the claimed maximum of 0.9.

Table 8: IPA Cross-Loadings

Indicator	Intention to use	Attitude	Trust in IPA	Trust in Manufacturer
I1	**0.919**	0.580	0.363	0.256
I2	**0.807**	0.523	0.283	0.323
I3	**0.917**	0.505	0.379	0.257
I4	**0.771**	0.389	0.314	0.115
A1	0.569	**0.872**	0.438	0.252
A2	0.462	**0.909**	0.472	0.258
A3	0.556	**0.919**	0.531	0.290
TI1	0.211	0.389	**0.803**	0.374
TI2	0.234	0.320	**0.821**	0.428
TI3	0.168	0.500	**0.818**	0.398
TI4	0.537	0.475	**0.775**	0.655
TM1	0.291	0.335	0.649	**0.865**
TM2	0.206	0.245	0.477	**0.783**
TM3	0.276	0.273	0.371	**0.824**
TM4	0.129	0.056	0.435	**0.797**

Structural Model

The R^2 is moderate for our target construct *Intention to Use* (R^2=0.450). *Attitude* (R^2=0.665) and *Perceived Disadvantages* (R^2=0.502) and *Trust in IPA* (R^2=0.365) achieve as well a moderate level, but *Attitude* just missed the threshold for a substantial explanatory power. *Perceived Advantages* (R^2=0.317) achieves a weak level. The VIF indicates that there is neither multicollinearity nor a condition index higher than 30 (Hair *et al.*, 2006, p. 227; Hair, Sarstedt and Ringle *et al.*, 2012, p. 430; Huber *et al.*, 2007, p. 109). Regarding the structural relationships between the constructs, support for nine of twelve hypotheses was found. The constructs *Attitude* and *Perceived Advantages* are found to be positively related to *Intention to Use* (H1, H2b) with a significance level of 1% (H2b) and 10% (H1). The path coefficient between the constructs *Trust in Manufacturer* and *Perceived Disadvantages*, *Trust in IPA* and *Perceived Disadvantages*, and *Perceived Disadvantages* and *Intention to Use* are below -0.10 which implicates a negative relation between the constructs (H4e, H4c, H3b) with a significance level of 1% (H4e), 5% (H4c) and 10% (H3b). H3a is not supported by the data. The hypotheses H2a, H4a, H4b and H4g could be confirmed with a positive influence and a significance level of 1% (H2a, H4b, H4g) and 10% (H4a) whereas H4d and H4f are not supported by the data. Figure 5 shows the hypotheses with their path coefficients, significance, and effect sizes f^2. For each construct, the R^2 and the predictive relevance $Stone - Geisser\acute{}s\ Q^2$ is provided.

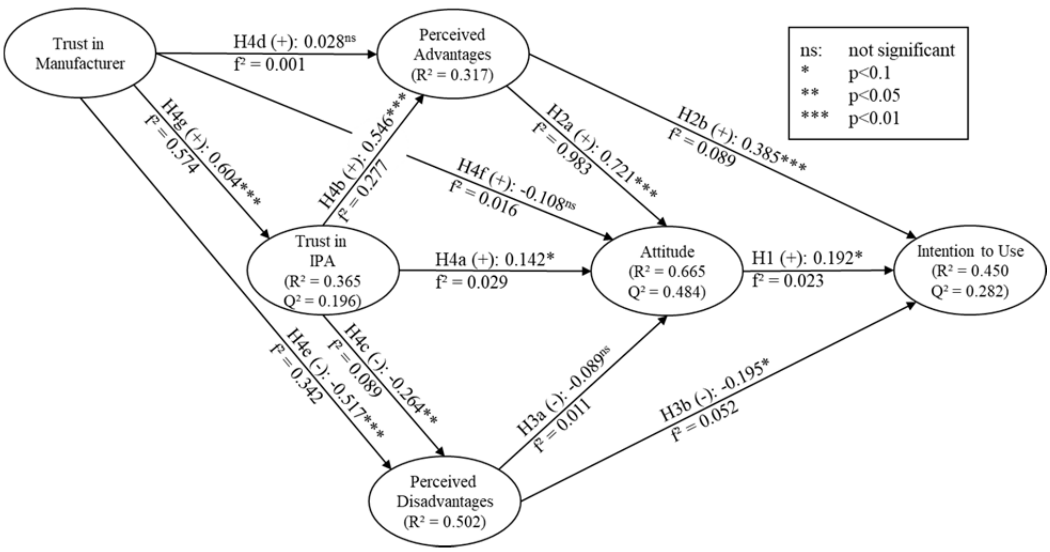

Figure 5: IPA Results

Results

Discussion

The results of our study are very satisfying. Only three (H3a, H4f and H4d) out of twelve hypotheses could not be confirmed. The explanatory power of the model is medium with 45% for the *Intention to Use*. Other constructs like *Attitude* (66.5%), *Perceived Disadvantages* (50.2%), as well as *Trust in IPA* (36.5%) also are on the medium level, but *Attitude* misses the threshold for substantial only slightly. The *Perceived Advantages* only have weak explanatory power (31.7%). The aim of this survey was to identify the factors influencing the intention to use IPAs of potential users. For this purpose, the advantages and disadvantages of IPAs were taken from the literature and their influence on the attitude and intention to use was measured. In addition, the influence of trust on the advantages and disadvantages as well as on the attitude was examined. A distinction was made between trust in the IPA as a device and trust in the manufacturer of the IPA.

Concerning research question 1.1 *"Which factors drive the acceptance of intelligent personal assistants?"* several driving and inhibiting factors could be found. The most important of the advantages studied was the control of the apartment or house via the IPA (music, light, TV) (PA5), followed by the possibility of obtaining information via the IPA (PA2). While the advantages of both, the control of the house/apartment (60%) and the possibility to obtain information about the IPA (45.2%), were partially and fully approved by a large number of respondents, the possibility of booking and ordering via the IPA (PA4) was ambiguous. Although this possibility has an influence, most respondents (35.3% disagree; 30.8% rather disagree) did not consider this function of the IPA to be advantageous. The possibility of being reminded of things by the IPA (PA3) had a significant influence and was also considered advantageous by most respondents (35.9% partially agree; 36.5% fully agree). The control of the IPA via speech (PA1) had no influence. In contrast, a total of 77.1% partially and fully agreed that voice control of the IPA was advantageous. One possible explanation is that voice control is already regarded as a basic component of these assistants and is therefore considered to be advantageous, but has no effect on adoption.

Concerning the disadvantages examined, the following picture emerges. The strongest influence is the aversion to talking to a machine (PD3). However, the opinion of the interviewees differs greatly. Although 31.2% do not agree that speaking with a machine is disadvantageous, the remaining 68.8% are relatively evenly distributed between "rather disagree" and "fully agree" (between 14.3% and 20.1%). This shows that communication is perceived very diversely, but a large proportion of respondents have no problem talking to a machine. This is followed by user concerns about data security. An important disadvantage is that the user's data is evaluated and used elsewhere (PD6) and that there is a high risk that the personal data is not secure with the service provider (PD1). This is supported by descriptive statistics. For example, 62% (PD1) and 68.1% (PD6) agreed partially or fully that IPAs do not necessarily provide data security. Privacy is perceived as a relatively weak problem. Thus, the fear that the user will become transparent through the use of the IPA has only a weak influence (PD4). The fact that privacy is not perceived as an important disadvantage is also underlined by the fact that the fear that all conversations will be recorded has no influence (PD5). This contradicts the literature, which identifies privacy risk as the most important influencing factor (Balta-Ozkan *et al.*, 2013, p. 369 et sqq.). In both cases, however, the interviewees with more than 60% (62.5% for PD4 and 71.5% for PD5) partially or fully agree that they become transparent and are monitored. A possible explanation could be that the respondents are already used to expose their data and are desensitised to their data privacy. Also, the fear that IPAs will do things that are not intended by the user has no influence (PD2). However, 69.9% of the respondents said that they at least partially agreed with this fear (34.6% agree in part and 35.3% fully agree).

Regarding the constructs Trust in IPA and Trust in Manufacturer, all indicators are important. In summary, the descriptive statistics in Table 6 show that IPAs are considered medium to less reliable and trustworthy, as are their manufacturers.

Overall, the model confirmed established hypotheses of the TAM and subsequent models.

Implications

The results allow several recommendations for action for companies. The *Attitude* towards IPA is mainly influenced by the *Perceived Advantages*. Since, as described above, the *Perceived Advantages* are similar to the *Perceived Ease of Use* and the *Perceived Usefulness*, this confirms already existing knowledge (Davis, 1986). If the functions of the IPA are regarded as advantageous, the persons are also more positive towards the IPA (Attitude) and their *Intention to Use* increases. In order to promote the use of IPAs, companies should increasingly communicate the advantages of the functions to their customers and develop these functions further. Particular attention should be paid to the control of the house or apartment. New applications could also be developed in which the IPA can be used as a control system. In contrast to *Trust in the IPA*, *Trust in the Manufacturer* has no influence on the *Perceived Advantages*. Thus, it is particularly important to increase the customer's confidence in the product so that the positive effect of the *Perceived Advantages* on the *Intention to Use* can be fully exploited. Interestingly, the *Perceived Disadvantages* have no influence on the *Attitude* and only a weakly significant influence on the *Intention to Use*. Since the descriptive statistics clearly show that respondents perceive disadvantages of IPAs, the low influence on *Intention to Use* may perhaps be justified by the low damage that respondents fear from the disadvantages. Even if disadvantages only play a minor role, they can be reduced by trusting both the product and the manufacturer. Especially in view of the fact that data security and privacy appear to be central disadvantages of IPAs, companies should dispel their customers' concerns by building trust.

Limitations and Future Work

The presented study also has limitations. The number of respondents is low at 129. In order to be able to make more meaningful conclusions, this study should be repeated with more respondents. Most of the respondents were between 20 and 29 years old. People from other age groups may think differently about using an IPA. The intention of older people to use an IPA may decrease considerably, as they may not be as enthusiastic about technology or find it less intuitive to use. Thus, the perceived advantages could be much less significant and perhaps even the perceived disadvantages could become the focus of attention. In future studies, a better balanced sample concerning age would be helpful to create more meaningful results. The analysis also did not examine any differences between the genders that might exist. There may also be a cultural bias in the study, as mainly German respondents were interviewed. For example, the technology affinity in other countries may be different, which may distort the results of this study. The study should be carried out in several countries in order to be able to make well-founded conclusions.

2.3.1.2 Survey B: Direct Load Shifting

In 1990, Germany regulated the energy market for renewable energy sources and guaranteed a payment that for example enabled wind turbines to produce energy economically. Ten years later, the so-called EEG ("Gesetz für den Vorrang erneuerbarer Energien") was enacted and replaced the former law of 1990. The EEG of 2000 differentiated the payments for each renewable energy source separately and defined a limit for solar energy. If more than 350MW were produced, the support for solar energy would be stopped. Because this limit was reached in 2003 which would have implied a collapse in the photovoltaic market, a new EEG was enacted for 2004. In the meantime, the EU also published several directives concerning renewable energy (2001/77/EC, 2003/30/EC, and later on 2009/28/EC). Germany reacted with a revision of the EEG in 2009. Then, in 2011, the Fukushima accident took place and changed pace rapidly. Germany again revised its EEG in 2012. Now, it comprises a schedule towards the year 2050. In 2030 at latest, half of the power production in Germany has to consist of renewable energy. Taking into account that in 2011 after 20 years of encouraging renewable energy only 20.4% of the power consumption in Germany was covered by renewable energy sources (AG Energiebilanzen e.V., 2014), this goal does not seem to be reached easily. The problem is not to produce enough renewable energy but to provide it when needed and to control it such that the electricity system does not collapse. While conventional energy sources like coal, gas, or nuclear energy can be controlled easily with respect to special requirements concerning power up and down times, the production of renewable energy heavily depends on natural factors like the weather (sun, wind, water). On a cloudy, windless day, photovoltaic systems and wind turbines can hardly be used while on windy and very sunny days, often more renewable energy is produced than it is needed. However, Germany managed to raise the share of renewable energy to nearly 25% in 2013 (AG Energiebilanzen e.V., 2014) and therefore already exceeds the target value of 18% of EU directive 2009/28/EC for the year 2020. This current value is more than double of the share that is estimated for the US for the year 2020 (Cappers *et al.*, 2012, p. 420).

But the higher the share of renewable energy sources is, the more difficult it is to plan and to control the energy production in total (Bartels *et al.*, 2006; Finn, O'Connell and Fitzpatrick, 2013, p. 679; Paulus and Borggrefe, 2011, p. 433) such that there is neither an overproduction nor an underproduction. Therefore, in periods of underproduction conventional energy sources have to be used. In a period of overproduction, it may happen that power plants for renewable energy have to be shut down for a stable energy supply because the storage capacity for energy is not sufficient (Schill, 2014, p. 71). Then, all renewable energy that cannot be stored during this period is completely lost while in other periods conventional energy had to be used.

In general, there exist two approaches to avoid this wasting of power: The first approach deals with the possibilities to accumulate the energy so that it can be used in periods of power shortage. But studies have shown that the current storage capacity is not sufficient (Schill, 2014, p. 71). The second approach is called Demand Side Management (DSM), Demand Response (DR), or Demand Side Integration (DSI). Its general idea is to influence the demand side such that the energy demand is adapted to the energy production. DSM comprises all activities that concern the energy management at the demand side, e.g. saving energy by using power saving utilities or monitoring the energy consumption (Paulus and Borggrefe, 2011, p. 432). The term DR is used when measures of the supply side are used that aim to induce special responses of the demand side, e.g. different pricing strategies (Cappers *et al.*, 2012, p. 422). DSI is the superordinate concept and includes both points of view (Chuang and Gellings, 2008, p. 1).

This research model deals with the second approach of DSI for households. The technological progress and the triumphal procession of the internet make it possible to communicate with any kind of technical equipment in households like heating, coffee machines, refrigerators etc. This makes suppliers of energy as well as research or politics dream of remote controlling energy consuming equipment in households in order to arrange the power consumption such that it is steadier and more constant as well as to balance the oscillation of renewable energy production. In many recent publications, this concept of direct load control (DLC) is seen as a great opportunity to solve the big problem of the Energiewende, the problem of energy production in times of low power demand and vice versa (Paetz, Dütschke and Fichtner, 2012, p. 24; Zhou, Gao and Li, 2008, p. 545). Indeed, DLC is promising. If it is possible to shift the power consumption from periods with low renewable energy production to periods with high renewable energy production, the more renewable energy can be used and the less power is wasted or has to be stored. But obviously it is not possible to shift the working time of each electric device (Paetz, Dütschke and Fichtner, 2012, p. 38). Usually, only a few home appliances are suitable for load shifting (LS) like heating systems, refrigerators, washing machines, or dishwashers. For other devices like televisions or coffee machines, consumers would not accept a time shifting (Paetz, Dütschke and Fichtner, 2012, p. 35). But despite some promising pre-tests (Hargreaves, Nye and Burgess, 2010; Mert, Suschek-Berger and Tritthart, 2008), it is questionable if and to which degree consumers would accept that energy suppliers control their home appliances. Reasons to disapprove DLC and LS may not only be a possible loss of convenience (Mert, Suschek-Berger and Tritthart, 2008, p. 19; Paetz, Dütschke and Fichtner, 2012, p. 25) but also a lack of trust towards the energy supplier (Balta-Ozkan *et al.*, 2013, p. 369 et sqq.; Chen, Xu and Arpan, 2017, p. 101; Hargreaves, Nye and Burgess, 2010, p. 6116; Park, Kim and Kim, 2014, p. 217). If the supplier who is paid for the energy controls the appliances that consume the energy, one could suspect that the supplier follows his own agenda of maximising his profit instead of minimising the costs of his customers (Annala, Viljainen and Tuunanen, 2012, p. 5; Balta-Ozkan *et al.*, 2013, p. 370; Goulden *et al.*, 2014, p. 27). Therefore, this survey focuses on the user acceptance of the DSI measure load shifting. For this, the benefits users expect and the disadvantages they fear to suffer from and prohibit them to participate in LS programs are modelled. In particular, the role of trust towards the energy supplier is in the focus. If users mistrust their energy supplier and fear that their participation in LS programs is misused, it can hardly be imagined that they would provide home appliances for LS. Hence, the following research question should be answered:

RQ1.2: What drives consumers to accept or refuse load shifting of home appliances?

Literature Review

DSI measures for industry and craft like LS are used since many years (Chu, Chen and Fu, 1993; Sanghvi, 1989, p. 87) on an individual basis (Weers and Shamsedin, 1987, p. 657). Its potential depends on the branch so that usually only case studies are presented (e.g. Ashok and Banerjee, 2000; Middelberg, Zhang and Xia, 2009) or special branches are analysed (Paulus and Borggrefe, 2011). During the past years, many studies and field tests are done concerning private households. Beside the analysis of technical details and requirements (e.g. Deese *et al.*, 2013; Moneta *et al.*, 2007; Weers and Shamsedin, 1987), the consumer perception of DSI is getting more and more into the focus of investigation. Some papers try to find out who is receptive for energy saving (Herter, 2007; Mills and Schleich, 2012) and special tariffs (Ericson, 2011), which tariffs consumers prefer (Dütschke and Paetz, 2013; Dütschke, Unterländer and Wietschel, 2012), if contracts should provide an opt-in or opt-out option (Toft, Schuitema and Thøgersen, 2014), how consumers react when they are informed about their energy consumption (Hargreaves, Nye and Burgess, 2010), and how much energy is saved then (Schleich *et al.*, 2011).

Smart meters that offer a bidirectional communication are a prerequisite for DLC and LS (Stragier, Hauttekeete and Marez, 2010, p. 136). While in Italy for example most households are already equipped with smart meters (Torriti, Hassan and Leach, 2010, p. 1580), the diffusion in Germany is still low (Bundesnetzagentur and Bundeskartellamt, 2017, p. 242). Therefore, many authors investigated the acceptance of smart meters by consumers using different approaches. Krishnamurti *et al.* (2012) investigated the expectations towards smart meters and found that many consumers have erroneous beliefs regarding their purpose and functionality and overestimate their benefits. Therefore, most interviewees have been very open-minded about smart meters although they also perceived several risks. Gerpott and Paukert (2013) had a look at the willingness of consumers to pay (WTP) for smart meters. They found that the trust in the provider and the intention of users to change their energy consumption behaviour are the best predictors for WTP. However, they could only explain 28% of the variance so that many influencing factors remain in the dark.

Chou and Gusti Ayu Novi Yutami (2014), Chen, Xu and Arpan (2017), Kranz, Gallenkamp and Picot (2010), Kranz and Picot (2011, 2012), Park, Kim and Kim (2014), Wunderlich, Veit and Sarker (2012a, 2012b), and Wunderlich, Kranz and Veit (2013) analysed the acceptance of consumers in different countries concerning smart meters. Although several studies mention the enabling role of smart meters for LS, none of them considers LS, its advantages, and disadvantages in the questionnaires. Hence, interviewees are asked about their general attitude towards smart meters and influencing factors like expected usefulness, ease of use, behavioural control etc. Other factors under investigation are for example program features and complexity (Chou and Gusti Ayu Novi Yutami, 2014), trust, energy saving habits, and political disposition (Chen, Xu and Arpan, 2017), price consciousness and environmental concerns (Kranz and Picot, 2011, 2012), subjective control (Kranz, Gallenkamp and Picot, 2010), perceived locus of control (Wunderlich, Kranz and Veit, 2013; Wunderlich, Veit and Sarker, 2012a, 2012b), or perceived reliability of the provider (Park, Kim and Kim, 2014). But one of the most important features for matching energy demand and supply, namely the possibility for utilities to switch off and on devices and shift the operating time to other periods is not mentioned to interviewees within the surveys. Therefore, although different factors like privacy concerns, trust towards the energy provider, or costs have been under investigation, their impact on the acceptance of LS is still unclear.

In contrast, Stragier, Hauttekeete and Marez (2010), Paetz, Dütschke and Fichtner (2012), Balta-Ozkan *et al.* (2013), Toft, Schuitema and Thøgersen (2014), and Ahn, Kang and Hustvedt (2016) focus on smart devices and as such on their possibility of self-control. Stragier, Hauttekeete and Marez (2010) analyse the perception of consumers towards smart devices and the changing energy management in the daily life. They found that the general attitude of consumers mediates usefulness and usability and has a high impact on the intention to use smart devices. Balta-Ozkan *et al.* (2013) investigate the barriers for adopting smart meters. Their results show that in general users like the idea of devices that save energy for them. But they have concerns about the costs and the privacy of personal data. Paetz, Dütschke and Fichtner (2012) introduced interviewees to a smart home prototype so that they are aware of the functioning of smart devices. In general, participants had a positive attitude towards the smart home. The best motivators to use smart devices are cost savings but consumers have an ambivalent view on the cost saving potentials as they mistrust the utility. Toft, Schuitema and Thøgersen (2014) as well as Ahn, Kang and Hustvedt (2016) focus on smart heating and cooling systems. Toft, Schuitema and Thøgersen (2014) found that besides usefulness feelings of moral obligations towards the environment have a positive impact on the acceptance of smart heating. But Ahn, Kang and Hustvedt (2016, p. 88) could not confirm an impact of environmental concerns on the intention to use such smart thermostats.

Although these papers investigate smart devices that act self-controlled or can be controlled by energy providers, the focus was more on the devices and how they are perceived by consumers. In contrast to these papers, Annala, Viljainen and Tuunanen (2012) as well as Mert, Suschek-Berger and Tritthart (2008) focused on DLC itself. While Annala, Viljainen and Tuunanen (2012) had a more general look at the attitude of consumers towards DLC, Mert, Suschek-Berger and Tritthart (2008) also investigated different home appliances and to what extent these would be accepted to be shifted. Annala, Viljainen and Tuunanen (2012, p. 4) observed a general wish among the respondents of retaining their own control and a concern about data security. Mert, Suschek-Berger and Tritthart (2008, p. 20) found a high acceptance rate of usually more than 85% for DLC. However, respondents would only partly accept a change of their usage behaviour. On average, they would accept LS of three hours. Interestingly, many interviewees had no concerns about the collected data but about technical failures and a loss of comfort.

Unfortunately, neither Annala, Viljainen and Tuunanen (2012) nor Mert, Suschek-Berger and Tritthart (2008) analysed causal relationships between benefits and concerns on the one side and the acceptance of respondents to participate in DLC programs on the other side. Therefore, this research is the first that analyses factors influencing the acceptance and intention of consumers to participate in DLC programs. In particular, the focus lies not only on benefits but also on potential disadvantages users may fear to suffer from. Additionally, the role of trust towards of the energy supplier is investigated who controls smart devices instead of the consumer and therefore receives much information about the habits of his customers. Hence, the perception of the energy supplier may play an important role for the acceptance of consumers.

Model Adjustments and Specification of the Indicators

Various studies have already investigated benefits that consumers expect from DLC. Among all expected advantages, consumers name financial benefits (indicator PA3) in the first place (Annala, Viljainen and Tuunanen, 2012, p. 6; Hargreaves, Nye and Burgess, 2010, p. 6113; Mert, Suschek-Berger and Tritthart, 2008, p. 39; Paetz, Dütschke and Fichtner, 2012, p. 27). This is usually followed by ecological reasons (PA4) (Hargreaves, Nye and Burgess, 2010, p. 6119; Kranz and Picot, 2011; Mert, Suschek-Berger and Tritthart, 2008, p. 39; Paetz, Dütschke and Fichtner, 2012, p. 27; Toft, Schuitema and Thøgersen, 2014). Other expected advantages of DLC are to do domestic work quicker (PA1) (Balta-Ozkan *et al.*, 2013, p. 369) and to have more convenience (PA2) (Balta-Ozkan *et al.*, 2013, p. 369; Mert, Suschek-Berger and Tritthart, 2008, p. 41 et sqq.). Although not initially postulated, Davis (1986, p. 177) found a relation between perceived usefulness and the intention to use an innovation. Therefore, concerning the perceived advantages it is hypothesised:

H2a: The perceived advantages positively influence the attitude towards DLC.

H2b: The perceived advantages positively influence the intention to use DLC.

The perceived usefulness of DLC is not only measured in terms of its advantages but also the disadvantages in terms of potential threats and personal confinements. To a certain degree, users hand the control over their home appliances over to the energy supplier. This loss of control (indicator PD5) is reported to be critical to users (Annala, Viljainen and Tuunanen, 2012, p. 5 et sqq.; Mert, Suschek-Berger and Tritthart, 2008, p. 45 et sqq.) as they fear that they cannot plan their daily routines exactly (PD6) (Goulden *et al.*, 2014, p. 26 et sqq.; Paetz, Dütschke and Fichtner, 2012, p. 35). In addition, consumers scrutinise the general functionality and safety of appliances being remotely controlled by utilities (PD4). They fear for example that goods are spoiled in the refrigerator and that these appliances are exposed to higher risks of fire or water damage (Mert, Suschek-Berger and Tritthart, 2008, p. 32). But the main risk of DLC and LS is said to be the privacy risk (Annala, Viljainen and Tuunanen, 2012, p. 5 et sqq.; Balta-Ozkan *et al.*, 2013, p. 369 et sqq.). Due to the remote control of appliances, usage data is collected that can and will be used to derive user profiles, in particular when appliances should learn the behaviour of users. These profiles can be threatened by unauthorised access (PD2) (Annala, Viljainen and Tuunanen, 2012, p. 4), used for other purposes (PD1) (Annala, Viljainen and Tuunanen, 2012, p. 5; Chen, Xu and Arpan, 2017, p. 101), or can make the routine of the day transparent to others (PD3) (Annala, Viljainen and Tuunanen, 2012, p. 5; Balta-Ozkan *et al.*, 2013, p. 369; Goulden *et al.*, 2014, p. 25; Paetz, Dütschke and Fichtner, 2012, p. 26). In addition, the smart meter can be hacked so that there is the risk that home appliances are manipulated by unauthorised third parties (PD7) (Krishnamurti *et al.*, 2012, p. 795). All these factors may influence the attitude of users towards LS. As a result, it can be hypothesised:

H3a: The perceived disadvantages negatively influence the attitude towards DLC.

H3b: The perceived disadvantages negatively influence the intention to use DLC.

In terms of trust, the trustor is the user who participates in DLC and the trustee is the energy provider. The user enables the energy provider to control the home appliances. Then, trust in the other party means that the user believes in the benevolence of the provider (McKnight, Choudhury and Kacmar, 2002b, p. 337). He trusts the energy provider to act in the agreed way. That means the provider turns on and off the devices when it is needed to balance energy supply and demand and does not abuse his control over the devices such that they are turned on when energy costs are just high (Annala, Viljainen and Tuunanen, 2012, p. 4; Balta-Ozkan *et al.*, 2013, p. 372; Goulden *et al.*, 2014, p. 26 et sqq.; Mert, Suschek-Berger and Tritthart, 2008, p. 19; Paetz, Dütschke and Fichtner, 2012, p. 35). Without trust towards the energy provider, it is therefore doubtful if consumers would participate in DLC (Yang, Lee and Zo, 2017, p. 78 et sqq.). Therefore, it is hypothesised:

H4a: Trust in the energy provider positively influences the attitude towards DLC.

The control mechanisms are scarce in the case of DLC. The only possibility for users is to check the billing if it is unnaturally high. Only if additional tools are provided like overviews of the energy demand and supply, real-time energy costs etc., a better control can be established. Therefore, it can be hypothesised:

H4b: Trust in the energy provider positively influences the perceived advantages of DLC.

H4c: Trust in the energy provider negatively influences the perceived disadvantages of DLC.

While TAM was developed to analyse the usage behaviour of people, it mainly focuses on system characteristics and their perception by users. But usage behaviour also depends on users themselves and their personal and business environment. Therefore, further developments of TAM were expanded by these factors (Venkatesh and Davis, 2000; Venkatesh, Morris and Davis, 2003). In the context of DLC, factors like job relevance cannot be applied and due to DLC's early stage, performance expectancy as well as output quality must be assumed as given. However, the social influence might play an important role (Kranz and Picot, 2011). The more people of a user's social environment accept an innovation, the more likely this person will usually do so, too (Venkatesh, Morris and Davis, 2003, p. 452). This phenomenon is usually called subjective norm and depicts the social pressure that people from the personal environment exert knowingly or unconsciously on the user. Therefore, also the subjective norm of the further developments of TAM that measures how much the environment influences a person to use the discussed innovation is employed (Venkatesh and Davis, 2000; Venkatesh, Morris and Davis, 2003). Besides its influence on the intention to use an innovation (Venkatesh and Davis, 2000, p. 195; Venkatesh, Morris and Davis, 2003, p. 451 et sqq.), the subjective norm is also found to influence the perceived usefulness (Chou and Gusti Ayu Novi Yutami, 2014, p. 347; Venkatesh and Davis, 2000, p. 196), respectively the advantages, and therefore the perceived disadvantages. Accordingly, it is hypothesised:

H5a: The subjective norm positively influences the perceived advantages of DLC.

H5b: The subjective norm negatively influences the perceived disadvantages of DLC.

H5c: The subjective norm positively influences the intention to use DLC.

The resulting research model is depicted in Figure 6.

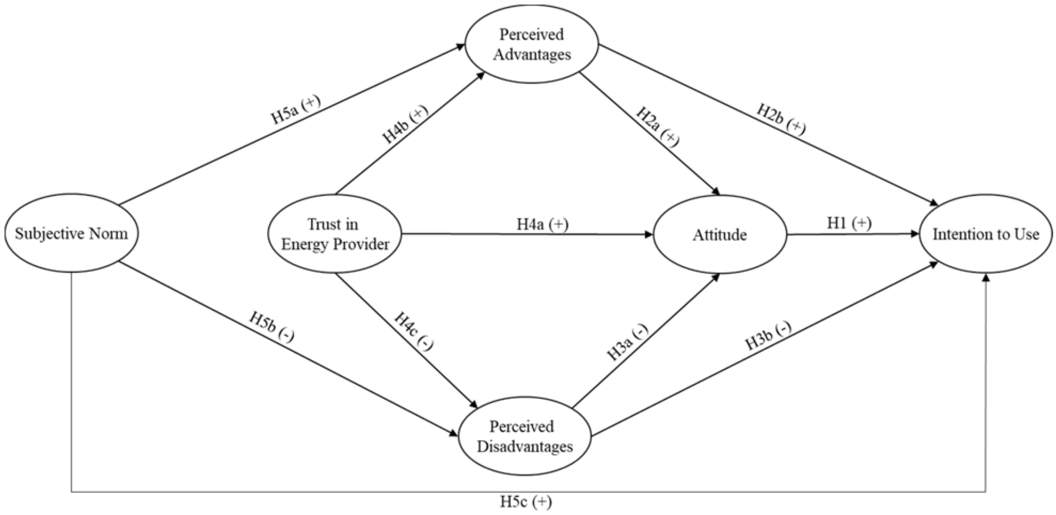

Figure 6: DLC Research Model

Analysis

DLC and LS offer promising opportunities to manage the Energiewende but due to the disadvantages and concerns discussed above, the willingness of end consumers to participate in such programs is questionable. To assess that willingness for participation in DLC, an online survey in August 2017 was conducted, consisting of 24 questions to analyse the structural equation model developed above and five demographic questions. In total, 653 consumers participated in the survey. Considering the recommendation of Hair *et al.* (2014, p. 51), 303 observations with more than 15% missing values had to be eliminated resulting in a total of 350 observations which is beyond the recommended sample size of Chin (1998b, p. 311) for receiving stable results of the model estimation.

The remaining sample can be described as follows (due to missing values, shares do not necessarily sum up to 100%): The share of male (female) respondents is 66.57% (27.43%). 34.86% of the respondents are between 20 and 29 years old, 30.00% between 30 and 39, 12.57% between 40 and 49, and 15.71% are older. Concerning the level of education, 63.43% are at least graduated. 72.57% of the interviewees are in regular work while only 16.57% are students. The monthly income is quite uniformly distributed in the range of 0€ to 6,000€.

Measurement Model

Beginning with the reflective constructs, the indicator reliability is given for all constructs at a significance level of 1% (see **Fehler! Verweisquelle konnte nicht gefunden werden.**). Concerning the convergence criterion, the AVE is greater than 0.5 for all constructs, the composite reliability exceeds the threshold of 0.7, and Cronbach's alpha is beyond the critical value of 0.7. Having a look at the discriminant validity, the squares of the highest correlations of a construct on *Intention to Use*, *Attitude*, *Subjective Norm* and *Trust in Energy Provider* are smaller than the respective AVEs (see Table 11). Thus, the reflective constructs share more variance with their appropriate indicators than with other constructs (Hair *et al.*, 2014; Segars, 1997; Venkatraman, 1989) so that the Fornell-Larcker criterion is met. Because all loadings of each construct are lower on other constructs than on their belonging constructs (see Table 12), the reflective constructs differ sufficiently from the other constructs. Also, the predictive validity is fulfilled for each construct so that a prediction of the latent variables is obtained through their indicators (see Stone-Geisser´s Q^2 in Figure 7).

Table 9: DLC Results

Construct	Indicator	**loadings**/ weights	**AVE** /VIF	Composite Reliability	Cronbach's Alpha
Intention to Use (reflective)	I1	**0.940** ***	**0.815**	0.929	0.885
	I2	**0.938** ***			
	I3	**0.826** ***			
Attitude (reflective)	A1	**0.926** ***	**0.816**	0.946	0.924
	A2	**0.915** ***			
	A3	**0.919** ***			
	A4	**0.850** ***			
Perceived Advantages (formative)	PA1	0.040 ns	3.049		
	PA2	0.414 ***	3.115		
	PA3	0.389 ***	1.379		
	PA4	0.503 ***	1.274		
Perceived Disadvantages (formative)	PD1	0.006 ns	1.832		
	PD2	0.264 ***	1.988		
	PD3	0.097 ns	1.374		
	PD4	0.328 ***	1.466		
	PD5	0.435 ***	1.805		
	PD6	0.158 **	1.439		
	PD7	0.124 ns	1.718		
Subjective Norm (reflective)	SN1	**0.779** ***	**0.729**	0.889	0.812
	SN2	**0.884** ***			
	SN3	**0.893** ***			
Trust in Energy Provider (reflective)	T1	**0.935** ***	**0.874**	0.954	0.928
	T2	**0.953** ***			
	T3	**0.916** ***			

*Significance of loadings/weights: ns=not significant; *p<0.10; **p<0.05; ***p<0.01*

Table 10: DLC Shares of Answers

Construct	Indicator	Share of Answers						
		1	2	3	4	5	6	7
Intention to Use	I1	16.40%	11.80%	7.50%	14.40%	30.50%	12.10%	7.20%
	I2	17.60%	13.50%	10.10%	16.10%	24.20%	13.50%	4.90%
	I3	23.30%	19.00%	13.00%	19.60%	13.50%	7.50%	4.00%
Attitude	A1	9.40%	9.70%	7.10%	20.90%	25.70%	18.00%	9.10%
	A2	8.60%	9.10%	8.60%	17.70%	22.00%	22.60%	11.40%
	A3	17.10%	12.30%	7.10%	18.00%	21.40%	14.60%	9.40%
	A4	26.30%	12.30%	7.70%	28.30%	16.00%	4.90%	4.60%
Perceived Advantages	PA1	24.00%	18.60%	13.70%	10.60%	14.90%	10.00%	8.30%
	PA2	15.70%	19.40%	16.90%	14.90%	12.90%	13.10%	7.10%
	PA3	12.00%	17.10%	17.10%	25.10%	20.90%	6.30%	1.40%
	PA4	5.40%	8.00%	5.70%	17.70%	23.10%	23.10%	16.90%
Perceived Disadvantages	PD1	2.90%	3.70%	6.90%	14.30%	16.30%	30.00%	26.00%
	PD2	3.40%	4.00%	6.30%	14.90%	19.10%	24.60%	27.70%
	PD3	4.80%	7.00%	5.60%	11.20%	22.40%	22.40%	26.60%
	PD4	6.30%	11.70%	9.40%	12.90%	17.70%	19.70%	22.30%
	PD5	8.00%	13.70%	10.30%	12.60%	22.30%	16.00%	17.10%
	PD6	11.40%	15.40%	12.60%	21.70%	15.10%	12.00%	11.70%
	PD7	4.30%	7.40%	6.60%	7.10%	20.90%	23.10%	30.60%
Subjective Norm	SN1	15.70%	22.90%	13.40%	23.10%	14.60%	8.30%	2.00%
	SN2	9.70%	20.30%	12.00%	34.60%	14.90%	7.70%	0.90%
	SN3	11.10%	21.40%	10.90%	33.70%	12.30%	8.60%	2.00%
Trust in Energy Provider	T1	10.00%	13.10%	15.40%	18.60%	21.10%	16.90%	4.90%
	T2	10.00%	14.60%	15.40%	16.00%	23.70%	14.90%	5.40%
	T3	12.60%	14.90%	15.40%	19.70%	18.60%	13.40%	5.40%

Table 11: DLC Fornell-Larcker Criterion

Construct	Highest Correlation to other Constructs	Squared Correlation	AVE
Intention to Use	0.8735	0.7630	0.8150
Attitude	0.8735	0.7630	0.8155
Subjective Norm	0.4650	0.2162	0.7286
Trust in Energy Provider	0.5421	0.2938	0.8735

The analysis of the formative constructs shows that a few indicators of different constructs are not significant as either their t-statistic or their weight is below the required threshold (see **Fehler! Verweisquelle konnte nicht gefunden werden.**). In more detail, regarding the construct *Perceived Advantages* one (PA1) of four indicators is not significant. Two (PD1 and PD3) non-significant indicators occur among the seven indicators in the construct

Perceived Disadvantages. Except for one indicator (PD6) with a significance level of 5%, all other indicators are significant at the 1%-level. As there is no indication for multicollinearity (for all indicators $VIF < 5$ and $condition\ index < 30$) and therefore all indicators are sufficiently different and independent, no indicator must be dropped. Also, the discriminant validity is given for the formative constructs as the highest latent variable correlation that occurs between *Perceived Advantages* and *Attitude* is 0.7212 and therefore beyond the claimed maximum of 0.9.

Table 12: DLC Cross Loadings

Indicator	Attitude	Intention to Use	Perceived Advantages	Perceived Disadvantages	Subjective Norm	Trust
A1	**0.9257**	0.7862	0.6925	-0.5703	0.3993	0.5113
A2	**0.9152**	0.7520	0.6687	-0.5522	0.4114	0.5337
A3	**0.9190**	0.8617	0.6871	-0.6524	0.4069	0.4878
A4	**0.8502**	0.7484	0.5483	-0.5665	0.4686	0.4230
I1	0.8526	**0.9400**	0.6749	-0.6605	0.4434	0.5105
I2	0.8171	**0.9379**	0.6651	-0.5851	0.4481	0.4971
I3	0.6845	**0.8257**	0.5404	-0.5226	0.3390	0.4494
SN1	0.3802	0.4031	0.3524	-0.3206	**0.7790**	0.3287
SN2	0.4145	0.3954	0.3968	-0.3353	**0.8839**	0.2791
SN3	0.3916	0.3683	0.3089	-0.3041	**0.8932**	0.2561
T1	0.5058	0.4966	0.4431	-0.5255	0.3186	**0.9351**
T2	0.4830	0.4716	0.4302	-0.5691	0.3101	**0.9525**
T3	0.5290	0.5390	0.4600	-0.5922	0.3216	**0.9159**

Structural Model

The results of the model are as follows. The R^2 value is substantial for the target construct *Intention to Use* ($R^2 = 0.786$). *Attitude* ($R^2 = 0.64$) and *Perceived Disadvantages* ($R^2 = 0.397$) achieve a moderate level. *Perceived Advantages* ($R^2 = 0.3$) achieves a weak level. The VIF indicates that there is neither multicollinearity nor a condition index higher than 30 (Hair *et al.*, 2006, p. 227; Hair, Sarstedt and Ringle *et al.*, 2012, p. 430; Huber *et al.*, 2007, p. 109). Regarding the structural relationships between the constructs, support for ten of eleven hypotheses was found. The constructs *Attitude* and *Perceived Advantages* are found to be positively related to *Intention to Use* (H1, H2b) with a significance level of 1%. The path coefficient between the constructs *Subjective Norm* and *Perceived Disadvantages*, *Trust in Energy Provider* and *Perceived Disadvantages*, *Perceived Disadvantages* and *Attitude*, and *Perceived Disadvantages* and *Intention to Use* are below -0.10 which implicates a negative relation between the constructs (H5b, H4c, H3a, H3b) with a significance level of 1%. The hypotheses H2a, H4a, H4b and H5a could be confirmed with a positive influence and a significance level of 1% whereas H5c is not supported by the data. Figure 7 shows the hypotheses with their path coefficients, significance, and effect sizes f^2. For each construct, the R^2 and the predictive relevance Q^2 is provided.

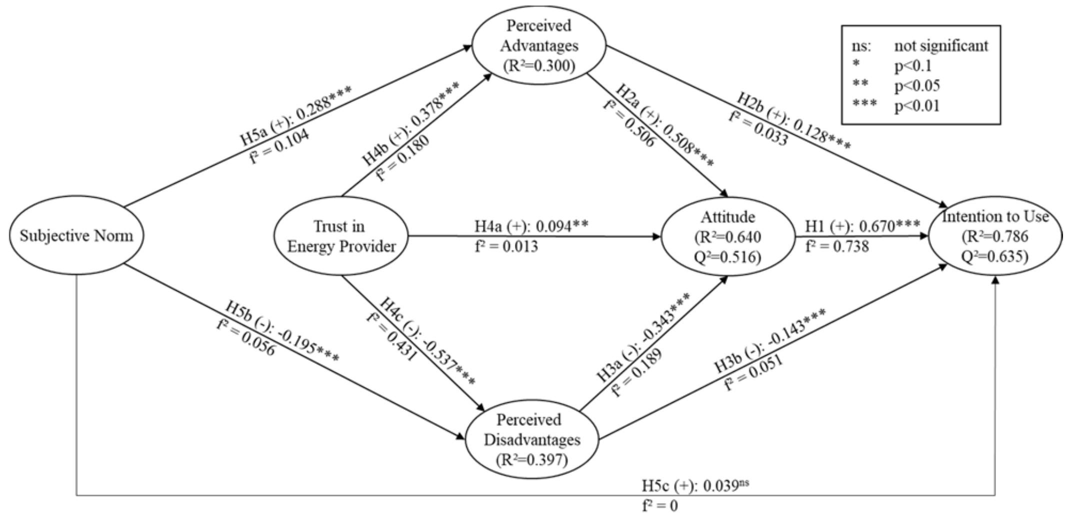

Figure 7: DLC Results of the SEM

Results

Discussion

The results of the study are very satisfactory. Only one hypothesis (H5) out of eleven could not be confirmed, a second one is at a very weak level but still significant. In addition, the explanatory power of the model is substantial, explaining more than 78% of the variance. The aim of this paper was to analyse factors that drive or inhibit consumers to participate in direct load control and load shifting. Several advantages and disadvantages of DLC were derived from previous literature and have been analysed for their impact on the acceptance of DLC and LS. In particular, the model focused on the role of the energy supplier and the consumers' trust towards him.

Concerning the research question "*What drives consumers to accept or refuse load shifting of home appliances?*" several driving and inhibiting factors could be found. Among the advantages, the ecological impact (PA4) has the highest influence followed by increased comfort (PA2) and financial benefits (PA3). This is in line with previous, mostly qualitative studies that identified financial benefits and ecological reasons as the most relevant advantages (Annala, Viljainen and Tuunanen, 2012, p. 6; Hair, Sarstedt and Ringle *et al.*, 2012; Hargreaves, Nye and Burgess, 2010, p. 6113; Mert, Suschek-Berger and Tritthart, 2008, p. 39; Paetz, Dütschke and Fichtner, 2012, p. 31 et sqq.). But in contrast to these studies, the impact of financial benefits is lower than that of the other two factors. A reason is that consumers are sceptical if they would profit financially from DLC. Only 7% expect a financial pay-off ("totally agree" and "mostly agree"), but 55% do not ("totally disagree" and "mostly disagree"). Concerning the ecological reasons, the picture is inverted. While 40% of the respondents agree to these benefits, only 14% do not. The increased comfort is perceived by 21%, 40% dissent. Only the increased efficiency for home tasks (PA1) could not be confirmed as a significant advantage although 20% ascribe this to DLC, but 40% do not.

The analysis of the disadvantages draws an ambiguous picture. Although 55% of the respondents expect that their usage profile will be used for other purposes (PD1), while only 7% do not (the highest and lowest values for all disadvantages), this disadvantage besides PD3 and PD7 could not be proven to be significant for the perceived disadvantages. Any other disadvantage is significant, but being unable to plan (PD6) has only a weak effect. The opinion concerning PD6 is balanced (24% vs. 27%). Among all disadvantages, loss of control (PD5) shows the highest impact (34% vs. 21%), followed by technical safety (PD4: 43% vs. 17%) and not well protected usage profiles (PD2: 52% vs. 7%). That means although privacy risks are said to be most important (Annala, Viljainen and Tuunanen, 2012, p. 5; Balta-Ozkan *et al.*, 2013, p. 369 et sqq.), only one risk (PD2) has a high impact while another has only a very low one (PD3) and the third is not significant (PD1). The reason could be that consumers are already used to the situation that much data about them is gathered and that this private data is constantly exposed to risks like misuse, disclosure, or other misappropriation.

Interestingly, trust does not play a role for the attitude of consumers towards DLC but only for the perceived advantages and disadvantages. In particular, trust in the energy provider has a higher impact on the perceived disadvantages than on the advantages, but the advantages are more important for the attitude towards DLC than the disadvantages are. The reason may be that although the opinion concerning the energy provider is balanced (about 20% positive vs. 26% negative), there is a slight tendency to mistrust. This enforces the perceived disadvantages. But if consumers perceive the advantages of DLC and LS, this perception leads to a more positive attitude than disadvantages reduce the attitude. However, the influence of trust on attitude via advantages is only slightly lower than via disadvantages.

Overall, the research model confirmed well approved hypotheses and constructs of TAM and successive acceptance models. But interestingly, the relation between subjective norm and intention to use could not be confirmed while its impact on advantages and disadvantages could. A possible explanation is that energy management takes place in a private environment where usage behaviour can hardly be controlled by other people not living in the same household. Hence, the opinion of others forms the opinion about DLC and LS and therefore influences the perceived advantages and disadvantages, but does not impact the (intended) behaviour directly.

Implications

Several lessons can be learned from this study. First of all, although the privacy risk is a little bit less important than expected, it nevertheless plays an important role. In particular, energy providers should work on the data protection and communicate their efforts and measures to consumers. Concerning the technical safety, a general misconception of consumers regarding home appliances that are remotely controlled can be observed like other studies do (Mert, Suschek-Berger and Tritthart, 2008, p. 32). Although such appliances are not more prone to technical risks than conventional appliances, respondents perceive that risk as high. Therefore, energy providers should better explain the concept of DLC and LS and that the technical risk does not increase but decreases on the contrary as appliances are then permanently monitored. Also, a new safety label for these appliances could help. Secondly, the perceived loss of control is the major problem for the diffusion of DLC and LS. Although this results from the core idea of DLC, energy providers can work on this problem by ensuring that the consumer remains the one who controls his appliances and that he does not hand over this control completely to the provider. Consumers should always have the option to override control decisions of the energy provider so that they still have the feeling of being the one who "is wearing the pants around here". Thirdly, energy providers should emphasise the increased comfort and the ecological advantages. As many consumers do not know or believe that DLC can improve the electrical system and therefore has positive impacts on the ecological environment (Mert, Suschek-Berger and Tritthart, 2008, p. 34; Paetz, Dütschke and Fichtner, 2012, p. 35), better elucidation is needed. Concerning the comfort, energy providers could combine DLC with other services like notifications when the appliances have finished, additional maintenance etc. so that consumers perceive even more a gain in comfort. Fourthly, energy providers should provide enough financial benefits. Saving only a few cents is not attractive for consumers (Hargreaves, Nye and Burgess, 2010, p. 6117). They should receive an adequate compensation for participating in such programs. Finally, energy providers should work on their reputation. Trust has been proven to be an important factor for the perception of advantages and disadvantages and therefore for the acceptance of DLC. But the perception of energy providers as being trustworthy is balanced at best so that there is much room for improvement.

Also for research, the results of this study provide several insights. First of all, the core of TAM and successive models could be confirmed but the subjective norm did not show an impact on the behavioural intention. That means that in contexts where the usage of an innovation cannot be monitored by others pressure from other people might not play such an important role. Secondly, the model shows that disadvantages act like an antipode to advantages or the usefulness of an innovation and should therefore be integrated in acceptance models. Thirdly, trust is an important factor for the perception of advantages and disadvantages. Its integration into the model improved the predictive power.

Limitations and Future Work

As always, several limitations have to be considered when interpreting the results. First of all, regarding the sample. Although the number of participants was quite high, about 50% of the observations had to be eliminated due to incompleteness. In addition, the sample is to some extent biased. 70% of the respondents were male and only 30% were female. But women are still said to do most of the work in households and therefore are more responsible for participating in DLC. A similar bias can be observed in several other studies concerning smart metering (Chen, Xu and Arpan, 2017, p. 97; Chou and Gusti Ayu Novi Yutami, 2014; Kranz, Gallenkamp and Picot, 2010; Wunderlich, Kranz and Veit, 2013, p. 9; Wunderlich, Veit and Sarker, 2012b, p. 7). The reason for this phenomenon is that in households men are usually responsible for the decision-making concerning energy (Wunderlich, Kranz and Veit, 2013, p. 9; Wunderlich, Veit and Sarker, 2012b, p. 7). Hence, they are most likely the ones who make the initial step to register for DLC programs. If this first step is made, the barrier for the following second step to allow and participate in DLC and LS is much lower than before. The reason for this gender bias in the study may also be the cooperation an IT service provider and consulting being active in the field of energy management. For this, many respondents were interested in this field and are disproportionately well educated. That means that less well educated people who account for a share of more than 50% of the German population (Statista, 2018) are underrepresented in this survey. Future work should focus on this population as the DLC and LS can only be successful if enough people are willing to participate. In spite of this educational bias, the sample has the advantage that in contrast to other studies (e.g. Kranz and Picot, 2011; 2012) it comprises a wide range concerning age and employment and is not restricted to students. Furthermore, the sample might have a cultural bias as only German consumers participated in the survey. In other countries, the situation might be different, in particular in countries with a greater diffusion of smart meters. However, as Germany takes a pioneering role in the field of renewable energy, the role of German consumers is very important for the success of the Energiewende. Secondly, DLC is still a theoretical concept in Germany and cannot be used. Therefore, even if the relation between intention and usage is found in many studies, this does not necessarily mean that the intention to participate in DLC of about 20% will also hold at the same level for the later usage. Therefore, future work should focus on the question which incentives are needed and how people can be triggered to participate in DLC and LS.

2.3.1.3 Survey C: Autonomous Driving

Autonomous driving (AD) is said to be the future of mobility (Corwin *et al.*, 2016, p. 2). What was first seen as science-fiction became more and more reality. During the past years, the discussion about AD accelerated (KPMG, 2013, p. 6). Examples for the first automation of cars are automatic headlamps, rain sensors and cruise control. The purpose of automation is to increase the comfort of the driver and the ease of use of the car. With fully automated vehicles even impaired people can experience the advantages of using a car. According to the National Highway Traffic Safety Administration (NHTSA) full automation means that *"An Automated Driving System (ADS) on the vehicle can do all the driving in all circumstances. The human occupants are just passengers and need never be involved in driving."* (NHTSA, 2016). Hence, the role of the active driver changes to a passenger (Elbanhawi, Simic and Jazar, 2015, p. 6).

Traditional car manufacturers already started to develop autonomous vehicles (AV) (Fagnant and Kockelman, 2015, p. 168). This development was forced by technology and IT companies like Google or Uber who forced the pace by developing AV themselves (Spinrad, 2014, p. 528). Some states of the USA already permitted to test AV on public roads (Guerra, 2015, p. 36). Since then, most of the AV on the roads are developed by Google (Harris, 2015) with an overall distance of 500,000 km without any accident (Pettersson and Karlsson, 2015, p. 694). Hence, we are facing the next market where disruption may take place due to innovations driven by IT companies. Therefore, it is crucial to know how people regard this new technology.

In the current state, AD is promoted by its advantages like the increased safety (Vahidi and Eskandarian, 2003), the efficient use of the roads (Hoogendoorn, van Arerm and Hoogendoom, 2014, p. 113), the increased mobility of impaired or older people (Fagnant and Kockelman, 2015, p. 171), or the more ecologic driving style (Pakusch *et al.*, 2018, p. 2). But this is only one side of the coin. Several incidents in the recent past (Greenemeier, 2016) have raised doubts concerning the reliability of AV (Schoettle and Sivak, 2014b, p. 9 et sqq.). Other arguments against AD are legal regulations (Ilková and Ilka, 2017, p. 428), moral questions (Gogoll and Müller, 2017, p. 686), reduced driving pleasure (Payre, Cestac and Delhomme, 2014, p. 260), or the feeling of being infantilised (Jirovský and Cappas, 2016, p. 5). Therefore, it is questionable if AD is widely accepted in the society. But the deployment of AV without the acceptance of the consumers bears high risks for the companies (Chiesa and Frattini, 2011, p. 440). Therefore, the acceptance of the potential users of AV is crucial for the successful deployment (Bansal, Kockelman and Singh, 2016, p. 1; Nordhoff, van Arem and Happee, 2016, p. 63 et sqq.; Plötz *et al.*, 2014, p. 97). Because of this, the research question for this study is:

RQ1.3: What drives consumers to accept or refuse autonomous driving?

Traffic accidents are reported to be a huge problem in the whole world. Approximately 1.25 million people are killed each year and 20–50 million get injured (WHO, 2016). 93% of all these car accidents can be attributed to human errors (NHTSA, 2008). The solution of this problem can be AV as they are said to increase the safety on the streets (Vahidi and Eskandarian, 2003, p. 150). But on the other side, there are fatal accidents like the one of the Tesla Autopilot in 2016 (Rushkoff, 2016) or the one that Uber caused (The Economist Explains, 2018). These incidents raise doubts concerning the reliability of AV and generate mistrust towards AD and its developers (Smith, 2018). For the acceptance of AD, this is a dangerous trend because trust is a key factor for user acceptance (Abe and Richardson, 2006, p. 578; Arndt, 2010, p. 167; Choi and Ji, 2015, p. 692; Gold *et al.*, 2015, p. 3026; Hakimi *et al.*, 2018, p. 60; Lee and See, 2004, p. 51; Walker, Stanton and Salmon, 2016, p. 178). Although the impact of trust has been investigated several times before, the different roles of trust, i.e. trust towards the manufacturer and trust towards the car or the technology in general, have not been distinguished. Therefore, this study pursues the following sub research questions:

RQ1.4: Which role does trust towards the car manufacturer play for using autonomous vehicles?

RQ1.5: Which role does trust towards the car play for using autonomous vehicles?

The NHTSA defines six automation levels from level 0 (no automation) to level 5 (full automation) (NHTSA, 2016). On the highest level, people feel powerless and show an increasing need for control (Fraedrich *et al.*, 2016, p. 81). They are afraid of relinquishing control of the vehicle and are relieved when they regain control (Accenture, 2011, p. 24; Howard and Dai, 2014, p. 2). It is conceivable that this perceived loss of control reduces acceptance of AD (Eckoldt *et al.*, 2012, p. 168). Hence, the last sub research question is:

RQ1.6: Which role does the perceived control of the driver play for using autonomous vehicles?

Literature Review

Three different research streams can be distinguished regarding the adoption of AD. The first stream distinguishes potential users of AD and other road users as different stakeholders of AD and examines their different point of view regarding the attitude towards AD. Hulse, Xie and Galea (2018) surveyed pedestrians about their attitude to AD. They observed that the perceived risk of AD depends on the road user perspective. Pedestrians experience AV as less risky than passengers of these vehicles. The perception is also affected by demographic factors, i.e. the age is negatively correlated to the acceptance of AD. Even if AD is perceived as less risky than manual driving (MD), autonomous trains were perceived as even more safe. The acceptance of AV in public transportation constitutes the second research stream. Kaur and Rampersad (2018) for example interviewed students about their attitude regarding the deployment of an AV for public transport on their campus. They found, that students most likely adopt AV in closed environments, while car parking, in public transport with a chaperone, and on highways with the option to take full control for the passenger. They also showed that safety, privacy, trust, performance expectancy, and reliability have a significant influence on the adoption of AV.

The third stream of literature focuses on the potential drivers of privately-owned AV. This stream is most related to this study. Existing papers of this field can be differentiated by the degree of automation of the vehicles defined by the NHTSA (NHTSA, 2016). Beggiato *et al.* (2015, p. 76) proved the role of experience for the acceptance of AD. For this, they conducted an on-road study where participants drove a not-fully automated vehicle in up to ten driving sessions. The car was automatised with Adaptive Cruise Control (ACC) to keep a constant safety buffer to the car in front. The acceptance of the ACC was surveyed before the first and after each driving session. Starting at the midpoint of the scale before the first drive, the acceptance grew degressively with each session. Underwood (2014) surveyed experts of AV on the Automated Vehicles Symposium 2014. In the eyes of these experts, the biggest challenges for fully-AD (level 5) are legal liabilities and regulations, the smallest challenges social and consumer acceptance. Concerning the deployment of AV, participants expected the introduction of vehicles classified as SAE 3, SAE 4 and SAE 5 in 2018, 2025 and 2030. Vehicles classified as SAE 3 are found to be impractical because the driver may have to take back the control over the car quickly. Further studies on acceptance of not-fully automated driving can be found e.g. in Adell (2009), Arndt (2010), and Huth and Gelau (2013).

In this study, the focus is on the acceptance towards fully automated vehicles (SAE Level 5). In this field several descriptive studies examined the acceptance of fully-AV which showed that 70% of drivers are at least interested in AV. Moreover, 60% intent to replace their vehicle with an AV (Markwalter, 2017, p. 125). At least a slight positive attitude towards AD of 56.8% of the respondents was observed by Schoettle and Sivak (2014a, p. 7) among people from UK, USA, and Australia. 13.8% of the respondents raised concerns about AD and 29.4% had a neutral attitude about that topic. Schoettle and Sivak (2014b, p. 5) extended their research to China, India, and Japan. Big differences between these states were observed regarding the attitude towards AD. While in China and India 80% of the respondents showed a positive attitude towards AD, this number decreased to 43% for Japanese respondents. Concerning the intended adoption of AV, the same differences were noted (China: 76%; India: 80%; Japan: 41%). Kyriakidis, Happee and Winter (2015) had a closer look on the demographic factors. They surveyed concerns about AD and measured the user acceptance of AD and the willingness to buy a partially, highly, and fully AV in 109 countries. While focusing mainly on cross-national differences and correlations with personal variables, biggest concerns were misuse and software hacking as well as legal issues and safety. Hohenberger, Spörrle and Welpe (2016) investigated the impact of gender, anxiety, and pleasure regarding the willingness to use AV. They found that young males experience less anxiety than young women regarding the use of AV but that there is no difference concerning pleasure. Payre, Cestac and Delhomme (2014) conducted their study among French drivers concerning the acceptance of fully-AD. 68% accepted fully-AD whereby the acceptance of men regarding AD was higher. The respondents preferred AD over MD particularly in traffic congestions, on highways, and for parking. Examining the effect of age, Payre, Cestac and Delhomme (2014, p. 259) found a higher price sensitivity but also a higher level of acceptance of older respondents.

Beside these descriptive studies where the public opinion concerning AD was rather positive, there are also several studies using multivariate methods to examine the influencing factors for the acceptance of AD. Hartwich, Beggiato and Krems (2018) showed the participants a video of a ride in an AV with different driving styles. Via physiological measuring instruments during the video and questionnaires afterwards they examined the participants' comfort, acceptance, and driving enjoyment. They found that AD increases the comfort of all drivers. While elderly participants enjoyed the driving style of AV, that is more sportive in comparison to their own style, the driving pleasure of younger drivers decreased significantly. Besides the already named effects of demographic characteristics, Haboucha, Ishaq and Shiftan (2017, p. 41) found the five factors technology interest, environmental concerns, driving pleasure, public transit attitude and pro-AV sentiments to have an influence on the intention to use AV among people from the USA and Israel. Also Howard and Dai (2014) showed a video of a ride in an AV to likely AV adopters. They found that safety (75%) and reliability (70%) are the most important factors for adopting AV. The expected high costs of AV (69%) and the convenience of the ride (61%) are further influencing factors.

In contrast to discussions about MD where main topics are engine and transmission of cars, discussions of AD mainly focus on handling, safety and trust (KPMG, 2013, p. 17). Although trust is such an important topic for AD, just a few studies included trust as an influencing factor into their research models. Buckley, Kaye and Pradhan (2018) enhanced a combination of the Theory of Planned Behavior (TPB) and the Technology Acceptance Model (TAM) with trust towards the car as an additional construct influencing the intention to use AD. The participants first drove 20 minutes in a simulation of an AV (SAE level 3) and answered a questionnaire afterwards. All constructs from TPB and TAM as well as trust had a significant effect on the intention to use. Also Choi and Ji (2015) based their investigation on the TAM extended by the constructs trust, perceived risks, external locus of control (belief that accidents can be prevented whether the car is automated or not), sensation seeking, system transparency, technical competence, and situation management. Surprisingly, not all hypotheses of the TAM could be confirmed, but trust had a significant effect on perceived risk, perceived usefulness, and behavioural intention. Also, the locus of control had a significant effect on the behavioural intention.

Except for KPMG (2013) who addressed the trust in the manufacturer but did not measure its influence on the usage intention, all other studies neglect this perspective and focus only on the trust towards the car. Therefore, this paper takes this factor into account. In this regard, the loss of control may play an important role (Krasnova *et al.*, 2010) as people are deterred from driving and suffer from the loss of driving pleasure (Hartwich, Beggiato and Krems, 2018, p. 1023). As this could explain the acceptance of AD, this study incorporates this perspective into the research model.

Model Adjustments and Specification of the Indicators

For autonomous driving, several advantages are usually listed. As there is no human driver, autonomous driving relieves people from the driving task so that they can use the travel time more efficiently (indicator PA3) (Anderson *et al.*, 2016, p. 1; De Winter *et al.*, 2014, p. 200; Fagnant and Kockelman, 2015, p. 174; Howard and Dai, 2014, p. 9 et sqq.; Merat *et al.*, 2014, p. 120) and get less tired (PA7) (De Winter *et al.*, 2014, p. 204). In addition, driving with an AV is less stressful, particularly when the weather is bad, when there is a traffic jam, when the traffic situation is generally arduous (PA6) (Arndt, 2010, p. 95; Becker *et al.*, 2014, p. 52) or an unknown address in an unknown area is the destination (PA8) (e.g. Kummerle *et* *al.*, 2009, p. 3395). Hence, as driving the car is less influenced by tiredness (Brookhuis, Waard and Janssen, 2001, p. 246) and stress, it is more secure to drive with an AV (PA1) (Pettersson and Karlsson, 2015, p. 694). Human driving errors are reduced to zero (Fagnant and Kockelman, 2015, p. 176; Markwalter, 2017, p. 126) so that streets can be used more efficiently (PA4) (Fagnant and Kockelman, 2014, p. 8; Roncoli, Papageorgiou and Papamichail, 2015, p. 241 et sqq.). As a result, the traffic situation is enhanced (Roncoli, Papageorgiou and Papamichail, 2015, p. 241 et sqq.) and the environment is strained less as less braking manoeuvres are necessary (PA5) (Howard and Dai, 2014, p. 5). And lastly, autonomous driving enables less mobile people like disabled or elderly persons to travel and participate in life (PA2) (Howard and Dai, 2014, p. 5; Meyer and Deix, 2014, p. 72; Polders *et al.*, 2015, p. 151). All these advantages should make people be positively attuned to autonomous driving. Hence, it can be hypothesised:

H2a: The perceived advantages positively influence the attitude towards autonomous driving.

H2b: The perceived advantages positively influence the intention to use autonomous driving.

Opposed to the advantages, critics also quote several risks of autonomous driving. One of the most discussed point is the judicial situation. In particular, it is not clear who is responsible in the case of an accident (PD1) (Kyriakidis, Happee and Winter, 2015, p. 130) and which rules should be applied when the AV has to decide between different alternatives in an accident situation (Bonnefon, Shariff and Rahwan, 2016, p. 1573). In particular, different moral aspects have to be settled in this regard (Goodall, 2014, p. 58). Another important factor consists in the costs of autonomous driving as AV are said to become more expensive than traditional cars (PD4) (Howard and Dai, 2014, p. 6; Ykhoff, 2012, p. 2). Other disadvantages are the loss of driving pleasure (PD2) (Arndt, 2010, p. 65 et sqq.; Howard and Dai, 2014, p. 13) or a suspected complexity of AV (PD3) (Hohenberger, Spörrle and Welpe, 2016, p. 381). The last risk concerns the plethora of data that are generated with autonomous driving (PD5) (Viereckl *et al.*, 2015, p. 20). AV know the starting point and destination of any journey as well as the exact route. They will communicate with other cars to enhance the driving performance and the traffic situation (Narla, 2013, p. 22 et sqq.). Hence, there is the risk that this data will be subject to theft and misuse (PD6) (Viereckl *et al.*, 2015, p. 22). Therefore, also the disadvantages of autonomous driving are investigated and the following can be hypothesised:

H3a: The perceived disadvantages negatively influence the attitude towards autonomous driving.

H3b: The perceived disadvantages negatively influence the intention to use autonomous driving.

However, perceived advantages and disadvantages highly depend on how the car manufacturers shape the general image of AV in the society. Accidents caused by AV of Uber (Davies, 2017) and Tesla (Tesla, 2018) left a negative image among a big share of people and made them raise doubts in the reliability of AV (Bonnefon, Shariff and Rahwan, 2016, p. 1573; Howard and Dai, 2014, p. 10; Lin, 2016, p. 82; Wintersberger and Riener, 2016, p. 298). The Diesel-Gate of Volkswagen during the past years where several author manufacturers got involved over time raised mistrust against car manufacturers (Mačaitytė and Virbašiūtė, 2018, p. 11). But trust is an important antecedent for the interaction of people and therefore for the behaviour of a person towards another person or an artefact (Gefen, Karahanna and Straub, 2003, p. 60; Reichheld and Schefter, 2000, p. 108). Hence, it is conceivable that the mistrust of people against car manufacturers influences their trust against the AV and its reliability and therefore reduces people's attitude towards autonomous driving.

Regarding the two involved parties, the trustor is the potential user of the car and the trustees are the car and its manufacturer. The user confides his life to the car that shall drive him to his destination. Therefore, the user needs to trust the car that it functions correctly (Rödel *et al.*, 2014, p. 1). As the car has no own will but its actions are determined by the programming and training of the manufacturer, users not only have to trust the car but also the manufacturer. Without this belief in the manufacturer, the user will hardly trust the car itself. Hence, it can be hypothesised:

H4a: The trust in the manufacturer positively influences the user's trust in the car.

Both, the trust in the manufacturer and the trust in the AV influence how people perceive the characteristics of the car and therefore autonomous driving. If people mistrust the manufacturer and the car, benefits like security or stress-free travelling are debatable as they highly depend on the competence of the manufacturer. As a result, trust influences the attitude towards the innovation of autonomous driving and how benefits and risks are perceived (Chen, Xu and Arpan, 2017, p. 94; Krasnova *et al.*, 2010; Park, Kim and Kim, 2014). As a result, it can be hypothesised:

H4b: The trust in the manufacturer positively influences the user's attitude towards AD.

H4c: The trust in the car positively influences the user's attitude towards AD.

H4d: The trust in the manufacturer positively influences the perceived advantages.

H4e: The trust in the car positively influences the perceived advantages.

H4f: The greater the trust in the manufacturer is, the less severe are the disadvantages perceived.
(The trust in the manufacturer negatively influences the perceived disadvantages.)

H4g: The greater the trust in the car is, the less severe are the disadvantages perceived.
(The trust in the car negatively influences the perceived disadvantages.)

As trust is *"the willingness of a party to be vulnerable to the action of another party [...] irrespective of the ability to monitor or control the other party"* (Mayer, Davis and Schoorman, 1995, p. 712), it is not only related to the involved parties, also the control mechanisms are of great importance (Tan and Thoen, 2000a, p. 850). As long as people in the role of trustors feel to be the master of a situation and to be able to control the action of the trustee, the less trust is needed as the actions of others can be monitored (Krasnova *et al.*, 2010, p. 109). In this case of control, they are more inclined to trust the trustee. Hence, the more people have the impression to be able to control the situation in AV, the more they will trust the manufacturer who hands the control over to the user, the more they will trust the car that can now be controlled and the less they will perceive the advantages of autonomous driving as severe. Therefore, it can be finally hypothesised:

H5a: Perceived control positively influences the trust in the manufacturer.

H5b: Perceived control positively influences the trust in the car.

H5c: The greater the perceived control is, the less severe are the disadvantages perceived.
(Perceived control negatively influences the perceived disadvantages.)

The resulting research model is depicted in Figure 8.

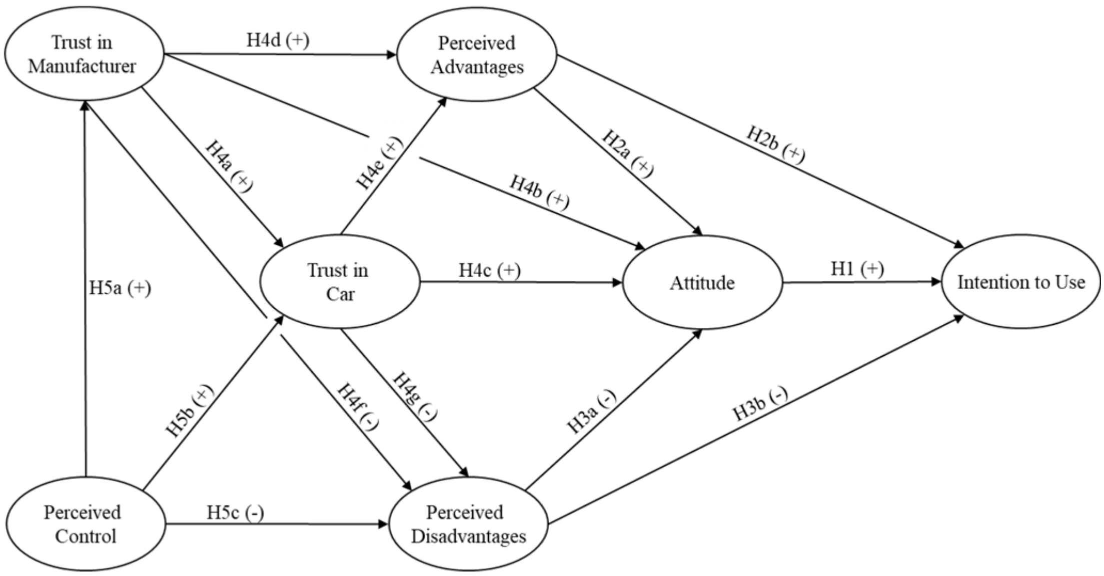

Figure 8: AD Research Model

Analysis

In March 2016, an online survey was carried out which consisted of 34 questions derived from the model and three additional demographic questions. In total, 370 people participated in the survey. They were not obliged to answer all questions but could decide for each question to answer or omit it. Due to the chosen approach, 128 responses had to be excluded from the analysis according to the recommendations of Hair *et al.* (2016, p. 51) because they had more than 15% missing values. The remaining number of 242 responses is still above the required minimum of responses (Chin, 1998b, p. 311).

59.5% of the respondents are male and 40% female. 8.26% of the respondents are under the age of 20, 57.44% between 20 and 29, 13.64% between 30 and 39, 9.09% between 40 and 49, and 11.16% at least 50. 44.21% of all respondents are graduated. Due to missing values, the percentages do not add up to 100%.

Measurement Model

According to the criteria of Jarvis, MacKenzie and Podsakoff (2003, p. 201), the SEM consists of five reflective constructs (*Intent to Use*, *Attitude*, *Trust in Manufacturer*, *Trust in Car*, *Perceived Control*) and two formative constructs (*Perceived Advantages*, *Perceived Disadvantages*). For all reflective constructs the indicator reliability at a significance level of 1% is given (see Table 13). Further, the AVE is over 0.5 for all constructs, the composite reliability exceeds 0.7, and each Cronbach's alpha is above 0.7. This satisfies the convergence criterion. In Table 15, for each reflective construct the highest correlation to the other constructs is reported. All correlations are below the respective AVE. Therefore, the

Fornell-Larcker criterion is met. Looking at the cross loadings (Table 16), it can be seen that the reflective constructs differ sufficiently from one another. Since the Stone-Geisser´s Q² is greater than 0 for each reflective construct, predictive validity is given (see Figure 9).

Table 13: AD Results

Construct	Indicator	**loadings**/ weights	VIF	AVE	Composite Reliability	Cronbach's Alpha
Intention to Use	I1	**0.952** ***		0.848	0.957	0.940
	I2	**0.935** ***				
	I3	**0.933** ***				
	I4	**0.861** ***				
Attitude	A1	**0.879** ***		0.677	0.912	0.880
	A2	**0.846** ***				
	A3	**0.799** ***				
	A4	**0.717** ***				
	A5	**0.861** ***				
Perceived Advantages	PA1	0.204 ***	1.330			
	PA2	0.131 ns	1.328			
	PA3	0.253 ***	1.606			
	PA4	0.045 ns	1.859			
	PA5	0.297 ***	1.539			
	PA6	-0.006 ns	2.018			
	PA7	0.647 ***	1.738			
	PA8	-0.084 ns	1.453			
Perceived Disadvantages	PD1	0.122 ***	1.036			
	PD2	0.569 ***	1.066			
	PD3	0.308 ***	1.320			
	PD4	0.220 ***	1.322			
	PD5	0.344 ***	1.204			
	PD6	0.203 ***	1.184			
Trust in Manufacturer	TM1	**0.883** ***		0.654	0.904	0.868
	TM2	**0.796** ***				
	TM3	**0.831** ***				
	TM4	**0.779** ***				
	TM5	**0.747** ***				
Trust in Car	TP1	**0.879** ***		0.677	0.862	0.760
	TP2	**0.868** ***				
	TP3	**0.711** ***				
Perceived Control	PC1	**0.726** ***		0.694	0.871	0.777
	PC2	**0.878** ***				
	PC3	**0.885** ***				

*Significance of loadings/weights: ns=not significant; *p<0.10; **p<0.05; ***p<0.01*

Table 14: AD Shares of Answers

Construct	Indicator	Share of Answers				
		1	2	3	4	5
Intention to Use	I1	33.9%	26.0%	14.5%	14.0%	11.6%
	I2	24.9%	25.3%	15.4%	24.5%	10.0%
	I3	31.7%	22.5%	10.4%	20.8%	14.6%
	I4	31.1%	32.0%	20.7%	12.4%	3.7%
Attitude	A1	23.2%	31.5%	15.8%	17.4%	12.0%
	A2	27.9%	22.5%	12.1%	28.3%	9.2%
	A3	24.6%	42.5%	12.1%	14.2%	6.7%
	A4	5.8%	6.6%	11.6%	37.6%	38.4%
	A5	11.2%	16.5%	14.5%	33.9%	24.0%
Perceived Advantages	PA1	3.8%	6.7%	14.6%	50.0%	25.0%
	PA2	1.3%	3.8%	8.8%	41.7%	44.6%
	PA3	9.1%	13.3%	14.1%	37.3%	26.1%
	PA4	4.2%	13.4%	16.7%	43.5%	22.2%
	PA5	2.9%	3.8%	9.6%	50.4%	33.3%
	PA6	8.7%	10.8%	14.9%	39.0%	26.6%
	PA7	9.2%	20.0%	7.9%	29.6%	33.3%
	PA8	2.9%	7.1%	13.7%	45.6%	30.7%
Perceived Disadvantages	PD1	4.2%	5.0%	5.5%	16.0%	69.3%
	PD2	6.6%	10.4%	5.0%	27.4%	50.6%
	PD3	13.3%	25.3%	30.3%	20.7%	10.4%
	PD4	8.9%	22.1%	31.9%	24.3%	12.8%
	PD5	4.6%	15.9%	13.0%	28.9%	37.7%
	PD6	3.3%	14.9%	22.4%	30.3%	29.0%
Trust in Manufacturer	TM1	15.7%	18.6%	19.0%	36.8%	9.9%
	TM2	11.2%	22.4%	12.9%	43.2%	10.4%
	TM3	14.9%	11.6%	16.1%	37.2%	20.2%
	TM4	28.9%	22.3%	18.6%	23.1%	7.0%
	TM5	19.7%	28.5%	17.2%	26.4%	8.4%
Trust in Car	TP1	19.1%	36.9%	26.1%	14.9%	2.9%
	TP2	16.9%	33.5%	17.8%	24.0%	7.9%
	TP3	18.7%	30.7%	21.2%	19.1%	10.4%
Perceived Control	PC1	8.3%	12.4%	7.9%	41.1%	30.3%
	PC2	7.7%	15.7%	15.7%	32.3%	28.5%
	PC3	15.4%	22.0%	13.3%	27.0%	22.4%

The analysis of the formative constructs shows that a few indicators of different constructs are not significant as either their p-value or their weight is below the required threshold (see Table 13). In more detail, regarding the construct Perceived Advantages three (PA2, PA4, PA6) of eight indicators are not significant. All other indicators are significant at the 1%-level. As there is no indication for multicollinearity (for all indicators $VIF < 5$ and

$condition\ index < 30$) and therefore all indicators are sufficiently different and independent, no indicator must be dropped. Also, the discriminant validity is given for the formative constructs as the highest latent variable correlation that occurs between Perceived Advantages and Attitude is 0.631 and therefore beyond the claimed maximum of 0.9.

Table 15: AD Fornell-Larcker Criterion

Construct	Highest Correlation to other Constructs	$\sqrt{\text{AVE}}$
Intention to use	0.792	0.921
Attitude	0.792	0.823
Trust in Manufacturer	0.572	0.809
Trust in Car	0.644	0.823
Perceived Control	0.639	0.833

Table 16: AD Cross Loadings

Indicator	Intention to Use	Attitude	Trust in Manufacturer	Trust in Car	Perceived Control
I1	**0.952**	0.784	0.468	0.643	0.631
I2	**0.935**	0.715	0.469	0.607	0.531
I3	**0.933**	0.773	0.467	0.684	0.628
I4	**0.861**	0.632	0.430	0.496	0.477
A1	0.745	**0.879**	0.349	0.565	0.644
A2	0.783	**0.846**	0.479	0.655	0.549
A3	0.592	**0.799**	0.318	0.497	0.563
A4	0.463	**0.717**	0.200	0.369	0.409
A5	0.609	**0.861**	0.249	0.511	0.524
TM1	0.449	0.338	**0.883**	0.478	0.251
TM2	0.409	0.303	**0.796**	0.433	0.332
TM3	0.323	0.219	**0.831**	0.372	0.221
TM4	0.457	0.457	**0.779**	0.559	0.357
TM5	0.326	0.232	**0.747**	0.423	0.067
TP1	0.595	0.555	0.461	**0.879**	0.442
TP2	0.599	0.641	0.447	**0.868**	0.560
TP3	0.426	0.357	0.529	**0.711**	0.318
PC1	0.473	0.535	0.190	0.410	**0.726**
PC2	0.510	0.543	0.315	0.470	**0.878**
PC3	0.565	0.580	0.294	0.484	**0.885**

Structural Model

The R^2 is moderate for the target construct *Intention to Use* ($R^2 = 0.659$), but just missed the threshold for a substantial explanatory power. *Attitude* ($R^2 = 0.549$), *Perceived Disadvantages* ($R^2 = 0.511$) and *Trust in Car* ($R^2 = 0.468$) achieve a moderate level. *Perceived Advantages* ($R^2 = 0.297$) and *Trust in Manufacturer* ($R^2 = 0.101$) achieve a weak level. The VIF indicates that there is neither multicollinearity nor a condition index higher than 30 (Hair *et al.*, 2006; Hair, Sarstedt and Ringle *et al.*, 2012; Huber *et al.*, 2007). Regarding the structural relationships between the constructs, support for fourteen of fifteen hypotheses has been found. The constructs *Attitude* and *Perceived Advantages* are found to be positively related to *Intention to Use* with a significance level of 1% (H1) and 10% (H2b). The path coefficient between the constructs *Trust in Manufacturer* and *Perceived Disadvantages*, *Trust in Car* and *Perceived Disadvantages*, *Perceived Disadvantages* and *Attitude*, *Perceived Disadvantages* and *Intention to Use*, and *Perceived Control* and *Perceived Disadvantages* are below -0.10 which implicates a negative relation between the constructs (H4f, H4g, H3a, H3b, and H5c) with a significance level of 1% except H4g with significance level of 5%. The hypotheses H2a, H4a, H4c, H4e, H5a and H5b could be confirmed with a positive influence and a significance level of 1%. H4d has also a positive influence, but just a significance of 10%. H4b is not supported by the data. Figure 9 shows the hypotheses with their path coefficients, significance, and effect sizes f^2. For each construct, the R^2 and the predictive relevance $\text{Stone} - \text{Geisser´s}\ Q^2$ is provided.

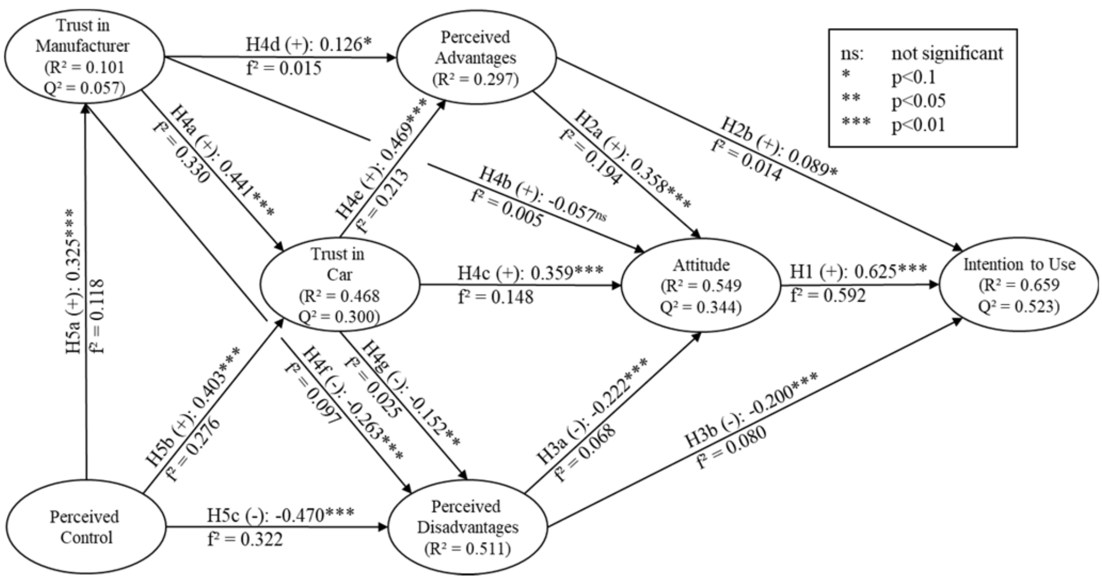

Figure 9: AD Results of the SEM

Results

Discussion

The results of the study are very satisfying. Only one (H4b) out of 15 hypotheses could not be confirmed. Two other hypotheses (H2b, H4d) are at a weak level but still significant. The explanatory power of the model is medium but the final construct *Intention to Use* misses the threshold for substantial only slightly (65.9%). Other constructs like *Attitude* (54.9%), *Perceived Disadvantages* (51.1%), as well as *Trust in the Car* (46.8%) also are on the medium level.

The aim of this study was to analyse the acceptance of AD among people and in particular the perceived drivers and barriers (*RQ1.3*). Having a look at the acceptance, the majority of interviewees has no intention to use AV (50.2% to 63.1% "totally disagree" and "mostly disagree"). Aggravating, the attitude towards autonomous driving is quite negative. The majority (50.4% to 67.1%) has a negative impression of and reservations towards AV. However, most interviewees accept when other people would use AV (76% "totally agree" and "mostly agree") and are generally open towards the general innovation of autonomous driving (57.9%). That means that even if people would not use AV, there is a general acceptance of the technology itself but not concerning the individual personal usage.

The reasons for this situation seem to lie in the benefits and drawbacks of autonomous driving. While the advantages have a much higher influence on the attitude than the disadvantages, the influence of the disadvantages on the intention to use AV is higher. Hence, the usage intention is low, but the attitude is ambiguous. The latter also holds for the advantages. More than 62.9% (max. 86.3%) agree on the benefits but three of these eight benefits do not have a significant impact: the mobility for elderly people, the better usage of streets and therefore improved traffic situation, as well as the stress-free driving. In contrast, all disadvantages are proven to be significant. Three of these disadvantages score very high among the interviewees: the uncertainty concerning the question who is accountable for accidents (85.3%), the loss of driving pleasure (78%), and the insecurity of personal data (66.5%). In particular the loss of driving pleasure has a very high impact on the perceived disadvantages. Only with some distance, the fear follows that personal data is not secure. Concerns about costs as well as complexity are quite equally distributed. In addition, people generally mistrust AV and their reliability (49.4% to 56%) and fear a loss of control (49.4% to 71.4%). Thus, the general perception of autonomous driving seems to be more negative than positive.

To answer research questions *RQ1.4*, *RQ1.5*, and *RQ1.6*, one has to dig deeper into the relations between the constructs, there are significant influences of the *Perceived Control* on the *Trust in Manufacturers*, the *Trust in Cars*, and the *Perceived Disadvantages*. The *Trust in Manufacturers* in turn has a positive influence on the *Trust in Cars* and *Perceived Advantages*, and a negative impact on the *Perceived Disadvantages*. The *Trust in the Car* could be proven to have a significant positive impact on the *Perceived Advantages* and the *Attitude* and a negative one on the *Perceived Disadvantages*. As a result, we have a reinforcing effect of the negative factors associated with autonomous driving. Because the control is perceived as low, trust in manufacturers and trust in AV are also low. All these three constructs have a significant influence on the *Perceived Disadvantages* which as a consequence are perceived as very high.

However, not all manufacturers are regarded as untrustworthy. In general, the majority of people think that manufacturers of AV are reliable (46.7%) and in particular traditional car manufacturers (57.4%). But most people mistrust IT companies like Google or Apple (51.2%) and think that the cars will not be faultless (48.1%) and immature (49.4%). Hence, trust in manufacturers cannot be assessed unequivocal. Therefore, its influence on the perception of advantages is weak and not significant on the attitude towards autonomous driving. It only plays a strong role for the trust in AV and the perception of disadvantages.

Implications

Several research and managerial implications can be derived from this study. In general, the results are in line with previous research based on the TAM (e.g. Choi and Ji, 2015) proving again that the TAM is a good basis for the examination of to what extent people accept a technical innovation. Adding the perceived disadvantages to the basic TAM is helpful to investigate the barriers of the technological innovation without disturbing the influence of attitude and advantages on the usage intention. Hence, using disadvantages in addition to advantages is improving the explanatory power of the model with regard to more factors being considered for explanation.

However, in contrast to many other studies, this study used a formative measurement model for *Perceived Advantages* and *Perceived Disadvantages* instead of a reflective one as the aim was to investigate the drivers and barriers of autonomous driving in detail. This resulted in two well functioning constructs of which one (*Perceived Disadvantages*) had a medium and one (*Perceived Advantages*) a weak explanatory power concerning the sub models. The advantage of this modelling with formative constructs is that advantages and disadvantages can be measured as items with direct questions. Then, firstly, the influence and significance of (dis)advantages can be measured directly. Secondly, it is not necessary to build separate constructs for each (dis)advantage but only two, one for the advantages and one for the disadvantages. This results in fewer questions that have to be asked.

For car manufacturer and policy makers several lessons can be learned. First of all, autonomous driving generally has a relatively bad image that will prevent many people from using AV. Before the main concerns like the responsibility for accidents and the usage of personal data are not resolved satisfactorily, the trust in and the attitude towards those cars will not improve. Hence, it is crucial to find legal solutions for the responsibility question and the usage of personal data that will be acceptable for people. Secondly, the loss of control is a major concern of potential users. Driving pleasure is not only important but the most influential factor concerning the disadvantages. Hence, car manufacturers should find a substitute for driving pleasure and promote this. In addition, people do not want to be infantilised. They still want to have the control over the car and do what they like to. Hence, AV should still provide the opportunity to control the car and drive manually. This would foster the trust in the car itself which in turn would enhance the perception of and attitude towards AV. Thirdly, traditional car manufacturers should not allocate the development of AV to IT companies but develop themselves. They should make use of the higher trust that people show towards them in comparison to IT companies. People are annoyed of the permanent errors and faults of software they experienced over the years in the IT sector. In contrast, conventional cars usually show much less problems and do not need permanent updates like software products. This is also a big fear of people that AV will not function faultlessly. Hence, they trust traditional car manufacturers more than IT companies to build reliable cars. Fourthly, the concerns of people about the handling of personal data by cars and manufacturers should be taken seriously. The questions of data security and the usage of personal user data have to be solved. Many data is collected and stored in AV. While the temptation is great to use this data for analyses, it is crucial to understand that people do not want their data to be analysed and become transparent for car manufacturers. Hence, at least, car manufacturers have to ensure credibly that if data is collected, it is made anonymous so that nobody can infer personal information. Finally, car manufacturers should better promote the advantages of autonomous driving. Although many people see the advantages of autonomous driving, this does not result in a positive attitude and usage intention. For example, the relief during long travels has highest impact on the perceived advantages. But as people do not travel that often that far, this advantage cannot outweigh the disadvantages. In contrast, the disadvantages seem to outweigh the advantages. Hence, it is crucial to highlight the relevant benefits like the better usage of streets and therefore improved traffic situation or the increased driving security. In this regard it is crucial to avoid scandals like deathly accidents. The incidents of the recent past caused by Uber and Tesla (Tesla, 2018; The Economist Explains, 2018) obviously were counterproductive. Car manufacturers should take the time needed to develop absolutely reliable and safe cars and should avoid bringing semi-developed products on the market.

Limitations and Future Work

As always, several limitations have to be considered when interpreting the results. First of all, the sample comprises only people from Germany. Germany is said to be an automotive country where cars are valued very much (Dittmann and Goebel, 2010, p. 503). Driving pleasure and a feeling of freedom when driving a car are very important to people and a long-term argument in advertising (Beirão and Cabral, 2007, p. 484). Therefore, the picture may be different in other countries where cars play a less important role and are seen more as a means to move from one place to another. Secondly, there is a bias towards younger people between 20 and 29 years of age in the sample. People of other age may think differently, in particular concerning the advantages of being mobile when aged and the lower risk of accidents. Then, also disadvantages like loss of driving pleasure or freedom could be less important. However, younger people will be the ones who will experience autonomous driving most. They will be the generation that has to buy those cars. Therefore, it is crucial to know for car manufacturers and policy makers how this generation thinks of that new technology. Thirdly, there is also a slight bias concerning gender. As male people are usually more interested in cars (Polk, 2004, p. 190), more male interviewees could be found than female interviewees. This might also distort the results as men are said to enjoy cars more than women (Benson, Macrury and Marsh, 2007, p. 36). While most women regard cars as a tool or thing, many men feel to have a relationship with their car (Benson, Macrury and Marsh, 2007). However, due to the quite unequivocal results concerning the low acceptance of autonomous driving, it is doubtful if the results would change when the sample is more balanced. Nevertheless, in future studies, a better balanced sample concerning age and gender would be helpful to create more meaningful results. An examination of gender as a moderating variable on the model presented here could also be part of future studies. In addition, other countries should be taken into account with different situations concerning the automotive conditions like towns, countryside, distances between towns etc.

2.3.2 Comparison

In the following, the results of the three studies will be compared. For this purpose, the results of the hypothesis tests of the individual models will be compiled. An interpretation and discussion of the results will take place in the conclusion of this section. Only the hypotheses of the Basic Research Model will be discussed. Extensions that did not appear there are therefore not included in the comparison. The exception is the differentiation of the trust construct. In two studies (Survey A: IPA and Survey C: DLC), trust in the smart system was considered along with trust in the manufacturer of the device. In the study regarding DLC, it is not possible to clearly differentiate between the manufacturer and the product, since the smart system is not the underlying household appliance itself, but the intelligent control of this appliance. The underlying household appliance is not an integral part of the smart system and is interchangeable. Therefore, trust in the manufacturers of household appliances is only of secondary importance when investigating smart systems. First, the hypotheses regarding the influence of *Attitude* on the *Intention to Use* of a smart system (H1) and the influence of *Perceived Advantages* on *Attitude* (H2a) and *Intention to Use* (H2b) will be compared. The key figures compiled from the individual models can be found in Table 17.

Table 17: Comparison of H1, H2a and H2b

Hypotheses	**H1(+)**		**H2a(+)**		**H2b(+)**	
	Path Coefficient	Effect Size	Path Coefficient	Effect Size	Path Coefficient	Effect Size
Intelligent Personal Assistant	0.192*	0.023	0.721***	0.983	0.385***	0.089
Direct Load Control	0.670***	0.738	0.508***	0.506	0.128***	0.033
Autonomous Driving	0.625***	0.592	0.358***	0.194	0.089*	0.014

*Significance: ns=not significant; *p<0.10; **p<0.05; ***p<0.01*

The hypothesis **H1(+)** was confirmed in all three models. This also corresponds to the current literature (Davis, 1986). The path coefficients are positive throughout and lie above 0.1. Thus a positive *Attitude* towards smart systems also has a positive effect on the *Intention to Use*. The coefficient increases strongly from IPA (0.192) to DLC (0.670) and then remains at a high level with AD (0.625). Looking at the significance with which the hypothesis could be confirmed, it is noticeable that for the IPA the hypothesis could only be confirmed at the 10% significance level, whereas for DLC and AD the 1% significance level was reached. The effect strength first increases strongly from IPA (0.023) to DLC (0.738), but then decreases slightly to AD (0.592). With DLC and AD, one can speak of a strong effect of *Attitude* on the *Intention to Use*, whereby in the first model only a small effect can be observed ($effect\ size \geq 0.02$: small effect; $effect\ size \geq 0.25$: medium effect; $effect\ size \geq 0.35$: strong effect (Cohen, 1988, p. 79)).

Looking at the influence of *Perceived Advantages* in the three models, the picture is almost entirely satisfactory. The hypothesis **H2a(+)** describes the positive influence of the *Perceived Advantages* on the *Attitude*. Across all three models, the hypothesis of a 1%

significance level was confirmed. The path coefficients are above the threshold of 0.1 according to which the *Perceived Advantages* have a positive influence on the *Attitude*. A clear negative trend can be seen in the comparison between the models. Thus, the path coefficient decreases steadily from IPA (0.721) via DLC (0.508) to AD (0.358). The positive influence of the *Perceived Advantages* on the *Attitude* thus decreases. Similar to the path coefficients, the effect sizes decrease. Thus in the first model a very strong effect can be observed with respect to the IPA (0.983), which weakens with DLC (0.506), but remains at a strong level, and finally is only a medium effect with AD (0.194). Also with regard to the postulated positive correlation between *Perceived Advantages* and intention to use of a smart system (**H2b(+)**), a significant positive influence can be measured in each of the three models. The level of significance of 1% for IPA and DLC drops to 10% for AD. A decrease can also be observed in the path coefficients. Thus, both IPA (0.385) and DLC (0.128) have positive path coefficients above the threshold of 0.1. With AD, however, the path coefficient falls below this limit (0.089). The same can also be observed for the effect size. While with IPA (0.089) and DLC (0.033) at least small effects can still be observed, with AD (0.014) the effect is negligible. Thus, the effect strength also decreases.

Table 18: Comparison of H3a and H3b

Hypotheses	**H3a(-)**		**H3b(-)**	
	Path Coefficient	Effect Size	Path Coefficient	Effect Size
Intelligent Personal Assistant	-0.089 ns	0.011	-0.195 *	0.052
Direct Load Control	-0.343 ***	0.189	-0.143 ***	0.051
Autonomous Driving	-0.222 ***	0.056	-0.200 ***	0.080

*Significance: ns=not significant; *p<0.10; **p<0.05; ***p<0.01*

Next, the influence of the *Perceived Disadvantages* construct will be compared between the models (Table 18). Analogous to hypothesis H2a(+), hypothesis **H3a(-)** postulates a negative influence of the *Perceived Disadvantages* on the *Attitude*. While the *Perceived Disadvantages* of the IPA have no significant influence on the *Attitude*, the hypothesis can be confirmed for the models of DLC and AD at the 1% significance level. The consistently negative path coefficients show that the *Perceived Disadvantages* have a negative effect on the *Attitude*. However, the path coefficient for IPA (-0.089) is between -0.1 and 0.1. The influence is therefore negligible. The path coefficients for DLC (-0.343) and AD (-0.222), on the other hand, indicate a clear negative influence, which decreases only slightly from IPA to AD. This course becomes clearer when looking at the effect sizes. The effect size in IPA (0.011) is negligible, whereas in DLC a medium effect is already achieved (0.189). However, the effect decreases again with AD to only a small effect (0.056). The negative influence of the *Perceived Disadvantages* on the *Intention to Use* (**H3b(-)**) could be confirmed in all three models. The significance level at which the hypothesis could be confirmed decreased from 10% (IPA) to 1% (DLC, AD). The negative path coefficient was below 0.1 in all three models (IPA: -0.195; DLC: -0.143; AD: -0.200), which shows a significant influence of the *Perceived Disadvantages* on the *Attitude*. The path coefficients are relatively close to each other, with the highest patch coefficient being observed for DLC and the lowest for AD. The effect size is similar. In all three models only a small effect can be observed (IPA: 0.052; DLC: 0.051; AD: 0.080), which increases slightly towards AD.

Finally, the construct *Trust* as an influencing factor on *Attitude* (Table 19), *Perceived Advantages* (Table 20) and *Perceived Disadvantages* (Table 21) will be investigated. Within the three models, the influence of *Trust* on *Attitude* was partly tested using two hypotheses. In IPA and AD, a distinction was made between the trust in the smart system and the trust in the manufacturer.

Table 19: Comparison of H4a

Hypothesis	**H4a(+)**			
Trust in …	System		Manufacturer	
	Path Coefficient	Effect Size	Path Coefficient	Effect Size
Intelligent Personal Assistant	0.142*	0.029	-0.108 ns	0.016
Direct Load Control	0.094**	0.013	-	-
Autonomous Driving	0.359***	0.148	-0.057 ns	0.005

*Significance: ns=not significant; *p<0.10; **p<0.05; ***p<0.01*

Starting with hypothesis **H4a(+)**, the aim is to compare how the influence of *Trust* on *Attitude* changes between models (Table 19). If we first look at the *Trust in the Smart System*, the underlying hypothesis can be confirmed in all three models. The significance with which the hypothesis can be confirmed rises through the three models. Thus, a 10% significance level is still required for the IPA to confirm the hypothesis, but for DLC a 5% significance level and for AD a 1% significance level is required. The path coefficients, however, paint an ambiguous picture. While IPA (0.142) and AD (0.359) show a positive influence, the path coefficient in DLC (0.094) is too low to indicate an actual influence on *Attitude*. A similar picture emerges when considering the effect sizes. The small effect size at IPA (0.029) is reduced to a negligible effect at DLC (0.013), where AD again almost exceeds the limit of a medium effect (0.148). Neither with IPA nor with AD could the influence of the *Trust in the Manufacturer* of the smart system on the *Attitude* be confirmed as significant. A consideration of the path coefficients and effect sizes therefore makes no sense.

Table 20: Comparison of H4b

Hypothesis	**H4b(+)**			
Trust in …	System		Manufacturer	
	Path Coefficient	Effect Size	Path Coefficient	Effect Size
Intelligent Personal Assistant	0.546***	0.277	0.028 ns	0.001
Direct Load Control	0.378***	0.180	-	-
Autonomous Driving	0.469***	0.213	0.126*	0.015

*Significance: ns=not significant; *p<0.10; **p<0.05; ***p<0.01*

The postulated positive influence of *Trust* on the *Perceived Advantages* (**H4b(+)**) could be confirmed in all three models, at least in the form of *Trust in the Smart System*, with a significance level of 1%. The path coefficients in all three models are well above the threshold of 0.1 and vary between 0.378 (DLC) and 0.546 (IPA). The effect size of all three models is also high enough for a strong effect to be observed (IPA: 0.277; DLC: 0.180; AD: 0.213). However, a different picture emerges when the influence of *Trust in the Manufacturer* on the *Perceived Advantages* is considered. For example, the hypothesis cannot be confirmed for IPA and only for AD at the 10% significance level. The path coefficient for AD (0.126) is also only slightly above the threshold value of 0.1. The effect size (0.015) is negligible.

Table 21: Comparison of H4c

Hypothesis	**H4c(-)**			
Trust in …	System		Manufacturer	
	Path Coefficient	Effect Size	Path Coefficient	Effect Size
Intelligent Personal Assistant	-0.264**	0.089	-0.517***	0.342
Direct Load Control	-0.537***	0.431	-	-
Autonomous Driving	-0.152**	0.025	-0.263***	0.097

*Significance: ns=not significant; *p<0.10; **p<0.05; ***p<0.01*

The last hypothesis to be compared concerns the postulated negative influence of *Trust* on *Perceived Disadvantages* (**H4c(-)**). Here again *Trust in the Smart System* will be considered. In all three models, the hypothesis of a 5% significance level (IPA and AD) or a 1% significance level (DLC) was confirmed. The negative influence is clearly shown by the path coefficients, which are below -0.1. The path coefficient for AD is only slightly below the threshold value (-0.152). A strong influence can be observed with DLC (-0.537) and a slightly weaker influence with IPA (-0.264). While IPA (0.089) and AD (0.025) have only a small effect, *Trust* (0.431) in DLC has a strong effect on the *Perceived Disadvantages*. Looking at the *Trust in the Manufacturer*, this is the first hypothesis that can be confirmed at a significance level of 1% for both IPA and AD. The path coefficients are also below the threshold of -0.1 here, whereby the IPA value is significantly lower (-0.517) than the AD value (-0.263). It can also be observed that the effect size at IPA (0.342) is only slightly below the limit value for a strong effect and the effect size at AD (0.097) only describes a small effect.

2.4 Conclusion Section I

2.4.1 Discussion

With regard to the effects of the degree of automation and the effect-related risk on the adoption of smart systems, various effects could be observed. The results partially confirm that there is a linear influence on the adoption of smart systems. The linear influence of automation, which has already been postulated by Kyriakidis, Happee and Winter (2015) as well as Nordhoff, van Arem and Happee (2016), was therefore also observable in this study. It was shown that an increased degree of automation and an increased effect-related risk increase the perceived advantages of the smart system and attenuate the perceived disadvantages. Increasing the importance of the perceived advantages as well as mitigating the perceived disadvantages has a positive influence on the intention to use and thus on adoption. However, the linear influence is not entirely positive. The effect of advantages on attitude and intention to use is constantly decreasing. But the influence remains positive throughout. The path coefficients on intention to use of Perceived Advantages are lower in all models than on the attitude. This shows that the advantages are important to create a positive attitude towards the product, but the influence is always smaller if the adoption is to become more concrete.

More complicated are the effects of the degree of automation and effect-related risk on the rest of the model. A non-linear influence on the relationship between the attitude and the intention to use was observed. This confirms findings of Rödel *et al.* (2014) as well as Verberne, Ham and Midden (2012) regarding the non-linear influence of the degree of automation. As a tendency, however, the importance of the attitude for the intention to use increases. In addition, it could be observed that the relationship between the disadvantages and the attitude or intention to use is influenced, but this is not linear. However, the influence is significantly negative in almost all models. Trust in the smart system is also stimulated by the increase in automation and effect-related risk. Thus, the influence of trust in smart systems on attitudes towards these systems fluctuates. A direction of development is not discernible, the influence is therefore not linear. However, trust in the smart system has a consistently positive effect on attitudes. Increasing the degree of automation and the effect-related risk also influences the relationship between trust in the smart system and the perceived advantages or disadvantages. Even if the effect is not linear, the changes in these two relationships are opposing. Thus an interplay of advantages and disadvantages can be observed. With low automation the advantages have a high influence, whereas with high automation the disadvantages gain weight.

No influence was found on the relationship between trust in the manufacturer and attitude. Regardless of the degree of automation, trust in the manufacturer had no influence on Attitude and therefore no influence on the adoption of smart systems.

In summary, Research Question 1 *"How does the degree of automation influences the intention to use a smart system?"* shows that the degree of automation affects all postulated contexts of the Basic Research Model. The effect of the perceived disadvantages on the intention to use increases with the degree of automation. A possible explanation for the increasing effect size of the Perceived Disadvantages on the intention to use is the loss of control associated with automation. A disadvantage in highly automated smart systems is that it may not be easy for the user to correct it, and the consequences of a malfunction would be fatal in the high-risk area. Thus, 71.4% partially or completely agreed that they were afraid of a loss of control in an autonomous vehicle. The fact that the occupants have fewer possibilities to intervene and therefore feel at the mercy of the car is shown by the 60.8% of those questioned who partly or completely agreed that autonomous vehicles patronise the occupants. This confirms findings from the literature (e.g. Weyer, 1997, p. 246). The decreasing control over the smart system results in new disadvantages, which are becoming more and more important the more automatically the smart system performs the operations, as the users hand over more and more control to the system. This is also confirmed by the results of Hoff and Bashir (2015, p. 424) that the disadvantages of increasing degrees of automation have an increasingly negative influence, as users have less and less control. With low automation, the functions and advantages of the smart system are important for the intention to use such a system. With a high degree of automation, the actually advantageous functions play a minor role. This contradicts the hypothesis initially put forward, based on the literature, that the benefits have an ever greater influence with increasing automation, since the user has to do less and less to enjoy the benefits (Parasuraman, Sheridan and Wickens, 2000, p. 286). For the formation of intention to use, other factors become much more important than the perceived advantages. Decisions as to whether to adopt a smart system are based less and less on the perceived advantages and disadvantages as the degree of automation increases. Attitude as a central influencing factor is massively influenced by user trust in the smart system. This means that increased automation also requires increased trust in the smart system (Muir, 1994, p. 1905). However, the functions of highly automated systems are still perceived as advantageous. For example, each of the characteristics and functions of autonomous driving queried by at least 62% was perceived as advantageous or very advantageous. The highest value was achieved by the advantage that autonomous driving increases mobility in old age (86.3% saw this as advantageous or very advantageous), followed by the advantage that autonomous driving would mean more environmentally friendly driving (83.7% saw this as advantageous or very advantageous).

In summary, with regard to Reasearch Question 2.1 *"How does the effect-related risk influences the intention to use a smart system?"*, influences of the effect-related risk can also be found for all postulated relationships of the basic research model. Attitude gains in importance with increasing risk for the formation of intention to use. The influence of the perceived advantages on the intention to use decreases when the effect-related risk increases. It becomes clear that with increasing risk other things become more important than the advantages of the smart system. Users pay much more attention to the disadvantages and need trust in the system to form an intention to use it. If the effect-related risk of using a smart system increases, then the influence of the perceived disadvantages on the intention to use also increases. Even if this effect is small, it is observable and can be explained by the increased expected damage. The effect that high risks emphasize the disadvantages of the smart system and thus lower the intention to use can be compensated by trusting the smart system and the manufacturer. In general, the perceived disadvantages of a smart system can be reduced by trusting the system. Above all, however, a lack of trust in the smart system can reinforce the perceived disadvantages. Due to the increasing effect-related risk, it is becoming increasingly important for the user to be able to trust the smart system, as malfunctions of the smart system could cause considerable damage. This underscores findings from the existing literature (Hoff and Bashir, 2015, p. 424). The perceived advantages can also be increased by a high level of trust in the smart system. Above all, however, the sometimes increasing link between trust and perceived advantages also means that the advantages of a smart system can only have a strong effect on intention to use if the smart system is also trusted that these advantages really apply. Trust in the manufacturer consistently plays a significant role in perceived disadvantages. This may be due to the fact that the disadvantages partly include the lack of data security and privacy. The manufacturers are the actors who have to manage and protect the data. With IPA, the effect-related risk is still very small. One of the biggest risks is that the data provided will not be handled properly. This could be one reason why trust in the manufacturer has a significant impact on these smart systems. However, this influence decreases with increasing effect-related risk. With autonomous driving, the risk level is much higher. Data protection risks play a subordinate role here. Regarding these application areas of smart systems with high effect-related risk, big names can give trust to the industry. For example, 57.4% partially or completely agreed that large car manufacturers such as BMW, Daimler or Audi can be trusted in the development of autonomous vehicles. However, as with trust in the smart system, mistrust on the part of the manufacturer can also increase the perceived risks.

2.4.2 Implications

The development of highly automated smart systems in areas with high effect-related risk is promising, but the adoption of these systems is not always given. The studies carried out and the findings drawn from them allow the derivation of implications for practice. A central implication refers to the development of trust in the smart system and the manufacturer. Trust in the smart system has an increasing influence the more automated a smart system is and the higher the effect-related risk is. Trust in the manufacturer, on the other hand, only becomes important in highly automated and high-risk application areas. To take advantage of this effect, suppliers of these smart systems should take trust-building measures, primarily with regard to the smart system. If the smart system is a highly automated system with a high risk, confidence in the manufacturer should also be strengthened. When introducing new highly automated products or smart systems with high effect-related risk, the product should be published under an existing brand that already has high user confidence. Not only communicate advantages, as these have a decreasing influence, but increasingly eliminate disadvantages. Also a communication with the user to overcome fears that may not apply due to existing disadvantages increases the intention of using highly automated smart systems with high risk. If existing systems are to be advanced in their automation, it should therefore be noted that first the disadvantages are kept as low as possible and trust in the product is created by intensive communication. A further measure to achieve the adoption of smart systems is to reduce the feeling of paternalism in the user. Smart systems should be designed in such a way that the user retains the feeling of control as far as possible and, if necessary, is shown the possibility of interrupting the actions of the smart system. In the literature, the user's level of information also plays a major role in this context (Verberne, Ham and Midden, 2012, p. 807). For example, the smart system should inform the user as much as possible about the actions performed, so that transparency is increased and the feeling of paternalism is reduced.

2.4.3 Limitations

The studies and results presented have limitations. First, not all degrees of automation and risk were considered. The considered degrees of automation were rather vague and did not cover the complete spectrum of the automation scale by (source). Rather, care was taken to consider a smart system with a low degree of automation (IPA), one with a medium degree of automation (DLC) and one with a high degree of automation (AD). The effects described are partially linear. If further degrees of automation are considered, this may no longer be the case. The effect-related risk was not exactly quantified. This is usually difficult and partly dependent on the subjective assessment of the user. An attempt was made to select a smart system with low effect-related risk (IPA), a system with medium effect-related risk (DLC), and a system with high effect-related risk (AD). Here, more degrees of risk could also lead to more precise conclusions regarding its influence.

Secondly, although it was attempted to select three smart systems for the investigation in such a way that they should be sorted into the three degrees (low, medium, high) of automation and effect-related risk considered as far as possible, the distances between the degrees are not necessarily the same. Although the tendency is correct, it is not necessarily the case that the distance of the effect-related risk between IPA and DLC is the same as the distance between DLC and AD.

Thirdly, no further combinations of automation and risk were considered. If the three degrees of automation and effect-related risk are retained, a total of 9 possible combinations would have to be examined in order to examine possible mutual effects. However, this number of empirical studies is difficult to achieve with the chosen study design.

Fourthly, the differences found in effect size and path coefficients strength cannot be checked for significance by statistical tests. Here a metastudy could help to determine the significance of the differences.

Finally, it must be noted that the differences found between the automation levels and risk levels can also be induced by the differences in the smart systems considered. In order to exclude this bias, the same smart systems should be investigated in several degrees of automation and with different effect-related risks, if possible.

Section II

Influencing Factors of the Actual Use of Smart Systems

3 Section II: Influencing Factors of the Actual Use of Smart Systems

After Section I was dedicated to the degree of automation and the effect-related risk, among other influencing factors, in this section the cause-related risk as influencing factors on the adoption of smart systems, among other influencing factors, will be examined.

The influencing factors to be investigated in this section allow the adoption to be measured directly via the actual use. The utilization of actual use is the most accurate way to assess the adoption of a smart system (Abraham *et al.*, 1999, p. 2607; Davis, 1986, p. 39). There are also several empirical evidences for this claim. For example, showed Gollwitzer (1999, p. 501) sowed that the relationship between the intention to use and the actual use is imperfect. Sheppard, Hartwick and Warshaw (1988, p. 336) also emphasized this by demonstrating that the two quantities only have a correlation of 0.53. Morwitz, Steckel and Gupta (2007, p. 361) even reports a decreasing correlation between intention and actual use when it comes to new products like smart systems may be. For this reason, no survey was conducted and an attempt was made to utilize the actual use of users as a data basis for the study. The data basis was collected via a self-developed online game that simulates decision-making situations. The online game is a card game in which the player randomly draws cards from a stack and has to decide whether the next randomly drawn card is higher or lower than the present card. The cause-related risk to be considered is represented by the uncertainty of the decision situation. Thus, depending on the randomly drawn cards, different uncertain decision situations arise in which the user should decide. To help the user make this decision, an expert system is available as a smart system. This expert system gives the user recommendations as to how he should behave.

With this smart system, the Sensoring Element captures the cards revealed. The sensor is therefore not a physical sensor, but a collection of digital data. The Data Processing Element calculates the probability that the next card is higher and passes a decision to the Actuating Element. The Data Processing Element relies on additional information. In this case, this additional information is information that the system does not get from the decision situation at hand. These are the cards that have already been played. If only the information of the present decision situation is used to make a prediction, this prediction is a naive prediction (further explanations on the naive prediction can be found in Chapter 3.4). However, the smart system uses historical data as additional information. This historical data includes all of the player's past games. Thus, a calculation of the probability that the next card will be higher is much more accurate. Characteristic for a smart system is the solution space, which the smart system reduces. The solution space is represented here by the alternative recommendations the system can give. Since the right decision is not deterministic due to the random drawing of cards, all possible action alternatives that the smart system can give is the solution space. The solution space is reduced by processing the additional information and calculating the probability. The decision, which the smart system then passes on to the Actuating Element, is the action recommendation to the user. In this case, the Actuating Element is a simple output on the screen. Thus, the user is given a forecast of the smart system's recommendations for action.

In order to investigate the actual use of the smart system, the collected data will be analysed for both a decision tree and several linear regressions. The content of this section is based on the publications listed below.

Table 22: Publications Section II

Title	**Publishing Status**
The Effect of Uncertainty and Quality Perception on the Usage of Forecasting Tools–A Game Based Analysis	Published in the Proceedings of the International Conference on Games And Learning Alliance 2017 (Jourqual 3: **C**).
What Drives Decision Makers to Follow or Ignore Forecasting Tools-A Game Based Analysis	Published in the Proceedings of the 51st Hawaii International Conference on System Sciences 2018 (Jourqual 2: **C**).
What Drives Decision Makers to Follow or Ignore Forecasting Tools-A Game Based Analysis	Published in the Journal of Business Research (Jourqual 3: **B**).

Section II is structured as follows. First, an introduction on forecasting expert systems as smart system is given. The existing literature on influences on the use of these systems will then be reviewed. Afterwards, the game on which this study is based will be described in more detail, as well as the functionality of the forecast and the decision tree. In the following analysis, the collected data will be evaluated and a robustness check will be carried out with regard to the game elements used. This section concludes with a conclusion in which the results regarding the research question RQ2.2 are discussed, implications for practice are pointed out and limitations of this study are dealt with.

3.1 Forecasting Expert Systems as Smart Systems

Forecasts are an inherent part of a firm's planning activities and have an important impact on the decision-making process and a firm's final outcome (Moon, Mentzer and Smith, 2003, p. 5; Stock and Lambert, 2001, p. 559). Usually, software tools like expert systems (ES) support the forecasting process completely or partly. But finally, a forecast is used by individuals to make a decision. Thus, the quality of a decision depends on the one side on the quality of the forecast. On the other side the employment of forecasts highly depends on the involved decision makers, their discernment, and the way they make use of the forecast (Smith and Mentzer, 2010, p. 159). Even if a forecast is as accurate as possible, a decision maker may deviate from the forecast's objective advice. On the one hand, users may have additional information which the forecast could not take into account so that its predictive power is limited. In this case, scrutinising the forecast is inevitable. On the other hand, human behaviour is not only determined by objective observations and reasons but also by subjective belief of individuals (see for example the research of Fishbein and Ajzen, 2011, p. 20; Simon, 1957). There are innumerable sources for mistakes during the decision-making process (Dörner and Schaub, 1994, pp. 434–446). For example, users can question the forecast if it is not in line with their expectations. But if a forecast is not faulty, does not use outdated information, or if the user does not have additional information, the question is why individuals do not use forecasts and rely on their own personal assessment of a situation instead.

The reasons for this seem to be manifold and to some extent contradictory. While some researchers found that the quality of a forecast significantly influences its usage (Smith and Mentzer, 2010, p. 170), others could not confirm these findings (O'Connor *et al.*, 2005, p. 1265). The reason may lie in different fields of application, research methods, or sample data. However, a consensus is that forecasts influence the behaviour of decision makers (Gaynor and Kelton, 2014, pp. 206–208; Huang, 2016, p. 269; Rupar, 2017, p. 850; Stone, 1995, pp. 34–35). While forecasts are in the focus of research for many years, especially to improve accuracy, research concerning the use of forecasts and the usage reasons is scarce (Aziz and Manap, 2008, p. 95). Behavioural sciences have emphasised the role of affect (Loewenstein and Lerner, 2003, p. 619), emotion (Lerner *et al.*, 2015, p. 801), self-confidence (Chuang *et al.*, 2013, pp. 671–672; Krueger and Dickson, 1994, p. 385), self-esteem and anxiety (Wray and Stone, 2005, pp. 140–141) for the decision making itself and how these factors influence the choice of risky or more certain alternatives. But the role of individuals using forecasts as a smart system is hardly investigated and should be put into focus (Jones and Bretschneider, S., Gorr, Wilpen L., 1997, p. 241; Stekler, 2002, pp. 235–236). This is particularly of interest as even decision makers who constantly and systematically make bad decisions can survive in a leadership position for a long time (Dragota, 2016, p. 123).

It is reasonable to assume that the aforementioned factors not only influence the decision making of individuals itself but also have an impact on the usage of smart systems. The more decision makers are convinced of their abilities, the more likely they may adjust or override a forecast and act in accordance to their own beliefs (Fildes and Hastings, 1994, p. 15). In particular, self-confidence, self-esteem, and anxiety are influenced by the experience of decision makers and their perceived success. Besides these factors, also the forecast itself, in particular its perceived quality (Smith and Mentzer, 2010, p. 170), and the decision situation may have an impact on the usage of forecasts. Usually, decision situations differ concerning their degree of uncertainty. Some situations are quite unequivocal and only a small rest of uncertainty remains, some are much more difficult to assess. Depending on the situation, the quality of a forecast can therefore be assessed easily or not. In an uncertain situation, decision makers might more likely follow a forecast than in more certain situations. This uncertainty represents the cause-related risk. The research question of this section is stated below:

RQ2.2: How does the cause-related risk influences the use of a smart system?

First, the influencing factors which make individuals rely on or discard forecasts in uncertain situations should be investigated. The influencing factors can be derived by the explanations above. Therefore, the role of experience, success of the decision maker and the quality of the forecast as influencing factors will be in the focus. Afterwards, the role of the cause-related risk, in form of uncertainty, for relying on or discarding forecasts as smart systems will be investigated.

In this connection, this section focusses on the factors of the decision making itself without external influences from a specific situation. As recent investigations have shown, the simple presence of others influences the actions of people (Anthony, Wood and Holmes, 2007, pp. 428–430; Chou and Nordgren, 2017, p. 679). If a person is surrounded by a peer group, he usually acts more risk taking than if he was alone (Chou and Nordgren, 2017, p. 673). This holds particularly if the decision maker has low self-esteem (Anthony, Wood and Holmes, 2007, p. 430). To eliminate influences of others and to focus on the role of former experience and success, the concept of gamification is employed to the study by using the simple game High or Low. As the behaviour of people in games is similar to their behaviour in real life (Hamari, Huotari and Tolvanen, 2015, p. 148; Sermat, 1970, p. 92), this approach provides several advantages. First of all, influences from others on the decision maker are excluded. Secondly, because of the solo game, a human opponent also does not have any impact. And lastly, all the benefits of gamification can take effect (Griffiths, 2002, pp. 47–51; Hamari, Koivisto and Sarsa, 2014, p. 3025).

Within the game, the decision maker has only two options for his decision and is supported by a forecast that gives advice which alternative to choose. But the forecast is manipulated such that it gives the wrong advice in some situations. With the help of this setting it can observed if a decision maker scrutinises the outcomes of the forecast, ignores it, or follows the advice blindly. As experience is said to be important for the assessment of decision situations and of the quality of forecasts (Higgs, Polonsky and Hollick, 2005, p. 53; Smith and Mentzer, 2010, p. 170), the more experienced a decision maker is, the more he is expected to recognise the manipulation.

3.2 Literature Review

Forecasts can be found in many business areas and have many different applications. Therefore, the body of literature analysing the usage of forecasts is diverse. One stream investigates when forecasts are used by decision makers. O'Connor *et al.* (2005, p. 1271) found that perceptions of the risk situation are influencing the usage of forecasts much more than reliability. In quite comfortable situations, decision makers tend to disregard even as reliable and accurate perceived forecasts and only make use of them in risky situations. However, in their analysis O'Connor *et al.* (2005, p. 1273) cannot explain more than 20% of the variance. This indicates that there are more factors to be examined.

Glaum, Schmidt and Schnürer (2016), Smith and Mentzer (2010), as well as Sarens and D'Onza (2017) have a look at the forecast itself. Glaum, Schmidt and Schnürer (2016) focus on the quality of the forecast output. They found that the effort a firm invests in the forecast, the efficiency with which the forecast is done, and the quality of the input data positively influence the outcome of forecasts. Sarens and D'Onza (2017) show that when performing a forecast, analysts pay more attention to individual risks than to general risks. Smith and Mentzer (2010) analyse the role that forecast accuracy plays for the usage of forecasts. They show that forecast accuracy positively influences the perceived quality and thereby the usage of forecasts by users. As they focus on logistics, they also show that the logistics performance can be improved. Also, Gaynor and Kelton (2014) as well as Rupar (2017) focus on the credibility of forecasts. Gaynor and Kelton (2014) analyse how different forecasts of firms and analysts are perceived and used by investors. They find that if the firm's forecast is in line with the earnings trend, the analyst's forecast is perceived as less useful. Otherwise, if the firm's forecast deviates from prior trends, investors are geared to the analyst's forecast. Rupar (2017, p. 862) observes related results. If the forecast precision provided by firms does not meet the expectation of investors, they mistrust the forecast. This is in line with Huang (2016, p. 267) who found that the disclosure of reduced forecasts dampens expectations regarding a firm's development and can limit the loss in comparison to the situation when bad news are announced.

Another stream of literature focuses on the interpretation of forecasts. Interestingly, users have problems to interpret forecasts and their own behaviour correctly. Juanchich and Sirota

(2016, p. 395) found that more than 50% of the participants of their survey are not able to interpret a forecast correctly. This is in line with Maines and Hand (1996, p. 330) who found that individuals do not weight time series information correctly when performing a forecast by themselves. Lucarelli, Uberti and Brighetti (2015, p. 479) observed that individuals could not assess their risk tolerance level correctly. Although a high share of participants of their study stated that they are risk averse, they act like a risk taker. Both phenomena may usually lead to inappropriate decision making.

Another research stream investigates characteristics of the decision maker. Lo and Repin (2002, p. 332) as well as Lo, Repin and Steenbarger (2005, p. 357) found that experience reduces emotional reactivity and improves the usage of forecasts during the decision making process.

This study is most related to those works that analyse the situation when the decision-making takes place. It is most related to the work of O'Connor *et al.* (2005), Smith and Mentzer (2010), Lo and Repin (2002) as well as Lo, Repin and Steenbarger (2005). In contrast to O'Connor *et al.* (2005), this research focusses on short-term decision marking instead of long-term decisions. Compared to Smith and Mentzer (2010) who conducted a survey among managers and therefore relied solely on self-report without considering the decision situation, experiments were conducted and a game to observe the behaviour in different situations of uncertainty employed. While Lo and Repin (2002) as well as Lo, Repin and Steenbarger (2005) focused on the impact of (long-term) experience as some kind of skills on physical reactions during day trading, this section measures the experience during the experiments. In addition, Lo and Repin (2002) and Lo, Repin and Steenbarger (2005) investigated the decision making itself while here the usage of forecasts is in the focus.

In contrast to other studies, solely the decision situation, the performance of the forecast, and the experience that the decision maker made during the past periods is considered. In addition, the forecast accuracy by manipulating the outcome in a certain way so that it is less reliable in some situations is controlled. This situation equals to some degree the setting of Gaynor and Kelton (2014). The provided forecast to decision makers corresponds to the firm’s forecast while the decision makers own calculations corresponds to the analyst’s forecast.

3.3 Methodology

Games are an inherent part of our lives and exist nearly since the dawn of mankind (Seaborn and Fels, 2015, p. 14). As games are fun and usually played voluntarily and with great ambition, game concepts have been applied to many non-game applications during the past years like crowd sourcing (Morschheuser *et al.*, 2017, p. 26), brand web sites (Harwood and Garry, 2015, pp. 533–543), or many others (Morford *et al.*, 2014, pp. 31–34; Seaborn and Fels, 2015, pp. 17–18). This process of using game design elements in non-game contexts is usually referred to as gamification (Deterding *et al.*, 2011, p. 11). Its main purpose is to encourage users to do things, to do them more often and longer than they would have done otherwise (Hamari, Huotari and Tolvanen, 2015, p. 140; Seaborn and Fels, 2015, p. 18).

In this sense, we apply the game High or Low (game concept) to the non-game context of data gathering for a research study to encourage participants to stay longer for being observed in their decision making. But if the outcome for the user is a fully-fledged game, the nature of gamification is often denied (Seaborn and Fels, 2015, p. 16). However, distinguishing a game from a non-game application is not as easy as it seems (Huotari and Hamari, 2012, p. 18, 2017, pp. 25–27; Seaborn and Fels, 2015, pp. 17–18). While for person A an application can be a game, for person B this may not hold. Therefore, Huotari and Hamari (2012, 2017) used a different approach to define gamification based on service marketing:

"Gamification refers to a process of enhancing a service with affordances for gameful experiences in order to support users' overall value creation." (Huotari and Hamari, 2017, p. 25).

According to this definition, any service, be it a non-game application or also a game, can be enhanced by game design elements if users experience this enhancement as an improvement and as gameful (Huotari and Hamari, 2012, p. 18, 2017, p. 26). In this respect, the data gathering of this study is enhanced with a game for bringing a joyful experience to users while they create the data of decision making. A game as a motivator is used to make the application of data gathering more interesting, more playful, and more exciting for the participants so that users keep on playing/producing data.

As the use of the forecast and the decision making are the core of the game, it is possible to focus on the risk behaviour of people without having them influenced by other people. Otherwise, users would judge risk situations differently depending on the presence of others (Chou and Nordgren, 2017, p. 673). Other methods could be a survey, experiments, or observations in real decision making but any of these alternative methods bears several shortcomings. In surveys, interviewees often try to comply with the views of the interviewer or other people. As the outcome is self-reported, distortions occur as people often are not able to judge their own situation or abilities correctly (Juanchich and Sirota, 2016, pp. 388–389). Experiments and observations in real life are complex and costly. Besides it is difficult to obtain a sufficient number of samples. Therefore, the game is used as a deputy for a decision situation under risk. The advantages are that the decision situation is easy (Hamari, 2013, p. 244) but always new. The motivation of the participants is kept high. The forecast can easily be manipulated so that two different situations can be realised. And lastly, although there is no group pressure, participants have the incentive to play the game seriously as they can compare their outcome to others on a leaderboard.

To test the influence of gamification and its elements on the results of such experiments, a leaderboard was provided where players can see their own score in the game and their overall high score. One group was initially told about the leaderboard. The players of this group could see their score during the whole game play and have a look at the leaderboard at any time. A second group was informed about their achieved score and the leaderboard only after finishing the game so that no pressure was exerted at all.

3.3.1 The High or Low Game

To analyse the behaviour of decision makers concerning the usage of forecasts, a study was conducted where participants are observed when they play the simple card game High or Low. This game is one of the simplest card games played with either 32 or 52 cards. For calculation simplicity, the game was restricted to 32 cards. The order of the cards colours shall be (from high to low) clubs, spades, hearts, diamonds, the order of the cards shall be ace, king, queen, jack, 10, 9, 8, and 7. The game play is as follows: In the first step, the dealer (here: the computer player) takes the first two cards from the pile of cards and shows one card to the player (referred to as he in the following). The other card is hidden. Then, the player can choose if the hidden card is higher or lower. If the player is right, he gets one point for this round. If he is wrong, no points will be added to his account. At the end of this round, both cards are put on the pile with the played cards. With a deck size of 32 cards, a game lasts 16 rounds. After each game, the cards are shuffled. Because the probability that the hidden card is higher or lower than the revealed card depends on the value of the revealed card and the cards that are still in stock, players are made aware of the decreasing number of cards in the pile of unused cards and when the pile of used cards is shuffled.

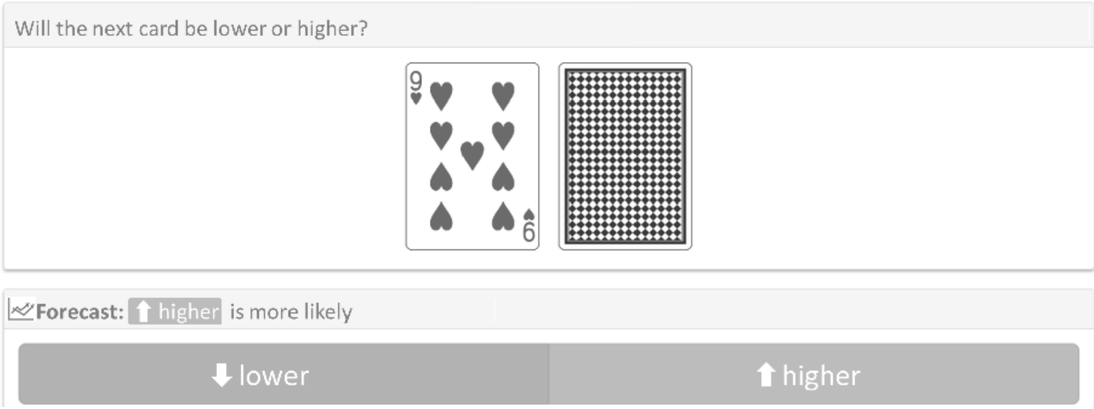

Figure 10: Screenshot of the High or Low Game

The card game was implemented as an online game playable in a web browser.

3.3.2 The Forecast

As mentioned above a smart system was implemented in the form of a forecasting expert system to help the player. The forecast calculates the probability that the next card will be higher. This probability depends on the number of unused cards with a higher value as the shown card and the overall number of cards remaining in the pile of unused cards. Therefore, the forecast remembers all played cards. The probability that the next card is higher is calculated as follows:

$$exact\ probability = \frac{\#remaining\ cards\ above}{\#all\ remaining\ cards} \tag{1}$$

The following examples will help to explain the forecast. Example A: If the player gets the 9 of hearts as first card in the deck, 22 cards have a higher value and 31 cards are remaining in the unused pile. The probability that the next will be higher is $22/31 \approx 0.71$. Example B: During three rounds only cards below 9 of hearts were drawn. Then, when 9 of hearts is drawn, the probability will be $22/25 = 0.88$. A forecast is provided that predicts if the hidden card is higher or lower than the revealed card. In both examples, the forecast would be “higher”. Since the forecast is not deterministic but stochastic, the forecast does not have to be right. Hence, the prediction “uncertain” was implemented which will reduce the negative perception of the forecast. In situations where the probability is close to 50% a false prediction is more likely. By predicting “uncertain” no false prediction was given, but even no right prediction was given either. Therefore, three different forecasts can be distinguished that are based on formula (1):

- Higher: The hidden card is probably higher than the first card.
- Lower: The hidden card is probably lower than the first card.
- Uncertain: The probabilities are too close to make a prediction.

If the exact probability is above 0.6, the forecast advises to choose higher. If it is below 0.4, the forecast is „lower”. Between 0.4 and 0.6 the forecast tells that it is uncertain. The intention behind the uncertain forecast is to build trust in the forecast. Since the game is probabilistic and not deterministic, the forecast does not have to predict the correct card in each round, but in the long run, an orientation to the forecast will lead to a positive game result.

To answer the research questions, the forecast is manipulated as depicted in Figure 11. For probabilities between 0.55 and 0.8 as well as 0.2 and 0.45, the forecast is inverted such that it predicts higher for (0.2, 0.45] and lower for [0.55, 0.8). To avoid fast detection of the manipulation, all obvious cases where the probability is in the ranges of [0.0, 0.2] or [0.8, 1.0] are correctly predicted. The range of uncertainty was reduced to probabilities between 0.45 and 0.55 to receive more cases of manipulated forecasts.

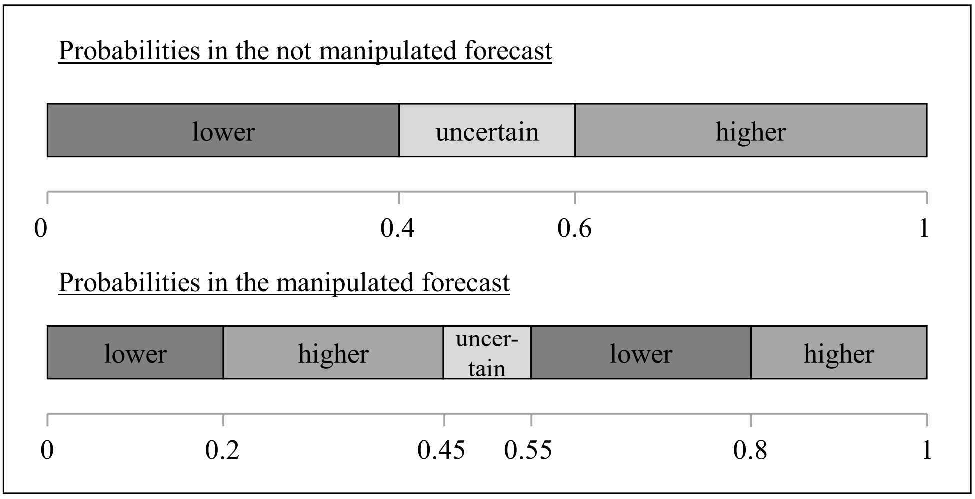

Figure 11: Probabilities of the Forecast

According to the examples above: In example A the prediction would have changed from “higher” to “lower” and in example B the prediction remains as “higher”. The manipulation is applied after the player finished the first two decks till the end of the game. The reason for manipulating the forecast not at once but only after two decks is that forecast accuracy plays an important role for the trust in the forecast (Smith and Mentzer, 2010, p. 170). Therefore, the first two decks act as a trust building measure so that the player gets used to an accurate forecast. This setting allows to analyse which factors influence decision makers such that they do not make a decision based on their own thoroughly done calculations but just blindly rely on expert systems like the provided forecast.

3.3.3 The Decision Tree

To analyse the role of experience, success of the decision maker and the quality of the forecast for relying on or discarding a forecast in an uncertain situation, first a decision tree is used. By applying a decision tree it is desired to get rules, when a decision maker follows a faulty forecast in an uncertain decision situation. Afterwards the rules should be clustered to get characteristics of situations where a decision maker uses the smart forecasting system. First the concept of a decision tree will be explained. The rule extraction and clustering will be described in Chapter 3.4.

A decision tree is a classifying technique that does not only classify data sets into predefined classes but also provides insights into the classifying rules (e.g. Quinlan, 1987). Figure 12**Fehler! Verweisquelle konnte nicht gefunden werden.** gives an example of a decision tree.

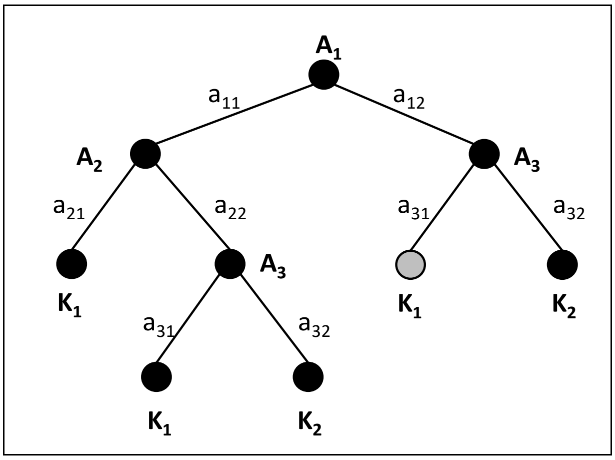

Figure 12: Example of a Decision Tree

There, we have two classes, K_1 and K_2. Each inner node including the root node of the tree represents one attribute of the data set. The edges represent distinct values (or distinct intervals or groups of values) of the attribute. Then, a data record is classified as follows: Starting by the root node, the dataset traverses the tree to a leaf node. In each node, it goes down to next node along the edge that matches its own value of the attribute in the node. When the data record enters a leaf node, it is classified to the class that is indicated by the leaf node. The path from the root of the tree to a leaf represents a rule. All records classified into a leaf have taken the same path within the tree and therefore fulfil the same comparisons. In our example, the grey leaf represents the rule:

IF $A_1=a_{12}$ *AND* $A_3=a_{31}$ *THEN* K_1

The quality of a rule is indicated by two measures: confidence and support. The confidence of a rule indicates its reliability. It is calculated as the share of records classified correctly by the rule to all records classified by the rule. The support indicates how often the rule can be applied. It is calculated as the share of records classified by the rule to all records of the data set. While the confidence of a rule should be as great as possible in order to avoid faulty classifications, the support does not necessarily need to be great because due to the usually big number of data records a rule cannot be used for all situations. Instead, finding a set of reliable rules is usually sufficient if it is not necessary to classify any data record. Then, these reliable rules can be used to identify promising data records and to develop a decision strategy.

3.4 Analysis

To examine the influence of the uncertainty on the behaviour of players to follow a faulty forecast, a proxy for how uncertain the player judges the situation regardless of the forecast provided is needed. A risk neutral decision maker should orientate to the exact probability but for this he has to remember all used cards. Usually, a player will remember some of the played cards but not all. Instead, it is conceivable that decision makers use a naïve estimation that does not take the cards already played into account. This naïve probability is calculated as follows:

$$\textit{naïve probability} = \frac{\#\textit{all cards above}}{\#\textit{all cards}} \tag{2}$$

That means the naïve forecast sets the number of cards above the drawn card in relation to the number of all cards of the deck, regardless of used cards. Thus, the probability of the naïve forecast in example A and B is equal ($22/31 \approx 0.71$). That means, that the naïve probability may deviate from the exact probability and can lead to different forecasts and decisions (i.e. example B).

The experience of each player can simply be measured by the rounds he played. His success is measured by the ratio of won rounds to played rounds:

$$\textit{success rate} = \frac{\textit{won rounds}}{\textit{played rounds}} \tag{3}$$

However, the influence of the success can be different according to the time period under consideration. Therefore, the player's success is subdivided into three categories: Short-, mid-, and long-term. As one game comprises 16 rounds (with the last round being deterministic), the length of one game was divided into three equidistant periods of five rounds such that the short-term success comprises the last five rounds, the mid-term success the last ten rounds, and the long-term success the last 15 rounds. The same categorisation is done for the forecast's quality perceived by players. As a proxy for the perceived forecast quality, the ex-post success rate of the forecast was used, i.e. the ratio of correctly predicted rounds to all rounds:

$$forecast\ quality = \frac{correctly\ predicted\ rounds}{played\ rounds} \tag{4}$$

In addition, it should be studied how the player's decision is influenced by different degrees of dominance i.e. if the player's success dominates the quality of the forecast and vice versa.

$$dominance = \frac{success\ rate}{forecast\ quality} \tag{5}$$

Cause-related risk as one of the most important influencing factors was already named. In this game the cause-related risk should be depicted by the uncertainty of the decision situation. Concerning the uncertainty of the decision situation, a proxy is needed for how uncertain the player judges the situation regardless of the forecast provided. As such, the naïve probability of formula (2) is used as a basis. The closer the naïve probability is to 50%, the more uncertain the situation is. Therefore, the difference between the naïve probability and 50% is mapped to the interval [0,1] where 1 represents a complete uncertain situation (probability of 50%) and 0 a complete certain situation (probability of 0% or 100%).

$$uncertainty = 1 - 2 * |naïve\ probability - 0.5| \tag{6}$$

Then, two cases can be distinguished: (a) the manipulated forecast equals the naïve forecast and (b) the manipulated and the naïve forecasts are distinct.

For the analysis, two key figures are calculated: the percentage of players following the forecast in a situation of uncertainty and the degree of uncertainty of the situation. The percentage of following players is calculated for every possible situation by dividing the number of situations in which the manipulated forecast was followed by the number of times the situations appeared.

$$percentage\ of\ following = \frac{\#situations\ forecast\ was\ followed}{\#situations} \tag{7}$$

3.4.1 Data Collection

The study was conducted in several rounds from the beginning of the year 2016 until winter 2017. Participants were mainly students who are said to be adequate surrogates for decision makers (Remus, 1986, p. 23) so that this sampling hardly distorts the results. They were assigned to one of two groups: Players of the first group had access to their score and a leaderboard during their whole game play (case 1) while players of the second group only knew about score and leaderboard after finishing the game (case 2). In each round of the study, players were assigned to only one group to avoid that they were informed about the leaderboard by others. Each player could play the game in only one session as long as he wanted to. After finishing the game, he could not return and play a second session.

In total, 212 players participated and generated 16,793 data records. Each record represents one playing round and contains the played cards, the forecast, the hand id and the user id. As only 162 players reached the third deck where the forecast was manipulated, 3,212 records had to be eliminated. 4,993 of the remaining 13,581 data records (36.76%) contain a manipulated forecast and are therefore in the focus of the following analysis. However, all data records with manipulated as well as with not manipulated forecast must be used to describe the specific decision situation (e.g. player success and forecast quality) when a player decides whether to make use of the (manipulated) forecast or not.

3.4.2 Rule Extraction

First, the rules derived from the decision tree will be examined. In addition to the success of the decision maker and the forecasts (in short-, mid- and long-term), the experience, the consecutive wins and defeats were used as attributes for the construction of the decision tree. The experience represents the number of rounds a player has played so far. The consecutive wins and defeats represent the number of consecutive winning and losing rounds in retrospect from the current round. The used Attributes are depicted in Table 23.

Table 23: Attributes for the Decision Tree

Attribute	Term	Scale
Success category user	Short-term	{low; medium; high}
	Mid-term	{low; medium; high}
	Long-term	{low; medium; high}
Success category forecast	Short-term	{low; medium; high}
	Mid-term	{low; medium; high}
	Long-term	{low; medium; high}
Number of played rounds		Continuous
Consecutive wins		Continuous
Consecutive defeats		Continuous

For classification, two classes were formed, following the manipulated forecast (Class = 1) and not following the manipulated forecast (Class = 0). This data set was used to build a binary decision tree. Based on the explanation above, the focus was more on a high confidence than on a high support. The minimum support was set to 1%. This means that every rule applies for at least 26 of the 2,626 datasets. In total, 38 rules were found. In the evaluation, all rules with at least a confidence of 75% were considered. The support and confidence of the remaining 11 rules are depicted in Table 24.

Table 24: Support and Confidence of the Rules

Rule number	Support	Confidence	Class
1	1%	82%	1
2	1%	82%	1
3	8%	81%	1
4	8%	80%	1
5	2%	80%	1
6	1%	80%	1
7	2%	80%	1
8	1%	76%	1
9	1%	76%	1
10	3%	75%	1
11	12%	75%	1

The overall support of these 11 rules is 41%. Hence, 41% of all rounds where the manipulated forecast was followed can be described by these rules with at least 75% confidence. To facilitate the evaluation, the number of played rounds was categorized into unexperienced (<100 played rounds), mid-experienced (100 to 250 played rounds), experienced (250 to 1,250 played rounds), and old stager (>1,250 rounds).

Table 25: Rule Descriptions

			Success of User			**Success of Forecast**				
Situation	**Rule Number**	**Experience level**	**Short-term**	**Mid-term**	**Long-term**	**Short-term**	**Mid-term**	**Long-term**	**Consecutive wins**	**Consecutive defeats**
B	1	Unexperienced to experienced		High	Low to Medium			Medium	>=3.5	
A	2	Mid-experienced		Low to Medium				Medium		
B	3	Unexperienced			High			Low		0
A	4	Mid-experienced to experienced			High	Medium		Low		0
B	5	Unexperienced		High	Low to Medium			Medium		
A	6	Unexperienced to experienced			High	Medium to High	Low	Medium to High		
C	7	Unexperienced to experienced			high			Low		>=2
C	8	Unexperienced	Medium	Medium	High			Low		1
C	9	Mid-experienced to experienced	Medium	High	Low to Medium			Medium	<4	
C	10	Mid-experienced to experienced		Medium	High			Low		1
A & B	11	Mid-experienced to experienced			High	Low or High	Low to Medium	Low		0

Table 25 shows the final rules. Every attribute value is a condition of the rule. If there is an empty space, a further split of the decision tree did not increase the purity of the adjacent nodes. This means that the rule applies for all values of the attributes with the empty entry. As one can see, the long-term success of the forecast is involved in every rule as well as the user's long-term success except of one (rule 2). By that one can assume that the long-term success has the highest influence on the decision whether to follow the manipulated forecast or not. Also experience has an impact on the decision making. Old stagers who played more than 1,250 rounds did not fall for the manipulated forecast. Due to their experience they are aware of possibly manipulated forecasts and therefore sceptical regarding the prediction. They know the situations in which the manipulated forecast can be attractive and the outcome of following in that case. Therefore, old stage users are the only user group that is able to avoid a false forecast in any situation.

For further analysis, similar rules are aggregated. Since rules can be interpreted as situations in which the individual has chosen to follow the manipulated forecast, the rules were interpreted and translated into situation characteristics. Due to the fact that some situations are very similar, clusters were formed which aggregate similar situations. In the evaluation three different types of situations were formed:

Situation A: The player follows the manipulated forecast because it seems that this can improve his success. Either the success of the user is permanently below the success of the forecast (rule 2) or the success of the forecast is improving (rule 4, 6 and 11). Therefore, it is comprehensible to follow the manipulated forecast. A manipulated forecast does not imply that the outcome is wrong. By hazard, a consecutive manipulated forecast can still have success. Rule 2 describes the situation where the mid-term success of the user is below or equal to the long-term success of the forecast. This situation can occur if the play of the user is worse than the manipulated forecasts or if the prediction just switched to the manipulated mode and the success level of the forecast is still influenced by the right predictions. In both cases it is reasonable to choose the manipulated forecast, since it leads at least to the same success the user already has. The argumentation for rules 4, 6 and 11 is similar to the previous one with the exception that the success of the forecast is below the success of the user. As shown in Table 25, the success of the forecast is increasing. This is enough for the user to rely on the manipulated prediction. It is very unlikely that the user can calculate the exact success rates. It is supposable that he just develops a feeling about the level of the success rates as it was modelled with the three levels. Assuming that the user cannot compare close success levels, he will just notice the gain of success of the forecast. This could be an explanation for his decision. This assumption is underpinned by the observations of the following situations. Rule 11 can also be interpreted to be a characteristic of situation B.

Situation B: If the success of the player is increasing or high in the long-term, the player tends to follow the manipulated forecast. The long-term success of the player makes him careless concerning the evaluation of the forecast even if the success of the forecast is low or medium (rule 1, 3, 5 and 11). At rule 1 and 5 a stagnating success level of the forecast and a rising success level of the user are observable. The success of the user even outreached the success of the forecast. The consecutive number of wins in rule 1 underlines the high level of perceived success. Even though, the user did not question the forecast and followed the manipulated prediction. As mentioned above, it can be assumed that the user is not able to compare the exact levels of his success the one of the forecast. Therefore, he is not aware of his superior success level in comparison to the success level of the prediction. Thus, he just recognizes the increase of his own success level. A possible explanation to change the strategy at this point is the sense of security and euphoria of the user which leads to careless decisions. Due to his good performance, he takes more risks. If we take a closer look at rule 1 and 5, there is a slight difference concerning the experience of the user. According to rule 5, unexperienced users do not even need a high number of consecutive wins to fall for the manipulated prediction. Considering rule 3 and 11, the users are already blinded by a win in the last round when they encounter a long-term success of their own while the success of the forecast is low in the long-run.

Situation C: Many lost rounds in the short-term force the player to change his strategy and to follow the manipulated forecast. The success of the forecast remains on a low or medium level. The setbacks in the short-term induced a nervousness which conditioned a not reflected action (rule 7, 8, 9 and 10). The general situation is dominated by the decreasing success level of the user. The success level of the forecast stagnates at low or medium. Although the success level of the user is not falling below the success level of the prediction, the user tends to follow the manipulated forecast with his decision. This situation underpins the assumption that the user cannot compare his success level to the forecast. A possible explanation is that the user gets nervous or desperate after he recognizes his falling success level. He tries to prevent a further loss by using the manipulated forecasts. In all of four rules of situation C (rule 7, 8, 9 and 10), the number of consecutive wins and defeats does not allow a high number of wins or even demands defeats in the short-term.

3.4.3 Playing Strategies

After characterizing situations in which people follow the smart forecast system, the uncertainty is now additionally to be considered as cause-related risk. To analyse the impact of experience, success, forecast quality in combination with the uncertainty of the situation on the decision to follow a manipulated forecast, a linear regression model for each of the above-mentioned factors being the independent variable X is used. Then, the percentage of situations where the manipulated forecast was followed is the dependent variable Y:

$$Y = \beta_0 + \beta_1 X \tag{8}$$

Before examining the situations when players followed a manipulated forecast, first the quality of the forecasts and the possible playing strategies are considered. The manipulated forecast had a quality of 33.37% and the not manipulated of 82.37%. However, it was not obvious to players if a forecast was manipulated or not. Therefore, they mostly realised the overall forecast quality (manipulated and not manipulated) of 63.14%. In comparison, the naïve forecast had a quality of 67.11%. If a player would have been able to distinguish between the manipulated and not manipulated forecast, his optimal strategy would have been to follow the not manipulated forecast and to discard the manipulated one. This strategy would have resulted in a success rate of 75.37% on average. In total, players followed the naïve forecast in 82.67% and the provided forecast in 71.44% of the cases.

To examine the relation between the decisions of players to follow a certain type of forecast (manipulated, not manipulated, overall, naïve) and their success, a linear regression with the success of a player being the dependent variable Y and the share of followed forecasts being the independent variable X was used. Results show that the more players followed the not manipulated, the naïve or even the forecast in general, the more success they had (see Table 26). In contrast, following the manipulated forecast had a slightly negative impact on the success. But as the R^2 of this model is rather small, the influence should not be overestimated.

Table 26: Relation between Player's Decision and Success

X	β_0	β_1	SE(β_1)	*t*	*Sig. (p)*	R^2	*Correlation*
naïve	0.3	0.486	0.038	12.788	<0.001	0.502	0.711
overall	0.505	0.282	0.062	4.554	<0.001	0.109	0.339
not manipulated	0.311	0.464	0.038	12.161	<0.001	0.477	0.693
manipulated	0.732	-0.132	0.032	-4.148	<0.001	0.091	0.312

Values in italic indicate non-significant results.

All this means that there was no obvious strategy to follow or ignore the forecast in general. Instead, the best strategy would have been to make an own judgement of the situation and either follow the naïve forecast or calculate the correct probabilities.

3.4.4 Results of the Regression Model

For the regression models, the dependent variable Y, i.e. the percentage of following players, is calculated for the number of played rounds, the different success rates and the perceived quality of the forecast in the short-, mid-, and long-term, as well as for every possible situation of perceived uncertainty and each case. The latter is done by dividing the number of situations in which the manipulated forecast was followed by the number of times the situations appeared.

Table 27: Results of the Regression Models

X		β_0	β_1	SE(β_1)	*t*	*Sig. (p)*	R^2	*Corr.*
experience		*0.370*	*<0.001*	*<0.001*	*-0.498*	*0.619*	*<0.001*	*0.029*
success	short-term	0.530	-0.247	0.039	-6.350	0.003	0.887	0.954
	mid-term	0.689	-0.451	0.076	-5.931	<0.001	0.792	0.903
	long-term	0.846	-0.669	0.112	-6.002	<0.001	0.745	0.875
forecast quality	short-term	0.317	0.073	0.024	3.104	0.036	0.633	0.841
	mid-term	0.279	0.144	0.038	3.750	0.006	0.592	0.798
	long-term	*0.199*	*0.296*	*0.151*	*1.965*	*0.070*	*0.160*	*0.465*
dominance	short-term	0.343	-0.165	0.022	-7.625	<0.001	0.781	0.892
	mid-term	0.350	-0.286	0.105	-2.724	0.017	0.314	0.603
	long-term	0.374	-0.450	0.038	-11.896	<0.001	0.875	0.939
uncertainty	*manipulated = naïve*	*0.742*	*0.015*	*0.182*	*0.084*	*0.935*	*<0.001*	*0.026*
	manipulated ≠ naïve	0.133	0.293	0.056	5.233	<0.001	0.638	0.813

Values in italic indicate non-significant results.

The results of the regression models are given in Table 27. For the regression model investigating the experience, data points encompassing less than 0.05% of the data set are removed.

As one can see, three regression models have to be rejected. The player's experience, the long-term quality of the forecast, and the uncertainty of the situation when the manipulated equals the naïve forecast have no significant impact on the player's decision to follow the manipulated forecast. The short-, mid-, and long-term successes of players all have a significant influence on the players' decision not to follow a manipulated forecast. That means that the more players are successful, the less they tend to follow (manipulated) forecasts and favour doing their own assessment of the situation. In this connection, the influence of the success horizon seems to play an important role. The slope of the long-term success model is more than twice as high as the one of the short-term success model.

While the influence of the forecast's long-term quality on the players' decision to follow could not be confirmed, the one of short- and mid-term quality could but with a quite low impact. However, the more the forecast is able to predict the next card correctly, the more players are inclined to follow the forecast.

If we have a look at the combination of players' success and quality of the forecast, results show that the more players are more successful than the forecast, the more they tend to rely on their own estimation in the short-, mid-, and long-run. This holds vice versa when the forecast is more successful than players. As it seems, also concerning this dominance the time horizon plays an important role. The slope of the regression nearly triplicates from short- to long-term dominance.

Concerning the uncertainty of the situation, two cases are distinguished: (a) The manipulated forecast equals the naïve forecast or (b) they differ. While case (a) is not significant, case (b) reveals that the more uncertain the decision situation is, the more players follow the manipulated forecast although it is not in line with the naïve assessment of the situation. Although one could expect the opposite, the result of case (b) is conceivable. The uncertainty of the situation makes players less confident so that they do not follow the naïve assessment (of which they know that it is not necessarily correct) but the provided forecast whose manipulation players are not aware of.

3.4.5 Robustness Check

Within the High or Low game, an additional game design element, i.e. a leaderboard, is used. Leaderboards are one of the most used elements in gamification (Hamari, Koivisto and Sarsa, 2014, p. 3027) that are mostly proven to increase the performance of users (Christy and Fox, 2014, p. 74; Domínguez *et al.*, 2013, p. 391; Landers, Bauer and Callan, 2017, p. 513 et sqq.; Landers and Landers, 2014, p. 779 et sqq.; Mekler *et al.*, 2017, p. 531). However, some papers have not found any relations between the usage of leaderboards and performance (Zuckerman and Gal-Oz, 2014, p. 1714 et sqq.) or even negative impacts (Hanus and Fox, 2015, p. 159; Mollick and Rothbard, 2014, p. 39). While other papers usually investigate how to use game elements in a non-game context in order to improve the behavioural outcome (Morford *et al.*, 2014, p. 37; Seaborn and Fels, 2015, p. 27 et sqq.), the use of gamification for research purposes is still scarce. Besides papers in game theory who use the Prisoner's Dilemma Game and derivates to analyse risk behaviour and risk strategies (e.g. Hogan, Fisher and Morrison, 1974, p. 1080 et sqq.), this study is, to the best knowledge, the first who employs a simple card game for its purposes. While Musthag *et al.* (2011, p. 436) pay money incentives to participants of a lengthy survey, Rapp *et al.* (2012, p. 227) award participants of a field study with points so that they can compare their performance to the ones of other participants on a leaderboard.

As a game is used in a research setting, it is crucial to know, if the employment of gamification elements influence the outcome of such an experimental study. The use of game elements like leaderboards fosters competition (Sailer *et al.*, 2013, p. 34) among participants and may therefore impact their behaviour and decision making. To validate the results, a robustness check was conducted. The sub-question for the robustness check is:

SQ: *Do gamification elements (particularly leaderboards) have an impact on the outcome of experimental studies?*

To analyse the impact of the gamification element leaderboard on the results of such an experimental study, the players were divided into two different groups. One group had permanently access to a leaderboard (case 1) the other group got to know about the leaderboard only after the game (case 2). With these two groups, the regression models are performed again. The results are shown in Table 28.

Table 28: Results of the Regression Models Using a Leaderboard

	X		β_0	β_1	SE(β_1)	*t*	*Sig. (p)*	R^2	*Corr.*
Case 1: with leaderboard	*experience*		*0.379*	*<0.001*	*<0.001*	*-0.794*	*0.428*	*0.002*	*0.046*
	success	short-term	0.555	-0.270	0.054	-5.020	0.007	0.829	0.929
		mid-term	0.736	-0.514	0.078	-6.600	<0.001	0.842	0.928
		long-term	1.022	-0.913	0.103	-8.842	<0.001	0.846	0.926
	forecast quality	*short-term*	*0.336*	*0.042*	*0.017*	*2.531*	*0.065*	*0.519*	*0.785*
		mid-term	*0.369*	*0.014*	*0.054*	*0.257*	*0.805*	*0.009*	*0.097*
		long-term	*0.445*	*-0.095*	*0.066*	*-1.435*	*0.182*	*0.088*	*0.413*
	dominance	short-term	0.349	-0.211	0.039	-5.406	0.001	0.758	0.886
		mid-term	0.439	-0.327	0.102	-3.204	0.008	0.416	0.679
		long-term	0.424	-0.346	0.100	-3.444	0.003	0.376	0.641
	uncertainty	*man. = naïve*	*0.739*	*0.037*	*0.184*	*0.202*	*0.844*	*0.004*	*0.064*
		man. ≠ naïve	0.063	0.412	0.059	7.012	<0.001	0.763	0.882
Case 2: without leaderboard	*experience*		*0.308*	*0.001*	*0.001*	*0.811*	*0.424*	*0.023*	*0.152*
	success	*short-term*	*0.507*	*-0.232*	*0.103*	*-2.264*	*0.086*	*0.452*	*0.749*
		mid-term	0.451	-0.144	0.047	-3.086	0.015	0.486	0.737
		long-term	0.516	-0.225	0.064	-3.516	0.005	0.486	0.727
	forecast quality	short-term	0.263	0.143	0.033	4.350	0.012	0.782	0.909
		mid-term	0.057	0.436	0.071	6.109	<0.001	0.801	0.907
		long-term	0.072	0.418	0.105	3.987	0.002	0.554	0.769
	dominance	short-term	0.334	-0.175	0.036	-4.878	0.001	0.717	0.865
		mid-term	0.330	-0.254	0.111	-2.295	0.039	0.234	0.537
		long-term	0.294	-0.233	0.082	-2.836	0.011	0.260	0.545
	uncertainty	man. = naïve	1.106	-0.457	0.145	-3.153	0.012	0.472	0.725
		man. ≠ naïve	*0.190*	*0.186*	*0.093*	*1.988*	*0.067*	*0.165*	*0.469*

As one can see, some results remain the same, but also several differences occur. In both groups, the player's experience still has no significant influence on the decision to follow a forecast. Concerning the player's success, the short-term success has no significant influence in the group without leaderboard. Interestingly, the forecast quality, irrespective of the time horizon, shows no significant influence on the decision to follow the forecast anymore when a leaderboard is in place. All regression models with leaderboard cannot be confirmed, while all models without leaderboard can still be confirmed. Concerning the uncertainty of the decision situation, we face two inverted situations. With leaderboard, the results equal the overall situation. If the manipulated forecast equals the naïve forecast, the influence is not significant, if they differ, there is a positive influence of the uncertainty situation on the decision to follow. Without leaderboard, there is no significant influence if manipulated and naïve forecast differ, but a significant negative influence of the uncertainty situation if the forecasts are equal. The latter is quite surprising as one would expect that players follow the forecast if it is in line with the naïve assessment. A possible explanation could be that although the naïve forecast aims to be an assessment of the risk situation, it does not necessarily depict the correct perception of players in the current situation. If several very high (or very low) cards have been shown, players may remember this circumstance so that the putatively uncertain situation is much more unequivocal than the naïve forecast suggests. However, the general level of forecast followers is much higher if the forecasts equal than if they differ. In fact, when the forecast is in line with the naïve forecast, the share of players following this assessment is in the same situation of uncertainty always higher than when the forecasts differ.

All in all, these results show that if the leaderboard is in place, players tend to follow the manipulated forecast less often. This holds in particular for the quality of the forecast. Although players perceive high quality, a relation between quality and the decision to follow the forecast cannot be confirmed. The reason is most probably that the leaderboard fosters competition among players. Therefore, they try to make their decisions more thoroughly so that they resign to follow the manipulated forecast and prefer to rely on their own assessment.

3.5 Conclusion Section II

3.5.1 Discussion

This section aimed to shed light on the question which factors influence decision makers to rely on a smart forecasting system or to discard them and follow their own assessment of an uncertain situation. In particular, the focus was on the experience of decision makers, their success during different time horizons, the perceived quality of the provided forecast, and the uncertainty of the decision situation.

To study the role of the success of the decision maker, the quality of the forecast and the experience of the decision maker, a decision tree was applied, rules were extracted and then clustered to three different situations. In particular, this examination focused on how experience and success influence false decision making. In total, eleven rules could be identified that characterize when a decision maker relies on a faulty forecast. These rules could be classified into three categories/situations. In situation A, the decision maker either permanently performs worse than the forecast or the forecasts slightly improves over time. In situation B, the decision maker is blinded by his success in the mid- and long-term range so that he acts with less care. In situation C, the decision maker had some consecutive disappointments in the near past so that he follows the wrong forecast. Therefore, success as well as past experiences influence the decision making process. If the decision maker performs badly, he is geared to avoiding future mistakes and relies on the wrong forecast. This result is in line with findings from behavioural sciences. If a decision maker believes in his competence, he takes more risky choices because he thinks that he can avoid losses due to his skills (Krueger and Dickson, 1994, p. 385). Vice versa, if a decision maker encounters defeats, he loses self-efficacy and self-confidence (Krueger and Dickson, 1994, p. 385) so that he tends to avoid risky situations (Chuang *et al.*, 2013, pp. 671–672). In this case, avoiding a risky situation means to follow the (wrong) forecast. Interestingly, users do not seem to be able to remember success over a longer period. Instead, they have a diffuse impression of their success and the success of the forecast. This distorted impression interferes their ability to take the right decision.

Further the influence of cause-related risk, beside the success of the decision maker, the success of the smart forecasting system, the experience of the player and the perception of the forecast should be investigated. To study these factors, a simple card game that had two purposes was employed. First of all, the game provides a variety of uncertain decision situations so that the decision makers have to assess the situation each time anew. Secondly, the game served as a motivator for decision makers to participate and to remain in the study and not to quit too early. Having a look at the factors under investigation, the role of experience is negligible. Experienced decision makers do not discard faulty forecasts more seldom than inexperienced. As it seems, decision makers are unable to make good estimations based on prior situations which is in line with Maines and Hand (1996, p. 333). In contrast, the success plays an important role for the decision to follow forecasts. While the impact of the short-term success for players without leaderboard could not be confirmed, in any other cases success regardless of the time horizon significantly influences the decision making particularly when competition is perceived. If there is no competition, the perceived quality of the forecast is also of importance. However, the greater the difference between the decision maker's success and his perception of the forecast's quality is, the more he relies on his personal assessments. This is in line with findings from behavioural science. Particularly self-assured decision makers tend to believe that they can avert potential damage from risky decisions and therefore often take risks (Krueger and Dickson, 1994, p. 385). Here, the putative certain choice is the manipulated forecast and the risky option is to follow one's own assessment.

Also, the uncertainty (cause-related risk) of the decision situation influences decision makers to follow forecasts. In particular when the forecast differs from the naïve forecast, the more uncertain the situation is, the more decision makers tend to follow the forecast. However, the share of following decision makers remains below 50%. In contrast, if the forecast is in line with the naïve forecast, more uncertain situations make decision makers discard the forecast more often but only if there is no competition. A possible explanation could be that in uncertain situations, decision makers pay more attention and calculate the correct probabilities themselves. Nevertheless, the share of followers hardly drops below 60%. However, the results show that decision makers can distinguish between certain and uncertain situations and that they get alienated when the degree of uncertainty increases.

3.5.2 Implications

Several lessons can be learned from this study. Expert systems are often part of the decision process in a company. Since these systems are just focusing on a small part of the real world, false forecasts are possible. Especially in a dynamic and stochastic environment forecast tools can be wrong. Problems occur in situations where the forecast gives a faulty advice and the individuals who use the system solely rely on the forecast. To avoid such situations, several measures can be taken. First of all, the reasoning behind the forecast should be made clear to users (Armstrong, Green and Graefe, 2015, p. 1722). Hence, additional information should be provided to users of a forecast like the probabilities for different possible situations. In uncertain situations, decision makers tend to choose the middle option that is not necessarily the best (Chuang *et al.*, 2013, p. 661). If the uncertainty of the situation and the possible outcomes are described properly, users get a better understanding of the situation which reduces their perception of uncertainty so that the correct alternative will be favoured. Also, ex post analyses of forecasts and the history of own decisions should be presented so that decision makers can better judge if their past decisions were correct or not. Then, failures that can occur although the decision was correct do not entangle them too easily. Secondly, decision makers should perceive some competition. As the analysis has shown, their decisions are then based on more thoroughly done calculations so that they do not rely blindly on forecasts.

Research on forecasts has generated conflicting results. For example, Smith and Mentzer (2010, p. 170) found that the quality of a forecast significantly influences its usage in contrast to O'Connor *et al.* (2005, p. 1271). Now this study has shown that different time horizons matter. While for the success in the no leaderboard case the short-term horizon does not matter but mid- and long-term do, the general long-term quality of the forecast has no impact but the short- and mid-term quality have. Therefore, future research should take several time horizons into account as it seems that these are perceived differently by decision makers. This study has also shown that the naïve assessment seems to be an adequate proxy for how uncertain decision makers perceive a situation. In this regard, more research is needed to better understand how decision makers assess situations and what key figures they use intuitively.

Concerning the use of gamification in research studies, the result is promising like in many other gamification studies (Seaborn and Fels, 2015, p. 29). Although about 24% of the participants did not reach the third deck and therefore did not contribute to the study, other participants used the system extensively. Some participants played more than 600 rounds or in other words more than 37 games. This means that with the help of gamification surveys can be made more interesting for participants such that they can get into flow (Csikszentmihalyi, 1991, p. 2 et sqq.). However, the usage of game design elements must be considered carefully. On the one hand, the use of gamification elements can reinforce results and make them more significant so that better conclusions can be drawn. On the other hand, these influences may distort the insights of a study so that it shows a wrong picture of the reality. In this study, the leaderboard significantly influenced the experiments and reinforced some results so that different outcomes are more distinguishable. However, indicators for a distortion are not in place. In general, a game like it was used here supports the intrinsic motivation of users. If it is complemented with additional elements of external incentives like payments (for an analysis see Musthag *et al.*, 2011) or a lottery, these extrinsic motivational elements could hinder the success. If for example an additional lottery is used, participants may want to stop the study as soon as they fulfilled the minimum requirements for participating in the lottery.

At last, some lessons can be learned concerning experience, success, and the use of probabilities in general and in different applications. Users can easily be influenced by providing advice that seems to come from a trusted source. If game designers and providers slightly manipulate game outcomes and the success of users, they can sell for example additional items in games so that the user can proceed in the game more successful. While this manipulation seems promising, it is a red flag for politician and parents. Politics should ensure that such manipulations are not legal and pursued by law. For this, regulations are missing that ensure that such manipulations can be detected.

3.5.3 Limitations and Future Work

As always, there are some limitations to mention. First of all, the study encompasses only German students. Future research should be done in a more international context to eliminate a possible cultural bias. In addition, also professional decision makers should be under investigation as they might assess uncertain situations differently. Secondly, we performed a single linear regression model for each factor. Future research should use combined models like logit regression that investigate the collective influence on the decision. Adding more dimensions to the observation may also help to better identify the influencing factors. Thirdly, it is possible that users did not intentionally follow or discard the forecast. This “false” recording could not be excluded and may distort the results. Fourthly, false decisions in the game did not have real negative effects. Thus, the game decision situation might not be the same as the real decision situation. Finally, beside the game itself, only one gamification element was used. Future research could install other elements and investigate to what extent these elements affect the results.

4 Conclusion

4.1 Key Findings

The aim of this thesis was to investigate the adoption of smart systems. For this purpose, the influencing factors on adoption were to be investigated. The main influencing factors were the degree of automation (RQ1) and the risk (effect-related risk RQ2.1 and cause-related risk RQ2.2). Other influencing factors have also been identified that have an impact on the adoption of smart systems.

To answer RQ1 and RQ2.1, three smart systems were compared, which are increasingly automated and whose use is associated with an increasing effect-related risk: an intelligent personal assistant, direct load control and autonomous driving. A basic research model was defined for the comparison, which postulated various influencing factors on the intention to use (as a preliminary stage of adoption) of these smart systems. The influences were measured and their change between the smart systems considered. To answer RQ 2.2, the actual use of users was examined using a specially developed smart forecasting system.

Regarding RQ1 it can be stated, that the degree of automation has many effects on the adoption of smart systems. A fundamental effect is that the perceived disadvantages have an ever greater negative impact on the intention to use as the degree of automation increases. The reason for this is the fear of a loss of control as a result of the increase in the degree of automation. Automated functions of smart systems are perceived as advantageous, but this automation does not only lead to a feeling of relief for the user. This automation also results in people feeling partially at the mercy of the smart system. As a result of increasing automation, the functions and advantages of smart systems have become less and less important. The resulting fears of loss of control and the feeling of being at the mercy of automation thus mask the possible advantages of the system. Another effect was that with increasing automation, trust in the smart system becomes more and more important. Smart systems should therefore be designed and communicated to customers in such a way that users trust them as much as possible. A possible design of a smart system that is more trusted could look like the smart system giving the user information about the current execution of the task.

Concerning RQ2.1 it could be observed, that the effect-related risk also had a strong impact on the adoption of smart systems. Above all, effect-related risk has an impact on the perception of the advantages and disadvantages of smart systems. Thus, due to increasing effect-related risk, characteristics other than the advantages of smart systems move into the focus for the formation of the intention to use. While in smart systems with low effect-related risk the advantages still played a decisive role in the formation of the intention to use this smart system, in smart systems with high effect-related risk the disadvantages come to the fore instead. Another fundamental finding is that the increasing effect-related risk requires above all the user to trust the system in order to adopt the smart system. This is where trust in the smart system is helpful on the one hand, but also trust in the manufacturer of these smart systems on the other. By increasing trust, the advantages could in turn increase the intention to use the smart system in areas with a high effect-related risk.

In Section II, the study showed that the test persons were able to distinguish between certain and uncertain decision situations. Interesting findings were obtained regarding the adoption of smart systems in situations with high cause-related risk (RQ2.2). If the actions of the smart system do not correspond to the actions expected by the user, the more likely the user is to adopt a smart system in uncertain situations. Thus, in situations with high cause-related risk, users become more receptive to the use of smart systems if the smart system would do something different than the user. A possible reason for this could be trust in the smart system. Users often assume that automated systems functions mostly error-free (Parasuraman and Riley, 1997, p. 235). Users question their own abilities in uncertain situations and like to use the supposed competence of the smart system. However, the competence of the smart system in uncertain situations is also questioned. It became apparent that users are less likely to use a smart system with increasing uncertainty if it comes to the same result as themselves. In uncertain situations, users themselves become insecure in their decision-making and doubt their own assessment. A smart system that supports the user in his uncertain assessment is also doubted. It is therefore postulated that users who are insecure are more likely to be convinced by opposing opinions and react less strongly to the confirmation of their own uncertain opinion. However, these statements are not valid for all test persons. It could be observed that with increasing cause-related risk, never more than half of the test persons used the smart system if it came to a different result than themselves. Also, never less than 60% used the smart system with increasing cause-related risk if the smart system strengthened the user. In order to promote the adoption of smart systems, information on the cause-related risk (uncertainty) should be made available to the user. If the uncertainty of the situation and the possible outcomes are described properly, users get a better understanding of the situation which reduces their perception of uncertainty so that the correct alternative will be favoured Also, ex post analyses of the smart forecasting system and the history of own decisions should be presented so that decision makers can better judge if their past decisions were correct or not. Then, failures that can occur although the decision was correct do not entangle them too easily

In addition to these main influencing factors, further influencing factors on the adoption of smart systems were identified and discussed in the respective subchapters.

4.2 Limitations and Future Work

In the end, however, this work also has limitations. First of all, the different studies underlying this thesis differ in their design. In Section I, for example, adoption is examined using structural equation models, and in Section II adoption is examined using observations. In future studies, the study design should be standardized in order to exclude possible distortions of the results by the applied methodology.

Secondly, different measures of adoption were used. Whereas in Section I the adoption was measured by the intention to use, in Section II the adoption was measured by the actual use. As mentioned at the beginning, the two measures differ with regard to the concretisation of the adoption. Section I already showed a difference between the attitude (as the first stage of adoption) and the intention to use (as the second stage of adoption). Thus, the comparison of the intention to use from Section I with the actual use from Section II can be subject to a bias that can be traced back to the different measurement variables.

Thirdly, a bias in the conclusions would be possible due to too heterogeneous subsamples between the individual studies. The present thesis is to be placed in the area of between-subject designs, in which a high homogeneity between the subsamples is desired in order to be able to make valid conclusions. This homogeneity can be endangered due to the different survey methods, survey periods and the different groups of persons addressed. A possible solution would have been a within-subject design, which would have been difficult to carry out due to the large scope of the research.

Finally, this work is limited to only a few influencing factors. The adoption of smart systems can only be partially clarified by this work, as not all possible influencing factors have been examined in detail. Further investigations should focus on other influencing factors in order to supplement the findings made here.

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Appendices

Scale	1	2	3	4	5
A	Stimme nicht zu	Stimme eher nicht zu	Unentschlossen	Stimme teilweise zu	Stimme voll zu
B	nicht vorteilhaft	eher nicht vorteilhaft	Unentschlossen	vorteilhaft	sehr vorteilhaft
C	Sehr gering	Gering	Mittel	Hoch	Sehr hoch

Appendix 1

Construct	Indicator	Question	Scale
Intention to Use (reflective)	I1	Zukünftig möchte ich regelmäßig einen IPA nutzen.	A
	I2_r	Die Nutzung eines IPA kommt für mich nicht in Frage.	A
	I3	Ich beabsichtige, einen IPA zu kaufen.	A
	I4	Ich werde mir auf jeden Fall einen IPA anschaffen.	A
Attitude (reflective)	A1	Ich finde die Idee eines IPA gut.	A
	A2	Die Verwendung eines IPA ist sinnvoll.	A
	A3	Ein IPA ist ein guter Assistent/Begleiter im Haus.	A
Perceived Advantages (formative)	PA1	Die Steuerung eines IPA über Sprache empfinde ich als vorteilhaft.	A
	PA2	Ich empfinde es als vorteilhaft, dass mir IPAs Informationen liefern können.	A
	PA3	Ich empfinde es als vorteilhaft, dass IPAs mir helfen mich an Dinge zu erinnern.	A
	PA4	Ich empfinde es als vorteilhaft, Bestellungen und Buchungen über einen IPA ausführen zu können.	A
	PA5	Ich empfinde es als vorteilhaft, meine Wohnung/mein Haus über einen IPA steuern zu können (Musik, Licht, TV).	A
Perceived Disadvantages (formative)	PD1	Wie hoch schätzen Sie das Risiko ein, dass ihre persönlichen Daten nicht sicher beim Serviceanbieter sind?	C
	PD2	Ich befürchte, dass IPAs Dinge tun, die ich nicht möchte.	A
	PD3	Ich möchte nicht mit einer Maschine reden.	A
	PD4	Ich befürchte, dass ich durch die Nutzung eines IPAs gläsern werde.	A
	PD5	Ich befürchte, dass IPAs alle Gespräche aufzeichnen.	A
	PD6	Meine Daten werden ausgewertet und anderweitig verwendet.	A
Trust in IPA (reflective)	TI1	IPAs sind sehr verlässlich.	A
	TI2	IPAs enttäuschen mich nicht.	A

	TI3	IPAs sind extrem zuverlässig.	A
	TI4	IPAs behindern mich nicht.	A
Trust in Manufacturer (reflective)	TM1	Insgesamt sind die IPA-Anbieter vertrauenswürdig.	A
	TM2	Ich kann mich auf die Aussagen des IPA-Anbieters verlassen.	A
	TM3_r	Ich misstraue den IPA-Anbietern.	A
	TM4_r	Die IPA-Anbieter folgen ihrer eigenen Agenda.	A

r: reversed Item

Appendix 2

Construct	Indicator	Question	Scale
Intention to Use (reflective)	I1	Wenn sich die Gelegenheit bietet, würde ich fremdgesteuerte Haushaltsgeräte nutzen.	A
	I2	Ich würde wahrscheinlich fremdgesteuerte Haushaltsgeräte in naher Zukunft nutzen.	A
	I3	Ich würde viel Flexibilität bereitstellen, um die Haushaltsgeräte fremdsteuern zu lassen.	A
Attitude (reflective)	A1	Die Benutzung fremdgesteuerter Haushaltsgeräte wäre eine gute Idee.	A
	A2	Die Benutzung fremdgesteuerter Haushaltsgeräte wäre eine kluge Idee.	A
	A3	Ich mag die Idee, fremdgesteuerte Haushaltsgeräte zu nutzen.	A
	A4	Ich denke, jeder sollte fremdgesteuerte Haushaltsgeräte nutzen.	A
Perceived Advantages (formative)	PA1	Die Benutzung fremdgesteuerter Haushaltsgeräte würde mir die Möglichkeit geben, Haushaltstätigkeiten schneller zu erledigen, als mit herkömmlichen Haushaltsgeräten.	A
	PA2	Ich denke, dass die Benutzung fremdgesteuerter Haushaltsgeräte für mich einen Komfortgewinn bedeuten würde.	A
	PA3	Ich würde den finanziellen Vorteil durch die Benutzung fremdgesteuerter Haushaltsgeräte als groß einschätzen.	A
	PA4	Wenn ich meine Haushaltsgeräte fremdsteuern lasse, würde ich die Umwelt weniger belasten.	A
Perceived Disadvantages (formative)	PD1_r	Meine Nutzerprofile würden nicht an Drittanbieter verkauft werden.	A
	PD2_r	Meine Nutzerprofile würden nicht für andere Zwecke verwendet werden (z.B. Schutz vor Datenklau).	A
	PD3	Ich habe die Sorge, dass mein Tagesablauf anhand der Nutzerprofile transparent werden würde.	A

	PD4	Ich hätte Bedenken bezüglich der Sicherheit fremdgesteuerter Haushaltsgeräte (z.B. Feuer, Lebensmittelqualität).	A
	PD5	Die Benutzung fremdgesteuerter Haushaltsgeräte würde für mich einen Kontrollverlust bedeuten.	A
	PD6	Durch die Benutzung fremdgesteuerter Haushaltsgeräte könnte ich meinen Alltag nicht mehr genau planen.	A
	PD7	Durch die Nutzung der Fremdsteuerung würde ich das Risiko eingehen, dass die Haushaltsgeräte manipuliert werden könnten.	A
Trust in Energy Provider (reflective)	T1	Ich denke, dass der Netzbetreiber, der die Haushaltsgeräte steuern würde, zuverlässig ist.	A
	T2	Ich denke, dass der Netzbetreiber, der die Haushaltsgeräte steuern würde, seine Versprechen und Verpflichtungen hält.	A
	T3	Ich vertraue dem Netzbetreiber, dass er meine abgegebene Kontrolle bezüglich der Steuerung der Haushaltsgeräte sinnvoll einsetzen würde.	A
Subjective Norm (reflective)	SN1	Menschen, die für mich wichtig sind, würden mich zur Verwendung fremdgesteuerter Haushaltsgeräte ermutigen.	A
	SN2	Menschen, die mein Verhalten beeinflussen, würden denken, dass ich fremdgesteuerte Haushaltsgeräte benutzen sollte.	A
	SN3	Menschen, die für mich wichtig sind, würden denken, dass ich fremdgesteuerte Haushaltsgeräte benutzen sollte.	A

r: reversed Item

Appendix 3

Construct	Indicator	Question	Scale
Intention to Use (reflective)	I1_r	Ich möchte autonomes Fahren nicht selbst nutzen.	A
	I2	Wenn es meine finanzielle Situation zulässt, werde ich autonomes Fahren nutzen.	A
	I3_r	Ich sehe von der Nutzung autonomen Fahrens ab.	A
	I4	Sobald autonomes Fahren verfügbar sein wird, werde ich es nutzen.	A
Attitude (reflective)	A1_r	Ich habe ein negatives Gesamtbild vom autonomen Fahren.	A
	A2	Ich befürworte autonomes Fahren im Straßenverkehr.	A
	A3_r	Ich habe Vorbehalte gegenüber autonomem Fahren.	A
	A4	Ich akzeptiere es, wenn andere Menschen autonomes Fahren nutzen.	A
	A5	Ich stehe der Innovation autonomen Fahrens offen gegenüber.	A
	Bewerten Sie die Vorteilhaftigkeit folgender Aspekte:		
Perceived Advantages (formative)	PA1	Sicherheit (z.B. durch den Menschen verursachte Fahrfehler fallen weg)	B
	PA2	Mobilität im Alter (z.B. eingeschränktes Sehvermögen oder andere körperliche Einschränkungen haben keinen Einfluss auf die Nutzung autonomer Fahrzeuge)	B
	PA3	Effiziente Zeitnutzung (während der Fahrt können Insassen andere Aktivitäten, als das Steuern des Autos, ausführen)	B
	PA4	Gute Verkehrssituation (z.B. Fahrspuren werden effizient genutzt, da autonome Fahrzeuge geringeren Abstand halten können)	B

	PA5	Umweltbewusstes Fahren (z.B. unnötiges Bremsen oder Beschleunigen wird vermieden)	B
	PA6	Stressfreies Fahren (z.B. Stress durch das Fahren bei ungünstigen Wetterverhältnissen oder Verkehrssituationen wird reduziert)	B
	PA7	Entlastung bei langen Autofahrten (z.B. Müdigkeit bei langen Autofahrten hat keinen Einfluss auf das Fahrverhalten)	B
	PA8	Erleichterung bei Fahrten in unbekannten Gebieten (z.B. da das Fahrzeug eigenständig fährt, bedarf es auch in fremden Umgebungen keiner Anpassung der Fahrweise)	B
Perceived Disadvantages (formative)	PD1	Mir ist unklar, wer bei Unfällen autonomer Fahrzeuge haftet.	A
	PD2	Autonomes Fahren bedeutet einen Verlust des Fahrspaßes.	A
	PD3	Die Nutzung/Bedienung autonomer Fahrzeuge wird komplex.	A
	PD4	Autonomes Fahren wird zu teuer.	A
	PD5	Ich befürchte, dass autonome Fahrzeuge nicht sicher mit meinen persönlichen Daten umgehen werden.	A
	PD6_r	Die Hersteller selbstfahrender Autos werden zuverlässig mit persönlichen Daten umgehen.	A
Trust in Car (reflective)	TP1	Selbstfahrende Autos sind extrem verlässlich.	A
	TP2_r	Ich halte autonomes Fahren für unzuverlässig.	A
	TP3	Hinter autonomem Fahren steckt ein ausgereiftes System.	A
Trust Manufacturer (reflective)	TM1	Ich denke, dass ich den Herstellern selbstfahrender Fahrzeuge vertrauen kann.	A
	TM2	Ich denke, die Hersteller autonomer Fahrzeuge richten sich nach den Wünschen und Bedürfnissen der Kunden.	A

	TM3	Ich vertraue herkömmlichen Automobilherstellern wie BMW, Daimler oder Audi bei der Entwicklung autonomen Fahrens.	A
	TM4	Ich vertraue Google, Apple und anderen Unternehmen aus der IT Branche bei der Entwicklung autonomen Fahrens.	A
	TM5	Die Hersteller autonomer Fahrzeuge werden für fehlerfreie Systeme sorgen.	A
Perceived Control (reflective)	PC1	Ich fürchte mich vor einem Kontrollverlust über das autonome Fahrzeug.	A
	PC2	Autonome Fahrzeuge bevormunden den Insassen.	A
	PC3	Autonomes Fahren bedeutet den Verlust meiner Freiheit.	A

r: reversed Item