Mobility in the Advent of Autonomous Driving – Toward an Understanding of User Acceptance and Quality Perception Factors

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Jennifer Wiefel

Darmstadt, 10. Juli 2021

Abstract

Recent advancements in intelligent technologies and sensor-based data collections pave the way for autonomous driving and facilitate a radical transformation of today's mobility. Based on auspicious market projections, traditional automotive manufacturers and technology companies invest heavily in the development of autonomous vehicles (AVs). In addition to the profits that the industry expects from self-driving vehicles, this new type of mobility should also solve societal issues like reducing traffic accidents and fatalities by eliminating human driving errors. More efficient autonomous driving is expected to bring improvements in terms of fewer congestions and less fuel consumption, thereby reducing greenhouse emissions. Besides, AVs pledge to entail advantages for their users. Specifically, they increase mobility for the disabled and the older generation. In contrast, younger passengers associate autonomous driving with improved productivity and an enhanced hedonic experience as non-driving activities, such as working or watching a movie, are made possible.

Contrary to the above expectations, people also raise concerns regarding self-driving vehicles. They are worried about whether the sensors and systems can correctly interpret complex environmental conditions. Above all, there are doubts whether the technology, even being intelligent, can react appropriately in critical traffic situations made up of humans who sometimes behave unpredictably. In case of unavoidable traffic accidents, ethical questions come into play regarding how the vehicle makes decisions that could result in a person being injured or killed. Finally, the new and sophisticated technology could have vulnerabilities that can be exploited by cybercriminals or allow unauthorized third parties to obtain passenger data.

Motivated by the anticipated improvements that AVs entail and the breadth of factors that might influence their adoption, a large body of research investigating relevant adoption factors has accumulated. In order to collect, organize, and combine extant findings, research paper A conducts a structured literature review on the acceptance of autonomous vehicles. Based on 58 articles, it develops an AV acceptance framework consisting of individual user characteristics, vehicle characteristics, and political/societal elements. The framework indicates for each factor whether available research results identify the effect as either positively or negatively significant. Thereby, the paper also sheds light on diverging construct operationalizations, aiming to support researchers in comparing available findings. Eventually, paper A proposes future research avenues across various themes and methods, which build a foundation for further research pursued in this dissertation's subsequent papers.

However, solely balancing significant against non-significant results can come to wrong conclusions since the sample size alone can lead to varying significance levels. Because of this, paper B builds on the literature review and conducts a meta-analysis to include further quantitative analyses. It calculates the mean effect sizes for each AV acceptance factor based on published research results. By doing so, the paper identifies attitude, perceived usefulness, efficiency, trust in AVs, safety, and subjective norms to correlate most strongly with the behavioral intention to use an automated car. A subsequent moderator-analysis shows that almost all acceptance factors are influenced by the study's methodology and location, the AV's level of automation, and the examined ownership model, i.e., private cars, car sharing, or public transport. In doing so, paper B observes that most of the available research is on privately owned AVs and hence lacks to assess public as well as shared automated mobility.

To fill this gap, paper C investigates characteristics relevant for automated mobility as a service (AMaaS). Based on 23 exploratory interviews with the general public, the paper derives a set of AMaaS requirements. Mobility experts sort these requirements based on commonalities so that a cluster analysis can conceptualize the expected AMaaS characteristics from a practitioner's view. The paper identifies traffic safety, information privacy, cybersecurity, regulations, flexibility, accessibility, efficiency, and convenience to be relevant service characteristics. It discusses each required characteristic and thereby delineates the constructs' scopes so that subsequent research can build appropriate measurement instruments. Besides, paper C discovers strongly diverging priorities regarding the respective service characteristics when comparing the potential users' conversation shares with the experts' relevance ratings.

Paper D builds on the qualitative results of paper C as it develops and validates a hierarchical quality scale for AMaaS. The paper proposes a theoretical model and operationalizes the previously identified service characteristics. Throughout multiple empirical studies with 1,431 participants, the proposed quality scale is refined iteratively until satisfactory psychometric properties are achieved. Nomological validity ensures the scale's predictability. Paper D progresses research from focussing on the mere acceptance of autonomous driving to the user's quality perception, which significantly influences user satisfaction and the success of AMaaS. This, in turn, is necessary to realize the promised benefits of autonomous driving in a sustainable manner.

Zusammenfassung

Jüngste Fortschritte im Bereich intelligenter Technologien und sensorbasierter Datenerhebungen ebnen den Weg für autonomes Fahren und ermöglichen so eine radikale Umgestaltung der heutigen Mobilität. Aufgrund vielversprechender Marktprognosen investieren traditionelle Automobilhersteller und Technologieunternehmen stark in die Entwicklung autonomer Fahrzeuge (AFs). Neben den Gewinnen, die die Industrie von selbstfahrenden Fahrzeugen erwartet, soll die neue Art der Mobilität auch gesellschaftliche Probleme wie die Reduzierung von Verkehrsunfällen durch die Vermeidung menschlicher Fahrfehler lösen. Es wird erwartet, dass ein effizienteres autonomes Fahren Verbesserungen in Form von weniger Staus und geringerem Kraftstoffverbrauch mit sich bringt und so die Treibhausgasemissionen reduziert. Darüber hinaus versprechen AFs Vorteile für ihre Nutzer. Insbesondere können sie beeinträchtigten und älteren Menschen helfen, mobil zu bleiben. Im Gegensatz dazu bringen jüngere Fahrgäste das autonome Fahren mit einer verbesserten Produktivität und einem gesteigerten hedonistischen Erlebnis in Verbindung, da fahrfremde Aktivitäten, wie z. B. arbeiten oder einen Film ansehen, ermöglicht werden.

Entgegen den oben genannten Erwartungen äußern die Menschen auch Bedenken gegenüber selbstfahrenden Fahrzeugen. Sie machen sich Sorgen, ob die Sensoren und Systeme auch komplexe Umweltbedingungen richtig interpretieren können. Vor allem bestehen Zweifel, ob die Technologie, auch wenn sie intelligent ist, in kritischen Verkehrssituationen mit teils unvorhersehbar handelnden Menschen angemessen reagieren kann. Darüber hinaus wird bei unvermeidbaren Verkehrsunfällen die ethische Fragenstellung relevant, wie das Fahrzeug Entscheidungen fällt, die dazu führen könnten, dass eine Person verletzt wird oder stirbt. Schließlich könnte die neue und hochentwickelte Technologie Schwachstellen aufweisen, die entweder durch Cyberkriminelle ausgenutzt werden oder die es unbefugten Dritten ermöglichen, an Fahrgastdaten zu gelangen.

Angetrieben durch die erwarteten Verbesserungen, die AFs mit sich bringen, und der Breite der Faktoren, die ihre Akzeptanz beeinflussen können, hat sich eine große Anzahl von Forschungsarbeiten angesammelt, die relevante Akzeptanzfaktoren untersuchen. Um die vorhandenen Erkenntnisse zusammenzutragen, zu ordnen und zu kombinieren, führt Artikel A

eine strukturierte Literaturrecherche zur Akzeptanz von autonomen Fahrzeugen durch. Basierend auf 58 Artikeln wird ein AF-Akzeptanz-Framework entwickelt, das aus individuellen Nutzereigenschaften, Fahrzeugeigenschaften und politischen/gesellschaftlichen Elementen besteht. Das Framework gibt für jeden Faktor an, ob bestehende Forschungsergebnisse den Effekt als positiv oder negativ signifikant identifizieren. Dabei beleuchtet der Artikel auch divergierende Konstrukt-Operationalisierungen, um die Forscher darin zu unterstützen, vorhandene Ergebnisse zu vergleichen. Schließlich werden in Artikel A zukünftige Forschungsfelder über verschiedene Themen und Methoden hinweg vorgeschlagen, die eine Grundlage für die weitere Forschung in den nachfolgenden Artikeln dieser Dissertation sind.

Das alleinige Abwägen von signifikanten und nicht signifikanten Ergebnissen kann jedoch zu falschen Schlussfolgerungen führen, da die Stichprobengröße allein Grund für unterschiedliche Signifikanzniveaus sein kann. Aus diesem Grund baut Artikel B auf der Literaturrecherche auf und führt eine Meta-Analyse durch, um weitere quantitative Analysen einzubeziehen. Es wird die mittlere Effektstärke für jeden AF-Akzeptanzfaktor auf Basis bereits veröffentlichter Forschungsergebnisse berechnet. Dabei zeigt sich, dass die Einstellung, der wahrgenommene Nutzen, die Effizienz, das Vertrauen in AFs, die Verkehrssicherheit und subjektive Normen am stärksten mit der Absicht, ein automatisiertes Fahrzeug zu nutzen, korrelieren. Eine anschließende Moderatorenanalyse zeigt, dass fast alle Akzeptanzfaktoren durch die Methodik und den Ort der Studie, den Automatisierungsgrad des AFs und das untersuchte Besitzverhältnis, d.h. Privatfahrzeuge, Car-Sharing oder öffentliche Verkehrsmittel, beeinflusst werden. Die meisten Untersuchungen beziehen sich jedoch auf AFs in Privatbesitz und daher fehlt es an Untersuchungen der öffentlichen sowie geteilten automatisierten Mobilität.

Um diese Lücke zu schließen, erforscht Artikel C Merkmale, die für Automated Mobility as a Service (AMaaS) relevant sind. Basierend auf 23 explorativen Interviews mit der allgemeinen Bevölkerung werden eine Reihe von AMaaS-Anforderungen abgeleitet. Mobilitätsexperten sortieren diese Anforderungen anhand ihrer Gemeinsamkeiten, so dass eine Clusteranalyse die erwarteten AMaaS-Eigenschaften aus Sicht der Anwender konzeptualisieren kann. Der Artikel identifiziert Verkehrssicherheit, Datenschutz, IT-Sicherheit, Regulierung, Flexibilität, Zugänglichkeit, Effizienz und Komfort als relevante Service-Merkmale. Er diskutiert jedes geforderte Merkmal und grenzt hierbei die Konstrukte voneinander ab, sodass die nachfolgende Forschung geeignete Messinstrumente entwickeln kann. Außerdem zeigt Artikel C stark voneinander abweichende Prioritäten in Bezug auf die jeweiligen Serviceeigenschaften auf, wenn er die Gesprächsanteile potentieller Nutzer mit den Relevanzbewertungen der Experten vergleicht.

Artikel D baut auf den qualitativen Ergebnissen von Artikel C auf, indem er eine hierarchische Qualitätsskala für AMaaS entwickelt und validiert. Der Artikel schlägt ein theoretisches Modell vor und operationalisiert die zuvor identifizierten Dienstleistungsmerkmale. Durch mehrere empirische Studien mit 1.431 Teilnehmern wird die vorgeschlagene Qualitätsskala iterativ verfeinert, bis zufriedenstellende psychometrische Eigenschaften erreicht werden. Nomologische Validität sichert die Vorhersagekraft der Skala. Artikel D bringt die Forschung somit von der Konzentration auf die bloße Akzeptanz des autonomen Fahrens hin zur Qualitätswahrnehmung des Benutzers voran, was die Nutzerzufriedenheit und damit den Erfolg von AMaaS maßgeblich beeinflusst. Dieser wiederum ist erforderlich, um die versprochenen Vorteile des autonomen Fahrens nachhaltig zu realisieren.

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List of Abbreviations

ADAS	Advanced Driving Assistance Systems
AI	Artificial Intelligence
AMaaS	Automated Mobility as a Service
AF(s)	Autonome Fahrzeuge
AV(s)	Autonomous/Automated Vehicle(s)
AVE	Average Variance Extracted
BI	Behavioral Intention
CFI	Comparative Fit Index
CMB	Common Method Bias
CMIN	Chi-Square
CR	Composite Reliability
Cr. α	Cronbach Alpha
CTAM	Car Technology Acceptance Model
DF	Degrees of Freedom
ECIS	European Conference on Information Systems
EFA	Exploratory Factor Analysis
GDP	Gross Domestic Product
GM	General Motors
GPS	Global Positioning System
H	Hypothesis
ICIS	International Conference on Information Systems
IS	Information Systems
IT	Information Technology
km/h	Kilometer per hour
LCD	Liquid Crystal Display
LoA	Level of Automation
N	Number of individuals or cases in the population
PC	Personal Computer
PROXSCAL	PROXimity. SCALing

RMSEA	Root Mean Square Error of Approximation
RQ	Research Question
SAE	Society of Automotive Engineers
SEM	Structural Equation Modeling
SERVQUAL	Service Quality
SPSS	Statistical Package for the Social Sciences (Software)
SRMR	Standardized Root Mean Square Residual
TAM	Technology Acceptance Model
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Acceptance and Use of Technology
VHB	Verbands der Hochschullehrer für Betriebswirtschaft e.V

1 Introduction

"The potential here is enormous.
Autonomous vehicles will be as important as the Internet."

Sebastian Thrun, founder of Google's self-driving car team
(Canadian Automobile Association 2021)

1.1 Motivation

With the increasing automation of information technology (IT) artifacts (Lee and See 2004) and the advent of ubiquitous computing (Vodanovic et al. 2010), the replacement of human drivers by automated vehicles (AVs) will be the next disruptive step in the evolution of the transportation sector (Adnan et al. 2018). Self-driving vehicles gather information from their environment, interpret this information to derive driving instructions, and evaluate their driving performance by means of artificial intelligence (AI) (Ferràs-Hernández 2018). In this vein, AVs are expected to provide multiple advantages to the individual user (e.g., more convenience and less travel time) and the society (e.g., fewer traffic fatalities and reduced greenhouse emissions) (Papadimitratos et al. 2009). These substantial AV impacts are estimated to eventually save society a total of nearly $4,000 per AV yearly (Fagnant and Kockelman 2015).

However, these benefits will only materialize if people are willing to use automated vehicles. In an increasing number of contexts, AI achieves a human-like performance or even surpasses human abilities (Szegedy et al. 2017). Nevertheless, people sometimes do not want to rely on AI, even in cases where the technology outperforms the human counterpart (Polonski 2018). Compared to AI advisors in financial or e-commerce contexts, AVs have a unique characteristic that sets them apart from other areas: Driving in an automated vehicle is a matter of personal safety (Bruckes et al. 2019). Therefore, with advancing automation, trust is increasingly needed to use the vehicle (Söllner et al. 2012). Additionally, research has shown that the AI embodiment is likely to be relevant when assessing the intention to trust and use IT artifacts like automated vehicles (Glikson and Williams Woolley 2020), so that AVs need to be studied separately from other IT artifacts.

Consequently, several scholars from information systems (IS) to transportation started to assess the factors relevant for a far-reaching adoption of autonomous driving. Most papers investigate specific aspects which could influence the intention to use automated vehicles. For example, Ro and Ha (2019) found that convenience, safety, and monetary costs impact the users' attitudes and intentions. Zhang et al. (2019) showed that perceived usefulness, perceived ease of use, and perceived safety risk directly or indirectly affect the behavioral intention to use. Others looked at personal driving enjoyment (Ernst and Reinelt 2017), doing other things while driving (Hein et al. 2018), or the environmental impact (Wu et al. 2019).

Overall, a large body of knowledge provides insights into the factors that influence the adoption of autonomous driving. However, from an epistemological perspective, the individual knowledge pieces still need to be synthesized and codified as explicit domain knowledge. Furthermore, the identification of research gaps would contribute to the creation of explicit domain meta-knowledge (Schryen et al. 2015). To generate this missing knowledge, the following section elaborates on the research gaps and questions that should be answered within this dissertation.

1.2 Research Questions

As outlined above, practitioners and scholars identified the adoption of autonomous driving to be an essential and contemporary topic. This is the reason why a large amount of research has accumulated in recent years. However, there are some research questions still to be answered.

Paper A. Many researchers use questionnaires to assess the individual acceptance factors that affect the general public's intention to use automated vehicles. To do so, they use various operationalizations and constructs. However, while bearing the same name, the constructs sometimes differ in their meaning due to diverging operationalizations. For example, Zhang et al. (2019, p. 212) use items like "Using autonomous vehicles will decrease my accident risk" to assess the perceived usefulness of an AV, whereas Motak et al. (2017, p. 277) leverage items like "Using the autonomous [vehicle] would help to make my trips […] less time-consuming". This phenomenon is called jingle fallacy (Larsen and Bong 2016). In another kind of construct identify fallacy, called jangle fallacy, identical items are used to measure a construct, but the constructs' names are different (Larsen and Bong 2016). These issues make it difficult to compare and build on published results. In order to enable researchers to work with available findings and to conduct the subsequent analyses presented in this dissertation, research paper A answers the first research question:

How do various authors define and measure AV acceptance factors?

Extant publications report contradictory results when assessing the adoption of autonomous driving. For instance, user habits like public transport usage or annual vehicle miles traveled are positive significant in some studies (Shabanpour et al. 2018; Webb et al. 2019) and negative significant in others (Sener et al. 2019; Wang and Akar 2019). Simultaneously, vehicle-related characteristics like the ease of use are sometimes shown to have a positive significant influence on the intention to use (Choi and Ji 2015). In contrast, other studies reveal no significant effect (Lee et al. 2017). First literature reviews already synthesize different aspects concerning the adoption of AVs (e.g., Adnan et al. 2018; Becker and Axhausen 2017; Nordhoff et al. 2016), but none of them assesses personal, vehicle, and societal factors at the same time, and thereby analyzes the respective significance considering the aforementioned diverging operationalizations. In order to close this gap, this dissertation's first study also answers the following research question:

Which factors do significantly influence the acceptance of autonomous vehicles?

Paper B. While the acceptance factors' significance is relevant for statistics, it is particularly essential for practitioners to know the respective effect sizes (Borenstein 2009). Especially considering that researchers can influence the significance of their study results by using larger participant cohorts (Hunter and Schmidt 2004), the second study focuses on the overall effect sizes. With this, paper B builds on paper A's results and addresses the previous limitation that purely counting significant and non-significant results can come to wrong conclusions (Rosenthal and DiMatteo 2001). Thus, the second study is going to answer the following research question:

To which extend do existing acceptance factors influence the behavioral intention to use AVs?

Available studies are based on very different designs. Most researchers use questionnaires, whereas others leverage simulators or even experiments with real cars. Therefore, the assessed vehicle's level of automation also changes regularly. Furthermore, various ownership models, including car ownership, car-sharing, and public transport are analyzed in various studies. Finally, the participants come from differents areas of the world, having various backgrounds and cultures. As each of these contextual factors, i.e., the methodology, the level of automation, the ownership model, and the study's location, might influence the outcome of a published study (Cavoli et al. 2017; Davison and Martinsons 2016), paper B also answers the related research question:

How are the most relevant AV acceptance factors moderated by study design?

Paper C. During the literature review as well as the moderator-analysis, it turns out that many published papers focus only on privately owned cars. However, raising customer numbers in the shared mobility sector (Peter 2020) reinforce the need to understand not only for owned vehicles but equally for shared vehicles which factors drive their acceptance. Thereby, the preceding moderator-analysis showed that the levers affecting the intention to use shared AVs are different from privately owned AVs, and it is currently not adequately explored which factors promote the adoption of automated mobility as a service (AMaaS). To shed light on this largely under-researched topic, a qualitative study including potential future users' and subject matter experts' views will answer the question:

Which service characteristics are relevant for the adoption of automated mobility as a service?

Paper D. As observed in paper A, many researchers use varying operationalizations in their work, even when published scales are available. However, the published scales are not always empirically validated, so their reliability and predictive power could be improved (Hinkin 1995). Furthermore, for some of the identified characteristics relevant for AMaaS, e.g., flexibility or convenience, there are no scales available yet. Consequently, the last paper develops an AMaaS quality scale with good psychometric properties and predictive power to address these shortcomings. Thus, the final research question answered in this dissertation is:

How can relevant AMaaS quality characteristics be operationalized and measured?

1.3 Structure of the Thesis

This dissertation comprises seven chapters (see Figure 1). After introducing the thesis' motivation and outlining the respective research questions in this chapter, chapter 2 provides an overview of the theoretical and methodological foundations. Afterward, chapters 3 to 6 represent the heart of this cumulative dissertation. Each chapter presents a peer-reviewed and published research paper answering the above-stated research questions. Thereby, the first two papers (chapters 3 and 4) focus on autonomous vehicles, whereas the following two papers (chapters 5 and 6) assess required service characteristics for automated mobility as a service. Finally, chapter 7 discusses the overall contributions and limitations of this dissertation.

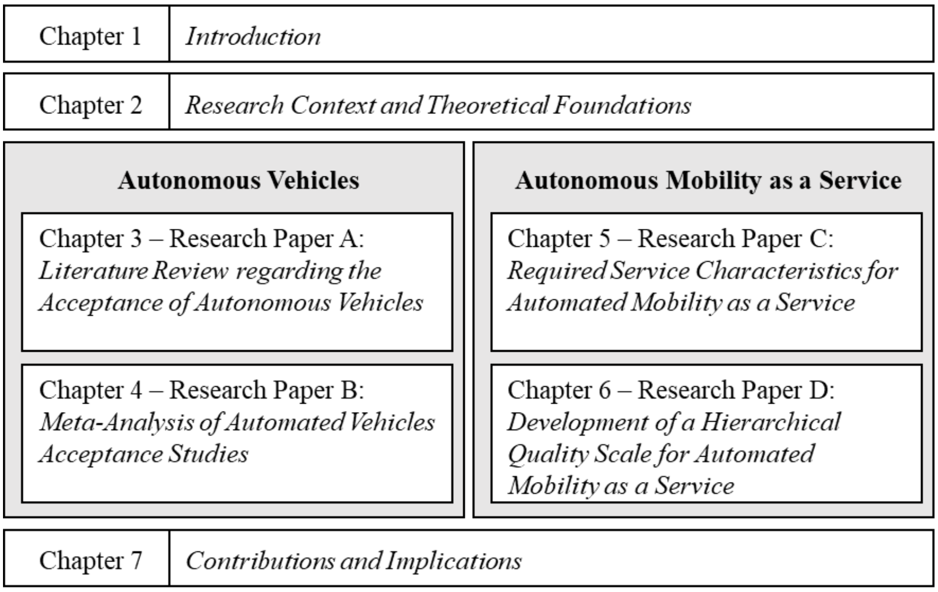

Figure 1. Structure of the Dissertation

The following list contains the four research papers making up chapters 3 to 6, together with their publication outlets, publication dates, and VHB rankings:

Research Paper A: Bornholt, Jennifer[1]; Heidt, Margareta (2019): „To Drive or not to Drive – A Critical Review regarding the Acceptance of Autonomous Vehicles.“ In: 40th International Conference on Information Systems (ICIS), Munich, Germany. VHB: A.

Research paper B: Wiefel, Jennifer (2020): „What Matters Most – A Meta-Analysis of Automated Vehicles Acceptance Studies.“ In: 28th European Conference on Information Systems (ECIS), A Virtual AIS Conference. VHB: B.

Research Paper C: Wiefel, Jennifer (2021): „Required Service Characteristics for Automated Mobility as a Service: A Qualitative Investigation.“ In: 29th European Conference on Information Systems (ECIS), A Virtual AIS Conference. VHB: B.

Research Paper D: Wiefel, Jennifer; Buxmann, Peter (2021): „Automated Mobility as a Service – Development of a Hierarchical Quality Scale.“ In: 29th European Conference on Information Systems (ECIS), A Virtual AIS conference - *Nominated for the Best Paper Award*. VHB: B.

The following of this section briefly summarizes each paper’s contents.

[1] Please note: At time of the paper’s submission, the author of this dissertation still had her maiden name (Bornholt). After marriage she took her husband’s name (Wiefel).

Paper A (chapter 3) serves as foundation for the remainder of the dissertation as it sets out to collect, organize and synthesize extant knowledge on the acceptance of autonomous driving. AVs, including the intention to use, are perceived as relevant and timely topics that have already attracted many researchers' attention. As a result, paper A identifies 58 articles on the acceptance of autonomous driving across various automation levels and ownership models, i.e., privately owned vehicles, shared vehicles, and public transport. Following the literature review process proposed by Okoli and Schabram (2010), the paper identifies all factors that significantly influence the behavioral intention to use AVs. Thereby, paper A observes varying operationalizations of these factors. As a consequence, the previously published results are only comparable when looking at item level. While paper A conducts this thorough analysis before presenting an AV acceptance framework to its readers, it also requests future research to agree on a common conceptualization. In addition to this call, a comprehensive overview of future research avenues is proposed, thereby spaning various identified shortcomings in prior literature to guide the prospective scholars' research orientation in a common direction.

Research paper B (chapter 4) builds on the results from paper A and conducts a meta-analysis to identify those AV acceptance factors that are not only significant but have a large effect size, too. Combining publicly available research evidence suggests that attitude, perceived usefulness, efficiency, trust in AVs, traffic safety, and subjective norms correlate most strongly with the intention to use automated vehicles. A subsequent moderator-analysis discovers moderating effects for most of these influencing factors on the intention to use. Results can be influenced depending on the study's location, the vehicle's level of automation, whether the car is privately owned, shared, or used for public transportation, and the methodology (i.e., self-reported surveys, simulator studies, or experiments with actual cars). The analysis helps researchers and practitioners to interpret extant results more carefully and can help to design future studies.

Research paper C (chapter 5) takes a new perspective and qualitatively investigates required service characteristics for the adoption of AMaaS. Based on 23 interviews with potential future users of AMaaS, a set of requirements is derived. Mobility experts sort these requirements by similarity resulting in an overall concept similarity matrix that is fed into a cluster analysis. The algorithm identifies eight clusters, i.e., required AMaaS service characteristics, that are most appropriately termed traffic safety, information privacy, cybersecurity, regulations, flexibility, accessibility, efficiency, and convenience. Interestingly, when comparing the experts' relevance ratings and the code frequencies from the user interviews, diverging priorities show up. While experts rate security-related attributes to be essential (e.g., traffic safety, regulations, cybersecurity), the general public demands service characteristics that make the use of AMaaS pleasant (e.g., flexibility, accessibility, convenience). Identifying these differing views provides important insights for practitioners and offers the opportunity to create new theories.

The lastly cited research paper D (chapter 6) in this dissertation evolves the results from paper C by developing a quality scale for AMaaS. In this vein, it picks up the issue of varying conceptualizations criticized in paper A. Based on the interviews of research paper C and three empirical surveys with a total of 1,431 participants, paper D presents a hierarchical, multi-dimensional quality scale that shows good validity and psychometric properties. The first hierarchy level consists of the primary quality dimensions: outcome quality and trust. Each primary dimension comprises quality attributes identified in paper C. However, regulations were omitted from the final scale due to low item loadings and the fact that the AMaaS providers cannot directly influence legislation. Structural equation modeling reveals that both trust and outcome quality strongly affect the quality perception, with trust being the stronger predictor. Traffic safety influences trust most strongly, whereas flexibility is the most vital aspect of outcome quality. Overall, the quality scale shows good predictability, with the nomological validity being ensured. Therefore, the scale and its constructs can be leveraged for future research on AVs as well as other contexts.

2 Research Context and Theoretical Foundations

This section provides an overview of the underlying theoretical background relevant to this cumulative dissertation's four papers. First, the concept of autonomous driving in its forms of privately owned vehicles and AMaaS is defined. In this regard, the technical foundations, as well as the expected advantages and related concerns, are described. The following subsections summarize current user acceptance research and outline how quality perceptions materialize when customers experience a service like AMaaS.

2.1 Autonomous Driving

Recent achievements in modern technologies prepare the next step in the transportation sector's evolution, which will be the replacement of human drivers by artificial intelligence (Adnan et al. 2018). Thereby, automated driving will be available in two different ways: as privately owned vehicles and automated mobility as a service.

2.1.1 Automated Vehicles

According to the Society of Automotive Engineers, automated vehicles are "the hardware and software that are collectively capable of performing the entire dynamic driving task on a sustained basis" (SAE International 2018). Thereby, the level of automation (LoA) can range from 0, i.e., all driving tasks are performed manually, up to level 5, in which the vehicle can drive fully on its own. Levels 1 and 2 include advanced driver assistance systems (ADAS). Higher levels of automation, i.e., 3 and 4, represent automated driving features that can operate the vehicle autonomously but only under limited conditions. The highest LoA 5 works with all traffic situations and is being termed "intelligent" because the embedded technology makes decisions based on built-in AI functionalities (Hengstler et al. 2016).

AI, being the heart of the autonomous vehicle, is a new form of technology that can actively interact with its surroundings (Ferràs-Hernández 2018). The vehicle processes large amounts of data collected via endpoint telemetry, cameras, and sensors (Ostern et al. 2018) or received via vehicle-to-vehicle and vehicle-to-road communication technologies (Coppola et al. 2016). In order to identify patterns and predict traffic events, it leverages cloud computing processing vast amounts of data in real-time (Zhu and Ukkusuri 2015). The results are used to instruct the driving systems of the vehicle. Finally, the AI evaluates the outcome of its driving decisions, learns from it, and improves the decision-making rules to enhance the driving performance and ensure the vehicles' safety (Rahwan et al. 2019). However, the complex automatization processes make it difficult for the general society to understand what AI exactly does within the vehicle. Consequently, people have various hopes and concerns regarding automated vehicles. A detailed overview will be provided in sub-sections 2.1.3 and 2.1.4.

2.1.2 Automated Mobility as a Service

As with traditional car-sharing, automated vehicles are going to be available on a shared consumption basis. AMaaS is defined as a "*provision of on-demand door-to-door mobility being offered by self-driving cars, which can be requested via an online platform for individual or shared rides*" (based on Pangbourne et al. 2020). The service represents a new transportation option without owning the vehicle. Instead, the vehicle is requested via an electronic platform with little or no direct human interaction (Dai and Salam 2020) to complete the service, e.g., providing the vehicle, handing over the keys, or processing the payment.

"The sharing economy [including AMaaS] is an internet-enabled, platform-based and trust-verified interaction of individuals or entities with the goal of providing temporary access […] to idle assets in exchange for monetary […] compensation" (Akhmedova et al. 2020, p. 1). Due to a redistribution of idle resources (Taeihagh 2017) and better exploitation of under-utilized assets (Zervas et al. 2017), AMaaS could help to reduce social problems like hyper-consumption and pollution (Hamari et al. 2016) even more efficiently than privately owned AVs. Consequently, AMaaS could be the primary mobility offering of the future (Richter et al. 2015).

The sharing economy has already become very popular with increasing numbers of consumers who prefer temporary access over ownership (Matzler et al. 2015). Several traditional industries like the hotel business or vehicle manufacturers got attacked by new market entrants like Airbnb or ShareNow. Forecasts predict further market growth for the sharing economy (Statista 2017) and automated vehicles (Weber et al. 2019), both promoting AMaaS' viability.

However, regardless of whether the autonomous vehicles are shared or privately owned, the success of the respective business model is subject to the user adoption rate and the ability of the provider to maintain a critical mass of consumers (Constantiou et al. 2017). Consequently, it is necessary to know customers' expectations and concerns.

2.1.3 Expectations of Autonomous Driving

Various societal and individual advantages are associated with AVs and AMaaS. They are expected to be strong adoption drivers for both types of mobility.

First of all, autonomous driving promises to have better driving capabilities than humans: Cameras and sensors are always very precisely aware of their environment, even at night or in bad weather situations. Besides, computers can react consistently, without error, and faster than humans (Young and Stanton 2007). In this vein, causes of accidents such as drug influences, fatigue, risky driving behavior, and lack of attention will be counteracted with autonomous vehicles. Considering that nine out of ten accidents are due to human error (NHTSA 2018; Statistisches Bundesamt 2019), the introduction of autonomous vehicles is expected to increase road safety significantly.

Additionally, self-driving vehicles should improve traffic flow (Lutin 2018) by driving smoother than humans do. For example, cars can leverage vehicle-to-vehicle and vehicle-to-infrastructure communication and find the optimal departure sequence at intersections to minimize delays (Yang et al. 2016). Furthermore, efficient driving styles leading to reduced greenhouse gas emissions should protect the environment (Motak et al. 2017). The ecological friendly consumption model of AMaaS could be another benefit for environmentally concerned users (Edbring et al. 2016). With AMaaS, people could share automated vehicles and related infrastructures, leading to an increased capacity of, for example, parking space in crowded cities (Waldrop 2015).

Besides, autonomous vehicles can enhance mobility for people who cannot drive a vehicle, such as the elderly, impaired, or drunk people (Bennett et al. 2019; Buckley et al. 2018a; Musselwhite 2019). Passengers of self-driving cars can spend their travel time with other leisure and work activities or sleep during longer rides (Hein et al. 2018). Moreover, AMaaS is practical for consumers who do not want to own a good because of the related risks, costs, and responsibilities (Benoit et al. 2017).

In this regard, the cost-reduction achieved through a shared consumption with AMaaS has been shown to be attractive for individual consumers (Barnes and Mattsson 2016). Finally, improved efficiency and safety are also expected to increase autonomous vehicles' economic benefits on a societal level (European Commission 2018).

2.1.4 Concerns about Autonomous Driving

While autonomous driving is associated with many benefits, the general society also sees multiple disadvantages related to the new technology. First, higher acquisition prices, as well as repair and maintenance costs, reduce the intention to use autonomous vehicles (Ro and Ha 2019). In addition, people's perceived risk (Liu et al. 2019e) or even anxiety (Hohenberger et al. 2017) prevent extensive AV usage. While automated vehicles are built to increase traffic safety, there exist doubts that the technology can act correctly under all road and weather conditions (Schoettle and Sivak 2014). Furthermore, in earlier studies, participants did not trust the new technology because the vehicle's program code could malfunction or break down (Tussyadiah et al. 2017).

Due to these apprehensions, most people are reluctant to release control entirely to the vehicle. People who love to drive themselves do not want to lose their driving fun (Ernst and Reinelt 2017), and the passenger's perceived autonomy influences trust and the intention to buy autonomous vehicles (Woisetschläger 2016). These findings are in line with earlier research studying the adoption of technology in the context of perceived threatened autonomy (e.g., Walter and Lopez 2008). Lack of control can further become relevant in an accident situation. In an emergency, autonomous cars should make ethical decisions (Ro and Ha 2019) that do not protect or harm some people disproportionately over others (Salonen and Haavisto 2019) and reflect culture-specific moral behaviors (Rhim et al. 2020).

Another risk related to automated and connected vehicles are information privacy violations in terms that the provider could collect and analyze sensitive data about the passengers without their consent. Such misbehaviors lessen the intention to use AVs (Hein et al. 2018; Zhang et al. 2019). Likewise, passengers fear system vulnerabilities that hackers could exploit (Bruckes et al. 2019; Buckley et al. 2018a).

From a societal perspective, in case of an accident, liabilities need to be clarified by law before people are willing to use automated vehicles (Ro and Ha 2019). Users want to know whether the passenger, vehicle company, or programmer is being held responsible for a potential accident. Finally, projected job losses for some occupations, e.g., taxi drivers, shed a bad light on autonomous driving (Fraedrich and Lenz 2016).

Due to the breadth of expected benefits and concerns, research needs to investigate the levers that significantly influence public acceptance of autonomous vehicles. Research and practitioners can only promote high usage levels if they know the most influential factors. Accordingly, the remainder of this thesis investigates the user acceptance and quality perception of autonomous driving.

2.2 User Acceptance Theories

User acceptance has been regularly evinced to be a prerequisite for a successful information systems' introduction (e.g., Venkatesh et al. 2003). Although user acceptance research is a well-established discipline that proposed many theories to predict user adoption, the application of the term acceptance varies widely (Adell et al. 2018). Some authors use tautological definitions, for example, "acceptance is the degree to which a law, measure or device is accepted"[2] (Risser et al. 1999, p. 36). Others perceive it as the willingness to use an application (Lee et al. 1995), and last, some researchers define acceptance as the actual use, which is, of course, influenced by the intention (Davis et al. 1989). Opposed to the above definitions, Schade and Schlag (2003) distinguish between acceptability, which is present before the actual usage, and acceptance, which develops afterward.

Considering these definitions, a uniform understanding of acceptance is missing due to the complexity of the concept. However, to provide the reader with a clear understanding, this dissertation considers the term acceptance as usage intention. This view is chosen, although the "intention-behavior correlation […] may sometimes be lower than we might wish or expect" (Sutton 1998, p. 1325) because of the unavailability of fully automated vehicles (Walker 2019). As AVs are not developed yet, study participants can only share information about their usage intentions. Besides, contrary to Sutton's assertion, prior research has confirmed a strong correlation between behavioral intentions and actual behavior (Venkatesh and Davis 2000).

For many years, researchers have adopted theories of human behavior to study technology acceptance. One of the most widely cited psychological theories used to explain human behavior is the Theory of Reasoned Action (TRA) (Fishbein and Ajzen 1975). The theory is based on the assumption that humans act as rational beings and use the information available to them. Presuming that socially relevant behaviors occur mainly under volitional control, one's intention to perform a behavior serves as a direct determinant of one's actual behavior. The intention is derived from motivational factors, i.e., the person's attitude and subjective norms, and can be defined as a person's likelihood of performing a behavior (Fishbein and Ajzen 1975). Later, Ajzen (1991) extended the TRA into the Theory of Planned Behavior (TPB) by including the person's perceived behavioral control as an antecedent of the intention. Following his reasoning, a person will only intend to do something if he/she perceives performing the behavior of interest as feasible.

In 1989, Davis (1989) developed the Technology Acceptance Model (TAM) as he found that extant behavioral theories predicted system usage insufficiently (e.g., Schewe 1976; Srinivasan 1985). He developed two scales for perceived usefulness and ease of use because these constructs were expected to be fundamental determinants of user acceptance in an IS context.

[2] The original publication is in Swedish, the English translation is taken from Adell et al. (2018).

A subsequent comparison of perceived usefulness, ease of use, attitude, and subjective norms revealed that perceived usefulness explains most of the variance in the intention to use a computer system (Davis et al. 1989).

While TAM is a very parsimonious theory, more differentiated models follow. For example, TAM 2 divides input variables into social influence and cognitive processes (Venkatesh and Davis 2000). Later, the Unified Theory of Acceptance and Use of Technology (UTAUT) proposes four fundamental constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al. 2003). In the same vein, very context-specific acceptance models emerge, e.g., the car technology acceptance model (CTAM), including factors like perceived safety and anxiety (Osswald et al. 2012). Overall, a broad spectrum of acceptance models and an even larger number of acceptance factors have been proposed. As a result, this thesis is going to structure available results to shed light on what influences the acceptance of autonomous driving.

2.3 Quality Perception Models

Whereas acceptance theories aim to predict an initial system usage, quality models should help identify those aspects of a product or service that satisfy existing consumers (Cronin and Taylor 1992; Rust and Oliver 1994). Satisfied customers are likely to have higher repurchase intentions and increased word-of-mouth behavior (Parasuraman et al. 2005). With this, service quality is argued to be the most essential determinant of a service's viability and success (Fassnacht and Koese 2006; Zeithaml et al. 2002).

Perceived quality is defined as the customer's judgment about the overall excellence or superiority of a service or product (Cronin and Taylor 1992; Dagger et al. 2007; Parasuraman et al. 1988). To evaluate the perceived service quality, a customer considers "the sum total of a number of specific activities that make up the overall performance of a particular industry's service" (Rossiter 2002, p. 314). For online shopping, this might be "efficient and effective shopping, purchasing, and delivery" (Parasuraman et al. 2005, p. 217), while AMaaS should allow the user to order a car conveniently, drive safely to the destination, and pay via seamless payment mechanisms. Due to the various contextual requirements, multiple quality scales have emerged (e.g., Amat-Lefort et al. 2020; Blut 2016; Parasuraman et al. 1988).

As a result, researchers disagree on how to measure perceived service quality (Dagger et al. 2007). Nevertheless, there is a general consensus that perceived quality is a multidimensional hierarchical construct (Grönroos 1984; Parasuraman et al. 1988). For example, Dabholkar et al.

(1996) argue that a hierarchical structure accounts for the complexity of human perceptions, and Parasuraman et al. (2005) outline that concrete clues like technical or design aspects are summarized in dimensions at which the evaluation occurs, which together make up the perceived quality.

Over the years, many service attributes have been identified to influence the overall quality perception. For traditional services, Grönroos (1984) was among the first researchers who argued that service quality is influenced by technical quality, i.e., what is provided, and functional quality, i.e., how a service is provided. A few years later, the often-cited service quality scale SERVQUAL proposes five quality dimensions: tangibles, reliability, responsiveness, assurance, and empathy (Parasuraman et al. 1988). Soon the attributes became less human-centric and more technology-specific. For online retailing, elements like website design and fulfillment (Wolfinbarger and Gilly 2003) became just as relevant as system availability and information privacy (Parasuraman et al. 2005). More recently, the sharing economy with its offerings like car-sharing got into the researchers' focus so that accessibility (Kim et al. 2019) or environmental impact (Arteaga-Sánchez et al. 2018) were identified as relevant service attributes.

Overall, there is a wide range of service attributes that impact the quality perception for various services. Thereby, it is not evident which of those factors might be applicable to AMaaS. AMaaS represents an electronic service within the sharing economy that comprises elements of car-sharing and autonomous driving. Hence, the papers within this dissertation are going to investigate the very context-specific factors that influence the adoption and the subsequent quality perception of autonomous mobility as a service. With this, researchers and practitioners get insights into how to attract and retain customers. Eventually, the expected benefits of autonomous driving technologies can materialize for the individual and society.

3 Paper A: To Drive or not to Drive

Title

To Drive or not to Drive – A Critical Review regarding the Acceptance of Autonomous Vehicles

Authors

Jennifer Bornholt, Technical University of Darmstadt, Germany
Margareta Heidt, Technical University of Darmstadt, Germany

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Abstract

With the advent of autonomous vehicles (AVs), research has put much effort in investigating the factors relevant for the acceptance of this new technology. In order to identify, critically assess, and combine extant findings, we performed a structured literature review regarding the acceptance of self-driving vehicles. Results of this review spanning 58 articles include (1) a comprehensive AV acceptance framework outlining significant factors across three areas: individual characteristics, vehicle characteristics, and policy/society. We also (2) analyze the operationalization of relevant constructs and items in the identified studies as they strongly diverge in extant literature. This new level of detail helps researchers and practitioners to pervade and compare the AV acceptance research in-depth. Additionally, we contribute to the AV research stream as we (3) identify possible future research avenues, which we examine regarding content, method, and focus.

Keywords

Autonomous Vehicles, Acceptance Framework, Construct Identity Fallacy, Literature Review

3.1 Introduction

Traditional automotive manufacturers as well as technology companies make big bets by investing large amounts in the development of self-driving cars or autonomous vehicles (AV). For example, the US car manufacturer GM has set an annual budget of $4.35 billion (Welch and Behrmann 2018) and the German automotive supplier Bosch plans to spend $4.6 billion by 2021 (Buchenau 2019) to boost the development of connected and autonomous vehicles. These bets are influenced by market projections as those of Rahul et al. (2018), who estimate a global autonomous vehicle market of $557 billion by 2026.

On a broader level, society expects to drastically reduce traffic deaths as 94 percent of today's crashes are due to human error (NHTSA 2018). Furthermore, expansive AV adoption concerns politics: Emission and congestion reductions might help to achieve the goals defined in the Paris climate agreements (Greenblatt and Saxena 2015). However, wide-spread AV adoption also entails policies considering questions regarding liabilities, ethics, or licensing requirements which need to be put in place in the near future (Fagnant and Kockelman 2015). Experts predict that "once technological and regulatory issues have been resolved, up to 15% of new cars sold in 2030 could be fully autonomous" (Mohr et al. 2016, p. 11).

However, there is no market without demand. So, (when) are individuals actually willing to use self-driving cars and adopt autonomous vehicles? By knowing the factors that influence usage and buying intentions, both companies and politics could aim to create respective vehicles and guidelines. Against this backdrop, a rapidly growing body of literature has emerged in recent years, which explores the drivers and inhibitors of AV acceptance (Gkartzonikas and Gkritza 2019).

While scholars extensively discuss acceptance factors for autonomous vehicles, they continuously investigate new factors leading to a large pool of results difficult to pervade. Thereby, the related stream of literature does not consistently leverage relevant constructs or items – a well-known issue in behavioral sciences, coined by Larsen and Bong (2016) with the term "construct identity fallacy". Decades earlier, Bacharach (1989, p. 501) stated: "If [theorists] are working with inappropriate constructs and variables, how these constructs and variables are assembled into hypotheses and propositions is irrelevant". Accordingly, this paper will answer the following research questions:

RQ1: Which factors do significantly influence the acceptance of autonomous vehicles?
RQ2: How do various authors define and measure these relevant AV acceptance factors?
RQ3: How does this open up possible future research avenues?

In order to answer these questions, we conduct an extensive literature review adhering the steps proposed by Okoli and Schabram (2010). Following Rowe's (2014, p. 242) call to "to publish more literature reviews […] for the [information systems] (IS) community", we create a comprehensive overview of acceptance factors derived from previously disconnected research streams.

This study specifically contributes to IS research by deriving an overview of the convergence and divergence of acceptance factors in current AV research. While scholars can utilize our findings to create enhanced theories, lawmakers and automotive companies can leverage our results for policy design and organizational decision-making. Additionally, we outline a roadmap for further research based on current research results, when they are either too scarce or ambiguous and thus require further attention of scholars.

The remainder of the paper is structured as follows: We introduce the related literature regarding AV acceptance research before describing the methodology applied during the literature search and analysis process. Based on thereby identified studies, we will present a comprehensive acceptance framework for autonomous vehicles. We complement our overview by a critical discussion of diverging constructs and items, which is fundamental for the holistic interpretation of our derived acceptance framework. During our analysis, we identify and outline avenues for further research. Afterward, we discuss the overall findings, their limitations as well as our theoretical and practical contributions.

3.2 Related Literature

We define autonomous vehicles according to the Society of Automotive Engineers (SAE) taxonomy, stating that automated driving systems are "the hardware and software that are collectively capable of performing the entire dynamic driving task on a sustained basis" (SAE International 2018). Thereby, the term is specifically used for SAE automation levels 3, 4, or 5 of driving automation with levels of automation ranging from level 0 (no driving automation) to level 5 (full driving automation). While SAE levels 0, 1, and 2 provide advanced driving assistance systems (ADAS) still requiring the driver to drive and constantly monitor the environment, levels 3, 4, and 5 allow the driver to hand over control to the vehicle with a decreasing degree of required supervision up until level 5 where the car can fully drive on its own.

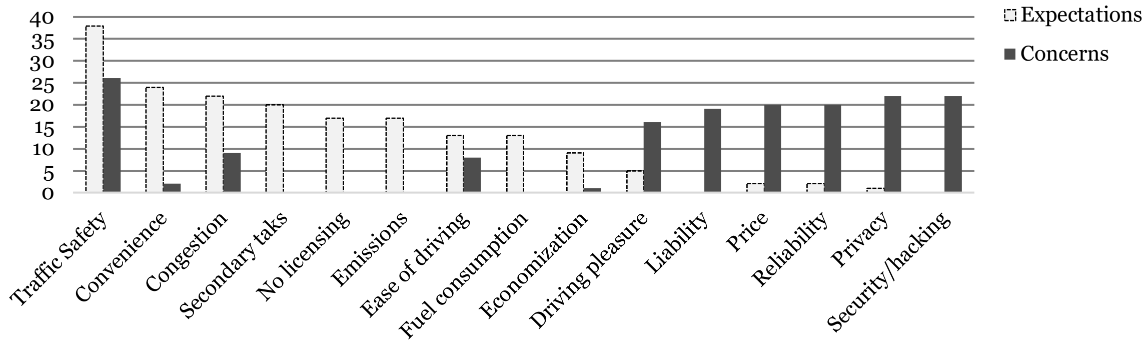

Figure 2. Perceptions of Autonomous Driving

With the advent of self-driving vehicles, research started investigating related user perceptions consisting of various expectations and concerns. Based on these, Figure 2 provides an overview of the most frequently discussed factors in descriptive AV acceptance literature. While *traffic safety* is the most relevant factor mentioned by potential users, it is also the most debated. On the one hand, survey participants expect higher traffic safety due to reduced human error, on the other hand, they worry that self-driving cars will not react properly in unforeseen situations (Hohenberger et al. 2017; Howard and Dai 2014). Factors which are perceived as predominantly positive are improved *convenience*, *reduced congestion* and travel times, *no licensing* requirements leading to increased mobility for the old and impaired, the ability to perform *secondary tasks*, reduced *emissions*, and less *fuel consumption* (Buckley et al. 2018a; König and Neumayr 2017). *Privacy*, *security* risks and hacking, *liability* issues, insufficient *reliability* and malfunctioning, higher purchase prices, and reduced *driving pleasure*, however, are the concerns or risks most often identified in surveys (Abraham et al. 2018; Kyriakidis et al. 2015; Shabanpour et al. 2018; Ward et al. 2017).

Besides the vehicle-related aspects mentioned above, the willingness to use a self-driving car appears also to be affected by *individual demographics* like gender, age, or household size (Bansal et al. 2016; Dong et al. 2017; Hassan et al. 2019; Hulse et al. 2018; Nazari et al. 2018). Attitude and character traits also have been shown to affect decision-making regarding AV use (Charness et al. 2018; Haboucha et al. 2017; Lee et al. 2018a). Furthermore, incentives from politics like special AV-lanes, and social influence can affect the willingness to use a self-driving vehicle (Madigan et al. 2017; Shabanpour et al. 2017).

From a theoretical perspective, two prominent acceptance models provide the base for the majority of studies: Technology Acceptance Model (TAM) (Davis et al. 1989) and Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al. 2003). According to TAM, perceived usefulness, perceived ease of use, and attitude towards AVs influence the behavioral intention to drive in an autonomous vehicle. In contrast, performance expectancy, effort expectancy, and social influence are relevant according to UTAUT. But also other models like the Car Technology Acceptance Model (CTAM) (Osswald et al. 2012), or the Theory of Planned Behavior (TPB) (Ajzen 1991) are used in AV acceptance research.

Given the large number of research investigating user perceptions and acceptance, several literature reviews have shed light on different aspects of this research stream. However, they neither focus in-depth on vehicle characteristics – which are especially important for car manufacturers – nor on the diverging specification and operationalization of constructs. Nordhoff et al. (2016) and Seuwou et al. (2016) both create conceptual acceptance models purely based on UTAUT, but do not critically discuss the constructs included or their statistical significance. Nishihori et al. (2018) and Furukawa (2019) concentrate on general advantages and disadvantages of self-driving vehicles but neglect their individual influence on AV acceptance. Others, however, put their focus solely on ethical issues or trust requirements (Adnan et al. 2018; Hakimi et al. 2018). In contrast, Becker and Axhausen (2017) and Gkartzonikas and Gkritza (2019) stay on a meta-level, outlining objectives, investigated factors, and demographic characteristics of available surveys – still leaving our stated research questions unanswered.

3.3 Methodology

We performed our literature review following the eight step approach proposed by Okoli and Schabram (2010) (shown in Figure 3), which leads to the following sub-sections. As such, we aim to be “systematic in following a methodological approach, explicit in explaining the procedures by which it was conducted, comprehensive in its scope of including all relevant material, and hence reproducible by others [in the IS community] who would follow the same approach” (Okoli and Schabram 2010, p. 1).

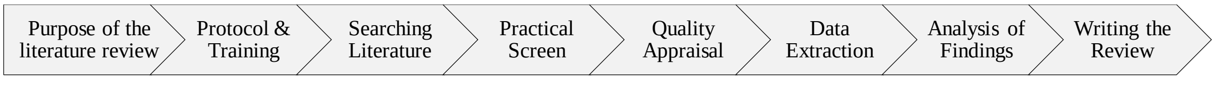

Figure 3. Literature Review Process by Okoli and Schabram (2010)

3.3.1 Purpose of the Literature Review

First, we would like to state the purpose and scope of our review by leveraging Cooper’s (1988) taxonomy (see Figure 4). Our focus is mainly on *research outcomes*, i.e., the combination and comparison of identified AV acceptance factors. Several acceptance models are adapted and applied in various contexts ranging from privately owned cars to car-sharing and to autonomous public transport while participants are asked to either fill in structured questionnaires or drive in (simulated) cars. This has led to very context-specific results (Langdon et al. 2017).

Our goal is thus to *integrate* consistent research outcomes in one comprehensive acceptance framework. Further, we emphasize *central research issues* like diverging results or under-researched aspects for further investigation. Thereby, we try to keep a *neutral position*. However, we also *criticize* the AV acceptance research using constructs and items, which are not comparable.

While the literature search process should lead to an exhaustive set of literature, the final analyzed and cited publications represent a *selective* subset. We organize our analysis around *concepts*, i.e., around constructs and items as they are of special interest for *scholars* and *practitioners* when leveraging them for theory advancement, policy design, or AV development.

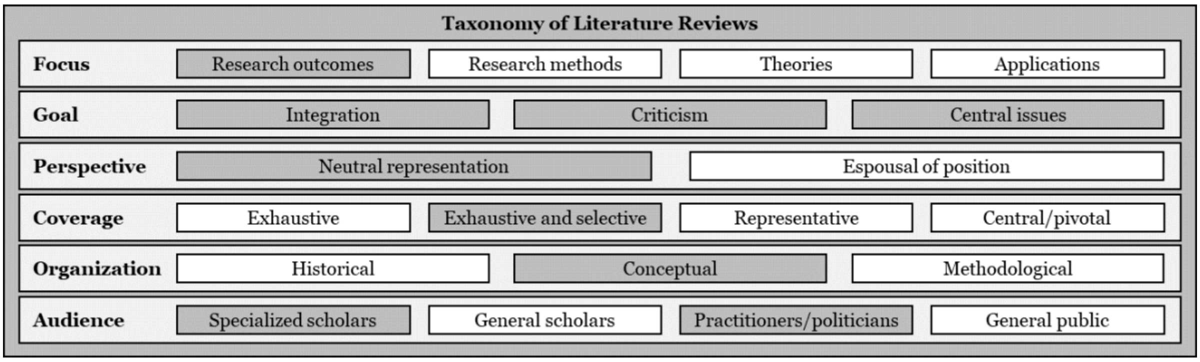

Figure 4. Applied Taxonomy of Literature Reviews (Cooper 1988)

3.3.2 Protocol and Training

Before actually searching the literature, we agreed on two researchers performing the review simultaneously. In order to allow both of them to include the same set of relevant literature, we agreed on a common research protocol. The reviewers regularly discussed difficulties and inconsistencies during their selection process and adjusted the inclusion and exclusion criteria accordingly. We will describe the contents of the protocol as we outline the performed review steps in the next sections.

3.3.3 Searching the Literature

We defined the search terms by conceptualizing the topic based on studies concerning acceptance of autonomous cars published in either behavioral science, transportation, or IS journals and proceedings (Vom Brocke et al. 2009). We also added *willingness to buy/pay* as synonyms for *acceptance* as we think that AVs are only fully accepted, if the consumers are willing to spend money for their usage. This resulted in the following search query: [automated OR autonomous OR self-driving OR driverless OR connected OR smart] AND [vehicle(s) OR car(s) OR driving] AND [accept* OR adopt* OR "willingness to buy" OR "willingness to pay"].

In order to identify appropriate studies, we chose suitable academic databases, which contain relevant behavioral science and IS publications as well as research from related fields like transportation and computer science (Levy and Ellis 2006): ACM Digital Library, AIS Electronic Library, EBSCOhost Business Source Premier, IEEE Xplore Digital Library, ScienceDirect, and WebOfScience. Within these databases, we conducted a keyword search focusing on the years 2014-2019 in January 2019. The initial search, including all databases and journals, resulted in 4557 articles, excluding any duplicates.

3.3.4 Practical Screen

In order to objectively decide which articles are relevant and appropriate for our final analysis, we determined inclusion and exclusion criteria (Webster and Watson 2002). We thus retained the following publications: (1) Studies investigating factors that affect the acceptance of autonomous driving (SAE level 3-5), (2) studies researching autonomous vehicle acceptance in the private context, and (3) completed or full scientific research papers written in English. These studies were not limited to only highly rated journals or conference proceedings to ensure a retrieval of an exhaustive result list of this young research field. On the other hand, we excluded: (1) Studies focusing on autonomous vehicle acceptance of other road users (e.g., pedestrians), (2) studies investigating how a specific acceptance factor, e.g., trust or convenience, can be influenced, and (3) studies focusing on smart applications within autonomous cars.

Scanning the document titles and abstracts for relevance by applying the above criteria, we already excluded most of the search results, leaving 117 articles for a more thorough inspection with a total of 66 full texts remaining. Following Levy and Ellis (2006), we conducted a reference backward and forward search. Using Google Scholar, we increased the set of unique relevant papers to a total of 124.

3.3.5 Quality Appraisal and Data Extraction

We sorted the final set of publications by type of research and agreed on a "hierarchy of evidence which ranks certain kinds of studies as intrinsically providing more valid and reliable results than others” (Okoli and Schabram 2010, p. 26). Following this approach, we only selected studies that apply structural equation models, regression analysis, or utility models since they simultaneously examine multiple acceptance factors.

As most of the 58 remaining publications use slightly different terms for similar constructs and items, we first performed an initial coding process as proposed by Okoli and Schabram (2010). We extracted the exact terms for constructs and items used in the literature and combined the terms into sets using pattern coding (Saldana 2009). Both researchers performed the coding individually and combined their results afterward.

We structured the research results following Webster and Watson (2002) by creating a concept matrix (a shortened version can be found in the Appendix) and analyzed which acceptance factors influence users’ intention to use a driverless car – either positively, negatively, or non-significantly. Through the inclusion of not only constructs but also items, we create the thus far missing transparency of what these studies actually assessed and what effectively influences user acceptance.

3.3.6 Synthesis of Studies and Writing the Review

We compared and aggregated the results per coded acceptance factor to answer the first research question. In cases where most studies have converging significant results, we included this factor in our comprehensive framework. Factors with diverging results, or those only examined in less than five studies have been excluded.

In order to assess the second research question, we investigated whether all constructs only have items assigned, that have the same code. We performed this analysis by creating a pivot table including all construct and item codes. The overview makes cases apparent, in which authors use different abstraction levels for constructs and items.

From an epistemological perspective, we make tacit knowledge explicit when writing our review. Following Schryen et al. (2015) our synthesis is based on already explicit domain knowledge. However, when we adopt a new perspective by including items in our analysis, we externalize previously tacit knowledge. The framework development combines explicit domain meta-knowledge into codified knowledge available for other researchers. Lastly, the identification of research gaps and inconsistent research results makes tacit domain meta-knowledge also explicit.

3.4 Analysis and Results

3.4.1 Factors Influencing the Acceptance of Autonomous Vehicles

We developed a comprehensive acceptance framework including congruent significant acceptance factors (constructs and items) from the analyzed publications to inform future research endeavors and practitioners. In order to build a solid framework, we only used constructs and items analyzed in at least five publications and with a clear tendency of a positive or negative significance. Factors excluded from the framework are listed in Table 1.

While several individual characteristics have not been assessed by many studies, the level of automation has not been extensively investigated using the included methodologies (regression, SEM, and utility models), either. Other forms of research, however, have shown a significant decrease in behavioral intention for higher levels of automation, which might be due to decreased perceived usefulness, ease of use, and safety (Hewitt et al. 2019; Rödel et al. 2014). Contrary to these findings, our analysis could not categorize perceived security as significant although the passenger's life can be at risk in case of a hacking attack. Thus, further research could analyze the relationship of perceived safety and perceived security.

	NOT analyzed in at least five publications	NOT showing a clear tendency of significance
Individual characteristics	Medical conditions, marital status, household Type, regular working times/flexible travel times, car ownership, parking constraints, technology experience, ADAS experience, emotional stability, desire for control, political attitude, agreeableness, extraversion, conscientiousness, carelessness, self-enhancement	Distances from home to X
Vehicle characteristics	Motion sickness, accessibility, level of automation, ethics, experiencing the AV, provided information	Perceived security, enjoyment, management of unforeseen situations
Policy/Society	Exclusive AV lanes, more urban space, facilitating conditions, image	-

Table 1. Acceptance Factors Excluded from the AV Acceptance Framework

The derived AV acceptance framework, shown in Figure 5, is broadly categorized into three areas: *Individual characteristics*, *vehicle characteristics*, and *policy/society*. The algebraic signs (+) or (-) added in parenthesis after each factor indicate if the majority of available studies identified the factor's influence as either positively significant or negatively significant. In order to underpin these results with more quantitative analysis, we also included the number of publications and the percentage split of positive significant, non-significant, and negative significant results for each acceptance factor.

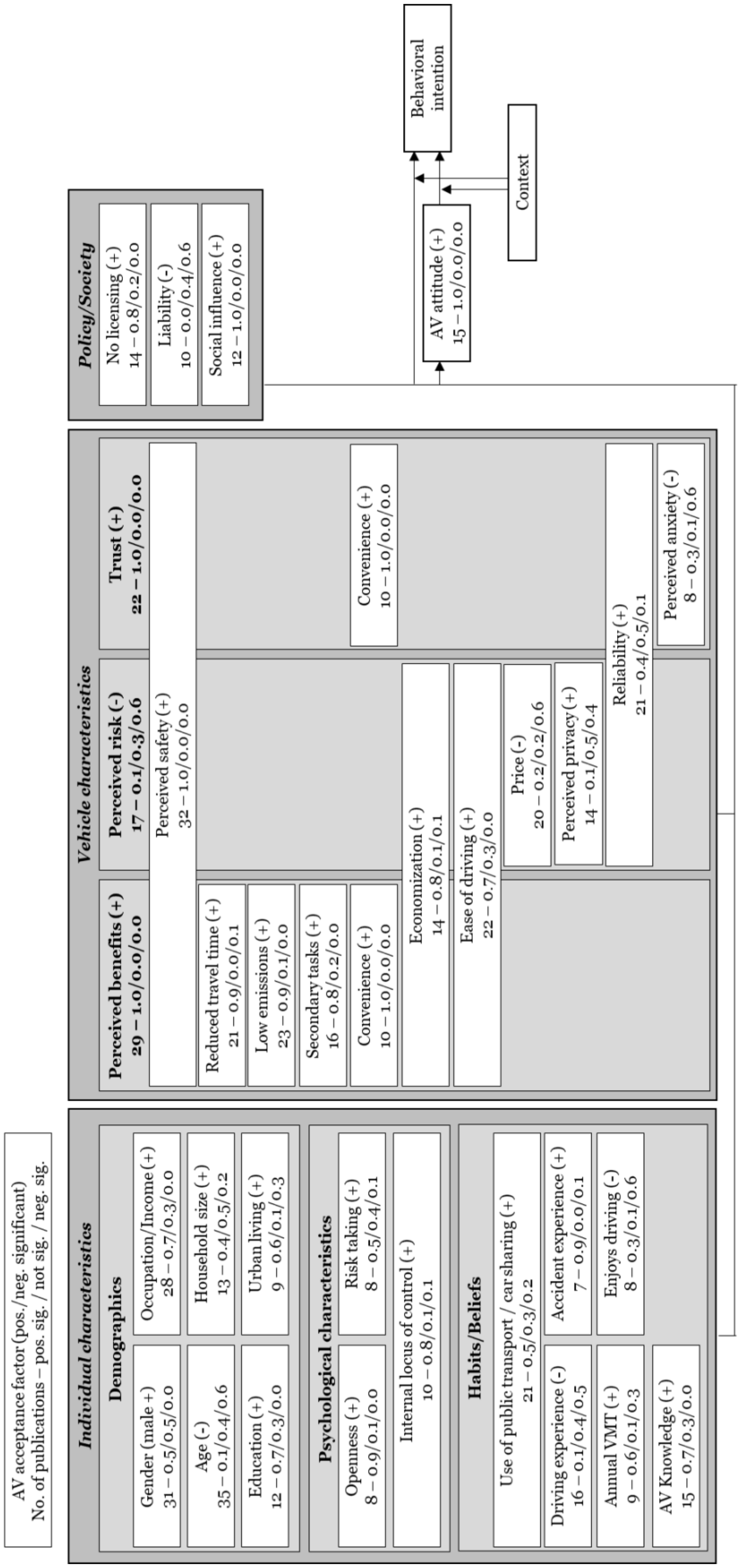

Figure 5. Significant Autonomous Vehicles Acceptance Factors

Individual characteristics can be split into demographics, psychological characteristics, and habits/beliefs. Young men, who have a high education and income living in a large household, are especially prone to be early AV adopters (Abraham et al. 2017; Hohenberger et al. 2016; Hudson et al. 2019; Wang and Akar 2019). Openness towards new experiences and an internal locus of control are further significant psychological predictors of AV adoption (Chen and Yan 2018; Motak et al. 2017; Spurlock et al. 2019; Woisetschläger 2016). While driving experience reduces the behavioral intention to use a self-driving car, accident experience increases the probability (Bansal and Kockelman 2018; Nazari et al. 2018; Raue et al. 2019; Shabanpour et al. 2018). Furthermore, technology savviness and AV knowledge increase the probability to choose an AV (Bennett et al. 2019; Hardman et al. 2019; Sener et al. 2019).

Vehicle characteristics are subdivided into perceived benefits, perceived risks, and trust since they emerge as the biggest clusters during our literature analysis. The framework in Figure 5 shows which items are related to which category with some factors like safety spanning across all subcategories since extant research classifies them as benefit, risk, and even trust-building factor. Other factors like economization or ease of driving, however, are not regarded as trust-building factor, but either as benefit when properly available or as risk when missing.

Perceived safety was assessed by 41 percent of the analyzed studies and thus the most discussed factor influencing AV acceptance and willingness to pay (Berliner et al. 2019; Lee et al. 2018b; Niranjan and Haan 2018). Related acceptance factors include perceived privacy, which, however, is mostly assessed on item level in the identified studies (Liu et al. 2019a; Panagiotopoulos and Dimitrakopoulos 2018). Convenience and ease of driving combined with the ability to perform secondary tasks influence consumer decisions positively (Koul and Eydgahi 2018; Lee et al. 2018b; Leicht et al. 2018; Wadud and Huda 2019). While less congestion and lower emissions might especially attract environmental friendly users (Wu et al. 2019; Yap et al. 2016), improved economy and higher prices will influence financial conscious users (Jiang et al. 2018; Liu et al. 2019e; Webb et al. 2019). Further vehicle characteristics that positively influence the behavioral intention are reduced travel time, high reliability, and driving ranges (Daziano et al. 2017; Hegner et al. 2019; Kaur and Rampersad 2018; Stoiber et al. 2019).

From a *policy/society* perspective, incentives from politics like no licensing requirements enable young or impaired people to use a self-driving car and demonstrably improve wide-spread AV adoption (Dong et al. 2017; Zhang et al. 2019). Exclusive AV-lanes and clear liabilities (e.g., with the car manufacturer) can affect the willingness to use a self-driving vehicle even further (Liu et al. 2019b; Shabanpour et al. 2017). Last, social influence is a significant influencing factor (Madigan et al. 2016).

Studies comparing the attitudes towards AVs before and after experiencing a ride in a simulator observed a positive effect of the system experience (Hartwich et al. 2018). A higher attitude in turn, positively influences the behavioral intention to use a self-driving car (Jing et al. 2019; Zhang et al. 2019). The context, however, also needs to be taken into consideration when assessing the acceptability of self-driving cars (Kaur and Rampersad 2018; Krueger et al. 2016; Lee et al. 2017). Payre et al. (2014) even identify contextual acceptability as the second most important factor following attitude to estimate the intention to use a self-driving car.

3.4.2 Critical Comparison of Constructs and Items

During the analysis of common acceptance factors, divergent constructs and items regarding policy and vehicle characteristics emerged. While we found variables regarding individual characteristics to be mostly consistent, we took a closer look into those papers explicitly outlining the items used to measure vehicle characteristics and policy elements. Despite this being only a limited set, we are able to highlight some crucial differences that are important to consider when evaluating the overall findings of extant AV acceptance research, and our contributions to this research stream.

			Ease of driving	Perceived safety	Reliability	Driving pleasure	Price	No licensing	Economization	Low emissions	Perceived privacy	Perceived security	Situation management	Reduced travel time	Secondary tasks	Convenience	Liability	Construct
Used as…	Item for	Perceived benefits	2	10	-	1	-	4	3	3	-	-	-	8	7	3	-	**19**
		Trust	-	4	9	-	-	1	-	-	-	2	1	-	-	1	-	**10**
		Perceived risks	1	3	6	3	4	-	1	-	4	4	4	-	-	-	4	**8**
	Construct		**15**	**5**	**5**	**4**	**3**	**2**	**2**	**2**	**2**	**2**	**2**	**1**	**1**	**1**	**1**	

Table 2. Construct and Item Usage Counted by Publication (N=30)

The overview in Table 2 demonstrates clearly, that almost all car-related characteristics are used both as items in some publications and as constructs in others. Furthermore, as already shown in Figure 5, some items are used for perceived benefits, perceived risks or trust, depending on the author. This makes current results difficult to compare and led us to include the item level in our above framework of AV acceptance factors.

Some factors like perceived security or the performance of secondary tasks (e.g., reading, sleeping, or watching a movie) are assessed more often as items of other constructs than as constructs themselves. As a result, the specific influence of these factors, for instance, secondary tasks, is diluted when measured as part of the construct of perceived benefits. This might lead to wrong interpretations in two ways: First, publications measuring perceived benefits with a diverging set of items are likely to report different effect sizes and significance levels. Second, influence factors just measured as items for other constructs might be crucial in understanding AV acceptance. However, this might not become explicit as other constructs would be strengthened.

These inconsistencies might stem from the context of TAM and UTAUT as underlying theoretical models. Many authors define perceived usefulness, for example, as "the extent to which consumers believe that using a particular technology system will enhance his or her job performance" in accordance with TAM (Davis et al. 1989, p. 986). Performance expectancy is mostly defined as "the degree to which an individual believes that using a (new) system will help him or her to attain gains in job performance" in accordance with UTAUT (Venkatesh et al. 2003, p. 447). Both definitions stem from an organizational context, where job performance is rather clearly defined. In the AV context, however, there is no common definition of performance or usefulness. This could explain why the items used for the measurement of this and other constructs like risks and trust diverge.

3.4.3 Identification of Possible Research Avenues

Autonomous vehicles present multiple opportunities to explore phenomena at the intersection of vehicle manufacturers, politics, and society. Especially the assessment of factors driving the acceptance of self-driving cars has been shown to be a challenging question explored by a large number of studies. In this paper, we present a number of common findings but also want to shed light on issues that we came across during our analysis that future AV researchers can tackle as they investigate these remaining challenges.

Although the society has many positive expectations towards autonomous vehicles, potential users also raised several concerns during qualitative interviews (compare Figure 2). Thus, it is important to specify the factors causing these negative perceptions and to define strategies how to improve it. Especially regarding the most discussed and significant factor, perceived safety, this could yield important insights for car manufacturers' research and development priorities.

During our analysis of AV acceptance factors, we realized that there are still potentially important aspects researched by only few researchers. For example, medical conditions could inform the willingness to use of impaired drivers. Furthermore, factors without a clear tendency of significance like perceived security could be a major influence factor not yet identified due to sampling variances. While the previous factors have been investigated in few studies, though, the political and social impact has been largely neglected so far. Further research should address potential levers shaping politics and public opinion and their impact.

This literature review aims at initiating a scholarly discussion about AV constructs and items, and represents a starting point for the research community to continue and advance the definition of context sensitive constructs and items to measure the acceptance of AVs. In order to arrive at a concrete definition of relevant AV acceptance factors including the related constructs and items, we invite the IS community to work on this challenge since suggesting solid construct definitions in the paper at hand would have diluted the focus of this review. This will allow further research to leverage explicit constructs with clearly associated items to measure the same latent variable.

Our review demonstrates that methodology and context matter considerably when exploring AV user acceptance (Langdon et al. 2018): Users deliberating the purchase of an AV will exemplify differing requirements than AV users in a public transport context. Furthermore, participants from survey-based studies purely state their intentions towards using an AV, which do not necessarily match actual behavior. Simultaneously, participants of "paper-based" studies might have very different perceptions of AVs leading to more variance in results compared to a more realistic laboratory setting. Accordingly, simulator studies try to provide an actual experience, which as of now however often fails to be very realistic for instance, when LCD displays are used to simulate a real ride (Cho et al. 2017). Lastly, studies utilizing actual cars cannot realistically assess level 5 automation, simply since this type of vehicle does not exist yet. In addition to that, the AVs used in some studies did not move faster than 8 km/h (Nordhoff et al. 2018c) leading to a reduced perceived usefulness. Hence, further research should combine and advance currently available methods to achieve a more realistic perspective.

As soon as the transportation and IS community understands which factors influence AV user acceptance, we do not need yet another acceptance model including an additional acceptance factor. It is more important to shift the focus towards elements influencing user satisfaction, e.g., by using a KANO analysis, which allows for a categorization into basic needs, performance needs, delighters as well as indifferent and reverse factors (Kano 1995). Starting there, research could examine which vehicle characteristics define the willingness to pay.

In summary, we present a succinct overview of our proposed research avenues in Table 3, covering the themes: Negative AV perceptions, limited research attention, diverging research results, construct identity fallacy, methodologies, and evolution of research focus.

Theme	We must overcome…	We need to…
Negative AV perception	• Providing a purely descriptive list of positive and negative AV perceptions	• Understand in depth what causes negative sentiments towards significant acceptance factors (e.g., regarding driving pleasure, security, and safety) (Ernst and Reinelt 2017; Salonen 2018) and how to improve respective car characteristics and associated user perceptions (Abraham et al. 2018)
Limited research attention	• Focusing acceptance research mostly on individual and vehicle characteristics • Preforming the majority of studies in the context of privately owned vehicles	• Assess potential impacts of policies and regulations (e.g., purchasing subsidies, guidelines permitting or prohibiting vehicles driving without passengers, licensing requirements, ethical guidelines for AV algorithms) (Brell et al. 2018; Hein et al. 2018; Karnouskos 2018) • Determine acceptance factors for other ownership models like public transport and shared vehicles with and without ride sharing
Diverging research results	• Contrary, ambiguous study results (Fraedrich and Lenz 2014) • Building future models only by adding additional constructs to TAM or UTAUT	• Focus future studies on factors not yet clearly identified as positive-, negative- or non-significant (e.g., urban living, annual vehicle miles traveled, usage of other means of transport, risk-taking preferences) (Földes et al. 2018; Woldeamanuel and Nguyen 2018) • Determine the explanatory power and parsimoniousness of research models by performing a meta-analysis (Chen and Yan 2018; Lee et al. 2018b)
Construct identity fallacy	• Missing comparability of research results (Larsen and Bong 2016) • Applying models from other contexts without adaption (Davison and Martinsons 2016)	• Clearly define what the AV research stream understands by benefits, risks, and trust-building constructs (Whetten 1989) • Be more explicit by using unambiguous constructs and items
Methodologies	• Pure survey-based assessments (König and Neumayr 2017) • Self-reported intentions' measuring (Nordhoff et al. 2018b)	• Use real cars or simulators when assessing users' perception (Brell et al. 2018; Hartwich et al. 2018) • Put emphasis on the measurement of actual usage (Haboucha et al. 2017; Xu et al. 2018b)
Evolution of research focus	• Focusing solely on user acceptance (Abraham et al. 2018) • Develop yet another acceptance model not significantly improving explanatory power	• Investigate, which AV characteristics do not only affect user acceptance but also user satisfaction (Pettersson and Karlsson 2015; Ro and Ha 2019) • Assess, for which features customers are willing to pay a premium (Hein et al. 2018)

Table 3. Proposed Future AV Acceptance Research Avenues

3.5 Discussion, Limitations, and Contributions

A fast growing number of studies assessing the AV acceptance of different user groups in different countries for different levels of automation in either private or public transport accumulates to a large body of knowledge. We organized this knowledge in an AV acceptance framework by performing a structured literature analysis.

Thereby, our work confirms the results of Becker and Axhausen (2017), who found young men living in urban environments and having technology experience as being positive about AVs. In addition to that, we identified traffic safety, even in unforeseen situations, and increased convenience, e.g., via smooth driving styles as relevant acceptance factors. Early adopters are interested in performing secondary tasks while driving, for example, watching a movie, performing some work, or just talking to others. Furthermore, the car should warrant the passengers' privacy. In contrast to Nordhoff et al. (2016), we included policy incentives like exclusive lanes or no licensing requirements in our analysis. They, on the contrary, focused just on individual and vehicle factors. Policies like updated licensing requirements could especially increase the usage intentions of impaired individuals, whereas clearly defined liabilities concern all users of autonomous vehicles.

However, extant research mostly neglects political and societal aspects when discussing user acceptance. Further under-researched fields and diverging research results have been outlined in Table 1. These diverging results are often based on different constructs and items used to assess potential acceptance factors. In order to advance AV research, we hope that our proposed research avenues will inspire some scholars to investigate the suggested areas and add transparency to AV studies by applying more concrete and context specific acceptance factors.

As with any extensive literature review performed by multiple researchers over a certain period of time, our review might not have spanned across all relevant pieces of knowledge or potentially lacked consistency between the two involved researchers. Preventive measures like a search protocol and regular sessions to discuss difficult decisions were pursued throughout the process, but the possibility of differing selections remains.

We decided to include both acceptance literature and willingness-to-pay literature in our review since they are closely related. On account of this, we do not consistently exclude factors affecting the willingness to pay but not necessarily the acceptance when creating our framework. Researchers interested in a distinction of studies assessing intention to use or willingness to pay can refer to Table 12 in the Appendix.

Our work has a number of unique contributions, compared to other systematic literature reviews. By developing a very comprehensive acceptance framework, we converted available meta-knowledge into domain knowledge which can readily be used for further research (Schryen et al. 2015). Our approach can be distinguished from extant work as our analysis demonstrates a higher granularity through the inclusion of assessed items. Thus, researchers and practitioners can easily extract what actually influences the acceptance of self-driving vehicles and develop improved AV acceptance theories based on our research. From a practitioners' perspective, car manufacturers can push their efforts towards areas that are most important for user acceptance as well as towards areas where today's user perceptions are foremost negative. Policymakers can recognize the urgency with which they should define regulations regarding AV usage on public streets, including exclusive lanes, licensing requirements, and liabilities, which all have been proven to influence AV acceptance significantly.

Moreover, current AV acceptance studies are difficult to compare. As long as researchers do not use the same constructs' abstraction levels when investigating AV acceptance, practitioners cannot use the outcomes, for example, for strategical project prioritization, and researchers cannot build on each other's results (Cooper 1998). Consequently, our literature review provides transparency concerning the operationalization and measurement of acceptance factors and gives new impulses to a more thorough debate about construct definitions and items used to explain and quantify AV acceptance. We hope that our call for more accuracy encourages researchers to not simply apply well-known constructs from other contexts, but adapt them to the specific opportunities and constraints that the AV context provides when proposing new acceptance models. In this regard, future meta-analyses could provide further valuable insight into the effect strength of constructs and the appropriateness of extant research models.

Furthermore, we are the first proposing a cross-sectional research agenda for AV acceptance research. In Table 3, we outline specific potential research areas from a content-, method-, and focus-wise perspective. We make implicit research gaps explicit by highlighting areas in the body of knowledge where consistent views are missing or that have only received limited attention (Cooper 1998). By presenting these areas, which need more research attention, we took an important step in guiding future research within this scattered young research stream.

4 Paper B: What Matters Most

Title

What Matters Most – A Meta-Analysis of Automated Vehicles Acceptance Studies

Authors

Jennifer Wiefel, Technical University of Darmstadt, Germany

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Abstract

In recent times, research has put much effort into investigating the factors relevant to the acceptance of automated vehicles (AVs). In order to identify the key influencing factors, we combine findings from extant literature in a meta-analysis assessing the main drivers of the behavioral intention to use automobiles with automated driving features. The analysis spanning 51 articles identifies attitude, perceived usefulness, efficiency, trust in AVs, safety, and subjective norms to correlate most strongly with the behavioral intention to use an automated car. On top of that, we analyze the moderating effects of design choices made in the considered primary studies. We investigate the influence of the study's location, the vehicle's level of automation, the ownership model, and applied methodology on the behavioral intention. Thereby, we identify moderating effects for almost all design characteristics. Our meta-analysis helps researchers and practitioners to determine the most relevant AV acceptance factors, and by conducting the moderator-analysis, we pave the way towards a more careful design of future studies.

Keywords

Automated Vehicles, Acceptance, Intention to Use, Meta-Analysis, Moderator-Analysis

4.1 Introduction

> *"I hear that human error is a major factor in driver crashes, but I would hate [...] to give up control of the vehicle. I just couldn't trust the technology."* (Musselwhite 2019, p. 96)

Comments like this illustrate the ambivalent user perspective on automated vehicles (AVs) and the need to understand, in more depth, the factors influencing the behavioral intention (BI) to use automated cars. People being interviewed about AVs often state both various hopes and concerns regarding this new technology. While one of the most prevalent topics is safety, the interviewees also see other opportunities arising with the introduction of self-driving cars:

- Increased mobility for the old and impaired: *"[Self-driving] vehicles could also help kids get to school, and elderly and disabled persons get around more."* (Bjørner 2015, p. 10)
- Higher sustainability: *"I think they could reduce pollution in London. I think they could also potentially have the ability to reduce congestion."* (Fernandez-Medina and Jenkins 2017, p. 8)
- Decreased operating costs: *"It would definitely minimize the operational costs [...], you can use the money saved for better purposes."* (Salonen and Haavisto 2019, p. 7)

On the contrary, people are anxious when they think about the adoption of AVs. Reasons for their concerns are:

- Missing legal regulations: *"This car is not a technological problem, but a legal one. Whose fault is it, then, if the car causes an accident? The driver's or Google's?"* (Fraedrich and Lenz 2016, p. 632)
- Privacy risks: *"I need to know, say with the insurance company, what exactly they're monitoring, what are they tracking?"* (Linehan et al. 2019, p. 9)
- Cybersecurity: *"I don't want to let the controls out of my hands! Certainly not to a computer that can be manipulated and hacked, just like PCs and cellphones!"* (Fraedrich and Lenz 2016, p. 633)

To understand why people accept or reject new technologies has proven itself to be one of the most challenging questions in Information Systems (IS) research (Swanson 1988). When Davis (1989) developed the technology acceptance model, technologies were designed to automate administrative and transactional tasks. Nowadays, digital innovations like wearables or smart homes have the potential to change our every day's personal life. Especially AVs are different from earlier technologies as the usage of AVs is a matter of personal safety (Bruckes et al. 2019) posing the question if former acceptance factors still hold to be relevant. As various factors influence the decision to use AVs in private contexts, scholars have increasingly published research results concerning relevant acceptance factors (Figure 6).

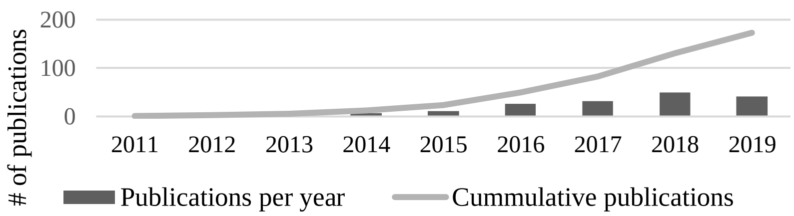

Figure 6. Published Research Articles regarding the Acceptance of AVs (as of June 2019)

While Rödel et al. (2014) leverage the constructs of the Technology Acceptance Model (TAM) (Davis 1989), other researchers use models like the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al. 2003), the Theory of Planned Behavior (TPB) (Ajzen 1991), or the Car Technology Acceptance Model (CTAM) (Osswald et al. 2012) to investigate AV acceptance. Further publications regularly enrich these models with additional constructs leading to a large pool of factors that potentially influence the users' decision of accepting or rejecting automated vehicles.

With the growing number of corresponding research articles, Hein et al. (2018, p. 3) demand "future studies [to] integrate these findings". Several literature reviews already gather and organize existing knowledge (Becker and Axhausen 2017; Bornholt and Heidt 2019; Nordhoff et al. 2016). But, despite their valuable contributions, these reviews have weaknesses which we aim to address in this article.

Literature reviews solely balancing significant positive results against significant negative ones might come to wrong conclusions (Hunter and Schmidt 2004) because even two studies reporting the same effect size can vary in significance due to their sample sizes. Because of this, "a focus on significance has often misled us in traditional narrative reviews of the literature" (Rosenthal and DiMatteo 2001). Furthermore, the literature reviews mentioned above do not report any aggregated effect sizes, although this is what matters when comparing the strength of multiple influence factors (Borenstein 2009). Accordingly, we are the first who leverage a quantitative meta-analysis to identify real effect sizes across all available publications. Our analysis will provide new insights regarding the relevance of AV acceptance factors as we answer our first research question:

To which extend do extant acceptance factors influence the behavioral intention to use AVs?

Current research investigates AV acceptance in a wide variety of contexts: Participants from multiple countries evaluate their intention to use AVs with diverging automation levels and ownership models. This has led to context-specific results (Cavoli et al., 2017). As Davison and Martinsons (2016) stress the importance of considering the context of empirical research to evaluate the validity of findings and conclusions, we want to understand how the adoption intention is influenced by study context. We contextualize earlier research and create a new perspective on potentially conflicting results by answering our second research question:

How are the most relevant AV acceptance factors moderated by study design?

To answer our research questions, we conduct a meta- and moderator-analysis adhering to the steps assembled by Card and Little (2016). To our knowledge, there does not exist any other AV meta-analysis so far, although King and He already found meta-analysis to be underutilized in IS research in 2005. Comparing the results from multiple primary studies allows us to make general conclusions about which factors are most relevant (Jak 2015) and to obtain new insights from those results (Glass 1976).

The remainder of this paper is structured as follows: We introduce relevant literature regarding automated vehicles before describing the methods applied for the literature search and analysis process. We present our population effect size calculations and determine the influence of the associated study design on those. To complement our work, we discuss the overall results critically and debate our work's limitations and contributions.

4.2 Related Literature

In order to have a common understanding of AVs, we adhere to the definition of the Society of Automotive Engineers' (SAE International 2018) levels of driving automation. They categorize automated vehicles using six consecutive levels of automation (LoA), with levels 0-2 providing driver support features and levels 3-5 automated driving features. In line with this definition, we consider levels 3-5 as automated vehicles for our analysis. With level 3, the driver still needs to take over control whenever the car requires. A vehicle with LoA 4 can drive autonomously in certain traffic conditions, e.g., on highways, whereas fully automated vehicles (LoA 5) can handle all traffic situations on their own.

With increasing levels of automation, users hand over more control to the vehicle. This leads to changing perceptions regarding the perceived behavioral control and trust in AVs (Hewitt et al. 2019; Rödel et al. 2014). As perceived behavioral control (Chen and Yan 2018; Jing et al. 2019) and trust (Choi and Ji 2015; Liu et al. 2019a) influence the BI to adopt automated cars, and changing LoAs affect the perception of those, we assume that varying LoAs serve as moderator for AV acceptance.

The automotive industry currently only produces vehicles with LoA 3 and 4. Hence, there are no level 5 vehicles available for research purposes (Walker 2019). This condition forces scholars to leverage paper-based surveys or simulator studies when assessing the intention to use fully automated cars. In the first instance, participants can have diverging ideas about AVs or receive descriptions/video material potentially influencing their perception (Charness et al. 2018). In the second case, simulators might not be able to provide a realistic setup, e.g., when monitors and computer consoles are used (Cho et al. 2017). In cases where researchers use real cars to test the acceptance of automated driving, the vehicles sometimes handle only certain parts of a test track autonomously (Hartwich et al. 2019) or drive with reduced speed due to safety reasons (Nordhoff et al. 2018c). As experience influences the adoption decision (Qu et al. 2019), we believe that the diverging contexts created by the chosen methodology will moderate the influence of acceptance factors on the BI to adopt automated vehicles.

Scholars evaluate different ownership models in the AV literature stream: Car ownership, car/ride-sharing, and public transport. While all of those studies investigate the acceptance of automated driving, earlier research lets us assume that the ownership model acts as a moderator. For example, users of car-sharing services rate the importance of specific characteristics in their choice of transportation means differently than car owners (Prettenthaler and Steininger 1999). Furthermore, attributes most effective in encouraging car users to switch to public transport are, in addition to the reliability and frequency of the service, largely affective and tied to individual perceptions and contexts (Redman et al. 2013).

To identify if the study location influences the acceptance of automated vehicles, current surveys from industry assess the willingness to use AVs in Asia, Europe, and the USA. The results indicate acceptance levels twice as high for Chinese consumers in comparison to European or American users (Holland-Letz et al. 2018). In line with this result, respondents from more developed countries are less comfortable with their vehicle transmitting data (Kyriakidis et al. 2015) and the GDP per capita of the respondents' country negatively correlates with the general AV acceptance (Nordhoff et al. 2018b). Cultural dimensions (Hofstede et al. 2005) could explain these differences as a moderator.

4.3 Methods

Within the next sections, we describe the steps followed during the literature search process, the coding of effect sizes and moderators, and the calculations conducted during the meta- and moderator-analysis.

4.3.1 Literature Search Process

As a meta-analysis is a structured literature review, including further quantitative analysis (Rosenthal 1995), we conducted a literature search following the steps proposed by Okoli and Schabram (2010).

For our literature search, we explicitly did not limit our search to any specific periodicals because highly rated journals and conferences typically obviate publications of non-significant results or low effect sizes (Rosenthal 1979). We chose academic databases containing articles from transportation, behavioral science, and information science (Levy and Ellis 2006): ACM Digital Library, AIS Electronic Library, EBSCOhost Business Source Primer, IEEE Explore Digital Library, Science Direct, and Web of Science. Transportation researchers examine, among other things, varying adoption scenarios or policy requirements. At the same time, social sciences and especially IS research is interested in the human-computer interaction and user acceptance of autonomous driving.

In June 2019, the search term consisting of synonyms for the terms automated, vehicle, and acceptance[3] resulted in 5,138 articles. To reduce the large number of hits, we defined precise inclusion and exclusion criteria (Webster and Watson 2002). We kept publications (1) written in English, (2) having its focus on AV acceptance factors in private transportation contexts, and (3) having the BI as the dependent variable. We excluded papers (1) focusing on the acceptance of other road users (pedestrians, bicyclists), (2) research investigating automation levels 0-2, and (3) studies determining how to improve certain acceptance factors (e.g., trust in AVs).

Applying the inclusion and exclusion criteria during the title and keyword screening let us remove articles focussing on other traffic participants or non-automotive vehicles like (under-) water and aerial vehicles, autonomous trucks, or self-driving wheelchairs. Furthermore, we removed technical publications aiming to optimize topics like sensor recognition, platooning,

[3] (automated OR autonomous OR self-driving OR driverless) AND (vehicle(s) OR car(s) OR driving) AND (“behavioral intention” OR accept* OR adopt* OR “willingness to use”)

or cruise control. We also expelled manuscripts from unrelated areas like health care. As a result, we already excluded 4,675 search results.

From the remaining papers, 272 abstracts could not meet the above inclusion and exclusion criteria. We especially removed articles focussing on connected vehicles, driving assistant systems, AV driving styles, or economic models. Last, we removed 124 full texts which did not meet the above criteria. At this point, the studies typically did not have BI as the dependent variable or assessed how to improve specific factors that influence user acceptance. Overall, we retained 67 publications.

From these articles, we excluded literature reviews, qualitative, and descriptive research. Usually, we would also have needed to expel multivariate analyses since a meta-analysis is best suited to compare bivariate effect sizes (Hunter and Schmidt 2004). But since Peterson and Brown (2005) argue to consider also articles reporting multivariate effect sizes to reduce the sampling error, we decided to include publications reporting beta coefficients from regression analysis and path coefficients from structural equation modeling (SEM). Although the required effect size transformations might have led to reduced accuracy, the inclusion allowed us to analyze a 25% larger set of publications and thereby to increase the overall precision of our population effect size estimations (Peterson and Brown 2005).

For the so remaining 36 articles, we performed multiple iterations of reference forward- and backward searches until we could not find any additional publications that fulfilled our inclusion criteria (Levy and Ellis 2006). As the reference search also revealed master’s thesis, reports, and unpublished articles, this step has led to an overall search result of 74 articles.

Poor-quality studies are one of the main validity threats of meta-analyses (Sharpe 1997). Because we found many studies not published in peer-reviewed journals, we conducted a quality assessment. The exclusion of bad quality studies has proven itself to be advantageous over coding study quality as a moderator (Valentine 2009). For the evaluation, we used the quality criteria developed by Malhotra and Grover (1998). We only kept studies conforming to the majority of their tests comprising the unit of analysis, sampling procedure, measurement and triangulation, validity, and statistical conclusion. The 51 remaining studies built the final set to be included in our meta-analysis (see Table 13 in the Appendix).

A single rater performed the evaluation process. After we defined the inclusion and exclusion criteria, the assessor was confident in selecting suitable publications. Also, when rating the quality of the papers, Malhotra and Grover (1998) offered clear rules making it unnecessary to discuss the inclusion with multiple raters.

4.3.2 Coding of Study Characteristics and Effect Sizes

For our analysis, we extracted the exact terms of constructs used in the selected literature and grouped similar ones using pattern coding (Saldana 2009). We reverse coded certain elements with opposite meanings, e.g., perceived safety and perceived safety risk to obtain consistent effect sizes. To ensure the replicability and reliability of our coding process, we coded the constructs twice and revised deviating allocations (Wilson 2009). Essential code definitions and construct examples are given in Table 4 on the next page.

Next, we decided to use the correlation coefficient (r) as primary effect size for our analysis as it is easier to interpret than other measures (Glass et al. 1981). In cases where researchers report other bivariate effect sizes, we transformed them into correlations Card and Little (2016, p. 97). For subsequent calculations, we also coded the studies' sample size and the reliability of each variable using the reported Cronbach's alpha coefficient.

As described earlier, we included multivariate beta coefficients (β) in our analysis because missing data is "the most pervasive problem in large scale meta-analyses" (Hedges 1992). To transform beta coefficients to correlation coefficients simulations have shown that $r_0 = 0.98\beta + 0.05x$ produces a close fit with x equalling 1 when β is positive and 0 when β is negative (Peterson and Brown 2005). For the inclusion of SEM path coefficients, Heise (1969) and Mitchell (1969) propose an approach based on iterative matrix multiplications.

In addition to the effect sizes, we coded potential moderators: Continent, level of automation, ownership model, and methodology (see Table 13 in the Appendix) as existing research lets us presume that these design factors might influence the research results.

During the coding process, we derived the continent from the study participants' countries or used the authors' countries as a fall-back. In most cases, the authors stated the ownership model like car ownership, car/ride-sharing, or public transport. We only coded those studies as "car ownership" where the fact was either clearly stated or where the items also included car purchase intentions. All unassignable studies have not been included in our meta-analysis. Regarding the automation level, the articles either contained exact LoAs, or we deduced them from the AVs' capabilities in line with the SAE automation definitions. Finally, we coded the methodology. Thereby, we distinguished between real cars, simulator studies, screened pictures or movies, and paper-based surveys. We could extract this information from the articles' methodology section.

Code	Definition	Example Constructs
Attitude	An individual's positive or negative feelings (evaluative effect) about performing the target behavior (Fishbein and Ajzen 1975)	Affect, affective satisfaction, attitude, attitudes toward self-driving vehicles, attitudes toward the behavior, **negative affect**, positive affect, positive affective attitudes
Efficiency	Pertains to the performance of the automated shuttle in comparison with existing travel modes (Nordhoff et al. 2018c)	Efficiency, perceived effectiveness, shuttle effectiveness, time benefit
Subjective norm	The person's perception that most people who are important to him think he should or should not perform the behavior in question (Fishbein and Ajzen 1975)	Group norm, personal norm, social influence, social norm, social trust, subjective norm
Perceived usefulness	The extent to which consumers believe that using a particular technology system will enhance his or her job performance (Davis et al. 1989)	Benefit, benefits in usefulness, benefit perception, helpfulness, performance expectancy, **performance risk**, perceived benefit, perceived usefulness
Safety	The degree to which a person believes that an autonomous car is able to bring him/her safely to his/her destination, i.e., without any accidents (Ernst and Reinelt 2017)	Perceived safety, **perceived safety risk**, perceived traffic safety, safety and security perceptions, safety benefit, **safety risk**, (trust and) safety
Trust	The attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability (Lee and See 2004)	Functional trust, perceived trust, trust, trust in self-driving cars, trust: functionality, trust: helpfulness

Table 4. Example of Codes Used for Meta-Analysis - Reverse Coded Items are Printed Bold

4.3.3 Data-Analytic Strategy

As a first step, we excluded correlations that have been assessed in only one publication. For those, we could not determine any overarching population effect sizes, heterogeneity, or moderating effects.

Before calculating the population effect sizes, we corrected the reported correlations for their respective measurement error because variables with low reliability attenuate the correlation (Hunter and Schmidt 2004). The subsequent analysis could have been done either using the corrected correlation coefficient r_c or a Fisher's transformed coefficient Z_r. While some researchers argue that r_c leads to better results (Hall and Brannick 2002; Hunter and Schmidt 2004), simulations have proven that Z_r tends to be more accurate (Hafdahl and Williams 2009). A reason might be that the distribution of r_c around the population mean is skewed, whereas the distribution of Z_r is symmetric which is desirable for combining and comparing effect sizes (Schulze 2004). Hence, we decided to use Z_r for our calculations.

$$Z_r = \frac{1}{2}\ln\left(\frac{1+r_c}{1-r_c}\right) \qquad (1)$$

We first determined the fixed effects weighted mean effect size. For the calculation of the mean effect size, we weighted Z_r with the inverse of the standard error. This weighting was based on the assumption that studies with many participants show lower imprecisions (Card and Little 2016). Afterward, we excluded all fixed effect sizes that were non-significant or underpowered from further analysis.

Only if the remaining fixed effect sizes had been homogeneous, we could have interpreted them as population effect sizes. We evaluated the homogeneity using the statistic Hedges' Q. Its value represented the amount of heterogeneity in effect sizes among studies included in our meta-analysis (Hedges and Olkin 2014).

$$Q_{total} = \sum(w_i {Z_i}^2) - \frac{(\sum(w_i Z_i))^2}{\sum w_i} \tag{2}$$

If the heterogeneity were significant, a moderating effect would likely exist, and we would need to apply a random-effects model conceptualizing the population distribution of effect sizes rather than a single effect size (Card and Little 2016). The use of random-effects models allowed us to generalize the calculations beyond the included set of articles to a general population (Hedges and Vevea 1998).

Therefore, we introduced new standard errors and weightings, which were based on the population variability in effect sizes. We calculated the respective random effects weighted mean effect sizes and determined the significance of the weighted mean effect sizes using a normal distribution. The corresponding two-tailed post-hoc power was calculated using the point biserial correlation model in GPower 3.1 (Buchner et al. 2019).

Last, the Z_r values needed to be back-transformed to population correlation coefficients, which allowed a better interpretation of the results.

Following our meta-analysis, we conducted a moderator-analysis to evaluate if and how the study design influences the BI to use an automated car. We compared the heterogeneity within and between certain groups of studies (Lipsey and Wilson 2001). Therefore, we calculated the heterogeneity using Equation 2 for each manifestation of a moderator, i.e., for the moderator continent, we calculated the heterogeneity for studies conducted in Asia, Europe, and the USA individually. Then we subtracted the sum of the calculated heterogeneity values of the respective groups from the total heterogeneity to determine the remaining heterogeneity between those groups.

$$Q_{between} = Q_{total} - \sum_{g=1}^{G} Q_{total_g} \tag{3}$$

The statistical significance of the between-group heterogeneity was evaluated by considering $Q_{between}$ in a χ^2 distribution. If the heterogeneity between groups was large enough, a moderating effect was present (Card and Little 2016).

4.4 Results

In the following sections, we present the results of our meta- and moderator-analysis. We calculate effect sizes and identify moderating study design characteristics.

4.4.1 Meta-Analysis

We first excluded factors from further analysis that were only analyzed in a single primary study[4]. Then, we computed the weighted mean effect size for all coded factors correlating with BI by using a fixed-effects model. Some effect sizes were either non-significant or underpowered[5]. Consequently, we did not consider them in the following steps of our analysis.

In the fixed-effects model, the majority of factors were significantly heterogeneous. Thus, the fixed effects weighted mean effect sizes did not represent the population effect sizes. But, as we had the objective to draw conclusions for the entire population from the available set of publications, we calculated the weighted mean effect sizes using a random-effects model (Hedges and Vevea 1998).

Table 5 outlines the results of the random-effects model. We calculated the weighted mean effect sizes and their respective confidence intervals. With the random effect model, the standard error became larger based on the extent of population variability, and thus the confidence intervals also got wider. Because of this, some correlations, which were significant in the fixed-effects model, were non-significant in the random-effects model, e.g., privacy.

For six relations, we could identify high population effect sizes with correlation coefficients being larger than 0.5 (Cohen 2013): Attitude, perceived usefulness, efficiency, trust in AVs, safety, and subjective norms.

[4] Cybersecurity, doing other things while driving, facilitating conditions, transparency, legality, liability, environmental concern, nationality, means of transportation, disability, car ownership, number of children

[5] Age, perceived driving control, place of living, likes driving, sensation seeking

Category	Factors correlating with behavioural intention	# of corre-lations	Total sample size	Random effects weighted mean effect size	Lower bound conf. intervall	Upper bound conf. intervall	Significance	Power
Attitude	**Attitude**	**13**	**5806**	**0.68**	**0.57**	**0.76**	**0.000**	**1.000**
	Willingness to pay	3	1604	0.44	0.33	0.54	0.000	1.000
Vehicle characteristics	*Environmental benefits*	*2*	*585*	*0.63*	*-0.86*	*0.99*	*0.310*	*1.000*
	Perceived usefulness	**28**	**12886**	**0.61**	**0.48**	**0.71**	**0.000**	**1.000**
	Efficiency	**3**	**2102**	**0.53**	**0.22**	**0.74**	**0.002**	**1.000**
	Trust in Avs	**14**	**6999**	**0.52**	**0.35**	**0.66**	**0.000**	**1.000**
	Safety	**12**	**5750**	**0.51**	**0.31**	**0.66**	**0.000**	**1.000**
	Ease of use	17	5982	0.47	0.35	0.57	0.000	1.000
	Enjoyment	7	3016	0.47	0.24	0.65	0.000	1.000
	Reliability	5	3135	0.31	0.09	0.50	0.010	1.000
	Convenience	*5*	*2515*	*0.27*	*-0.11*	*0.58*	*0.147*	*1.000*
	Symbolic value	*7*	*3551*	*0.17*	*-0.15*	*0.45*	*0.230*	*1.000*
	Experiencing the AV	2	1089	0.13	0.09	0.17	0.000	0.991
	Privacy	*4*	*1410*	*0.08*	*-0.09*	*0.25*	*0.265*	*0.854*
	Costs	*5*	*4235*	*-0.22*	*-0.52*	*0.14*	*0.194*	*1.000*
	Perceived risk	12	9445	-0.36	-0.52	-0.18	0.000	1.000
	Anxiety	4	2404	-0.45	-0.51	-0.38	0.000	1.000
Political factors	**Subjective norms**	**18**	**6518**	**0.58**	**0.42**	**0.70**	**0.000**	**1.000**
	Licensing	2	1927	0.45	0.41	0.49	0.000	1.000
	Ethics	*2*	*1839*	*0.41*	*-0.05*	*0.73*	*0.085*	*1.000*
Demographics/ personality	*Locus of control*	*11*	*4351*	*0.30*	*-0.03*	*0.57*	*0.080*	*1.000*
	AV knowledge	8	6959	0.27	0.15	0.39	0.000	1.000
	Attitude Towards Technology	4	2231	0.24	0.14	0.33	0.000	1.000
	Openness	6	2361	0.20	0.09	0.31	0.001	1.000
	Education	*2*	*1398*	*0.17*	*-0.18*	*0.49*	*0.251*	*1.000*
	Accident experience	*2*	*1362*	*0.16*	*-0.02*	*0.33*	*0.089*	*1.000*
	Gender	13	12276	0.08	0.04	0.12	0.001	1.000
	Driving experience	*4*	*7318*	*0.08*	*-0.02*	*0.18*	*0.126*	*1.000*
	Desire of control	4	1450	-0.12	-0.22	-0.01	0.035	0.996
	Income	*5*	*13199*	*-0.13*	*-0.53*	*0.33*	*0.347*	*1.000*

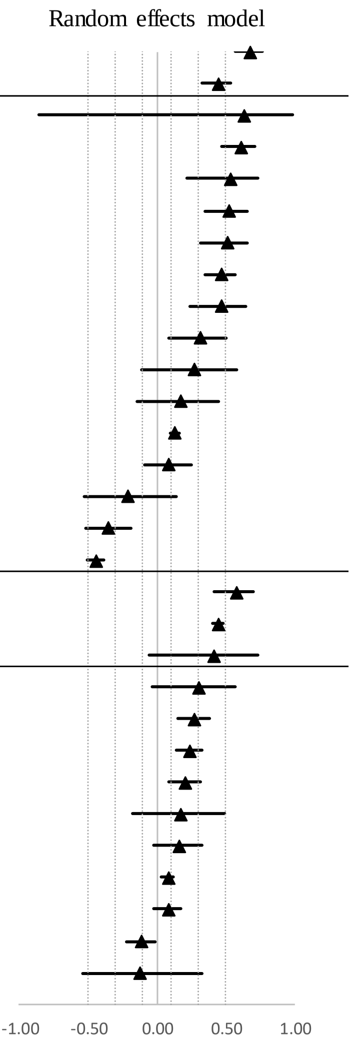

Table 5. Random Effects Model -
Strong Effect Sizes are Printed Bold, Non-Significant ones are Printed Grey Italic

Regarding the vehicle characteristics, perceived usefulness correlates most strongly with BI ($r = 0.61$). Efficiency ($r = 0.53$), trust in AVs ($r = 0.52$), and safety ($r = 0.51$) are also relevant when determining the intention to adopt automated cars. Environmental benefits ($r = 0.63, n.s.$), however, could not be identified as a significant factor, although the calculated effect size was the largest. The analysis proved the influence of subjective norms ($r = 0.58$) to be more important than licensing requirements ($r = 0.45$). While the person's openness ($r = 0.20$) and AV knowledge ($r = 0.27$) correlate positively with BI, gender ($r = 0.07$) does only have a minor impact on the users' adoption decision. Furthermore, the locus of control ($r = 0.30, n.s.$) does not have a significant influence on the BI to use an AV.

4.4.2 Moderator-Analysis

We conducted the moderator-analysis for those six constructs having a significant and large effect size (attitude, perceived usefulness, efficiency, trust, safety, and subjective norms) and evaluated four potential moderators (continent, level of automation, ownership model, and methodology).

We distinguished three **continents** where most studies took place: Europe, USA, and Asia. Our analysis has proven that the continent has a moderating effect on all constructs except efficiency. For this factor, we cannot testify a moderating effect as our literature search did not reveal any primary studies from the USA or Asia. Attitude correlates most strongly with BI in Europe ($r = 0.77$), whereas the perceived usefulness is most important for people living in the USA ($r = 0.68$). Perceived trust in AVs is most relevant in Asia ($r = 0.73$), and perceived safety correlates most strongly with BI in the USA ($r = 0.75$). In Europe, the correlation of subjective norms with BI ($r = 0.55$) is significantly lower than in other areas of the world ($r = 0.61$).

The **level of automation** acts as moderator for the correlation of BI with attitude, trust, efficiency, and safety. Although perceived usefulness seems to correlate less for level of automation 5 ($r = 0.57$), the analysis revealed that a considerable amount of heterogeneity is within the studies investigating LoA 5, so that the remaining heterogeneity between groups is considerably small, making the LoA not a moderator for perceived usefulness. Opposed to this, perceived safety ($r = 0.69$), efficiency ($r = 0.65$), and subjective norms ($r = 0.58$) correlate more with BI as the LoA increases.

The analysis confirms that the **ownership model** acts as a moderator for all six constructs. Thereby attitude ($r = 0.30$), perceived usefulness ($r = 0.50$), efficiency ($r = 0.27$), trust in

AVs ($r = 0.18$), and subjective norms ($r = 0.38$) correlate least with BI for automated public transport usage.

The **methodology** is a moderator for all constructs, too. The correlation of attitude with the BI is much higher in studies leveraging questionnaires ($r = 0.73$) and pictures/movies ($r = 0.71$) than in studies using simulators ($r = 0.49$) or real cars ($r = 0.42$). Perceived usefulness appears to be least influencing in simulator studies ($r = 0.49$), whereas the efficiency has a lower impact in real cars ($r = 0.27$) than in paper-based set-ups ($r = 0.65$). Both safety ($r = 0.16$) and subjective norms ($r = 0.30$) have only a minor influence in simulator studies.

Overall, we need to emphasize that the moderating effects of the ownership model, level of automation, and the methodology are strongly related and influence each other. Studies investigating car ownership tend to use paper-based surveys with higher LoAs, whereas studies concerning public transport use more often real cars having lower LoAs. Hence, it is difficult to state conclusively, which moderator has the strongest effect (Card and Little 2016).

Moderators	**Attitude**	**Perceived usefulness**	**Efficiency**	**Trust**	**Safety**	**Subjective norms**
Continent	yes	yes	no	yes	yes	yes
Europe	0.77	0.59	0.60	0.42	0.66	0.55
USA	0.70	0.68	-	0.57	0.75	0.61
Asia	0.72	0.54	-	0.73	0.63	0.61
Level of Automation	yes	No	Yes	Yes	Yes	No
3	0.66	0.68	-	0.66	0.43	0.52
4	0.81	0.67	0.27	0.48	0.62	0.57
5	0.69	0.57	0.65	0.67	0.69	0.58
Ownership model	yes	Yes	Yes	Yes	Yes	Yes
Private cars	0.78	0.52	0.65	0.51	0.72	0.71
Car/Ride Sharing	0.77	0.62	-	0.40	0.57	0.59
Public Transport	0.30	0.50	0.27	0.18	-	0.38
Methodology	yes	Yes	Yes	Yes	Yes	Yes
Questionnaire	0.73	0.61	0.65	0.61	0.66	0.59
Picture/Movie	0.71	0.63	-	0.54	0.75	0.62
Simulator	0.49	0.49	-	0.44	0.16	0.30
Real car	0.42	0.63	0.27	0.62	0.57	0.49

Table 6. Moderator-Analysis – Existence of a Moderating Effect (yes/no) and Correlation with Behavioral Intention per Moderator Manifestation

4.5 Discussion

The objective of our analysis was to investigate which factors influence the adoption of automated vehicles most and how the study design moderates these factors.

Attitude. Attitude has the highest effect size ($r = 0.68$) and is thus most relevant for the adoption of autonomous driving. Our moderator-analysis revealed that the correlation between attitude and BI is highest in Europe. This is especially interesting as most European studies are conducted in Germany, whose inhabitants are stereotypically classified as car lovers (Schulz and Haerle 1995), but Tennant et al. (2019) show that respondents' enjoyment of driving is associated with AV perceptions that are more negative. Similarly, respondents' technological optimism leads to positive perceptions regarding AVs (Tennant et al. 2019). Whereas the USA, for which the correlation of attitude and BI is lowest in our moderator-analysis, scores highest in a technology readiness assessment (Yoo et al. 2018).

A reason for the small effect size of attitude in simulators and real cars might be that participants of paper and video-based studies have higher expectations towards the ability of AVs. Experiencing the simulator or real car might lower the attitude scores based on the presence of more realistic capabilities. The own experience superposes the influence of information provided up-front (Hartwich et al. 2019).

Perceived usefulness. Regarding the car characteristics, perceived usefulness shows the strongest effect on BI. This result confirms, again, that constructs from traditional acceptance models like TAM are still able to predict the adoption of new IT, especially if the usage is voluntary (Wu and Lederer 2009). A reason for the validity of the construct perceived usefulness could be that improved "job performance" as mentioned in Davis' (1989) original definition is not clearly defined in an automotive context. The construct identity fallacy leads to the usage of divergent items when measuring the perceived usefulness of AVs (Bornholt and Heidt 2019) and allows many study participants to discover their personal benefits in at least one of the available items which results in a higher BI. Several benefits identified by qualitative studies like safety, mobility for older people, or feeling less exhausted after a ride (Li et al. 2019b; Linehan et al. 2019) are used as items for perceived usefulness.

In line with existing research (Mao et al. 2005; Schepers and Wetzels 2007), we showed that perceived usefulness is more important in Western cultures. We also could confirm a strong correlation of perceived usefulness with BI in car/ride sharing setups as observed by Wang et al. (2018). This could be related to the fact that all car-sharing studies were paper-based. On average paper-based studies turned out to result in higher correlations than simulator studies. A reason for this might be that participants sitting in a simulator do not perceive a personal benefit in this situation, whereas they can experience or imagine an advantage in a real car or a paper-based design.

Efficiency. Efficiency has a positive effect on the BI to use AVs because people think that automated vehicles have the opportunity to reduce congestions and provide time savings (Brinkley et al. 2017; Pettigrew et al. 2019). However, this will only be relevant for fully automated cars with automation level 5 when manual drivers can no longer impair the traffic flow. Because of this, the moderator-analysis reveals higher correlations for LoA 5 and questionnaire studies. People experiencing real shuttles usually drove very slowly due to safety reasons (Madigan et al. 2017). Hence, the perceived efficiency was low and less relevant for their adoption decision.

Efficiency correlates less for public transport with BI. Reasons could be extant barriers to adopt public transport: Buses' unreliability, long travel times due to many intermediate stops, low frequencies (Beirão and Sarsfield Cabral 2007). Most of these perceived shortcomings will not change with the introduction of automated public transport and thus, efficiency is not the main driver of acceptance for this ownership model.

Trust in AVs. After trust has been shown to be relevant in many IT adoption contexts (Wu et al. 2011), it is also important for AVs with LoA 3 and 5. Interviews have shown that trust is especially relevant when people need to give up control to the car (Frison et al. 2018). While level 3 introduces an automated driving feature, level 5 is characterized by the highest degree of uncertainty mentioned in Lee and See's (2004) definition of trust.

Trust in AVs also correlates strongly with BI in studies taking place in Asia because trust-based relationships are more important in Eastern countries (Hofstede et al. 2005). However, the trust correlation score is very low for public transport. This could be because aspects like service reliability and frequency (Redman et al. 2013) are more important for public transport contexts than the examined acceptance constructs.

Safety. Compared to the other factors, perceived safety is rather AV specific. It correlates most with the BI to use an AV for LoA 5 because the reduced feeling of control resulting from higher LoAs (Rödel et al. 2014) might lead to a perception that the car becomes responsible for the personal safety. In qualitative interviews, people worry that humans are better in observing and adapting to changing traffic situations than fully autonomous cars (Salonen and Haavisto 2019).

Perceived safety also correlates strongly with the BI in studies investigating the ownership of AVs. A reason for this aspect could be that people use privately owned cars most often (Brandt 2017) and thus require higher safety standards to reduce personal safety risks. However, we could prove this aspect to be irrelevant in simulator studies. Here, people feel very safe as they are sitting in front of a screen where even an accident will not physically harm them.

Norms. The high importance of subjective norms highlights that people admire a feeling of belonging and group conformity. Taking Hofstede et al.'s (2005) cultural dimensions into account, one would argue that the correlation of subjective norm and BI would be highest for Asian participants who are usually more collectivism oriented than people living in Western countries. However, in line with Schepers and Wetzels (2007), we could not find that norms are more relevant in Asian than American countries when adopting self-driving technologies. Furthermore, uncertainty avoidance, the extent to which the members of a culture feel threatened by ambiguous or unknown situations, is highest in Europe and thus leads to a lower correlation of subjective norms and BI. For European adopters, the opinion of others is less important than their own perceived certainty or safety.

Last, subjective norms influence the adoption of automated driving most for car owners. For them, it is most relevant, what family and friends think about their new car. Thereby, AVs provide a possibility for distinction through novelty, one of the two different sorts of distinction that prestige cars can offer (Swann 2001).

4.6 Further research

To guide further research, we identified under-researched areas that provide specialized scholars with new study opportunities. We revealed constructs only analyzed in a single study or being insignificant or underpowered due to an insufficient number of participants and thus posing potential research areas.

For example, perceived cybersecurity was assessed in only one study, while traffic safety seems to be a key aspect in AV acceptance research. Although IT security might be seen as a part of safety, we would argue that cybersecurity itself is vital for connected vehicles driving automated based on sensor information and algorithms, which could be the target of an attack. Both security and safety issues can result in severe risks (Kaur and Rampersad 2018). Thus, we invite the research community to analyze the interplay of safety, security, and behavioral intention.

The same holds for studies investigating the influence of the opportunity to concentrate on other things while driving with LoA 4 or 5. Only one study explicitly examines the impact of instrumental benefits like reading, chatting, or entertainment on the BI (Hein et al. 2018). Several researchers leverage the opportunity to do other things while driving as an item for perceived usefulness (e.g., Ro and Ha 2019; Zhang et al. 2019), but we think that it needs to be more prominent in future research to assess the influence of the new benefits coming along with high levels of automation.

We identified two influential constructs, efficiency and safety, that represent a dilemma, which potential adopters face when deciding to use an automated car. On the one hand, the new technology promises to reduce congestion and to enable the people to perform hedonic tasks while driving. On the other hand, the passenger needs to give up control and pass the responsibility for the occupant's safety to the car. Future research could elaborate on how to resolve this dilemma.

Our moderator-analysis points out that efficiency has not been analyzed in the USA and Asia. Besides, it highlights contradictory findings regarding the cultural influence on the attitude towards automated vehicles. While car lovers usually perceive AVs more negatively, tech lovers are attracted by new styles of driving. Our moderator-analysis, however, shows the highest correlation of attitude and BI for Europe. The reasons for this contradictory finding should be assessed in further studies.

Moving beyond the current work, we would like to provide suggestions for future research in the area. While we think that the acceptance research reaches a certain point of saturation, we agree with Bornholt and Heidt (2019) who argue that the research focus should move on. Further research should move from pure user acceptance towards user satisfaction. This means the quality criteria of automated vehicles need to be explored more deeply. Therefore, researchers could develop AV quality scales, categorize specific equipment factors as must-be, one-dimensional, or attractive quality using a Kano analysis, or assess the willingness to pay for specific equipment characteristics.

4.7 Limitations and Contributions

Our findings should be considered in light of its limitations. We decided to include regression and path coefficients whose transformations are not exact representations of the real correlation coefficients. However, this decision let us include 25% more publications and thus should increase the overall precision of our results. Nevertheless, as in any structured literature analysis, we cannot ensure that we included all relevant publications in our work.

The diverging sample sizes may affect some of our findings' generalisability. For example, we calculated the effect size of perceived usefulness based on 28 reported correlations and a sample size of 12,886 participants. Opposed to this, the effect size of efficiency was calculated based on three correlations and a respective sample size of 2,102. Nevertheless, we believe that the described results are valid, as we evaluated their significance and power as sufficiently high.

Despite these limitations, we contribute to theory development in multiple ways. Based on Kuhn's (1962) framework of scientific development, our meta-analysis helps to develop "normal science" which is specified by having a predominantly accepted paradigm. Following Chan and Arvey's (2012) structure of how a meta-analysis can support knowledge generation in a state of normal science we outline our study's contributions in (1) strategically guiding future research, (2) increasing the precision of the paradigm, and (3) broadening the scope of the paradigm.

First, our meta-analysis guides future research as it presents the current state of knowledge after collecting all analyses available at this juncture. It is necessary to know the current state of research to move with future studies in a strategic direction (Sackett 2003). Hence, we collected current knowledge, identified research gaps and contradictions in current findings, and guide future research beyond the scope of this work.

Second, we supported theory building as we increased the precision of the paradigm in clarifying the relationship between acceptance factors and BI. We determined the population effect sizes for all constructs that are available in existing literature. Thereby, we confirmed the relevance of traditional acceptance factors like attitude, perceived usefulness, trust, and subjective norms. While one could argue that their significance was to be expected, the effect sizes varied quite heavily in primary studies[6]. On top of this, we could show two additional factors, efficiency and safety, to be very influential for the adoption of AVs.

The calculation of effect sizes is of practical relevance, too. Whereas a young age and urban places of living are described as influencing factors in many AV acceptance publications (Becker and Axhausen 2017), our analysis shows that neither is the case. Both effect sizes are very small and not significant or underpowered. Similarly, gender is promoted in many acceptance studies as having a strong influence on the willingness to use AVs. Although gender could be confirmed to be significant, the meta-analysis including more than 12.000 participants from primary studies, however, revealed only a marginal effect size for gender ($r = 0.07$). Calculating a net effect might have canceled out gender relevance. It may also be the case that structural differences in the samples do create varying significances as the proportion of male participants in primary studies ranges from 36% to 85%.

[6] E.g. the correlation of perceived usefulness and BI varies from 0.01 to 0.8 or the correlation of trust and BI ranges from 0.04 to 0.74

Furthermore, we discussed the moderating effects of acceptance study designs which future research endeavors should take into consideration when designing their studies. We identified the continent of the participants' place of living, the level of automation, the ownership model, and the methodology to be influential for many acceptance factors. Knowing the influences helps researchers to interpret available results more skeptical, and we paved the way towards a more conscious design of future studies.

Third, we broadened the scope of the paradigm as we tested relationships between the focal variable BI and those variables introduced by primary studies (Maruyama 1991). We could examine the generalizability and robustness of the paradigm as the meta-analysis included more heterogeneous contexts, samples, and methods than a single primary study (Chan and Arvey 2012). We enlarged the boundaries of the AV acceptance theory (Bacharach 1989) as the effect sizes and moderating effects are generalizable across automated transportation settings.

5 Paper C: Required Service Characterisics for AMaaS

Title

Required Service Characteristics for Automated Mobility as a Service: A Qualitative Investigation

Authors

Jennifer Wiefel, Technical University of Darmstadt, Germany

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Abstract

Automated and shared mobility promises to be the new trend in transportation. But, in order to be successful, automated mobility as a service (AMaaS) providers need to convince future customers to adopt their services. While existing research mostly investigates which factors influence adoption intentions for either car-sharing or automated vehicles, this study elaborates relevant AMaaS service propositions. Based on 23 interviews with the general public, we derive user requirements and perform a card sorting exercise to conceptualize the expected AMaaS characteristics: traffic safety, information privacy, cybersecurity, regulations, flexibility, accessibility, efficiency, and convenience. We reveal how autonomous driving and shared mobility research results can be combined for AMaaS and we create construct clarity regarding the scope of each service characteristic. An assessment of code frequencies from our interviews with the general public in comparison to experts' relevance ratings provides insights which service characteristics are most relevant to promote AMaaS user adoption.

Keywords

Automated Mobility as a Service (AMaaS), Autonomous Driving, Shared Mobility, Service Proposition, Value, Adoption Intention, Construct Clarity

5.1 Introduction

Today's rapid developments in sensor-based technologies and intelligent real-time data processing enable new types of individual mobility. Accordingly, the industry invests heavily in vehicles that are going to be connected, automated, and shared between users (Möller et al. 2019). These investments are supported by market forecasts that predict increasing user numbers for shared mobility (Peter 2020) and an automated driving technology market for cars worth $270bn by 2030 (Weber et al. 2019).

On a societal level, shared mobility is associated with a sustainable way of life with less hyper-consumption and pollution (Hamari et al. 2016). Simulations demonstrate that it can fulfill the mobility needs with a fleet size of approximately one-third of the vehicles currently in use (Spieser et al. 2014). At the same time, connected cars should improve the vehicles' efficiency, safety, and comfort by analyzing massive amounts of data (Papadimitratos et al. 2009). Moreover, as 94 percent of today's traffic accidents are due to human error (NHTSA 2018), self-driving vehicles are expected to reduce traffic deaths by entirely removing human driver interventions.

A convergence of the two mobility trends of shared mobility and autonomous driving, i.e., automated mobility as a service (AMaaS), is beginning to develop with multiple pilots emerging worldwide (Stocker and Shaheen 2018). Based on Pangbourne et al.'s (2020) conceptualization of mobility as a service, we define AMaaS as a "*provision of on demand door-to-door mobility being offered by self-driving cars, which can be requested via an online platform for individual or shared rides*". However, to be successful in the market, society must be willing to adopt the new concept of AMaaS. Even though both underlying research streams of shared mobility and autonomous driving have independently studied the adoption factors in detail, it remains unclear *(1) how and whether we can integrate the extant adoption research results for the context of AMaaS, (2) which of these mobility concepts dominate the user's perception when being combined*, and *(3) which factors might become obsolete or additionally relevant* in order to promote high user adoption rates.

To understand the factors that account for customer shifts from their current, product-based mobility to automated and shared mobility, only a few studies have been published (Wiefel 2020). These studies focus mainly on the participants' latent beliefs and feelings towards the new mobility offering (Chen and Yan 2018; Jing et al. 2019; Nordhoff et al. 2018b) or on their demographics or habits (Hassan et al. 2019). As a result of this, they lack to assess how intrinsic AMaaS service characteristics that build the service's value proposition influence the users' adoption intention. Contrary to beliefs and demographics, service providers can easily design, implement, and adapt the service offering so that it is particularly relevant in practice to know the service characteristics required by users. In the same vein, user-derived service requirements can guide design science research in actively building and improving AMaaS services instead of only explaining the adoption factors (Iivari and Venable 2009).

A comprehensive literature review on car-sharing services supports our line of argument as it identifies "one of the biggest lacks in the literature: the absence of studies related to […] the value proposition" (Ferrero et al. 2018, p. 507). We think it is of utmost importance to identify and specify the service attributes defining the value proposition as they can affect the user's value-in-use, which is the evaluation of the service offering during consumption (Edvardsson et al. 2010). Eventually, high perceived value positively influences the adoption intention (Kim et al. 2007). Consequently, a better understanding of the expected service characteristics is needed (Kim et al. 2019).

Due to the gap in extant literature, this study gets underway to investigate relevant AMaaS characteristics in an explorative fashion. To do so, we first introduce the theoretical background on automated and shared mobility. Afterward, we outline our methodological approach. We derive user expectations regarding AMaaS from 23 qualitative interviews. Based on these, automotive experts familiar with the latest market trends and customer demands rate each statement's importance and perform a card sorting exercise to conceptualize the service characteristics. Finally, we present and discuss our results, followed by a critical evaluation of our work's contributions and limitations.

5.2 Theoretical Background

In the following sections, we summarize insights from AMaaS adoption research as well as traditional car-sharing and automated vehicles (AVs) literature. Furthermore, we introduce a theoretical constraint called construct identity fallacy (Larsen and Bong 2016) that is present in the AV research stream (Bornholt and Heidt 2019).

5.2.1 Automated Mobility as a Service

AMaaS represents a service system, i.e., a dynamic configuration of resources (people, technologies, and shared information) that interact with each other to co-create value (Maglio et al. 2009). In the automated mobility service system, the passenger and the automated car can be considered the interacting entities. Opposed to this, the passenger and the taxi driver have been the entities within traditional taxi service systems. While previously the human taxi driver controlled the technology, the autonomous vehicle now controls itself. Hence, the service encounter, i.e., the moment of interaction between a customer and a service provider, becomes increasingly technology-mediated (Bitner et al. 2000), and "this change has implications for the way the entire system works" (Storbacka et al. 2016, p. 3010). This development requires service systems designers to identify new ways to attract customers by exploiting the system's opportunities and managing its complexity (Glushko 2014).

Although the adoption of automated driving is generally intensely researched, studies on the context of AMaaS remain scarce (Bornholt and Heidt 2019; Wiefel 2020). In their comprehensive literature review on shared autonomous vehicle services, Narayanan et al. (2020) also report that a large number of pertinent studies either try to optimize AMaaS components (e.g., fleet size or vehicle distribution) or investigate the expected impacts of shared automated vehicles (e.g., traffic and safety, land use, or travel behavior), but less is published about the factors affecting the adoption of AMaaS services. Those studies that investigate the adoption of shared and automated vehicles identified the context (Wang and Akar 2019), socio-demographics (Acheampong and Cugurullo 2019; Becker and Axhausen 2017), and user attitudes (Dowling et al. 2018; Jing et al. 2019; Lee et al. 2018b) to be relevant.

However, with this study, we aim to uncover service-related adoption factors. After searching[7] and reviewing the literature diligently, we can only identify the following intrinsic AMaaS characteristics that influence user adoption: First, AVs need to guarantee high traffic safety standards (Nazari et al. 2018). Besides, exact pick-up and arrival times seem to be relevant in order to choose AMaaS (Philipsen et al. 2019). Last, the presence of strangers in a ride-sharing setup could limit user adoption – especially in a leisure context (Lavieri et al. 2017).

As extant results regarding AMaaS adoption factors are relatively scarce, we continue to investigate literature concerning shared mobility and automated driving.

5.2.1.1 Shared Mobility

Literature regarding shared vehicles affirms that satisfaction with car-sharing service characteristics can explain the customer's usage intention (Kim et al. 2019). Kim et al. (2015) distinguish between attributes of the vehicle, the booking and payment process, the availability, and the economic perspective. The vehicle's most relevant attributes are speed, comfort, noise,

[7] The search term was (automated OR autonomous OR self-driving OR driverless) AND (vehicle(s) OR car(s) OR driving OR mobility) AND (shared OR "on demand" OR "as a service") AND (adopt* OR accept* OR intention)

and cleanliness (Kim et al. 2015). Further vehicle attributes related to the consumers' usage motives are vehicle variety, design, size, and fuel efficiency (Lindloff et al. 2014; Schaefers 2013). Customers value flexible booking and payment processes with a reservation via an app (Hildebrandt et al. 2015), a pay-per-use fee structure (Hildebrandt et al. 2015; Schaefers 2013), and price transparency (Lindloff et al. 2014). While the availability of shared cars is one of the most relevant adoption factors (Cervero et al. 2007; Habib et al. 2012; Lindloff et al. 2014), further convenience related service characteristics have been found to be relevant: guaranteed parking spaces (Shaheen and Cohen 2007), flexibility, and interoperability between various car-sharing providers (Lindloff et al. 2014). Regarding the economic perspective, customers value reasonable prices (Schaefers 2013) and time savings (Lindloff et al. 2014).

We deem that these insights can inform our work but might not directly be transferred because AMaaS is different from traditional car-sharing in multiple ways. First, the occupant of an autonomous car gives up control when riding in the vehicle because the driving task is fully automated and cannot be intervened (SAE International 2018). This can create stress for the user, requiring specific service attributes that address the passenger's emotional well-being. Second, as the autonomous car drives independently, this can raise questions regarding the liability in the case of a traffic offense (Bruckes et al. 2019). Last, current requirements like car-sharing station accessibility or guaranteed parking spots might become obsolete when the cars pick-up/deliver the customers at any given place and then drive on independently to the next available parking space until they collect the next customer.

5.2.1.2 Automated Driving

Extant studies investigating the adoption of automated driving identify political/societal conditions, the users' characteristics, and vehicle characteristics to influence the adoption intention (Bornholt and Heidt 2019). Focusing on vehicle characteristics, we see users expecting higher efficiency in terms of being able to perform other things while driving (Hein et al. 2018). Reduced travel time compared to manually driven cars is another significant adoption predictor (Hohenberger et al. 2017; Nordhoff et al. 2018c). Closely linked is the users' expectation that riding an autonomous car will be more environmentally friendly (Liu et al. 2019c; Wu et al. 2019). Congruent with other services, self-driving cars need to be reliable (i.e., continuously operate properly and flawlessly) in order to be adopted by the passengers (Bruckes et al. 2019; Tussyadiah et al. 2017).

Next to these practical adoption factors, scholars find emotional aspects to be significant for the adoption of AVs. In this regard, traffic safety is a relevant adoption factor (Cho et al. 2017; Hohenberger et al. 2017; Lee et al. 2018b). Furthermore, people are concerned that an autonomous car could be hacked because of sophisticated information technology. Hence, passengers require cybersecurity assurance before adopting this new technology (Hein et al. 2018; Woisetschläger 2016).

Although the AV adoption research stream already developed a large body of knowledge, we cannot directly use the results for AMaaS, either. Most of the research examines AVs as privately owned cars, but users have different expectations for autonomous vehicles, based on whether the vehicle is owned or consumed as a service (Amanatidis et al. 2018; Wiefel 2020). In a service context, users create value by utilizing the providers' resources (Ranjan and Read 2016), which puts them in a dependent position. This poses the question if other service characteristics become relevant. Last, existing research falls victim to construct identity fallacy (Bornholt and Heidt 2019), an issue we outline in the next section.

5.2.2 Construct Identity Fallacy

Construct identity fallacy can arise two-fold (Larsen and Bong 2016). In the first case, called jingle fallacy, two constructs have identical names but describe different phenomena. In the context of automated driving, perceived risk is affected by this fallacy. While one author operationalizes perceived risk as financial loss, reliability issues, and general risks (Jing et al. 2019), another includes items regarding safety, privacy, and time constraints (Chen and Yan 2018). The second case, called jangle fallacy, is characterized by two constructs being named differently but referring to the same phenomenon. For example, cybersecurity is referred to as data risk in one study (Hein et al. 2018) and as security in another (Kaur and Rampersad 2018). Nevertheless, both studies include items regarding the risk of being hacked. These inconsistencies make it difficult to compare and build on existing knowledge.

Almost all vehicle characteristics identified in earlier adoption research are used both as an item to measure latent constructs and as a construct itself (Bornholt and Heidt 2019). The different layers of abstraction lead to varying scope conditions (Suddaby 2010), which also prevent researchers from working effectively with these factors. Even in cases where the vehicle characteristic is used as a construct from two researchers, boundaries vary as they are formed by the researcher's assumptions (Bacharach 1989). Coming back to the cybersecurity example, we found that the first study only refers to cybercriminals and hacking (Hein et al. 2018). In contrast, the second study also includes software failures and connectivity with infrastructure and other cars (Kaur and Rampersad 2018).

5.3 Methodology

This unsatisfactory situation makes us use an explorative research approach to identify all relevant user expectations regarding AMaaS and set clear boundaries between the inherent service characteristics. Instead of using a theory-driven approach, we first want to discover any generalizations leading to a deeper understanding of the concept at hand (Stebbins 2001). Thereby, the concept boundaries should not be derived from the researcher's view to facilitate a user-centered design of AMaaS.

We leverage concept mapping, a methodology that provides a representation of the group's thinking relative to the domain in focus (Trochim 1989). This approach involves three steps building on each other (see Figure 7): In the first step, we conduct interviews with the general public and gather high-level paraphrases about their expected AMaaS service attributes. In phase two, we ask mobility experts who are familiar with the general public's demands and with its implementation feasibility to cluster and rate these paraphrases so that the domain of AMaaS service characteristics can be conceptualized and prioritized from a practitioner's perspective. In the last step, we apply hierarchical cluster analysis to identify the AMaaS service characteristics.

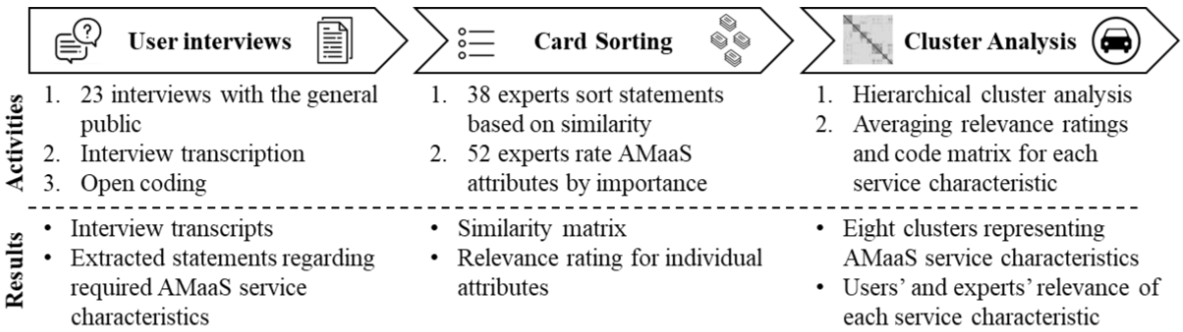

Figure 7. The Process Followed for Concept Mapping

5.3.1 User Interviews

Concept mapping begins with the generation of statements, i.e., high-level paraphrases derived from the interviews which represent the entire domain of expected AMaaS service attributes. We recruit a convenience sample of interview participants mainly living in Germany and sporadically in Great Britain, France, and the Netherlands with different backgrounds and mobility habits to represent the largest possible share of potential AMaaS consumers. The candidates include laypersons as well as IT experts, court personnel, and an ethicist. This way, the resulting concept map will be generalizable to the population of interest (Trochim 1989). The group includes a larger share of young respondents living in urban environments (see Table 7 for demographics) as they are likely to be early adopters (Rogers 2003) and in a relevant age when AMaaS is going to hit the markets.

Gender	Male Female	48% 52%	**Place of living (no. of residents)**	Rural (<5.000) Urban (5.001-100.000) Metropolis (>100.000)	13% 39% 48%
Age	15-24 25-34 35-44 45-55 55-64 >64	26% 34% 9% 9% 13% 9%	**Education**	Secondary school Bachelor's degree Master's degree PhD	48% 18% 30% 4%

Table 7. Demographics of Interview Participants (N=23)

While interviews with users are useful to capture their desires, it often comes to problems when investigating new and latent product requirements. They do not mention attractive product features because they do not expect them (Matzler and Hinterhuber 1998). Thus, it is necessary to reveal the users' current needs and problems to be solved by conducting outcome-focused interviews (Ulwick 2002). As automated driving is not existent yet, and research has proven the quality of current transportation modes to be influential for mode choices (Kim et al. 2017), our interview guide contains questions regarding AMaaS as well as current mobility offerings. For example, we ask the participants: (1) What do you like/dislike about today's mobility offers? (2) In which situations would you use AMaaS and why? (3) How would a value-adding AMaaS service look like for you in order to adopt it? (4) Which hopes and concerns do you have regarding AMaaS? This way, we can explore both which benefits and sacrifices influence the adoption of present transportation forms and how they form the expectations regarding automated mobility services. We conduct and transcribe 23 interviews lasting, on average, 26 minutes. We transcribe each interview verbatim and paraphrase relevant user requirements before conducting the next one until we notice a saturation of information. The final number of interviews is in line with Griffin and Hauser (1993), who state that 20-30 interviews reveal 90-95% of the needs.

5.3.2 Card Sorting

Building on our interview results, we conduct a follow-up study in which we approach 98 German mobility experts (sales representatives, consultants, and researchers) from our network, via LinkedIn, and at their business premises. We ask them to rate the derived user expectations by relevance and cluster them by conceptual similarity. Each aspect can be categorized as either (1) "not relevant", (2) "important, but not essential", or (3) "essential" for the implementation of AMaaS. While we receive 52 relevance ratings (a response rate of 51%), only 41 experts (a response rate of 40%) sort the quality statements into piles based on conceptual similarity (Weller and Romney 1988). The lower response rate for the sorting task is due to the higher time requirement and no offered compensation for study participation.

We exclude two responses from the relevance ratings, as the subjects rated less than 50% of the available quality characteristics. Besides, we remove three sorting exercises as two sorters grouped the quotes by relevance, and one only sorted those statements categorized as important in the previous step. Nevertheless, the resulting 38 sortings are still sufficient for analysis as results stay stable with sample sizes above 30 (Tullis and Wood 2004).

5.3.3 Cluster Analysis

Based on the resulting piles, we construct a matrix for each sorting. Cell values represent if a pair of statements are in the same group (1) or not (0). The individual sort matrices are added to obtain a combined group similarity matrix shown on the left-hand side in Figure 8 (Jackson and Trochim 2002). From the aggregated matrix, multi-dimensional scaling (PROXSCAL) creates two-dimensional coordinates for each statement. Instead of using the original similarity matrix, these coordinates serve as input for hierarchical cluster analysis using Ward’s algorithm (Jackson and Trochim 2002; Trochim 1989). This algorithm is most suitable for identifying categories if the structure is not already known (Afifi and Clark 1999). The algorithm proposes eight clusters representing the user-required AMaaS service characteristics. The average silhouette value equals 0.6, which indicates good cluster separation.

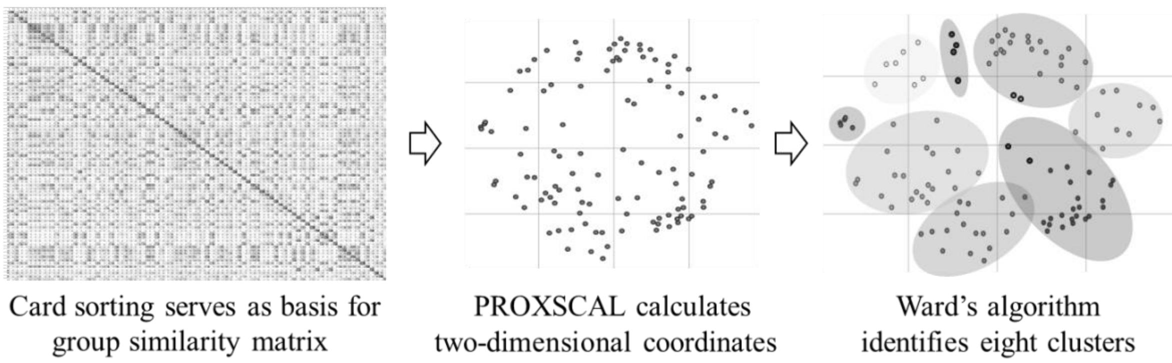

Figure 8. Steps Followed for Cluster Analysis

5.4 Results and Discussion

Looking at the statements in each cluster, we identify eight service characteristics required for AMaaS services to create adoption intentions: Traffic safety, information privacy, cybersecurity, regulations, flexibility, accessibility, efficiency, and convenience. At first glance, one could assume that the first four characteristics stem from autonomous driving studies and the last four from the car-sharing literature. However, a closer look reveals that the attributes that are presumably car-sharing related, like convenience and accessibility, include elements that are specific to automated vehicles. For example, convenience includes performing hedonic activities during a ride, and automated re-location strategies should provide accessibility. In order to equip practitioners and researchers with a more detailed understanding and clear boundaries of each identified AMaaS characteristic, we discuss our insights from the interviews in comparison to earlier research results in the following paragraphs.

Before we do so, we want to highlight that the two mobility trends of automated and shared mobility are not equally present in the general public's and the experts' minds when they think about AMaaS. To show this, we create a code matrix representing the code frequencies from our interviews with the general public in relation to each service characteristic across various demographic groups (see Figure 9). In addition to that, we calculate the average experts' relevance rating for each user requirement to identify the overall characteristic's importance (shown in the inner circle in Figure 10).

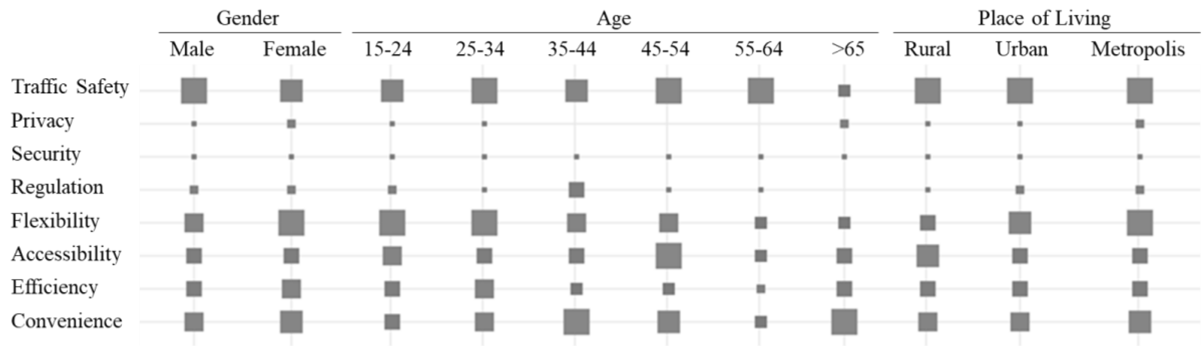

Figure 9. Interview Code Matrix Showing Number of Codes per Group

While all interview groups (except the oldest ones) talk a lot about traffic safety, the remaining autonomous driving related characteristics of information privacy, cybersecurity, and regulation are less often mentioned when people think about the new mobility service. Contrary to the low number of codes for these categories, the experts' relevance ratings for traffic safety, but also for cybersecurity, information privacy, and regulations are very high. The experts assigned even higher numbers to these service attributes than to the remaining service characteristics (i.e., flexibility, accessibility, efficiency, and convenience), although the latter show higher code frequencies across all user groups.

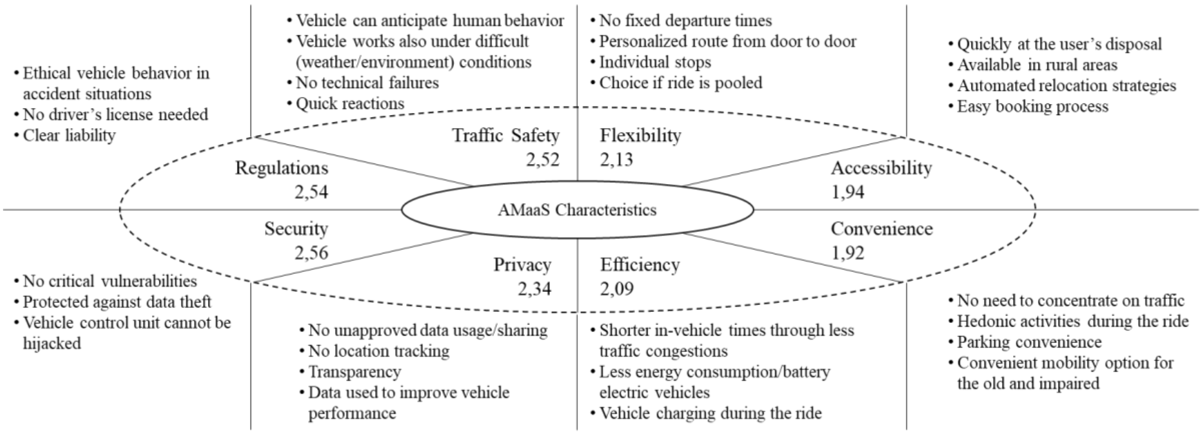

Figure 10. Experts' Relevance Ratings (1-3) and Exemplary Attributes per AMaaS Service Attribute

The disparate weights that we find associated with the quality attributes comparing the interviews with the experts' relevance ratings highlight that potential users initially mostly demand service attributes that are already known from existing services (i.e., car-sharing) and can be experienced actively. The diverging experts' view could be interpreted in two ways. Either the experts do not know the users' demands as well as expected, or people only start valuing how a service is delivered as soon as they know more about the service's functionality. The second explanation would be in line with Grönroos' (1984) observation that it is more important for experienced users how a service is delivered than the mere service outcome. This interpretation reveals the vital insight that mobility providers need to focus on different service attributes depending on whether they want to attract new customers or increase the quality perception of AMaaS for an experienced target population.

5.4.1 Traffic Safety

Perceived traffic safety is mentioned most frequently during the interviews and is also rated with a high relevance score of 2,52 out of 3 by the experts. It is the extent to which the consumer feels safe and not in danger or at risk while participating in traffic using AMaaS. While vehicle safety seems not to be relevant in public transport (Andreassen 1995), the willingness to use autonomous vehicles has already shown to increase with higher levels of perceived safety (Hohenberger et al. 2017).

Like Salonen and Haavisto (2019), who examined privately owned AVs, we experience that all our interview participants are concerned about traffic safety in a shared context, too. Thereby, the participants do not only care about their own physical integrity but also about others: "*If a* *child runs into the street, and you suddenly have to brake - I don't know if the car can see that*" (Gender = F, Age= 84). Consumers are hesitant in trusting the automated driving systems to properly integrate into mixed traffic situations because the engineers face complex challenges when constructing systems that react safely and effectively to every situation (Linehan et al. 2019). Our study participants are concerned that the "*technology misjudges the environment or surroundings*" (F, 30) or how the car will behave in "*any unusual weather conditions*" (F, 33). Some even suggested letting the vehicles drive detached from other traffic, "*maybe like a taxi or bus lane. Then it would be a little bit separate*" (F, 31).

The above concerns are related to the technical capabilities and reliability of the system. Reliability enhances trust in driverless cars (Kaur and Rampersad 2018), but the consumers are used to technical failures from other areas "*like a cell phone, that breaks down*" (M, 63). Consequently, "*equipment failure*" (F, 59) is one of the biggest concerns that potential future users have regarding traffic safety. Thus, a provider "*who takes care of the maintenance of these cars*" (F, 48) should actively communicate its efforts.

Particularly in cases of technology breakdowns, passengers wish to regain control over the vehicle: "*But if the technique fails and I cannot intervene, then it would not be good*" (F, 25). Hegner et al. (2019) showed that concerns about handing over control to a self-driving vehicle are strongly linked to the trust that passengers have in the system. However, our study participants seem not yet to be ready to give up control and trust the car. "*If I now assume that I really don't have to intervene at all, I can't imagine that at the moment. Now, I would still think that I still want to be able to intervene*" (F, 31). Hence, researchers and practitioners should investigate the levers to improve the passenger's trust in automated vehicles.

5.4.2 Information Privacy

Perceived information privacy is defined by the consumer's beliefs about a provider's ability and willingness to protect his/her personal information from improper use, disclosure to third parties, and secondary use without consent (adapted from Pavlou et al. 2007). Up to now, information privacy has shown to have only a non-significant influence on the autonomous vehicle passengers' trust and perceived usefulness (Hein et al. 2018; Kaur and Rampersad 2018). In line with these results, most interview participants in our study do not mention privacy at all. However, if they do, they say that "*privacy is definitely a big concern*" (F, 31). Experts generally rate the relevance of privacy as high (2,34 out of 3).

The interviewees make the provider's trustworthiness dependent on its transparent handling of the data: "*Well, I think it would also have to do with what kind of provider it is and how transparent it is. So basically, how trustworthy he is*" (F, 22). If they mention privacy in our conversations, people are anxious about individual analyses: "*What worries me is if someone knows where I'm going. Maybe even associate driving patterns of me as a person*" (M, 29). While this person was especially concerned about personalized advertisements, participants from earlier research were worried about data shared with insurance companies (Linehan et al. 2019).

Nevertheless, our participants support anonymized analyses to improve the vehicle's performance and traffic safety: "*... but only to analyze the driving behavior of the car [...] in the sense that the car has recognized everything correctly. To minimize the error rate, it's okay*" (F, 33). With this, value is created for the user and the provider, who can enhance the capabilities of the automated vehicle.

5.4.3 Cybersecurity

Information security is the degree to which the customer believes that protective measures are taken to make the AMaaS information systems safe from intrusions, unintentional corruptions, or breaches (Bruckes et al. 2019; Hein et al. 2018). Technical protection generally increases trust in technologies (Gefen et al. 2003) and self-driving vehicles (Bruckes et al. 2019).

Foremost, security is the least often mentioned quality characteristic in our interviews. Only a few participants require security measures against hackers. For them, the protection should include data security measures to address concerns like the following one: "*If there are any hackers who can hack in. Get access to the credit card, that they'll just sort of mug you*" (F, 22). Another participant is even afraid to get hijacked and physically harmed: "*Especially if such a car is hacked, probably the doors are also locked somehow electrically, and so, you can't get out of it anymore, you'll be trapped like this, right?*" (M, 26). To enable cybersecurity, providers need to ensure that preventive measures are taken to avoid vulnerabilities being exploited (Benlian et al. 2011).

Although extant AV research has only paid little attention to cybersecurity so far (Wiefel 2020), and our participants do not care much about it, the experts rate information security with 2,56 as the most relevant service characteristic for AMaaS. A reason might be that hacker attacks are a salient threat not recognized by the general public. Experts, however, already know that exploits can be perilous when causing severe traffic accidents. Hence, future AV research should investigate information security from a technical perspective and more closely from a user’s view.

5.4.4 Regulations

“Considering [the] fragility of trust, governments should establish efficient regulations […] since the initial stages of the automated vehicle technology” (Liu et al. 2019d, p. 366). Maybe because of the unavailability of AMaaS in the current development stage, experts who are concerned about a quick market introduction of autonomous driving desire guiding boundaries and rate regulations with 2,54 out of 3 as highly relevant. Legal protection refers to the extent to which traffic regulations and government regulations enforce passenger’s welfare when applied by the AMaaS provider (Bruckes et al. 2019).

While most study participants were less interested in regulations, some interviewees demand a robust regulatory solution to resolve liability issues: "*This should perhaps be properly anchored in the law, what if something should happen? Who’s liable?*" (F, 48). Earlier research already provided evidence that legal bonds help consumers trust new technologies (Pavlou 2002). The liability is also strongly related to the question if a driver’s license is still needed: "*When it’s all about autonomous driving, then we wouldn’t need a license anymore*" (F, 24). However, Ro and Ha (2019) have already shown that licensing requirements do not significantly affect the intention to use self-driving vehicles.

While liability plays an essential aspect after an accident, ethical decisions can become essential during the accident situation: "*There’s this dilemma, are you knocking down the grandma or the kid? That is the question, isn’t it? […] But the third option would also be there. Do you kill your driver? That’s a big question for me*“ (M, 24). To avoid manufacturers always to save the passengers’ lives, this decision-making should be regulated by law: "*Something like that can only work if it has been discussed by committees and of course expert commissions. That rough rules have already been laid down, which are then legitimized again by the parliament*” (F, 33). By having the government approve the ethical decision-making, we would oblige the algorithms to act in line with our social norms and not deliberately harm other people in favor of the driver (Salonen and Haavisto 2019).

Although the mobility provider cannot implement legal regulations on its own, we think that these aspects are still relevant to inform future discussions with the regulators.

5.4.5 Flexibility

Flexibility, the second most important characteristic according to our code matrix, defines the capability of AMaaS to support the individual passenger's mobility requirements. Providing users with flexible mobility offerings is essential because compatibility with daily life is the most important factor for users to adopt or reject new mobility forms (Burghard and Dütschke 2019).

According to our qualitative investigation, a service that offers customer value is available whenever the passenger requests a ride, collects him/her at an arbitrary pick-up place, and drives the passenger to the defined destination. If all of these fundamentals can be fulfilled, a feeling of independence will be present: "*Absolute flexibility […]. Not to be bound to anything or anyone*" (M, 35). As part of this, the frequency of departures is an important quality aspect of public transport (Andreassen 1995) and also for AMaaS. Users want to be "*[…] as flexibly as possible. So don't be dependent on fixed departure times*" (F, 59).

In addition to that, the personalized route arose as being an essential factor (Salonen and Haavisto 2019). Most desired, however, is the ability to choose any discretionary location as either starting point or destination: "*Because I can drive right from the front door and reach my destination directly and drive right up to the door*" (F, 59). This requires a sufficiently large business area. While today's car-sharing offerings are mostly restricted to the city centers, automated driving could enable mobility providers to enlarge the business district as the cars are able to re-locate themselves after each ride.

While pooled car-sharing is promoted to reduce greenhouse emissions, our study reveals that some interviewees want to decide themselves flexibly if they drive alone and who can join their car: "*The problem is, you never know who is going to get on. If I drive myself, I can decide who gets on*" (M, 63). In contrast, more environmentally concerned participants require a forced pooled car consumption: "*Because you still have the environmental factor in the background. It makes a lot of sense to say, no, it's not just for me, but also for others if someone happens to want to drive in the same direction*" (F, 33). Overall, our interviewees show a tendency to prefer flexibility over environmental protection, which is in line with Stoiber et al. (2019), who realized that specific push and pull mechanisms need to be in place to encourage people to a pooled usage. For example, our participants demanded a cost reduction and the least possible detour when picking up other passengers.

5.4.6 Accessibility

Interestingly, users of AMaaS still demand accessibility. We define this service characteristic as the extent to which an individual perceives that the AMaaS is easily available for use when needed. According to our participants, an accessible service offering needs to comprise multiple aspects:

First, the automated cars need to be at the user's disposal quickly: "*So, that means that if you call a taxi […], you might wait an hour, and if you have your own car, you can drive directly*" (M, 57). Consistent with this participant's concern, access time has already been shown to be significant in traditional car-sharing services (Ko et al. 2019; Li and Kamargianni 2020). Car-sharing customers are generally concerned that the car might not be quickly available when needed. Thus, availability significantly affects membership decisions (Kim et al. 2017; Ko et al. 2019; Yoon et al. 2017).

Contrary to these findings, the experts rated accessibility only as medium relevant (1,94 out of 3) for AMaaS. A reason might be that AMaaS offers multiple ways to improve accessibility. First, people could share privately owned cars to increase the number of vehicles available: "*An example of start-ups […] was a platform in which every user can offer his vehicle*" (M, 35). Alternatively, the vehicle can be automatically re-located based on active requests: "*If the software notices that somewhere there is no more car, then this car can drive back on its own*" (F, 25). Accordingly, current research already tries to improve the self-driving cars' availability in car-sharing offerings by optimizing the relocation algorithms (Herrmann et al. 2014; Kek et al. 2009).

Besides, our participants put particular emphasis on the availability in rural areas: "*I'd like to see it work in small towns, too*" (M, 46). However, they also recognized different availability levels in larger cities when they were asked for their car-sharing quality requirements: "*Car availability. But even within cities, there are differences*" (F, 30). While today's car-sharing offerings are mainly located in urban areas, first studies investigate the feasibility of car-sharing in municipalities. The authors find that inter-urban car-sharing service may be adopted, but only if the service is guaranteed and efficient (Luca and Di Pace 2015).

To be easily accessible, also an easy booking process needs to be in place. While younger participants "*imagine that the cars will be booked and called via an app in the future as well*" (F, 28), older interviewees think that "*you somehow have to call a switchboard*" (F, 84). Besides being able to request a car on demand, users were also interested in pre-ordering a ride for a defined time. Simulations show that a reservation system can help to reduce delays (Lamotte et al. 2017) and significantly increase vehicle use rates (Ma et al. 2017) so that service customers and operators can benefit from a pre-reservation feature.

Last, in case of damage, our interviewees would value service recovery. They imagine that the automated and connected car calls a replacement, which is routed to the current location so that the ride can continue without any major interruptions. This could be a key differentiator compared to present car-sharing services, and we are the first to identify this value proposition of AMaaS.

5.4.7 Efficiency

Both experts and the general public only gave efficiency a medium relevance. It refers to the degree to which a passenger perceives the autonomous ride as less time- and energy-consuming. While regular car-sharing presents an effective antidote to mitigate increasing traffic congestion and air pollution (Jian et al. 2017), autonomous car-sharing could be even more efficient "*because the autonomous cars drive more disciplined, perhaps even coordinated with each other, the traffic flow becomes very regular and fluid*" (M, 29). Being connected to the internet, automated cars can receive real-time traffic information, exchange their current locations, and coordinate among themselves at intersections. This results in fewer traffic congestions and less energy consumption, which is important as reduced travel times entail higher usage levels (Hohenberger et al. 2017).

However, the expected benefits (i.e., fewer cars needed, lower energy consumption, a quieter driving style leading to shorter traffic times) will not materialize if more vehicle kilometers are traveled as soon as automated driving is introduced. Wadud et al. (2016) expect an increase of 57% of vehicle kilometers driven, which will then still clog the roads. According to their research, replacing transit journeys with automated vehicles will furthermore double household greenhouse gas emissions.

In addition to a smooth driving style, our participants expected electric engines to protect the environment: "*Yes, I mean electric is better than diesel. [...] I mean for the environment*” (F, 84). Having electronic vehicles in the car-sharing fleet already increases the probability of switching today (Cartenì et al. 2016). Moreover, as a consequence, "*maybe we don’t even need a car for everyone anymore*” (M, 29). However, to purely rely on car-sharing services is more likely for individuals who value minimizing environmental impact (Spurlock et al. 2019; Wu et al. 2019).

To enable the expected efficiency gains, technical infrastructure needs to be expanded. Currently, the limited number of charging stations lead to car-sharing users avoiding limited-range electric vehicles, even if those vehicles still have sufficient range for the user's trip (Zoepf and Keith 2016). "*Putting coils into the tar, so that the car is automatically reloaded successively and slowly while driving*" (M, 32) was proposed to reduce the need for long charging stops.

5.4.8 Convenience

Convenience relates to if consumers perceive AMaaS as a facilitating mobility option that minimizes the driving efforts and provides well-being. Our experts rate it as the least relevant (1,92 out of 3) in comparison to the other service characteristics in our framework. Opposed to this, in the interviews, convenience was the third most often mentioned aspect. Hence, potential future users of AMaaS show different expectations than current public transport passengers, for whom Guirao et al. (2016) conducted a ranking of service attributes and identified comfort to be less relevant than frequency and accessibility.

In addition to the above utilitarian aspects, Sweeney and Soutar (2001) have shown that it is also essential to include hedonic elements when assessing consumer service evaluations. One participant sums it up as: "*Grab me a book, and the car will drive me. Or I close my eyes. Like I'm on a train, only I'm driving on my own*" (F, 59). In addition to that, most interviewees required an Internet connection to either work or surf the web. Some desired it for entertainment purposes: "*Netflix or so can be quite interesting that you watch some videos when you are on the road for a long time, but for short distances, Spotify would be enough*" (F, 25). These instrumental benefits can positively influence the occupants' perceived usefulness in an autonomous vehicle (Hein et al. 2018).

Autonomous cars can also offer a solution for the inconvenience related to perceived parking availability: "*I always have this wasted time of parking […]. Of course, you could save yourself by just getting off where you want to go and not bothering about the rest because the vehicle then automatically takes the next car park*" (M, 35). Research regarding traditional car-sharing already emphasizes the influence of perceived parking availability in short-term mobility decisions (Stoiber et al. 2019; Yoon et al. 2017). We expect this to become more relevant for autonomous car-sharing as the occupant does not need to park the car anymore.

Last, AMaaS can be a convenient form of transportation for physical or cognitive impaired people (Salonen and Haavisto 2019). This includes the elderly: "*We are not the youngest* *anymore, right? I mean, my husband can't even drive a car anymore*" (F, 69) and also the younger generation: "*when I'm drunk and want to come home*" (M, 26). Especially for the old ones, the physical design can increase the convenience in comparison to today's mobility options: "*Put a sliding door in the car, and then you can fix the walker. Now, I need to fold it up and carry it inside the trunk*" (F, 84).

5.5 Implications, Limitations, and Further Research

By identifying and specifying user-required AMaaS service characteristics, we advance IS research in an area where little prior research has been done: Exploring the value proposition required by users in order to adopt AMaaS offerings. Our results not only shed light on the general public's view but also on the experts' perceptions, and we observe large differences between both. Thus, our work entails important insights for mobility providers. Thereby, we break away from traditional acceptance theories like TPB (Ajzen 1991) or TAM (Davis 1989) and instead focus on the less abstract, intrinsic characteristics of the service proposition.

Our results show how the existing insights from the well-researched autonomous mobility and car-sharing contexts can be combined for AMaaS. Factors from both streams influence the adoption of AMaaS. Stronger are the factors known from shared mobility services like accessibility, flexibility, or efficiency. They are especially relevant before the general public is willing to use AMaaS. On the other hand, according to the mobility experts, traffic safety needs to be guaranteed, cybersecurity measures need to be in place, and regulations should define ethical behavior and liability - like it was observed for privately owned AVs.

Besides, our results highlight that the sum (i.e., AMaaS) is more than its parts (i.e., automated vehicles and shared mobility). We can observe expanded boundaries of characteristics initially relevant for car-sharing users. For AMaaS, convenience can only be achieved when passengers do not need to concentrate on traffic, accessibility is now provided by autonomously re-locating vehicles, and future efficiency gains are expected from vehicles communicating with each other at intersections.

By means of our mixed-method research approach, we were able to propose a new delineation of the services characteristics' scope from a practitioners' view. With this, we hope to make a first step in unifying the assumptions guiding researchers when investigating the phenomenon at hand. According to Suddaby, the achieved construct clarity has three advantages (Suddaby 2010): First, by demarcating service characteristics, we propose construct boundaries that can facilitate communication between scholars in the future. Second, our work enhances researchers' ability to empirically explore the phenomenon of AMaaS adoption as the service-related characteristics can be easier operationalized if all scholars share the same understanding. Finally, our contribution allows for greater creativity and innovation in research because our elaboration might stimulate insights that lead to new theories.

With our work, we support the microfoundation movement in strategic management (Barney and Felin 2013) as we uncover service-related AMaaS adoption factors. The microfoundation movement wants to make theory more relevant to managers as it provides explanations on multiple levels. For the AMaaS service system, three levels of analysis can be applied: "micro (actor engagement), meso (sets of actors and their resources), and macro (ecosystem and institutional logic)" (Storbacka et al. 2016). This study focuses on the micro-level where manageable conditions, i.e., the service value proposition, lead to observable actions, i.e., user adoption (Coleman 1994). As a result of this, practitioners gain an understanding of the service characteristics that potential future customers expect from AMaaS in order to adopt the service offering. Furthermore, the relevance ratings of each service characteristic help to steer the investment of scarce resources.

First, manufacturers of automated vehicles need to ensure high traffic safety standards, and automated mobility providers have to guarantee the perceivable service benefits like flexibility and convenience. Only if these most relevant functionalities are available the broader society will start to adopt AMaaS. Next, the focus needs to be on such service characteristics as security or privacy. Furthermore, from the experts' view, legal assurance is a prerequisite for AMaaS service providers to leverage automated cars.

Despite our contributions, we have to acknowledge that our conceptualization lacks operationalization. Still, it can serve as the first step in a scale development effort. Valid and reliable measuring instruments are needed to enable specialized scholars and mobility providers to statistically assess the influence of each AMaaS characteristic on the adoption intention. Thus, we propose a large-scale quantitative survey as the next necessary step to develop and evaluate this instrument in line with the procedures proposed in the literature (MacKenzie et al. 2011).

Furthermore, our results are likely to be time-sensitive. As AMaaS offerings are not existent yet, the identified service characteristics are especially relevant for new users. Experienced users, however, might place less emphasis on, e.g., traffic safety requirements but could develop a stronger need for a hedonic experience. At least Distler et al. (2018) could observe changed passenger perceptions after a ride in an experimental autonomous shuttle. Thus, we propose to repeat the effort with experienced users as soon as AMaaS is publicly available.

Besides, future research should investigate the observed discrepancy between the general public's and the experts' priorities. It would be interesting to see if more experienced users develop the same or different priorities as the experts did in our study. Discrete choice experiments could assess which service attributes are most relevant when people choose from various providers. Furthermore, structural equation modeling can be used to statistically assess the effect sizes of the identified service characteristics on both initial adoption intention and the quality perception after a ride in a real car.

Last, future research should investigate how to improve the identified service characteristics. While scholars already try to increase the accessibility of shared vehicles, additional efforts could focus on creating a feeling of flexibility and convenience. Overall our results can serve as a basis for the development of various new theories in the context of automated mobility as a service.

6 Paper D: Development of a Hierarchical Quality Scale

Title

Automated Mobility as a Service – Development of a Hierarchical Quality Scale

Authors

Jennifer Wiefel, Technical University of Darmstadt, Germany
Peter Buxmann, Technical University of Darmstadt, Germany

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Abstract

Despite the broad interest in shared and automated mobility and the need to understand customer expectations to guide further developments, no instrument exists that measures perceived service quality for automated mobility as a service (AMaaS). Using data from 23 exploratory interviews and three empirical surveys with a total of 1431 participants, this study develops and validates a hierarchical, multi-dimensional quality scale. After identifying relevant quality constructs, we purify the initial item set until satisfactory psychometric properties are achieved. Eventually, we identify two primary quality dimensions (outcome quality and trust) and seven significant quality attributes (time efficiency, environmental impact, convenience, flexibility, cybersecurity, privacy, and traffic safety). We confirm the nomological validity to strengthen the scale's predictability further. Our work supports practitioners in developing high-quality customer-oriented mobility offerings and researchers in building stronger theories utilizing thoroughly validated constructs and a measure that predicts customer perceptions reliably.

Keywords

Automated Mobility as a Service (AMaaS), Autonomous Driving, Shared Mobility, Quality, Scale Development

6.1 Introduction

The rapid expansion of service offerings in many industries over the last decades has resulted in a contribution of the service sector to the European gross domestic product (GDP) of approximately 65% in 2019 (The World Bank 2020). For instance, car sharing has been introduced in the late 1980s as a new form of mobility that allows users to share a fleet of cars instead of privately owning them (Wei et al. 2013). Despite the impact of the Covid-19 pandemic on the economy, a steady increase in user numbers is still expected (Statista 2020). The eventual adoption of automated vehicles in these fleets might further advance the use of on-demand mobility services (Hyland and Mahmassani 2020).

Consequently, mobility providers will be motivated to introduce a new type of transportation service that combines the two developments of shared and automated mobility: Automated Mobility as a Service (AMaaS). Based on Pangbourne et al.'s (2020) conceptualization of mobility as a service, we define AMaaS as a "*provision of on-demand door-to-door mobility being offered by self-driving cars, which can be requested via an online platform for individual or shared rides.*"

Across industries and especially in the vehicle-based transportation sector, the sharing economy presents an alternative to traditional business models (Marimon et al. 2019). New corporations challenge established car manufacturers by offering "'bundles' consisting of customer-focused combinations of goods, services, support, self service, and knowledge" (Vandermerwe and Rada 1988, p. 316). This so-called servitization allows mobility providers to continually align their offerings to the customers' expectations and improve the service outcome and the users' perceived quality (Akter et al. 2019).

For traditional services, high service quality leads to customer satisfaction (Spreng and Mackoy 1996), which in turn influences customer's post-purchase attitudes and future purchase intentions (Howard 1974). Consequently, service research considers quality as one of the most critical determinants of long-term business success (Fassnacht and Koese 2006; Zeithaml et al. 2002). We argue that this causality similarly applies to AMaaS because it affects travel choice (Diana 2012).

However, quality is "an elusive and abstract construct that is difficult to define and measure" (Cronin and Taylor 1992, p. 55). So far, there exists no all-encompassing quality model (Reeves and Bednar 1994). Because of that, Brown et al. (1993) argue that it is not sufficient to adapt the often-used SERVQUAL quality scale (Parasuraman et al. 1988) to assess service quality in some settings effectively. Instead, service quality attributes tend to be context-dependent

(Paulin and Perrien 1996). Consequently, extant research regarding service quality resulted in a rich body of knowledge entailing relevant service attributes that shape the user's quality evaluation in various contexts. Nevertheless, we deem that the perception of AMaaS quality cannot be fully explained by existing knowledge because automated and shared mobility is different from existing services.

In contrast to other services in the sharing economy, where two people, i.e., the service provider and the service consumer, interact with each other via a brokering platform (Amat-Lefort et al. 2020), for AMaaS, the user and the technology, i.e., the self-driving car, become the interacting entities. Thereby, the autonomous vehicle becomes an independent actor, which is different from other electronic services where the technology is used as a communication medium, e.g., for online shopping. Consequently, quality attributes concerning the car's and not the provider's service provision, but also regarding the regulation and liability might become more relevant (Bruckes et al. 2019).

Furthermore, passengers need to release control when sitting in a fully automated vehicle (SAE International 2018). For existing cab or shuttle services, the passenger usually knows that he/she can trust the driver's capabilities, but with AMaaS, a technology automates a highly complex human task (Koester and Salge 2020). Hence, the passenger's perception of the vehicle's functionality will be judged against a human driver's ability, and the passenger will typically prefer the method believed to be best (Lee and Moray 1992). Specific service attributes might become relevant to address the customer's feeling of being at the self-driving car's mercy.

As extant literature does not provide a suitable conceptualization considering all particularities of automated and shared mobility quality, we follow a structured scale development approach to investigate and theorize AMaaS service quality. With this, we respond to Blut et al.'s (2015) call for research to examine how service quality perceptions differ across products and markets. By identifying attributes associated with a positive experience with AMaaS (i.e., a smart service), we further contribute to the research gap pointed out by Ostrom et al. (2015). Last, Cheng et al.'s (2018) observation that only a few publications exist regarding perceived quality in ride-sharing services makes us confident to work on a relevant theoretical objective: developing a service quality scale for automated mobility as a service.

In order to fill the existing gap, this study aims to describe the development, refinement, and psychometric evaluation of a multi-dimensional and hierarchical AMaaS quality scale. After outlining the theoretical foundations, we identify salient quality dimensions employing an exploratory study. Next, we propose respective items that we refine and purify iteratively with multiple empirical studies to ensure construct validity. Afterward, we demonstrate the nomological validity of the developed scale, and, finally, we discuss the implications of our results and provide suggestions for further research.

6.2 Theoretical Foundations

The sharing economy is defined as an internet-enabled, platform-based interaction of individuals or entities providing temporary access to idle assets in exchange for monetary compensation (Akhmedova et al. 2020). Based on this understanding, three actors interact with each other: (1) a customer who seeks access to an automated vehicle and offers monetary compensation, (2) a service provider who offers temporary utilization of idle cars, and (3) an internet platform that connects both entities (Amat-Lefort et al. 2020). In contrast to other services in the sharing economy, like Airbnb, where the underutilized asset, i.e., the house, does not independently interact with the customer, for AMaaS, a fourth entity comes into play: (4) the self-driving vehicle. It reacts to incoming requests and serves the customer based on GPS information without the service provider's active involvement.

Based on this extended conceptualization, the vehicle provider, the technology platform, and the self-driving vehicle form a service system that integrates resources (i.e., people, technology, and information) to satisfy the customer needs (Maglio and Spohrer 2008). The service system's viability depends on the quality of the overall service system's elements (Vargo and Lusch 2008). Eventually, this quality is the primary driver in creating customer satisfaction and business success in the sharing economy (Akhmedova et al. 2020; Amat-Lefort et al. 2020).

Perceived service quality is defined as the customer's evaluation of the service's overall excellence or superiority (Zeithaml 1988). We thus define AMaaS quality as: "*the overall excellence or superiority that customers of automated mobility as a service experience when they order and ride a car, as well as pay for the mobility service*."

The assessment of service quality is individual to each customer, but specific service attributes or dimensions can generate a positive experience (Beltagui and Candi 2018). Based on the means-ends-chain theory, extant research arranges the dimensions hierarchically on three levels: Customers' overall perception of service quality, primary dimensions, and subdimensions/attributes (Dabholkar et al. 1996). As customers process information at multiple abstraction levels (Parasuraman et al. 2005), they evaluate their service experience in terms of particular service propositions (at the attribute level), which are combined to higher-order dimensions (Blut 2016). The aggregated evaluation of these dimensions then results in an overall judgment of the customer's service quality perception (Akter et al. 2019). Despite the agreement that service quality perceptions are based on multiple dimensions, there is no general consensus regarding the dimensions' nature or content (Brady and Cronin 2001).

The service literature stream that aims to identify these quality dimensions and attributes has a long tradition from the beginning of general service quality (e.g., Grönroos 1984; Parasuraman et al. 1988) to electronic service quality (e.g., Fassnacht and Koese 2006; Parasuraman et al. 2005; Wolfinbarger and Gilly 2003), and later investigations of services in the sharing economy (e.g., Amat-Lefort et al. 2020; Arteaga-Sánchez et al. 2018; Marimon et al. 2019). Each stream identified context-specific quality attributes that inform our scale development described in the next sections.

Grönroos' (1984) seminal work highlights the fact that in a face-to-face setting, perceived service quality not only depends on the service outcome but also on how a service is provided. The later developed SERVQUAL service quality scale (Parasuraman et al. 1988) identifies which attributes (i.e., tangibles, reliability, responsiveness, assurance, and empathy) influence a customers' quality judgment.

In a technology-mediated environment, human-related service dimensions like empathy become obsolete while other factors come into place. The fulfillment of online shopping orders has to be ensured (Parasuraman et al. 2005; Wolfinbarger and Gilly 2003), and customer data needs to be protected (Benlian et al. 2011; Blut 2016). Besides, efficiency (Parasuraman et al. 2005) and flexibility (Benlian et al. 2011) are critical characteristics of electronic services. Overall, trust is a prerequisite for the intention to use online services (Gefen et al. 2003; Loiacono et al. 2007)

Within the sharing economy, concerns about the environmental impact (Arteaga-Sánchez et al. 2018) start to guide user behavior. Service convenience is identified as a relevant service attribute (Akhmedova et al. 2020), and legal regulations should protect customers from problems that might occur in a peer-to-peer economy (Marimon et al. 2019). Again, both the value proposition of the service provided (Akhmedova et al. 2020; Clauss et al. 2019) and trust (Arteaga-Sánchez et al. 2018) affect the perceived quality and the intention to interact with shared services.

6.3 AMaaS Quality Scale Development

In order to strive for stronger theories, we recognize that construct measurement is a relevant issue (Venkatraman and Grant 1986). The unavailability of sound measurement instruments that can be used to assess AMaaS quality impedes new knowledge development and inhibits a thorough investigation of the phenomenon in practice (Lewis et al. 2005). Hence, we follow eminent scale development procedures (Churchill Jr. 1979; Lewis et al. 2005; MacKenzie et al. 2011) to compile an AMaaS quality scale within three steps (see Figure 11): In the next sections, (1) we conceptualize the domain of interest, (2) evaluate and refine the initial instrument, and (3) validate the final measurement properties.

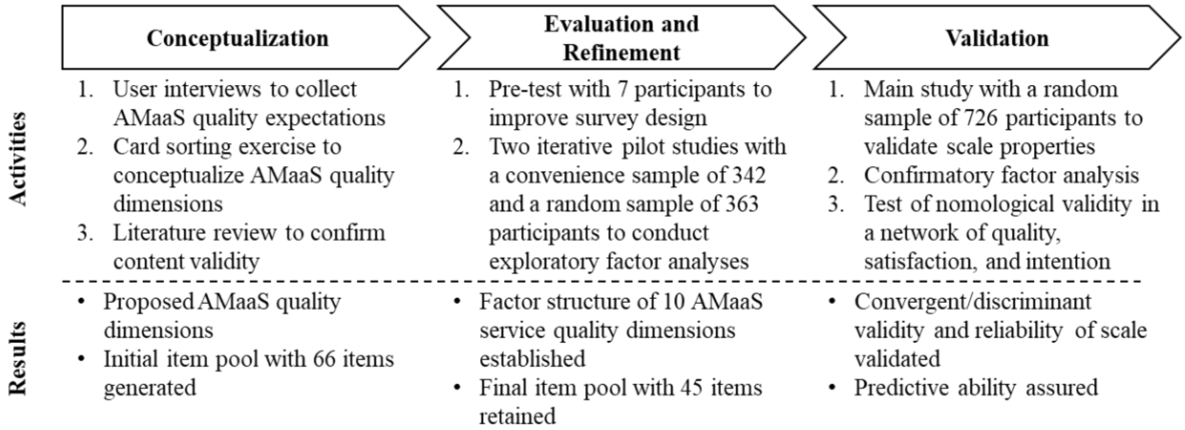

Figure 11. The Process Followed During Scale Development (Adapted from Benlian et al. (2011))

6.3.1 Step 1: Conceptualization

The development of good data collection instruments first requires specifying the domain of interest (Churchill Jr. 1979). However, AMaaS represents a new form of service delivery for which the service quality dimensions are not yet known. Nevertheless, our diligent review of past studies regarding commonly cited quality dimensions of (electronic) services and the sharing economy suggests two relevant primary dimensions of AMaaS quality: Outcome quality and trust.

From the beginning, service research recognized that "what the consumer receives as a result of his interaction with a service firm, is important to him and to his evaluation of the quality of the service" (Grönroos 1984, p. 38). Despite different naming conventions (i.e., outcome quality, technical quality, service product), various studies support the fact that the service outcome is a relevant factor for the customers' quality evaluation (Berry et al. 1985; Brady and Cronin 2001; Collier and Bienstock 2006; Grönroos 1984; Rust and Oliver 1994). The often identified quality dimension "fulfillment" follows the same rationale. It represents the delivery of a promised product/service as a result of an online service interaction (Blut et al. 2015; Parasuraman et al. 2005; Wolfinbarger and Gilly 2003). Also, in the sharing economy, the service's value proposition influences the customer's overall quality evaluation (Clauss et al.

2019). Likewise, we believe that the service outcome (i.e., individual mobility) needs to be fulfilled to perceive the AMaaS service encounter as high quality. We thus hypothesize:

H1: *Enhanced levels of outcome quality will increase the level of AMaaS quality.*

According to Grönroos (1984) and Berry et al. (1985), customers are not only interested in the outcome of a service process (the what) but in the process itself (the how). The evaluation of this quality dimension is very subjective as it resides in the interaction between a customer and the service organization (Lehtinen and Lehtinen 1991). There is a general agreement that trust is imperative to all kinds of personal interactions (Ping Li 2011) and technology usage (Gefen et al. 2003). Following this reasoning, assurance, which inspires trust and confidence within users, has been conceptualized as an element of interaction quality (Akter et al. 2019; Beltagui and Candi 2018; Fleischman et al. 2017). Besides, trust has been found in the service literature and in the sharing economy to influence the overall quality perception (Arteaga-Sánchez et al. 2018; Barnes and Vidgen 2002; Teo et al. 2008). Hence, we argue that:

H2: *Enhanced levels of trust will increase the level of AMaaS quality.*

Like Collier and Bienstock (2006), we do not believe that the latent constructs of outcome quality and trust can capture all dynamics during a service encounter. We model them as second-order dimensions made up of specific attributes. A hierarchical model's advantages are more theoretical parsimony and less model complexity (Edwards 2001; MacKenzie et al. 2005). Using the primary dimensions as a starting point, we leverage exploratory customer interviews to identify their relevant subdimensions.

We conduct interviews with 23 potential customers (see Table 8 for participant demographics and Wiefel (2021) for more details) to identify the key attributes that constitute the domains of outcome quality and trust. We interview practitioners because they can provide relevant ideas for the phenomenon at hand (Churchill Jr. 1979). As perceived quality also depends on the customer's assessment of alternative offerings (Monroe and Krishnan 1985), we first explore the perceived advantages and disadvantages of current mobility offerings. Then, we provide a common understanding of AMaaS and continue to investigate in which situations the participants would use the new mobility service and how a high-quality service would look like for them. Last, we address potential concerns regarding automated and shared mobility. Depending on the interviewee's answers, we examine the respective quality attributes in detail.

Category		Interviews (N=23)	Pilot study 1 (N=342)	Pilot study 2 (N=363)	Main study (N=726)
Gender	Male	48%	53%	49%	49%
	Female	52%	47%	51%	51%
Age	18-24	26%	21%	12%	12%
	25-34	34%	52%	22%	20%
	35-44	09%	11%	19%	21%
	45-55	09%	08%	20%	25%
	>55	22%	08%	27%	22%
Place of living (no. of residents)	Rural (<5,000)	13%	24%	13%	15%
	Urban (5,000-100,000)	39%	39%	51%	55%
	Metropolis (>100,000)	48%	37%	36%	30%

Table 8. Demographics of Participants

We transcribe the interviews and extract all statements regarding expected AMaaS quality attributes and their antecedents. To gain a conceptualization reflecting the customers' view, 38 additional consumers sort the statements into piles based on conceptual similarity. Using an aggregated similarity matrix, multi-dimensional scaling creates two-dimensional coordinates for each statement, which serve as input for hierarchical cluster analysis (Jackson and Trochim 2002). Throughout the card sorting process, we found support for four subdimensions related to outcome quality (i.e., efficiency, convenience, flexibility, and accessibility) and four subdimensions that can induce trust (i.e., cybersecurity, privacy, traffic safety, and regulatory). Table 9 outlines exemplary interview quotations for each quality dimension.

Next, it is imperative that we consult available literature to ensure construct validity and correctly modeled relationships between the identified quality attributes and the respective second-order dimensions. In extant publications, we find support for the four attributes related to outcome quality.

Efficiency in terms of short in-vehicle times has already been shown to have a strong influence on perceived service quality for most public transportation forms, i.e., air, rail, and busses (Abenoza et al. 2017; Rojo et al. 2012; Roman and Martin 2014). Besides, environmental efficiency influences the satisfaction of users traveling with shared mobility services (Arteaga-Sánchez et al. 2018). Thereby, energy consumption is related to outcome quality, for example, in the case of electric car rentals (Miao et al. 2014). This supports our empirically derived hypothesis:

H1a: *Enhanced levels of efficiency will increase the level of outcome quality.*

Attribute	Related statements
Efficiency	"Because the autonomous cars drive more disciplined, perhaps even coordinated with each other, the traffic flow becomes very regular and fluid." "If driving is autonomous, then I imagine it to be the same as today only faster, more efficient, straighter, and without traffic lights."
Convenience	"That within this driving I also have the possibility to do certain things, to deal with completely different things without having to pay attention to the traffic." "I always have this wasted time of parking. Of course, you could save yourself by just getting off where you want to go and not bothering about the rest because the vehicle then automatically takes the next car park."
Flexibility	"Getting from A to B in the fastest possible time and as flexibly as possible. So don't be dependent on fixed departure times." "Absolute flexibility, in fact, to get out at any time, to continue at any time. Not to be bound to anything or anyone."
Accessibility	"So, that means that if you call a taxi, you might wait an hour, and if you have your own car, you can drive directly." "I'd like to see it work in small towns, too."
Cybersecurity	"If there are any hackers who can hack in. Get access to the credit card, that they'll just sort of mug you." "Especially if such a car is hacked, probably the doors are also locked somehow electrically, and so, you can't get out of it anymore, you'll be trapped like this, right?"
Privacy	"So, privacy is definitely a big concern!" "What worries me is if someone knows where I'm going. Maybe even associate driving patterns of me as a person."
Traffic Safety	"If a child runs into the street, and you suddenly have to brake - I don't know if the car can see that." "Technology could misjudge the environment or surroundings."
Regulatory	"This should perhaps be properly anchored in the law, what if something should happen? Who's liable?" "Something like the car's behavior in an accident can only work if it has been discussed by committees and of course, expert commissions. That rough rules have already been laid down, which are then legitimized again by the parliament."

Table 9. Exemplary Quotes from Interview Participants for each Identified Quality Dimension

Marketers observe a general rise in consumer demand for convenience (Seiders et al. 2007). It has been identified early to be relevant for the quality perception in the auto industry (Andaleeb and Basu 1994). Ultimately, convenience has a strong influence on the quality perception of public transport services (Li et al. 2018; Liou et al. 2014), which lets us assume that:

H1b: *Enhanced levels of convenience will increase the level of outcome quality.*

Flexibility is one of the relevant quality attributes of electronic services (Parasuraman et al. 2005). It offers the customer the freedom to change the service's contractual and functional/technical aspects (Benlian et al. 2011). In a mobility context, this can include the maximum travel distance (Xu et al. 2017), service frequency (Allen et al. 2018), or operating hours (Seiders et al. 2007). We thus hypothesize that:

H1c: *Enhanced levels of flexibility will increase the level of outcome quality.*

Accessibility has repeatedly been found to be relevant for public transport (Aydin et al. 2015; Diez-Mesa et al. 2018; Hernandez et al. 2016) and car-sharing services (Kim et al. 2017; Ko et al. 2019). This includes the availability of a free car (Kim et al. 2019), the proximity to the station (Abenoza et al. 2017), and the waiting time (Wong et al. 2020). Based on these results, we deem that:

H1d: *Enhanced levels of accessibility will increase the level of outcome quality.*

In the following paragraphs, we validate the empirically revealed subdimensions of trust by consulting the literature.

For electronic services, cybersecurity is one factor that predicts the judgment of quality (Benlian et al. 2011; Wolfinbarger and Gilly 2003; Yang et al. 2004). Besides, it has been identified as an antecedent of online trust (Gefen et al. 2003; Kim and Peterson 2017). Furthermore, multiple researchers relate cybersecurity with the quality attribute assurance that is defined as the ability to convey trust (Barnes and Vidgen 2001; Field et al. 2004; Zhuo et al. 2013). This lets us argue that:

H2a: *Enhanced levels of cybersecurity will increase the level of trust.*

Like cybersecurity, information privacy is a predictor of the user's quality perception in online contexts (Blut 2016; Parasuraman et al. 2005; Wolfinbarger and Gilly 2003). In addition to that, privacy violations can reduce trust in the online vendor or service (Gefen et al. 2003; Martin 2018). This is why Collier and Bienstock (2006) defined privacy as an indicator of process quality and why we think that:

H2b: *Enhanced levels of privacy will increase the level of trust.*

In the public transportation context, traffic safety is one of the most relevant service attributes (Kuo 2011; Nathanail 2008; Policani Freitas 2013). Qualitative studies regarding automated driving observe traffic safety as the most controversial discussed factor (Wiefel 2020). Interviewees mention traffic safety together with the ability to have trust in autonomous public transport (Eden et al. 2017). Further studies support this relationship as they model safety as a subdimension of assurance, the attribute that conveys trust (Akter et al. 2019; Awasthi et al. 2011). Hence, we deem that:

H2c: *Enhanced levels of traffic safety will increase the level of trust.*

Structural assurance, including regulations and legislation, is another crucial factor that instills service quality in the mobility sector and the sharing economy (Cheng et al. 2018; Marimon et al. 2019; Policani Freitas 2013). Besides, legal protection promotes trust (Gefen et al. 2003; Marimon et al. 2019). Especially in a context in which design decisions can influence the accident outcomes, legislation could oblige the algorithms to act in line with social norms and not deliberately harm other people favoring the driver (Salonen and Haavisto 2019). Based on these reasonings, our last hypothesis is:

H2d: *Enhanced levels of regulations will increase the level of trust.*

As model misspecification "can have serious consequences for the theoretical conclusions drawn from that model" (Jarvis et al. 2003, p. 212), we diligently determine whether the perceived AMaaS quality should be reflective or formative. Based on the means-ends-chain theory, causality flows from the subdimensions to the primary dimensions and finally to the third-order quality construct. Thereby the indicators are not interchangeable, and the indicators do not need to covary with each other. Furthermore, the quality dimensions do not have the same antecedents and consequences. These four characteristics let us specify a formative model (Jarvis et al. 2003). As a formative measurement model on its own is underidentified and cannot be estimated (Bollen K. 1989), we add reflective indicators to each construct (Jarvis et al. 2003). Thereby, the assumption of error-free indicators is relaxed (Diamantopoulos et al. 2008). The proposed research model is shown in Figure 12.

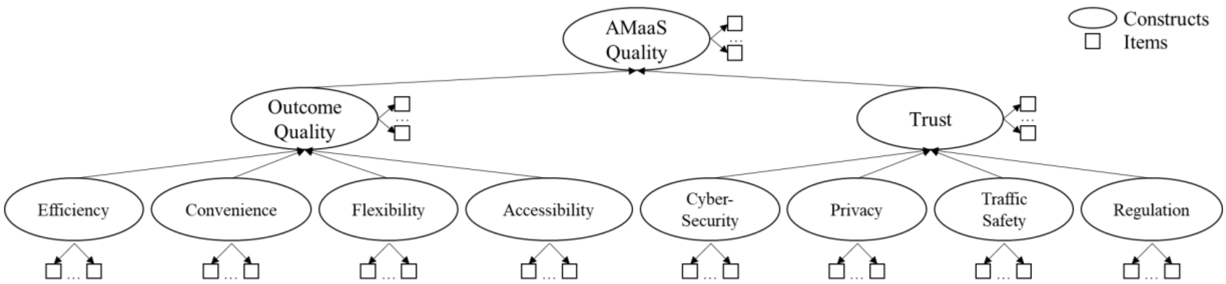

Figure 12. Proposed Research Model

After developing our model, we derive items for the subsequent analysis from the categorized responses and available literature (MacKenzie et al. 2011). For each (sub)dimension, we collect a set of items (Noar 2003) that should cover each aspect of the respective domain (Churchill Jr. 1979). As five to six items seem to be adequate for most measures (Hinkin 1995), we identify six items per dimension resulting in 66 statements for our AMaaS quality scale consisting of overall AMaaS quality, two primary dimensions, and eight subdimensions. We only use positively worded items to avoid method artifacts and achieve conceptually meaningful results (Babakus and Boller 1992). Besides, we frame all items as expectations as these are "the only types of evaluations customers would have, about service delivery that they have not yet tried"

(Dabholkar 1996, p. 31). To ensure sufficient variance among respondents for subsequent analyses, we employ a 7-point Likert-scale (Hinkin 1995).

6.3.2 Step 2: Evaluation and Refinement

In the next step of the scale development process, we collect data through multiple iterations to evaluate and optimize the AMaaS quality instrument's measurement properties (MacKenzie et al. 2011). First, we conduct a pre-test with 7 participants to improve our survey design. Based on the testers' feedback, we extended our description of AMaaS, which we used to familiarize participants with the subject of the new mobility service. Furthermore, we changed the wording of our attention check and adjusted some items to avoid a mixture of expected feelings and expected service capabilities.

To assess construct validity, we launch the updated survey for a first pilot study. Here, we collect 342 valid responses from a convenience sample. A 1:5 item-to-response ratio, as well as the total number of observations, should be sufficient for a first exploratory factor analysis (EFA) (Hinkin 1995). To ensure that the data is amenable for factor analysis in SPSS 26, we perform the Kaiser-Meyer-Olkin test, the Bartlett sphericity test, and check for multivariate normality (Lewis et al. 2005). During the EFA, we eliminate items with large cross-loadings (>0.3) on non-hypothesized dimensions or non-significant loadings on the hypothesized dimension (<0.7) (MacKenzie et al. 2011).

The results of the first EFA make us eliminate one subdimension: regulation. From a statistical point of view, the items do not load properly on a common factor. From a theoretical perspective, the AMaaS service provider cannot actively influence this quality dimension. The analysis also lets us split the efficiency dimension into two distinct attributes: time efficiency and environmental impact. The six efficiency items divide neatly into the two new factors, each consisting of three items.

After adding additional items to the newly identified constructs of time efficiency and environmental impact, we run a second analysis with 51 remaining items (see Table 14 in the appendix – including the strikethrough items) and a new sample. This time, a market research institute recruits 363 European participants. This counteracts potential selection biases and enables the consideration of representative quotas (Lowry et al. 2016).

Again, we first test if the data is eligible for factor analysis. Then, the maximum likelihood procedure with Promax rotation is used. The EFA is constrained a priori to 11 factors, i.e., overall quality and the previously identified ten quality dimensions. We again iteratively remove items with either low loadings or high cross-loadings. This process results in the final AMaaS quality scale consisting of 45 items (see Table 14 in the appendix – excluding the strikethrough items).

6.3.3 Step 3: Validity Testing

For our main study, we attain 726 valid responses from another random European sample. Before validating and estimating the measurement and causal models, we test for common method bias (CMB). CMB is a method artifact associated with unidimensional methodologies like our self-reported survey (Podsakoff et al. 2003). To avoid CMB, we encourage the participants to answer spontaneously and honestly. Furthermore, we add the theoretically unrelated marker variable blue attitude (Miller and Chiodo 2008) to test for CMB using the marker variable technique (Williams et al. 2010). The analysis reveals that no CMB is present.

A complete, confirmatory analysis should prove the validity of our measurement model of the AMaaS quality scale (Loiacono et al. 2007). Convergent validity is assessed following the recommendations of Fornell and Larcker (1981): All item loadings are significant and exceed the threshold value of 0.7 (see Table 14 in the appendix), all construct reliabilities (Cronbach alpha and composite reliability (CR)) are above 0.8, and the average variance extracted (AVE) of each construct exceeds 0.5. Additionally, discriminant validity is given as the AVE's square root is greater than the shared variance between the construct and the remaining constructs in the model (Fornell and Larcker 1981). Our data meets all requirements (see Table 10), and good model fit indices (CMIN/DF=1.998; CFI=0.973; SRMR=0.027; RMSEA=0.037; PClose=1.000) can be interpreted as further evidence for the validity of the measurement model (Hu and Bentler 1999).

The causal model specified earlier implies that AMaaS quality is a multi-dimensional and hierarchical construct. Hence, it can be seen as a third-order factor model which can be tested with structural equation modeling techniques (Brady and Cronin 2001). Like Blut (2016), we follow a step-wise approach in which we first examine the appropriateness of the primary dimensions, then the suitability of the respective subdimensions, and last the entire model. The model fit measures indicate the degree to which the hierarchical structure with its primary dimensions and subdimensions is supported by the data (Dabholkar et al. 1996). Our analysis produces an excellent model fit for each of the three causal models supporting our conceptualization (see Table 11).

Construct		Cr. α	CR	AVE	1	2	3	4	5	6	7	8	9	10	11
QUAL	1	.967	.967	.855	**.925**										
OUTC	2	.906	.907	.765	.788	**.874**									
TRUS	3	.981	.981	.946	.807	.823	**.973**								
TIME	4	.975	.976	.909	.610	.579	.604	**.953**							
ENVI	5	.956	.957	.849	.541	.524	.532	.672	**.921**						
CONV	6	.945	.947	.781	.756	.764	.795	.620	.498	**.884**					
FLEX	7	.932	.933	.776	.693	.804	.661	.514	.475	.733	**.881**				
ACCE	8	.933	.934	.739	.683	.640	.571	.515	.504	.611	.731	**.860**			
CYBE	9	.950	.950	.864	.217	.257	.302	.182	.216	.137	.172	.168	**.930**		
PRIV	10	.949	.950	.790	.649	.535	.576	.451	.435	.500	.492	.537	.327	**.889**	
TRAF	11	.954	.955	.841	.774	.763	.869	.701	.556	.792	.628	.554	.237	.519	**.917**

Table 10. Construct Reliability and Validity. Diagonal Elements (bold) are the Square Root of the Average Variance Extracted (AVE). Off-Diagonal Elements are the Shared Variance

Model	CMIN/DF	CFI	SRMR	RMSEA	PClose
1. Test of the primary dimensions	1.646	0.998	0.011	0.030	0.998
2. Test of the subdimensions	2.558	0.970	0.038	0.046	0.992
3. Test of the overall model	2.417	0.966	0.044	0.044	1.000

Table 11. Step-Wise Testing of the Hierarchical Model

The complete model (shown in Figure 13) explains a large portion of the variance for both the overall AMaaS quality (R^2=.705) as well as the primary dimensions of outcome quality (R^2=.752) and trust (R^2=.797). All but one (i.e., accessibility) hypothesized quality (sub-) dimensions are supported. Trust hast the strongest effect on AMaaS quality (β=.508; ρ=<.001), but outcome quality (β=.425; ρ=<.001) has practical relevance as well. Traffic safety (β=.783; ρ=<.001) has a very strong effect size while privacy (β=.154; ρ=<.001) and security (β=.065; ρ=.001) seem to be less relevant for the perceived level of trust. Outcome quality is explained mainly by flexibility (β=.471; ρ=<.001) and convenience (β=.328; ρ=<.001). Environmental impact (β=.078; ρ=.017) and time efficiency (β=.074; ρ=.034) are less predictive. Last, accessibility (β=.040; ρ=.291) has a non-significant effect on outcome quality.

The control variables of age (β=.011; ρ=.606) and place of living (β=-.021; ρ=.329) are not significantly affecting the overall quality, but we found gender (β=.043; ρ=.048) to have a small but statistically significant influence.

Next to ensuring the validity of the measure, we determine whether the measure behaves as expected in relation to other constructs (Churchill Jr. 1979; MacKenzie et al. 2011). This would provide further evidence of the validity of the measure (Hinkin 1995).

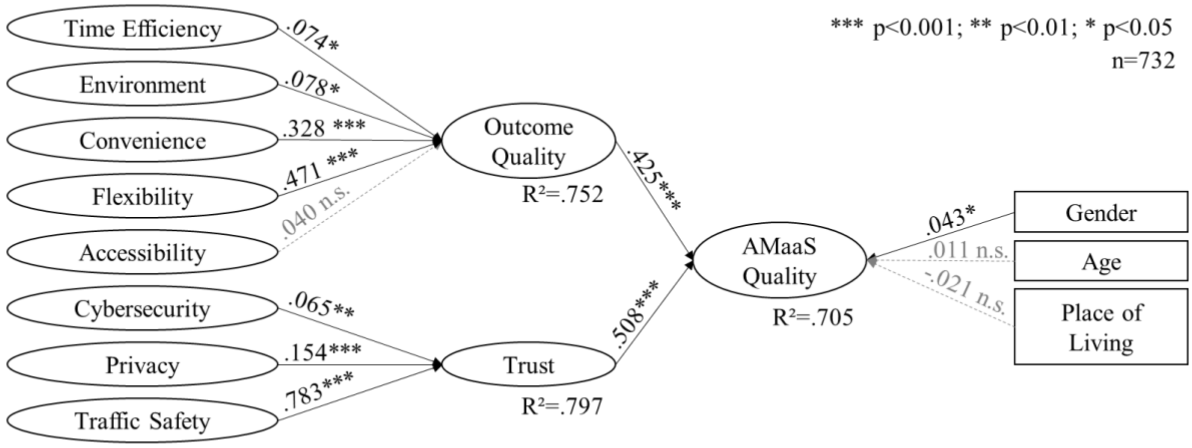

Figure 13. Results of the Causal Model

For perceived quality, extant literature suggests a positive relationship with satisfaction in general service contexts (Brady et al. 2005; Cronin and Taylor 1992), for IT services (Kettinger et al. 2009) as well as for the mobility context (Nguyen-Phuoc et al. 2020). Besides, perceived quality is expected to increase the user's behavioral intention (Cronin et al. 2000; Dabholkar 1996; Lin and Hsieh 2011). Last, satisfaction positively influences behavioral intention (Brady et al. 2005; Cronin et al. 2000; Kettinger et al. 2009). Thus, we conduct a nomological validity test with the related constructs of satisfaction and behavioral intention. To do so, we already included both constructs in our initial survey, where we used widely-cited items (Bhattacherjee 2001; Venkatesh et al. 2012).

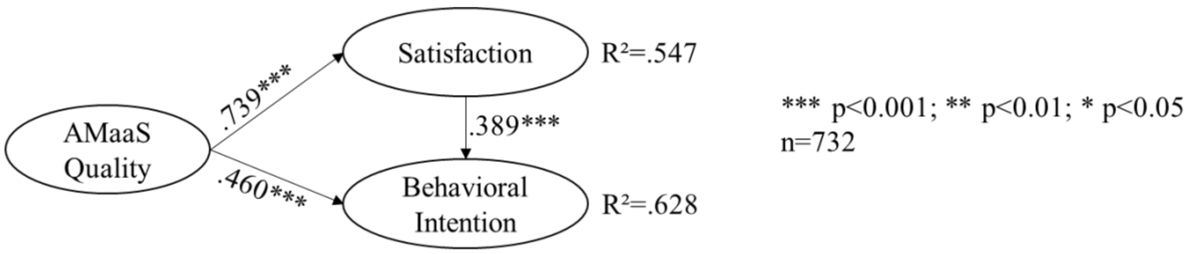

Figure 14. Nomological Validity

Structural equation modeling confirms that the nomological net of perceived quality, satisfaction, and behavioral intention behaves as expected (see Figure 14). Higher levels of AMaaS quality lead to higher levels of satisfaction (β=.739; ρ=<.001) and behavioral intention (β=.460; ρ=<.001). Besides, satisfaction increases the behavioral intention (β=.739; ρ=<.001). Thus, we can conclude that the predictive validity of the AMaaS quality scale is satisfactory.

6.4 Discussion

6.4.1 Theoretical and Practical Contributions

Although automated and shared mobility services are extensively researched, consumer evaluations of AMaaS service quality have not yet been investigated (Bornholt and Heidt 2019; Wiefel 2020). Accordingly, our main research contribution is the development of a context-specific AMaaS quality measure that shows good psychometric properties and offers new insights regarding the relative importance of AMaaS service attributes. AMaaS is an electronic transportation service offered in the sharing economy that leverages autonomous vehicles. Accordingly, our final scale consists of quality dimensions rooted in multiple research streams regarding traditional services (e.g., outcome quality), electronic services (e.g., security and privacy), the sharing economy (e.g., convenience), and automated vehicles (e.g., traffic safety). From an epistemological perspective, we are the first who synthesize the existing domain knowledge to adopt a new perspective for which we build and test a new theory regarding the quality of automated and shared mobility quality (Schryen et al. 2015).

Thereby, our observations support earlier investigations revealing that higher levels of trust increase the level of quality (Teo et al. 2008). We recognize that trust is even more influential than outcome quality. This is in line with Grönroos (1984), who stated that functional quality, i.e., how the service is delivered, is more important than the service outcome as long as the promised service is fulfilled on a satisfactory level.

We identify traffic safety to be the most relevant attribute to build trust in an autonomously acting vehicle. Other studies in the public transport sector have similar results (Kuo 2011; Policani Freitas 2013). Moreover, in a medical context, where a service consumer needs to give up control over his/her physical well-being, safety is strongly linked to the perceived service quality (Rathert et al. 2011). A reason might be that safety is one of the basic needs in Maslow's (1943) hierarchy of needs. Only if the customer's safety is ensured, a service can be perceived as trustworthy and therefore as high quality.

Contrary to earlier findings regarding electronic services, cybersecurity and information privacy are less important to build trust. While cybersecurity is one of the most influential quality elements for software as a service (Benlian et al. 2011), for AMaaS, it is least relevant. The reason might be that AMaaS passengers do not actively operate the vehicle. This missing involvement makes AMaaS different from other electronic services, where users strongly interact with the system. A consequence might be a reduced sense of cybersecurity and privacy issues. Besides, passengers might feel a less severe threat when comparing traffic safety with security and privacy. In the first case, our interview participants were concerned about their health and life, whereas they were worried about location tracking and data theft in the second case.

Looking at the outcome quality attributes, it is remarkable that accessibility is not a significant factor. For car-sharing, availability and proximity are strongly relevant factors (Kim et al. 2017; Ko et al. 2019). However, automated vehicles can reposition themselves to serve incoming requests. Research already conducts simulations assessing different relocation strategies (Li et al. 2019a) and fleet sizes (Spieser et al. 2014) to fulfill the customers' mobility needs with minimum waiting times, making the concerns regarding accessibility obsolete for AMaaS.

In contrast, flexibility plays a major role for the expected quality of AMaaS. Future customers are concerned that the automated car will not provide the same flexibility as their own car. For them, flexibility does not only mean being independent of anyone and taking a ride whenever they like. Instead, a service offering providing flexibility consists of large business areas in which customers can travel. Besides, customers require different cars with the required space or interior to fulfill various passenger needs, e.g., a desk for business trips or a comfortable seat and entertainment for longer trips. Again other customers demand the possibility to personalize the route, e.g., to collect/drop-off a friend. Thus, our understanding of flexibility is different from existing research requiring a system that can adapt to changing conditions (e.g., Nelson et al. 2005).

Convenience also has a strong influence on outcome quality. According to Seiders et al. (2007), convenience comprises the time and effort spent when purchasing and using the service and the core benefits of the offering, which links the construct to the outcome quality dimension. The core benefit expected from automated driving is the possibility of relaxing during the ride, i.e., to have less effort driving the car and doing other things while driving (Hein et al. 2018). This new and convenient way to travel would also enable the elderly to benefit from the service offering.

The last two attributes, time efficiency and environmental impact, have a minor impact on the outcome quality, although they have shown significant influence in car-sharing (Arteaga-Sánchez et al. 2018) and public transport (Abenoza et al. 2017). A reason might be that the expected benefits (i.e., fewer cars needed, reduced energy consumption, a smoother driving style leading to shorter traffic times) will be outweighed by more vehicle kilometers traveled. Wadud et al. (2016) expect an increase of 57% of vehicle kilometers driven, which will then still clog the roads. Moreover, according to their research, replacing transit journeys with automated vehicles will double household greenhouse gas emissions.

Overall we can conclude that although all quality elements have been identified in other research streams individually, AMaaS requires a particular composition. Besides, some attributes' definitions and effect sizes deviate from earlier research so that available quality scales would not deliver valuable support when evaluating AMaaS offerings.

Looking at the three process steps that we followed during the scale development, each phase results in a valuable deliverable (Lewis et al. 2005). We are among the first researchers who explore quality dimensions for an independently acting technology-based service. As a result of this, we identify two primary quality dimensions and seven significant subdimensions. Our results provide valuable insights for the conceptualization of AMaaS quality and the quality perception of other safety-related autonomous mobility services.

Second, we iteratively refine the measurement instrument until we achieve good psychometric properties in terms of validity and reliability. This allows other researchers to use our operationalizations to build strong theories based on sound measures. The usage of our (self-developed) constructs is not restricted to quality scales but can be used effectively in other theories, too.

Third, we test for nomological validity so that our instrument's predictive ability is ensured. Thoroughly validated instruments allow replications of studies in heterogeneous contexts (Cook and Campbell 1979) so that the scale is ready to use for specialized scholars from transportation, service science, and the IS community.

From a managerial perspective, our research supports mobility providers to continually meet customers' expectations, which results in a competitive advantage hard to overcome (Reeves and Bednar 1994). The key is to uncover among all potential quality attributes those dimensions that are most crucial to enhance the level of perceived quality (Yang et al. 2004). Only if the management knows the essential attributes leading to perceived service quality, investments can be prioritized. To achieve this target, service designers can leverage our measurement instrument to assess their individual mobility offering's quality and improve it accordingly.

6.4.2 Limitations and Further Research

Of course, our results need to be considered in light of their limitations. Our samples are all recruited within Europe. Service quality, however, is perceived differently within various cultures (Ueltschy et al. 2004; Witkowski and Wolfinbarger 2002). To address this shortcoming, we propose to conduct a cross-cultural study.

In addition to that, we had to build our research on the customers' expectations because automated mobility as a service is not yet available. Nevertheless, Dabholkar (1996) argues that a quality model that is based on expectations is equally applicable for quality perceptions. Hence, we asked the participants to imagine a realistic scenario. Besides, customer expectations seem to be stable over time (Clow et al. 1998), which makes us assert that our results will still be relevant when AMaaS hits the market. Nevertheless, our results need to be reconfirmed with customers who experienced an automated ride as soon as AMaaS becomes available.

Extant literature indicates that the quality dimensions' contributions change when new users become more experienced customers (Dagger and Sweeney 2007). Developing an understanding of this change's nature will become important soon to build customer long-term customer relationships. In the context of AMaaS, the strong influence of traffic safety might decrease as soon as people get used to this new form of mobility. Supporting this assumption, a study assessing the drivers of loyalty in the airline industry found safety not to be relevant (Vlachos and Lin 2014). Another study reports an increasing importance of time efficiency in a public transport context (Abenoza et al. 2017). Thus, the low relevance of time efficiency could increase for AMaaS, too. Future longitudinal research should investigate if and how customer perceptions change over time in regard to AMaaS quality.

Finally, given that the AMaaS services are just in their infancy and automotive manufacturers and IT companies primarily lead the development of such services, our work's practical utility should be validated through a joint research endeavor with a practitioner. For example, an evaluation from industry experts may be effective, and a pilot use of the developed quality measurement instrument could further validate its applicability in a realistic setup.

7 Contributions and Implications

This dissertation aimed to advance the knowledge about drivers that influence the adoption and quality perception of autonomous mobility. An improved conception of how AV acceptance develops has relevant implications for research, practitioners, and society as the usage of self-driving vehicles is expected to support solving public issues like clogged roads, traffic fatalities, and greenhouse emissions. Against this background, two types of autonomous driving have been regarded.

The first part of the dissertation has examined the acceptance of autonomous vehicles in general, including privately owned vehicles, shared vehicles, and public transport. Altogether, many research results were already available, so that the first two papers A and B, gathered, structured, and combined extant insights. Specifically, paper A identified various acceptance factors, including vehicle attributes, demographic and societal characteristics. Paper B then calculated for each known acceptance factor the mean effect sizes and moderating effects by combining all published empirical findings.

The second part of this dissertation, with papers C and D, took a more narrow focus on the largely under-researched concept of AMaaS. In addition to the general benefits ascribed to autonomous vehicles, a shared consumption model is expected to reduce the number of vehicles needed, leverage resources more effectively, and improve the societal situation even further. Besides focusing on AMaaS, the two papers exclusively looked at vehicle- and service-related factors as mobility providers can adjust them more easily than user characteristics or societal aspects. Thereby, paper C explored which service characteristics are required for AMaaS, and paper D developed a hierarchical quality scale.

7.1 Theoretical Contributions

Overall, the findings across the four research papers included in this dissertation contribute to the IS and transportation research streams by advancing our understanding of the public's AV and AMaaS perceptions and how they influence user acceptance and satisfaction.

Paper A set out by conducting a literature review on the acceptance of autonomous vehicles. The diligent collection and lucid presentation of existing research results made previously tacit domain (meta-)knowledge explicit (Schryen et al. 2015). However, during the analysis, the paper uncovered the issue of construct identity fallacy (Larsen and Bong 2016), leading to missing comparability of research results (Cooper 1998). As a result, the paper took an in-depth perspective to analyze which acceptance factors influence the behavioral intention to use automated vehicles by comparing constructs and their respective items leveraged in existing research. Hereby, the paper counteracted the discovered shortcoming and provided researchers with a transparent AV acceptance framework that integrates available findings. Consequently, researchers got an overview of where current research stands and can build on the accumulated knowledge with their future work. To guide scholars' prospective research endeavors, the paper proposed fruitful research avenues across various themes ranging from areas with limited research attention, over diverging research results, and methodologies to be used to an evolution of research focus. This cross-sectional research agenda is a means to lead the scattered young research stream in a common direction.

Paper B took up the challenge of diverging research results outlined in paper A and conducted a meta-analysis. While balancing significant and non-significant results, like done by paper A, can come to wrong conclusions (Hunter and Schmidt 2004; Rosenthal and DiMatteo 2001), a meta-analysis aggregates previously reported effect sizes to calculate the real strength of each acceptance factor. Hence, the analysis determined the explanatory power and parsimoniousness of extant research models. As a result, paper B showed, in addition to factors from traditional acceptance models like perceived usefulness, that vehicle-related factors of traffic safety and efficiency strongly influence the behavioral intention to use automated vehicles. Besides, the paper performed a moderator-analysis to explain diverging results in previously published studies. The gained insight that the study's location, the vehicle's level of automation, the ownership model, and the applied methodology influence the relationship between most acceptance factors and the behavioral intention contributed to the academic debate. The results supported future theory building in that paper B increased the precision of the applied paradigm in clarifying the relationship between acceptance factors and behavioral intention. Finally, the paper could broaden the AV acceptance theories' scope (Bacharach 1989) by including privately owned vehicles, shared vehicles, and public transport in its analysis. The results are, thus, generalizable across all automated mobility options.

Despite the achieved generalizability of paper B's results, both papers, A and B, have pointed out that only little research existed regarding automated and shared vehicles, i.e., AMaaS. Hence, paper C extended the so far limited research attention and examined the service characteristics relevant for AMaaS. Exploratory interviews showed that results from the underlying contexts of autonomous vehicles and car-sharing could be combined for AMaaS. However, the paper also revealed that AMaaS is more than simply adding up the insights from both research streams. It observed and outlined expanded boundaries of the relevant service characteristics. A cluster analysis delineated the identified service characteristics from a practitioner's and not the researcher's view to avoid being trapped by the previously discussed construct identity fallacy. Furthermore, the interviews revealed what users understand by each construct so that the AV research could gain an unambiguous understanding of the domain (Whetten 1989). By demarcating relevant AMaaS characteristics, the paper proposed construct boundaries that can facilitate scholarly communication (Suddaby 2010) and serve as a basis for operationalizing each AMaaS characteristic.

Paper D developed operational measurements for the previously identified AMaaS service characteristics. Although the paper used the resulting constructs to build a specific AMaaS quality scale, the validated operationalizations could be equally used in other theories (Cook and Campbell 1979). Paper D explored as one of the first research projects quality dimensions for AMaaS, i.e., an independently acting technology-based service. The final quality scale integrated dimensions from multiple related research streams. It synthesized existing knowledge by proposing and testing a new theory for automated and shared mobility quality. Thereby, the paper contributed to IS research with a quality scale that showed good psychometric properties and provided new insights regarding each service attribute's relative importance. The scale's predictability was ensured as it was positioned in a nomological net consisting of the scale itself, user satisfaction, and the behavioral intention to use AMaaS. The thoroughly validated scale can serve various research disciplines, from transportation to service science and IS. Paper D contributed to AV research because it took a new perspective regarding autonomous mobility. It did not focus on user acceptance but on the users' quality perceptions, which is considered the critical factor for a technology's long-term success (Fassnacht and Koese 2006; Zeithaml et al. 2002).

7.2 Practical Implications

Apart from having theoretical implications, this cumulative dissertation also informed practitioners offering automated vehicles or autonomous mobility services. The respective managerial contributions are outlined below.

Paper A began by compiling an overview of all characteristics that AV providers need to consider when designing and manufacturing the vehicle. Based on the insights that the diligent literature review provided, manufacturers can now exclusively focus on those acceptance factors significantly affecting user acceptance. Furthermore, vehicle attributes that negatively influence the adoption decision can be improved to mitigate existing concerns. Next to the vehicle-related factors, the paper described customer demographics that are significant for using and purchasing automated vehicles. These insights can be leveraged by practitioners when promoting automated vehicles. Lastly, the results of paper A urged policymakers to pass relevant regulations for AV usage. Providers and customers need to know who is liable in case of damage, if a driver's license is required and whether AVs will drive in mixed traffic or on separate lanes. Paper A, thus, provided valuable insights not only for industry but also for governments.

While the first paper identified relevant acceptance factors and the direction of effects, paper B calculated the overall effect sizes. Exact effect sizes are of particular relevance for practitioners because managers can adjust scarce human resources and budgets in a way that reflects the most relevant acceptance factors. Hence, the industry should mainly focus on the vehicle's usefulness, efficiency, and safety. The same applies to the more thorough investigation of customer demographics. Although gender could be reconfirmed to be significant, the meta-analysis, including more than 12,000 participants, revealed only a marginal effect size. Thus, marketers should not design gender-specific campaigns. Instead, it appeared to be more reasonable to focus on technology-oriented customers. Furthermore, the moderator-analysis equipped practitioners with knowledge about which acceptance factors are most relevant in Asia, America, and Europe. Similarly, the moderator-analysis revealed important differences among various levels of automation and the ownership model. The deepened understanding of how AV acceptance varies across contexts supports mobility providers and vehicle manufacturers in making strategic decisions.

Paper C shifted the focus from autonomous driving in general to automated mobility as a service. By now, only a few studies have investigated the specific context of automated and shared mobility. Therefore, the exploratory insights gained during customer interviews are precious for practitioners. To strengthen the practical contribution even further, the paper deliberately headed off from traditional acceptance theories. Instead, it supported the microfoundation movement in strategic management (Barney and Felin 2013) by investigating specific AMaaS related service characteristics. Together these attributes build the service proposition that is expected from potential customers. As a result, the paper identified AMaaS characteristics that practitioners can easily adjust to improve user perceptions. Various customer testimonials were included in the discussion to provide the mobility industry with a lively and precise understanding of each identified service characteristic. Managers can only design the mobility services accordingly if they know what is meant by convenience, flexibility, or safety. The paper uncovered differing perspectives from the general society and industry experts regarding the relevance of the identified AMaaS characteristics. Knowing that potential users have diverging priorities from experts enables managers to reconsider earlier decisions that might have been made based on expert consultants' recommendations.

Finally, paper D developed an AMaaS quality scale with which practitioners can judge their mobility offerings and improve them accordingly. The measurement instrument was explicitly designed for automated and shared mobility services. Hence, it combined various service characteristics from related areas, e.g., electronic services, the sharing economy, and automated driving, in a particular composition that showed excellent psychometric properties. Due to the proven nomological validity, the scale's predictive ability was ensured. The quality scale has far-reaching practical implications because the effect sizes for, e.g., information privacy or cybersecurity are diverging from earlier results concerning other electronic services. Thus, practitioners are now equipped with specific knowledge that was not available previously. It was shown that traffic safety and flexibility are highly relevant for customers to perceive a high-quality automated mobility service. Especially, flexibility has been largely disregarded in earlier research. Paper D supported mobility providers and service designers to fulfill customers' expectations and gain a competitive advantage hard to overcome (Reeves and Bednar 1994).

Overall, this dissertation strongly improved the understanding of user acceptance and quality perception factors for two emerging forms of autonomous driving: automated vehicles and automated mobility as a service.

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Appendix

Author	Context							Independent Variables												Dependent Variable			Item
	LOA	Ownership Model			Interaction			Individual Factors			Vehicle Characteristics			Policy/ Society		Other							
	SAE Level of Automation Considered	Public Transport	Shared Vehicle with / without Ride Hailing	Privately Owned Vehicle / Not Defined	Driving in a Real Car	Driving Simulation	No Interaction	Demographics	Habits / Beliefs	Psychological Characteristics	Perceived Benefits	Perceived Risks	Trust	Policies	Social Influence	Experiencing AV	Attitude	Context	Intention to / Willingness to / Interest in Using/Adoption	Intention to / Willingness to / Interest in Buying/Paying	Other (e.g., Choice, Approval, Attitude)	Items Provided?
(Abraham et al. 2017)	0-5			X			X	X		X			X							X		
(Bansal and Kockelman 2018)	3-4			X			X	X	X											X		
(Bansal et al. 2016)	3-4			X			X	X	X											X		
(Bennett et al. 2019)	5			X			X	X	X	X									X			
(Berliner et al. 2019)	4-5			X			X	X	X		X	X	X							X		
(Buckley et al. 2018a)	3			X		X				X	X		X		X		X		X			
(Charness et al. 2018)	5			X			X	X	X	X			X						X			
(Chen and Yan 2018)	3-5			X			X			X	X	X	X		X		X		X			X
(Choi and Ji 2015)	4			X			X			X	X	X	X						X			X
(Daziano et al. 2017)	3-5			X			X	X	X											X		
(Dong et al. 2017)	5	X					X	X	X		X	X	X	X					X			
(Ernst and Reinelt 2017)	5			X			X				X	X	X						X			X
(Haboucha et al. 2017)	5		X	X			X	X			X	X					X				X	X
(Hardman et al. 2019)	5			X			X	X	X		X	X	X								X	
(Hassan et al. 2019)	4-5			X			X	X	X		X	X	X						X			X
(Hegner et al. 2019)	5			X			X	X		X	X	X	X						X			X
(Hein et al. 2018)	5			X			X				X	X	X		X				X			X
(Hohenberger et al. 2016)	3-5			X			X	X				X							X			
(Hohenberger et al. 2017)	3-5			X			X	X		X	X	X	X						X			X
(Hudson et al. 2019)	5			X			X	X	X												X	
(Hulse et al. 2018)	5			X			X	X	X	X		X									X	
(Jiang et al. 2018)	3-5			X			X			X											X	
(Jing et al. 2019)	5		X	X			X		X		X	X	X		X		X		X			X
(Karnouskos 2018)	5			X			X							X								X
(Kaur and Rampersad 2018)	5	X					X				X	X	X					X	X			X
(Koul and Eydgahi 2018)	5			X			X	X	X		X	X	X	X					X			X
(Krueger et al. 2016)	5		X				X	X	X												X	

Author	Context							Independent Variables												Dependent Variable			Item
	LOA	Ownership Model			Interaction			Individual Factors			Vehicle Characteristics			Policy/ Society		Other							
	SAE Level of Automation Considered	Public Transport	Shared Vehicle with / without Ride Hailing	Privately Owned Vehicle / Not Defined	Driving in a Real Car	Driving Simulation	No Interaction	Demographics	Habits / Beliefs	Psychological Characteristics	Perceived Benefits	Perceived Risks	Trust	Policies	Social Influence	Experiencing AV	Attitude	Context	Intention to / Willingness to / Interest in Using/Adoption	Intention to / Willingness to / Interest in Buying/Paying	Other (e.g., Choice, Approval, Attitude)	Items Provided?
(Lee et al. 2017)	5			X			X	X	X		X	X	X	X	X			X	X			X
(Lee et al. 2018a)	3-5			X			X			X									X			
(Lee et al. 2018b)	3-5			X			X		X	X	X	X	X	X							X	
(Leicht et al. 2018)	5			X			X			X	X	X	X		X					X		X
(Liu et al. 2019a)	4-5			X			X				X	X	X	X					X	X		X
(Liu et al. 2019e)	5			X			X				X	X	X	X					X	X		X
(Liu et al. 2019b)	5			X			X	X	X		X	X	X	X						X		X
(Madigan et al. 2016)	4	X			X						X				X				X			X
(Madigan et al. 2017)	4	X			X			X			X	X		X	X	X			X			X
(Motak et al. 2017)	5	X			X			X	X	X	X				X	X	X		X			X
(Nazari et al. 2018)	5		X	X			X	X	X		X	X	X								X	X
(Niranjan and Haan 2018)	4			X			X				X	X	X				X				X	
(Panagiotopoulos and Dimitrakopoulos 2018)	3-5			X			X				X	X	X		X				X			X
(Payre et al. 2014)	4			X			X	X		X	X	X	X	X			X	X	X			X
(Raue et al. 2019)	4-5			X			X	X	X		X	X	X				X		X			X
(Ro and Ha 2019)	5			X			X				X	X	X	X			X		X			X
(Sener et al. 2019)	4			X			X	X	X		X	X	X		X		X		X			X
(Shabanpour et al. 2017)	5			X			X	X	X	X	X	X	X	X					X			
(Shabanpour et al. 2018)	5			X			X	X	X			X		X					X			
(Souders and Charness 2016)	3-5			X			X	X			X		X						X			
(Spurlock et al. 2019)	3-5			X			X	X		X	X								X			
(Stoiber et al. 2019)	4-5	X	X				X				X	X								X		
(Wadud and Huda 2019)	5			X			X	X	X		X								X			
(Wang and Akar 2019)	5		X	X			X	X	X								X				X	
(Ward et al. 2017)	5			X			X	X	X		X	X	X						X			
(Webb et al. 2019)	5		X				X	X	X		X	X							X			
(Woisetschläger 2016)	4			X			X			X	X	X	X							X		
(Wu et al. 2019)	5			X			X				X								X			X
(Xu et al. 2018b)	3-5			X	X		X				X	X	X						X			X
(Yap et al. 2016)	5		X				X	X			X	X	X								X	X
(Zhang et al. 2019)	3			X			X				X	X	X	X			X		X			X

Table 12: AV Acceptance Concept Matrix (Paper A)

Publication	Sample Size	Continent	Ownership Model	LoA	Methodology	Theoretical Model
(Anania 2018)	922	USA	-	5	Questionnaire	-
(Benleulmi and Blecker 2017)	313	Europe	-	4,5	Questionnaire	UTAUT 2
(Bennett et al. 2019)	177	Europe	Car Ownership	5	Questionnaire	-
(Bruckes et al. 2019)	286	Europe	-	3,4	Questionnaire	TAM
(Buckley et al. 2018b)	74	USA	-	3	Driving Simulator	TAM, TPB
(Charness et al. 2018)	441	USA	Car Ownership	5	Picture/Movie	-
(Chen and Yan 2018)	574	Asia	Car/Ride Sharing	5	Questionnaire	TPB
(Cho et al. 2017)	68	Asia	-	4,5	Driving Simulator	CTAM, TAM, UTAUT
(Choi and Ji 2015)	552	Asia	-	3-5	Questionnaire	TAM
(Dixon et al. 2020)	1008	USA	Car Ownerhsip	5	Questionnaire	-
(Ernst and Reinelt 2017)	100	Europe	-	5	Questionnaire	-
(Forster et al. 2018)	519	Europe	-	3	Picture/Movie	UTAUT
(Gambino and Sundar 2019)	404	USA	-	5	Questionnaire	TAM, TIME
(Hassan et al. 2019)	4436	USA	Car/Ride-Sharing	5	Questionnaire	-
(Hegner et al. 2019)	369	Europe	-	5	Questionnaire	TAM
(Hein et al. 2018)	642	Europe	-	5	Questionnaire	TAM
(Hewitt et al. 2019)	187	USA	Car Ownership	4,5	Questionnaire	CTAM, UTAUT
(Hohenberger et al. 2017)	1603	Europe	Car Ownership	3-5	Questionnaire	-
(Jing et al. 2019)	906	Asia	Car Ownership & Car/Ride-Sharing	5	Questionnaire	TPB
(Karnouskos 2018)	126	Europe	-	5	Questionnaire	-
(Kaur and Rampersad 2018)	101	Australia	Publicv Transport	5	Questionnaire	TAM, UTAUT
(Kelkel 2015)	115	Europe	Car Ownership	5	Questionnaire	TRA, TPB
(Koul and Eydgahi 2020)	377	USA	Car Ownership	5	Picture/Movie	TPB
(Lee et al. 2018b)	459	Asia	-	3-5	Questionnaire	TAM
(Lee and Mirman 2018)	985	USA	Car Ownership	5	Questionnaire	-
(Leicht et al. 2018)	241	Europe	Car Ownership	5	Questionnaire	UTAUT
(Liu et al. 2019a)	742	Asia	Car Ownership	4,5	Pictzure/Movie	-
(Liu et al. 2019d)	300	Asia	Car Ownership	3	Real Car	TAM, UTAUT
(Liu et al. 2019e)	441	Asia	Car Ownership	5	Picture/Movie	-
(Madigan et al. 2016)	349	Europe	Public Transport	4	Real Car	UTAUT
(Madigan et al. 2017)	315	Europe	Public Transport	4	Real Car	UTAUT
(Motak et al. 2017)	111	Europe	Public Transport	4	Real Car	TAM, TPB
(Motamedi et al. 2018)	250	USA	Car Ownership & Car/Ride-Sharing	5	Picture/Movie	TAM
(Nees 2016)	283	USA	Car Ownership	4	Questionnaire	UTAUT
(Nordhoff 2014)	413	Europe	Car Ownership	5	Questionnaire	TAM
(Nordhoff et al. 2018a)	384	Europe	Public Transport	4	Real Car	UTAUT
(Nordhoff et al. 2018b)	315	Europe	Public Transport	4	Real Car	PAD, UTAUT
(Nordhoff et al. 2018c)	7755	Multiple	Car/Ride-Sharing	5	Picture/Movie	-
(Panagiotopoulos and Dimitrakopoulos 2018)	483	Europe	Car Ownership	4	Questionnaire	TAM
(Payre et al. 2014)	421	Europe	Car Ownership	4	Questionnaire	-
(Qu et al. 2019)	1453	Asia	-	5	Questionnaire	-
(Raue et al. 2019)	1484	USA	-	5	Questionnaire	-
(Ro and Ha 2019)	1506	Asia	Car Ownership	5	Questionnaire	TRA, UTAUT

Publication	Sample Size	Continent	Ownership Model	LoA	Methodology	Theoretical Model
(Solbraa Bay 2016)	320	Europe	Car/Ride-Sharing	5	Questionnaire	TAM, TPB, DoI
(Tussyadiah et al. 2017)	325	USA	Car/Ride-Sharing	5	Questionnaire	-
(Ward et al. 2017)	1745	USA	Car Ownership	5	Picture/Movie	-
(Woisetschläger 2016)	239	Europe	Car Ownership & Car/Ride-Sharing	4	Questionnaire	-
(Wu et al. 2019)	470	Asia	Car Ownership	5	Picture/Movie	TAM
(Xu et al. 2018a)	315	Asia	Car Ownership	3	Real Car	TAM
(Zhang et al. 2019)	216	Asia	Car Ownership	3	Questionnaire	TAM
(Zmud et al. 2016)	556	USA	Car/Ride-Sharing	4	Picture/Movie	CTAM

Table 13: Studies Included in our Meta- and Moderator-Analysis (Paper B)

Var.	Items	Ld.	Source
QUAL	The quality of the AMaaS ride would be as expected or promised.	.916	(Dagger et al. 2007; Holloway and Beatty 2008; Xu et al. 2013)
	The service provided by the AMaaS is of a high standard.	.919	
	Overall, the level of service quality of AMaaS would be good.	.939	
	Overall, I would receive excellent service while driving with AMaaS.	.924	
	Overall, the quality of AMaaS would be high.	.925	
OUTC	I believe AMaaS substitutes quiet well for an own car.	.842	(Lamberton and Rose 2012; Loiacono et al. 2007); Self-Developed
	The AMaaS is pretty much what I need to be mobile.	.860	
	AMaaS would adequately meet my mobility needs.	.919	
	AMaaS would give me effective door-to-door mobility.	-	
	AMaaS would be an effective way to be mobile even without your own car.	-	
TRUS	I would have full trust in AMaaS.	-	(Hegner et al. 2019; Zhang et al. 2019)
	Overall, I expect that I can trust AMaaS.	.970	
	I expect that I can rely on an AMaaS.	.971	
	Overall, I expect AMaaS to be trustworthy.	.977	
TIME	I expect that traffic congestion will be reduced by the use of AMaaS. (E)	.934	(Hohenberger et al. 2017; Li and Kamargianni 2019; Ro and Ha 2019; Wu et al. 2019)
	I believe that the use of AMaaS can improve the traffic quality. (E)	.962	
	I believe that AMaaS will improve traffic flow. (E)	.970	
	AMaaS would help to reduce congestion.	.947	
ENVI	I expect automotive emissions to be reduced by AMaaS. (E)	.947	(Hohenberger et al. 2017; Liu et al. 2019a; Ro and Ha 2019; Wu et al. 2019)
	AMaaS could reduce vehicle emissions and pollution. (E)	.933	
	I believe that AMaaS would contribute to a more fuel-efficient way of driving. (E)	.862	
	I believe that the use of AMaaS can improve the air quality.	.940	
CONV	For me, AMaaS would be a convenient way to get to my destination.	.919	Self-Developed
	AMaaS would be a convenient way to travel.	.907	
	AMaaS would make the journey more pleasant for me.	.914	
	With AMaaS, I could easily reach my destination.	.860	
	After driving with AMaaS, I would feel less exhausted than when I drive myself.	.812	
FLEX	AMaaS would give me enough flexibility.	.916	Self-Developed
	Using AMaaS would not limit my flexibility.	-	
	With AMaaS, I could drive somewhere whenever I wanted.	.852	
	I would be flexible with AMaaS.	.905	
	I could use AMaaS at will.	.848	

Var.	Items	Ld.	Source
ACCE	The autonomous vehicles of AMaaS would be optimally distributed to serve the incoming requests as quickly as possible.	.874	(Blut 2016; Ko et al. 2019; Möhlmann 2015; Xu et al. 2013)
	The availability of AMaaS would be good.	.827	
	AMaaS would provide the cars within a reasonable time frame.	.840	
	AMaaS would have a large fleet to serve its customers quickly.	.864	
	With AMaaS, the vehicle would be available within a short time.	.892	
CYBE	I am concerned that the systems of AMaaS would be hacked.	.929	(Blut 2016; Hein et al. 2018; Liu et al. 2019b; Wolfinbarger and Gilly 2003)
	I fear that cybercriminals could gain control over AMaaS.	.922	
	AMaaS would not have adequate security features.	-	
	AMaaS would not be sufficiently protected against hacker attacks.	.938	
PRIV	The service provider would keep my personal information safe.	.910	(Blut 2016; Collier and Bienstock 2006; Zhang et al. 2019)
	My data would be treated according to EU data protection law.	.853	
	My pers. information would not be used for other purposes without my consent.	.895	
	My pers. information would not be shared with other entities without my consent.	.903	
	The service provider will not misuse my personal information.	.882	
TRAF	I expect that accidents will be reduced.	.930	(Payre et al. 2014; Ro and Ha 2019; Sener et al. 2019; Xu et al. 2018b)
	I would feel safe during riding in the AV.	.942	
	AMaaS would provide me safety compared to manual driving.	-	
	I expect to reach my destination safely.	.873	
	Using AMaaS would decrease accident risk.	.921	

Table 14: Items of the AMaaS Quality Scale. Var.=Variable; Ld.=Loading; (E)= Item of the original efficiency construct which was split into time efficiency and environment (Paper D)