Passenger Well-being in Highly Automated Vehicles

Wohlbefinden von Insassen hochautomatisierter Fahrzeuge

Von der Fakultät für Maschinenwesen der Rheinisch-Westfälischen Technischen Hochschule Aachen zur Erlangung des akademischen Grades einer Doktorin der Ingenieurwissenschaften genehmigte Dissertation

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I Abstract

Technical advances in vehicle automation make highly automated driving a realistic possibility within the next decade. With higher levels of vehicle automation, the driver will be able to transfer the driving task and supervision to the vehicle for extended periods and can engage in non-driving related tasks. The different driver/passenger behavior will change user requirements for automated vehicles and may increase the importance of a holistic view of the passengers' experience in an automated vehicle. One way to view the automated driving experience more holistically from a passenger perspective is to focus on passenger well-being. This work investigates the concept of passenger well-being in automated driving and explores reliable and valid subjective and objective measures to gauge passenger well-being in study settings and during real-world automated driving experiences. Based on these findings and prior findings in transportation research, a model of determinants of passenger well-being is developed. Empirical user studies are utilized to investigate the role of each element. The resulting model considers physical and technical features that affect passenger well-being through a dual processing mechanism. The features may have a direct effect (peripheral processing) or a mediated effect (central processing) on passenger well-being. Nine passenger needs categorized as utilitarian or hedonic needs act as mediators depending on the features. The impact of features on passenger well-being is further moderated by non-driving related tasks engaged in during the drive and by passenger characteristics. The resulting model is partially validated with two empirical studies. The model of determinants of passenger well-being in automated driving provides a framework for a user-centered development of automated vehicles. Further, this work yields implications and recommendations for the design of such vehicles.

II Zusammenfassung

Durch technische Fortschritte in der Fahrzeugautomatisierung ist eine Markteinführung von hochautomatisierten Fahrzeugen innerhalb des nächsten Jahrzehnts realistisch. Zunehmende Fahrzeugautomatisierung ermöglicht es dem Fahrer, die Fahraufgabe und Überwachung auch für längere Fahrabschnitte an das Fahrzeug abzugeben und sich stattdessen Nebentätigkeiten zu widmen. Diese Veränderung des Fahrverhaltens wird sich auch auf die Nutzeranforderungen auswirken, sodass das Fahrerlebnis in einem automatisierten Fahrzeug stärker ganzheitlich zu betrachten sein wird. Ein Ansatz zur ganzheitlichen Betrachtung des automatisierten Fahrerlebnis aus Nutzerperspektive ist die Betrachtung des subjektiven Wohlbefindens der Insassen. Diese Arbeit untersucht das Konzept von Wohlbefinden im Kontext automatisierten Fahrens und prüft subjektive und objektive Messinstrumente, um das Wohlbefinden der Insassen in verschiedenen Studien und während des automatisierten Fahrerlebnis reliabel und valide messen zu können. Ausgehend von diesen Ergebnissen und dem bisherigen Stand der Technik wird ein Modell von Determinanten des Wohlbefindens der Insassen beim automatisieren Fahren entwickelt. Dazu wurden empirische Studien durchgeführt, um die Rolle einzelner Modellelemente zu untersuchen. Das resultierende Modell schließt physische und technische Merkmale des Fahrzeugs ein, die das Wohlbefinden durch zwei Verarbeitungsrouten beeinflussen. Ein Fahrzeugmerkmal kann sich direkt auf das Wohlbefinden auswirken (periphere Verarbeitung) oder eine indirekte Auswirkung durch Mediatoren haben (zentrale Verarbeitung). Als Mediatoren wurden neun Nutzerbedürfnisse identifiziert, die sich in utilitaristische und hedonische Bedürfnisse aufteilen lassen. Der Einfluss von Fahrzeugmerkmalen auf das Wohlbefinden wird durch Nebentätigkeiten, die während der Fahrt durchgeführt werden, und individuelle Nutzercharakteristika moderiert. Das resultierende Modell ist durch zwei empirische Studien teilvalidiert. Das Modell von Determinanten des Wohlbefindens der Insassen beim automatisierten Fahren bietet einen Rahmen für die nutzerzentrierte Entwicklung von automatisierten Fahrzeugen. Des Weiteren werden Implikationen und Vorschläge für die Gestaltung solcher Fahrzeuge abgeleitet.

III Pre-published Results

Sauer, V., Mertens, A., Groß, S., Heitland, J., & Nitsch, V. (2020). Designing Automated Vehicle Interiors for Different Cultures: Evidence from China, Germany and the United States. *Ergonomics in Design*. https://doi.org/10.1177/1064804620966158

Sauer, V., Mertens, A., Groß, S., Nitsch, V., & Heitland, J. (2019). Comparing User Requirements for Automated Vehicle Interiors in China and Germany. In C. P. Janssen, S. F. Donker, L. L. Chuang, & W. Ju (Eds.), *Adjunct Proceedings - AutomotiveUI '19* (pp. 302–306). New York, NY: ACM Press. https://doi.org/10.1145/3349263.3351316

Sauer, V., Mertens, A., Heitland, J., & Nitsch, V. (2019). Exploring the Concept of Passenger Well-being in the Context of Automated Driving. *International Journal of Human Factors and Ergonomics*, *6*(3), 227–248. https://doi.org/10.1504/IJHFE.2019.104594

Sauer, V., Mertens, A., Heyden, A., Groß, S., & Nitsch, V. (2020). Measures for Well-being in Highly Automated Vehicles: The Effect of Prior Experience. In H. Krömker (Ed.), *Proceedings - MobiTAS 2020* (pp. 166–180). Springer Nature Switzerland. https://doi.org/10.1007/978-3-030-50523-3_12

Sauer, V., Mertens, A., Nitsch, V., & Reuschel, J. D. (2019). An Empirical Investigation of Measures for Well-being in Highly Automated Vehicles. In C. P. Janssen, S. F. Donker, L. L. Chuang, & W. Ju (Eds.), *Adjunct Proceedings - AutomotiveUI '19* (pp. 369–374). New York, NY: ACM Press. https://doi.org/10.1145/3349263.3351337

Sauer, V., Mertens, A., Reiche, M., Mai, C., Heitland, J., & Nitsch, V. (2020). Perception and Processing in Automated Driving - A Dual Process Application. In C. Stephanidis (Ed.), *Late Breaking Papers - HCII 2020* (pp. 1–14). Springer Nature Switzerland. https://doi.org/10.1007/978-3-030-59987-4_14

IV Table of Content

I Abstract .... **ii**

II Zusammenfassung .... **iii**

III Pre-published Results .... **iv**

IV Table of Content **5**

V Abbreviations **10**

1 Introduction **12**

2 Related Work **17**

2.1 The Concept of Passenger Well-being 17

2.1.1 Well-being from a Psychological Perspective 17

2.1.2 Well-being in Transportation Research 20

2.1.3 Differentiation of Well-being and Related Concepts 21

2.1.4 Methods for Measuring Well-being 23

2.2 Models Related to Passengers' Subjective Evaluation 29

2.2.1 General Models on Comfort as Subjective Evaluation 29

2.2.2 Models on Subjective Evaluation in Transportation 31

2.2.3 Processing Vehicle Features for Subjective Evaluation 37

2.3 Investigation of the Effect of Single Features 39

2.3.1 Physical Features 40

2.3.2 Technical Features 46

2.3.3 Social and Situational Features 49

2.3.4 Passenger Needs 50

2.3.5 Passenger Characteristics 53

2.3.6 Non-driving Related Tasks 55

2.4 Derived Research Questions 57

2.5 Research Scope 60

3 Utilized Methods 62

3.1 Qualitative Methods 62

3.2 Quantitative Methods 64

3.3 General Design of User Studies 67

4 Passenger Well-Being in the Context of Automated Driving 69

4.1 Experimental Setup 69

4.2 Procedure 70

4.3 Participants 71

4.4 Data Collection and Analysis 71

4.5 Results 71

4.6 Discussion 72

4.7 Limitations 73

4.8 Conclusion 74

5 Measuring Passenger Well-Being in Automated Driving 75

5.1 Subjective Measures for Passenger Well-being 75

5.1.1 Experimental Setup 77

5.1.2 Participants 77

5.1.3 Data Collection and Analysis 77

5.1.4 Results 77

5.1.5 Discussion 79

5.1.6 Limitations 79

5.2 Objective Measures for Passenger Well-being 80

5.2.1 Experimental Setup 81

5.2.2 Procedure 82

5.2.3 Participants 82

5.2.4 Data Collection and Analysis ... 83
5.2.5 Results ... 84
5.2.6 Discussion ... 85
5.2.7 Limitations ... 86
5.3 Conclusion ... 87
6 Physical and Technical Features of Automated Vehicles ... 89
6.1 Identifying Physical and Technical Features ... 89
6.2 Filtering Features for Relevance for Passenger Well-being ... 90
6.3 Evaluating Features from a User Perspective ... 90
6.3.1 Experimental Setup ... 90
6.3.2 Procedure ... 91
6.3.3 Participants ... 91
6.3.4 Data Collection and Analysis ... 92
6.3.5 Results ... 92
6.4 Discussion ... 95
6.5 Limitations ... 97
6.6 Conclusion ... 98
7 Perception Process of Vehicle Features ... 100
7.1 Identification of Passenger Needs ... 100
7.1.1 Study Design and Data Analysis ... 100
7.1.2 Results ... 101
7.1.3 Discussion ... 102
7.2 Investigation of Feature Processing ... 104
7.2.1 Experimental Setup ... 105
7.2.2 Procedure ... 106
7.2.3 Participants ... 106

7.2.4 Data Collection and Analysis ... 107
7.2.5 Results ... 108
7.2.6 Discussion ... 109
7.2.7 Limitations ... 113
7.3 Conclusion ... 114
8 Evaluation of the Basic Model ... 116
8.1 Experimental Setup ... 118
8.2 Procedure ... 118
8.3 Participants ... 119
8.4 Data Collection and Data Analysis ... 119
8.5 Results ... 120
8.5.1 Peripheral Processing of Vehicle Features ... 120
8.5.2 Central Processing of Vehicle Features ... 121
8.5.3 NDRTs as Moderator ... 122
8.6 Discussion ... 122
8.6.1 Peripheral Route Processing ... 124
8.6.2 Central Route Processing ... 125
8.6.3 Moderating Effects of NDRTs ... 126
8.6.4 Limitations ... 127
8.7 Conclusion ... 127
9 Cross-cultural Model Evaluation ... 129
9.1 Identifying Vehicle Features with Different Cultural Perceptions ... 129
9.2 Evaluation of Cultural Influence from the User Perspective ... 137
9.2.1 Experimental Setup ... 137
9.2.2 Procedure ... 138
9.2.3 Participants ... 138

9.2.4 Data Collection and Analysis 139
9.3 Results 139
9.3.1 Conjoint Analysis Results 139
9.3.2 Intercultural Comparison 141
9.3.3 Central Processing and Passenger Needs 142
9.3.4 NDRTs as Moderator 142
9.4 Discussion 144
9.4.1 Expert Survey 144
9.4.2 Cross-cultural User Study 145
9.4.3 Limitations 148
9.5 Conclusion 148
10 Conclusions 150
10.1 Implications for a Model of Determinants of Passenger Well-being 150
10.2 Implications for Future Research 156
10.3 Implications for Passenger Well-being in User-centered Development 158
10.4 Implications for the Design of Automated Vehicles 159
11 References 161
VI Figures 198
VII Tables 202
VIII Appendix 204

V Abbreviations

ACME	Average causal mediation effects
ADAS	Advanced driving assistance system
ANOVA	Analysis of variance
CI	Confidence interval
CN	China
CS+	Positive customer satisfaction coefficient
CS-	Negative customer satisfaction coefficient
DE	Germany
ECG	Electrocardiogram
EDA	Electrodermal activity
EL	Elaboration likelihood
ELM	Elaboration likelihood model
EWL	Adjectives list (German: Eigenschaftswörterliste)
FACS	Facial action coding system
H	Hypothesis
HF	High frequency
HMI	Human-machine interface
HRV	Heart rate variability
LF	Low frequency
LMM	Linear mixed models

M	Mean
MDBF	Multidimensional state survey (German: Mehrdimensionale Befindlichkeits-fragebogen)
NDRT	Non-driving related task
NT	Non-technical
NVH	Noise vibration harshness
OLS	Ordinary least square
PANAS	Positive and negative affect schedule
pNN50	Portion of successive NN intervals greater than 50ms of the total NN intervals
RMSSD	Root mean square of successive differences of NN intervals
RQ	Research question
SAE	Society of automotive engineers
SCAS	Swedish core affect scale
SD	Standard deviation
SWB	Subjective well-being
T	Technical
UI	User interface
ULF	Ultra low frequency
UMACL	Mood adjective checklist
US	United States of America
VLF	Very low frequency
WB	Well-being

1 Introduction[1]

Mobility is a central aspect of today's societies. Especially in industrial countries, individual transport by car is dominant. For example, in the US, 87.2% of the population aged 16 and older drive at least occasionally and spend, on average, 50 minutes per day driving (Kim, Anorve, & Tefft, 2019). So far, if being the driver, time spent driving is largely dedicated to the driving task. Yet, technical progress in advanced driving assistance systems (ADAS) and vehicle automation gradually relieves the driver from the driving task and ultimately allows the driver to spend time while traveling differently by engaging in non-driving related tasks (NDRTs).

Highly automated vehicles offering the possibility to engage in more elaborate NDRTs create the opportunity to rethink the vehicle design. Car manufacturers around the globe envision such automated vehicles to enable sleeping, working, or entertainment among other NDRTs (c.f. Figure 1.1). These novel vehicle concepts evolve from a functional interior to a living space. By accommodating additional user needs and requirements arising from automated driving, a user-centered approach in the design of automated vehicles is visible (Mao, Vredenburg, Smith, & Carey, 2005).

Volvo 360c (Volvo Car Group, 2018) | Mercedes-Benz F 015 (Daimler, 2015) | Rinspeed XchangE (Rinspeed, 2014)

Figure 1.1 Examples of automated driving concepts that evolve the interior to a living space.

In user-centered vehicle development, comfort is a main parameter to reflect the user's view (Kempfert, 1999). Comfort encompasses the subjective reaction to a physical stimulus or environment (Kempfert, 1999; Looze, Kuijt-Evers, & van Dieën, 2003), but not the subjective evaluation of one's self in this environment. Yet, when viewing automated vehicles as living space, it becomes essential also to consider passengers' state in the vehicle or, in other words, to consider passengers' subjective level of well-being.

[1] Parts of this chapter have been published in following publications: Sauer, Mertens, Heitland, and Nitsch (2019)

The role of passenger well-being grows with increasing vehicle automation that leads to a passenger car being less driver-centric and allowing more diverse and elaborate NDRTs. The gradual increase in vehicle automation can be split into different levels. A frequently utilized categorization is provided by the SAE standard J3016, which distinguishes six levels of vehicle automation (SAE, 2016). They range from no automation (level 0) to full automation (level 5) (c.f. Table 1.1). While a level 3 automation system takes over the dynamic driving task completely for the first time, the driver still has to remain able to serve as fallback in case of system errors. Ensuring the possibility to act as fallback limits the NDRTs the driver may engage in and their duration. For example, mentally or visually demanding tasks can impair the take-over reaction in case of system failures (Kim, Kim, Kim, & Yoon, 2018). A wider engagement in NDRTs is first possible in high automation (level 4) when the system is able to transfer the vehicle into a minimal risk condition without the driver in case of a system failure (SAE, 2016).

Table 1.1 Overview of vehicle automation levels based on SAE standard J3016.
* Conditions (e.g., road types, environment, traffic) in which automation is designed to function (SAE, 2016).

	0 No driving automation	**1 Driver assistance**	**2 Partial driving automation**	**3 Conditional driving automation**	**4 High driving automation**	**5 Full driving automation**
Dynamic driving task	Driver	Driver and System	Driver and System	System	System	System
Fallback	Driver	Driver	Driver	Driver	System	System
Operational domains*	-	Limited	Limited	Limited	Limited	Unlimited

As of today, cars available in the European market have reached level 2 automation. Conditional and high driving automation (levels 3 and 4) are expected to be available between 2020 and 2030, and full driving automation is likely to follow after 2030 bringing prospective societal benefits such as increased road safety and broader accessibility for mobility-impaired users (European Parliament, 2019). As the research and development of highly and fully automated vehicles are already underway (CBInsights, 2019), it is a suitable time to consider the role of passenger well-being in the user-centered development of highly automated vehicles.

The concept of subjective well-being is used in different disciplines such as psychology and social sciences and has evolved over time. Subjective well-being evolved from being defined as the absence of ill-being (Diener, 1984) to a positive definition as “a broad category of phenomena that includes people's emotional responses, domain satisfactions, and global judgments of life satisfaction” (Diener, Suh, Lucas, & Smith, 1999, p. 277). Research on well-being in transportation provides evidence that mobility using different modes affects well-being through experiences while traveling (Vos, Schwanen, van Acker, & Witlox, 2013) or experienced level of stress (Ettema, Gärling, Olsson, & Friman, 2010). In terms of road traffic, stressors such as congestions or long-distance commuting can impede well-being. Interestingly, car commutes are often objectively more stressful, yet users of this travel mode have a less negative perception of their choice of travel than other mode users (Novaco & Gonzalez, 2009). In a similar vein, car use can also have affective and symbolic motives (Steg, 2005). These findings constitute an additional reason why well-being in the development and design of automated vehicles may be fruitful. Published empirical studies on well-being in transport mainly utilize existing general definitions of well-being or sub-dimensions such as experienced affect or mood (e.g., Ahn, Kim, & Hyun, 2015; Chatterjee et al., 2019; Ma, Zhang, Ding, & Wang, 2018; Sirgy, Lee, & Kressmann, 2006). Research specific to well-being in automated driving and well-being as an optimization goal for automotive product development has been less thoroughly researched. Thus, it is not surprising that a specific investigation of the concept of passenger well-being in automated driving does – although necessary – not yet exist to the author's knowledge. The conceptualization of passenger well-being directly influences the appropriate operationalization and measurement of the concept. As passenger well-being in automated driving may differ from general definitions of subjective well-being, other measures may be required and need to be evaluated. This raises the following research questions:

RQ 1: What does passenger well-being in the context of automated driving involve?

RQ 2: How is passenger well-being in the context of automated driving appropriately measured?

The conceptualization and operationalization is a necessary foundation to be able to consider passenger well-being in automated vehicles. For a targeted development of automated vehicles with the goal to maximize passenger well-being, an understanding of the relevant design features that affect well-being is crucial. Product design is a multidimensional construct and includes physical features to fulfill product purpose and the positioning among competing products (Urban & Hauser, 1993). Physical features of a car that affect user evaluation in terms of satisfaction can include powertrain design, seating, and air conditioning. Further, the physical design of the interior and exterior and the embedded meaning of the design, such as distinctiveness and sturdiness, can influence satisfaction (Srinivasan, Lilien, Rangaswamy, Pingitore, &

Seldin, 2012). However, to the author's knowledge, a mapping of features of an automated vehicle to passenger well-being presents a research gap.

RQ 3: What physical features of an automated vehicle are relevant for passenger well-being?

The passenger is exposed to both well-being relevant and irrelevant physical design features when traveling in an automated vehicle. To understand why certain features are relevant for well-being, knowledge of passenger's perception and processing of said features is required. One of the advantages of high and full vehicle automation is the option to engage freely in NDRTs. This may influence the perception and processing process. When the passenger is distracted, attention is diverted away from the vehicle to the NDRT in varying degrees, and the ability to process is reduced. In addition, motivation to process physical features may be another factor in the perception process (Petty & Cacioppo, 1986). This raises the question of which role ability and motivation play in determining the level of passenger well-being.

RQ 4: How do motivation and ability influence the perception and processing of physical features of an automated vehicle relevant for passenger well-being?

From a user perspective, product design does not only have to provide utilitarian value in the form of functionality, but also additional aspects such as the product form, i.e., the aesthetical value, ergonomics or the usability aspect of the product and symbolic value (Jindal, Sarangee, Echambadi, & Lee, 2016). This is also important from a well-being perspective. Well-being is created by the fulfillment of needs (Deci & Ryan, 2000). These needs in the context of automated vehicles can be design dimensions like aesthetics (Bloch, 1995), but also psychological needs such as trust (Li, Hess, & Valacich, 2008) or physical well-being (Diener, Lucas, & Oishi, 2002). Thus, the link between physical features, the fulfillment of passengers' needs through different design dimensions, and passenger well-being needs to be investigated to ensure targeted product development.

RQ 5: What are relevant passenger needs in the context of automated vehicles, and how do they relate to the physical features of the vehicle and passenger well-being?

Knowing how the physical design, passenger needs, and passenger well-being relate to each other is a general basis for understanding the determinants of passenger well-being in automated driving. However, this view so far lacks one central aspect: the unique characteristics of the passenger that may influence how these three elements interact. Research shows that interpersonal differences can impact the experienced level of subjective well-being. Interpersonal differences can be gender, size, or age (Diener et al., 2002; Vankan, 2010). Also, psychological factors, such as culture or personality, may influence the level of subjective well-being (Diener, Oishi, & Lucas, 2003). As automated driving is a global trend in which multiple and culturally different markets play a role, the concept of culture may be of special importance. Knowledge of cultural differences allows appropriate design for different target markets and users.

RQ 6: How does culture as an example of individual passenger characteristics influence the relationship between the physical features of an automated vehicle, passenger needs, and passenger well-being?

This work aims to contribute to the emerging field of passenger well-being in automated driving by providing a model of determinants of passenger well-being in the context of automated driving and its empirical validation. An extensive understanding of determinants is necessary to provide recommendations for the targeted development of automated vehicles with the goal of maximizing passenger well-being.

The model of determinants is based on six key concepts: passenger well-being and its operationalization, physical features of the automated vehicle and the perception process thereof, passenger needs, and individual passenger characteristics (c.f. Figure 1.2). Each of the concepts and the corresponding research questions are discussed in the following after providing an overview of related work and methods utilized in this work (chapters 2 and 3). In addition, empirical evaluations of the model are provided (chapters 8 and 9), and conclusions and recommendations for user-centered product development with a focus on passenger well-being are derived (chapter 10).

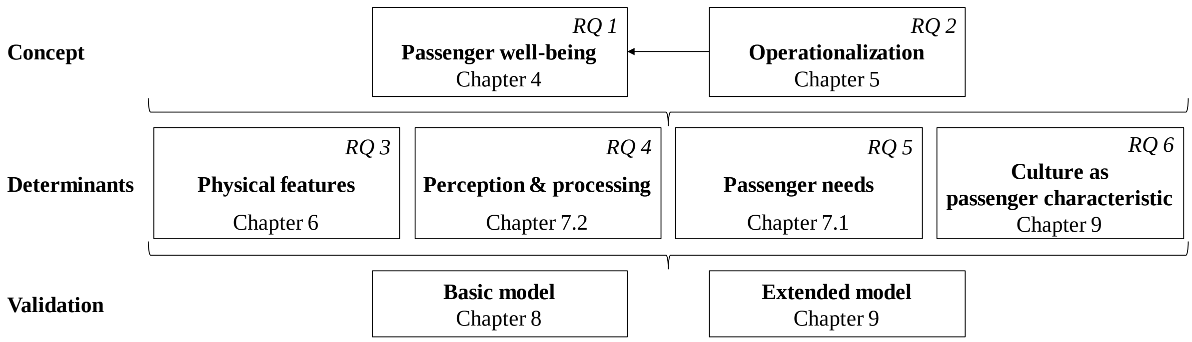


Figure 1.2 Overview of the chapter outline and corresponding research questions to build a model of determinants of passenger well-being.

2 Related Work[2]

To be able to derive a model of determinants of passenger well-being, related work from three areas is relevant:

1. Work on the concept of passenger well-being itself (addressing RQ 1 and 2),
2. Work on models that conceptualize the influence of external factors on passengers' subjective evaluation of the travel experience (addressing RQ 3-6),
3. Work investigating the effect of single features or feature groups of the travel experience on passengers' subjective evaluation of said experience (addressing RQ 3-6).

2.1 The Concept of Passenger Well-being

Well-being is a broad concept that attracts attention in different fields, such as psychology, politics, or social science, causing a number of different definitions to evolve (Diener, 1984). To the author's knowledge, there is no established definition of passenger well-being in automated driving. Therefore, definitions in psychology and other transportation context are called on for reference. Further, the concept of passenger well-being is differentiated from related concepts of subjective evaluation.

2.1.1 Well-being from a Psychological Perspective

Psychology has yielded a number of definitions and conceptualizations for well-being (Diener, 1984). In general, well-being can be differentiated between subjective and objective well-being (Diener, 1984; Veenhoven, 1991). As this work follows a user-centered approach and considers the passenger's evaluation of the automated driving experience, subjective well-being is emphasized.

[2] Parts of this chapter have been published in following publications: Sauer, Mertens, Groß, Heitland, and Nitsch (2020); Sauer, Mertens, Groß, Nitsch, and Heitland (2019); Sauer, Mertens, Heitland et al. (2019); Sauer, Mertens, Heyden, Groß, and Nitsch (2020); Sauer, Mertens, Nitsch, and Reuschel (2019); Sauer, Mertens, Reiche et al. (2020)

Definitions of well-being in psychology

The definitions of subjective well-being evolved over time. Early definitions view subjective well-being as the absence of ill-being (Diener, 1984). More recent approaches use a positive interpretation (c.f. Appendix A.1). These definitions have two elements in common: an affective aspect that well-being results from frequent positive and infrequent negative moods and emotions, and a cognitive judgment of one's life, showing that subjective well-being is a multidimensional concept. Whether positive and negative well-being are independent concepts or the extreme of one continuum remains open for discussion. Both views find empirical evidence (Keyes & Magyar-Moe, 2003). One frequently used definition of subjective well-being is "a person's cognitive and affective evaluations of his or her life […] that includes experiencing pleasant emotions, low levels of negative moods, and high life satisfaction" (Diener et al., 2002, p. 63). This definition will be utilized for subjective well-being in this work.

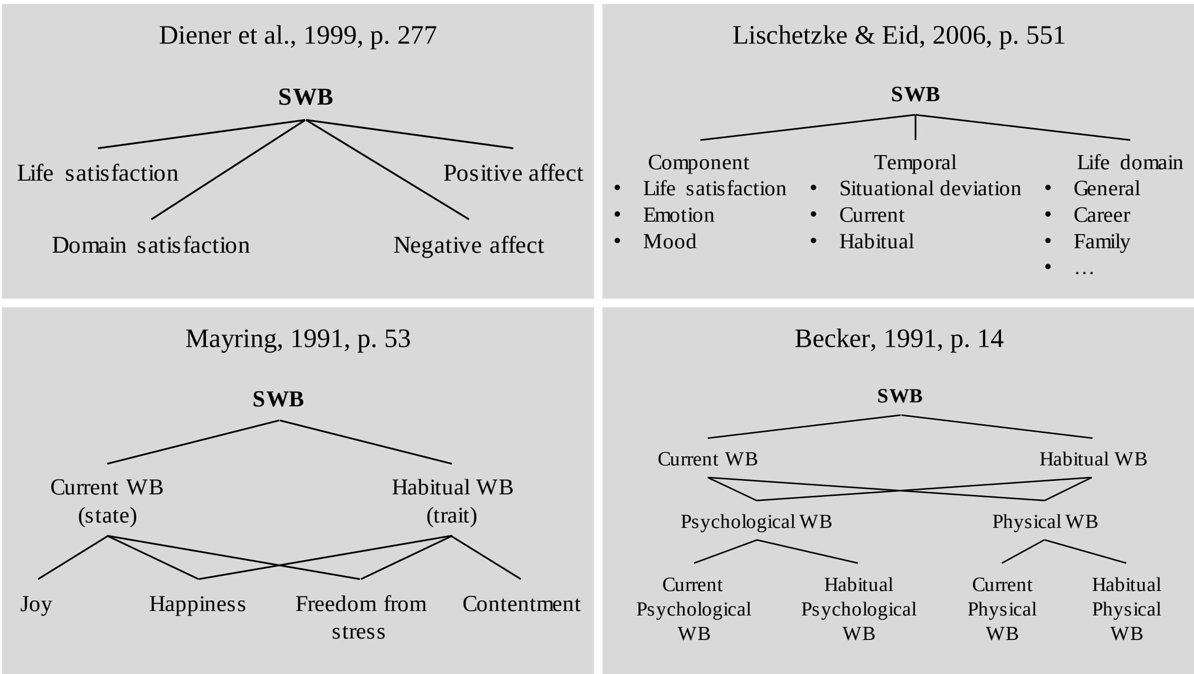


Figure 2.1 Overview of selected conceptualizations of subjective well-being.

Note: SWB: subjective well-being, WB: well-being; Figures are based on the definition provided by Diener et al. (1999) or translated and adapted from Lischetzke and Eid (2006), Mayring (1991) and Becker (1991) respectively.

Different attempts to divide SWB into its multidimensional components, in addition to the distinction between cognitive and affective evaluations exist. Selected conceptualizations view subjective well-being from different perspectives but still have significant overlaps (c.f. Figure 2.1). For example, Diener et al. (1999) distinguish between positive and negative affect and long-term or rather life satisfaction as many of the traditional definitions do, while other authors split subjective well-being into current and habitual well-being (Lischetzke & Eid, 2006; Mayring, 1991). All conceptualizations have a temporal component in common. While current well-being describes the momentary experience of positive emotions, moods, and physical sensations with regard to the current situation and environment, habitual well-being is more stable as a result of cognitive evaluations of life and its different domains and affective experiences (Becker, 1991). Also, subjective well-being can be differentiated regarding psychological and physical well-being (Becker, 1991) and various life domains (Lischetzke & Eid, 2006).

Views on achieving well-being

In terms of how well-being may be obtained, two views are dominant: Hedonism and Eudaimonia. The hedonic approach to well-being considers "what makes experiences and life pleasant or unpleasant" (Kahneman, Diener, & Schwarz, 1999, p. ix). In this view, subjective well-being is derived with a bottom-up approach by weighing up positive and negative affect experienced over time (Springer & Hauser, 2006). The eudaimonic approach to well-being suggests that well-being is achieved by fulfilling one's true potential (Ryff, Singer, & Dienberg Love, 2004; Waterman, 1993).

In contrast to hedonism, eudaimonia argues that the fulfillment of desires does not necessarily entail well-being. Self-determination theory is one perspective on eudaimonia. It argues that autonomy, relatedness, and competence are central needs that must be fulfilled to achieve self-realization (Ryan & Deci, 2001).

Implications for passenger well-being in automated driving

Definitions of subjective well-being often distinguish between current and habitual well-being. It is questionable whether the travel experience in an automated vehicle can influence both current and habitual subjective well-being. The purchase or use of an automated vehicle can impact life satisfaction through the domain of consumer life (Lee, Sirgy, Larsen, & Wright, 2002) and by improving mental health through reduced stress (Cottrell & Barton, 2013). Nevertheless, mobility is only one among many consumption decisions a person makes, just as consumer life is only one of many domains that enter the cognitive evaluation of life.

Further, there is empirical evidence that subjective well-being is stable over the course of life (Diener & Lucas, 1999). Therefore, it may be presumed that the use of automated vehicles plays a minor role in habitual subjective well-being (Jakobsson Bergstad et al., 2011). In contrast, current subjective well-being can be affected by driving (Cottrell & Barton, 2013; Steg & Tertoolen, 1999). Based solely on the psychological view of well-being, it may be assumed that passenger well-being in an automated vehicle relates to current subjective well-being. To gain a deeper understanding, research on well-being in transport is called on in the following.

2.1.2 Well-being in Transportation Research

The body of research on well-being in transportation can be divided into two groups: research on how access to and use of transportation affects well-being and quality of life for different population groups, and research on how well-being is affected while using a certain mode of transportation. For this work, the latter group of research is relevant.

When looking into research on well-being experienced when using a given mode of transportation, it appears that no established definition of passenger well-being in transportation contexts exists, which impedes the comparability of published results. Further, not all authors provide clear definitions of well-being. Some only provide details on their operationalization of well-being or leave it unclear (c.f. Appendix A.2). The majority of authors use definitions from the domain of psychology. In this case, the definition by Diener et al. (1999) combining cognitive evaluations of life with affective evaluations of positive and negative emotions is frequently used (e.g., Ma et al., 2018; Senn, Falter, Ruster, & Hadwich, 2018; Zhang, Ma, & Wang, 2017). Other authors add aspects to their well-being definitions that go beyond Diener et al.'s (1999) view. Ahn et al. (2015) add a product dimension by viewing well-being in transportation as the extent to which a good or service influences cognitive and affective evaluations. Reardon and Abdallah (2013) extend the elements of cognitive and affective evaluation by including personal flourishing and psychological functioning. Winzen, Albers, and Marggraf-Micheel (2014) and Marggraf-Micheel, Piewald, Winzen, and Berg (2010) use a different psychological approach. They understand well-being as a combination of physical and psychological well-being, which corresponds to conceptualizations by Becker (1991) and emphasizes a view on current well-being. Sirgy et al. (2006) follow an eudaimonic view and consider well-being as the satisfaction of developmental needs. A different approach to defining well-being used in transportation is by focusing on effects on health. Hinninghofen and Enck (2006) and Silla and Gamero (2018) use this approach. They do not provide clear definitions but operationalize well-being as health-related effects and use, for example, indicators such as burnout or general health (Silla & Gamero, 2018).

Implications for passenger well-being in automated driving

Based on the considered published research, a psychological definition appears to be a common approach to understand well-being in different transportation modes, including cars. Although having a common view of cognitive and affective evaluation, the definitions contain different nuances and focus. Thus, a deeper understanding of well-being in automated driving is required. Current subjective well-being in its psychological meaning is a promising starting point to build a definition of passenger well-being in automated driving. To be able to work toward a clear definition of passenger well-being in automated driving, a clear differentiation between well-being and related concepts is required.

2.1.3 Differentiation of Well-being and Related Concepts

Based on evidence from other studies on well-being in transport, passenger well-being may overlap with current subjective well-being experienced during automated driving. However, other concepts of subjective evaluation that are related and frequently used in transportation exist and are deserving of a closer investigation.

Comfort

Comfort is a frequently used parameter in transportation to reflect the passenger view (Oborne, 1978a). Investigations on the origin and meaning of comfort reveal different facets, including freedom from pain and annoyance, pleasure, well-being, aesthetics, relaxation, and relief as well as convenience (Ahmadpour, Lindgaard, Robert, & Pownall, 2014; Dumur, Barnard, & Boy, 2004).

Multiple conceptualizations of comfort and discomfort have developed over time (Looze et al., 2003). Among these, three different approaches appear to have received increased attention (Ahmadpour, 2014). The earliest theory defines comfort as the absence of discomfort and any other negative state (Hertzberg, 1972). The second approach views discomfort and comfort as extremes of one continuum (Vink, Looze, & Kuijt-Evers, 2005). Finally, work by Zhang, Helander, and Drury (1996) has shown that comfort and discomfort may be conceptualized as two independent variables with comfort being linked to relaxation or well-being, and discomfort to pain caused by biomechanical factors. Other approaches have a very strong overlap with well-being and define comfort as a manifestation of well-being (Oborne, 1978b; Vink, Bazley, Kamp, & Blok, 2012) or equate comfort with well-being (Marggraf-Micheel & Jäger, 2007).

Looze et al. (2003) argue that a common element to different definitions is that comfort is subjective, it is driven by physical, physiological, psychological factors, and it is elicited from the environment. Comparing these elements of comfort to definitions of well-being, both conceptualizations appear similar. However, the significant difference is that well-being is not limited to a reaction to the physical environment. It has a broader scope and, for example, also includes evaluations of one's self.

Satisfaction

Satisfaction is a construct that, just like well-being, entails an affective reaction (Westbrook & Reilly, 1983). However, rather than evaluating one's self, satisfaction is a judgment of a "postchoice […] specific purchase selection." (Westbrook & Oliver, 1991, p. 84). To derive a judgment of satisfaction, a comparison between perceived performance and expected performance is necessary (Day, 1984). Thus, satisfaction occurs only if expectations are met or surpassed, else dissatisfaction will ensue. Consequently, satisfaction comes into play when judging past experiences.

Further, research shows that empirical evidence for a relationship between satisfaction and global well-being is lacking (Ettema et al., 2010). Therefore, well-being in this work is viewed as an evaluation of the current experienced situation. It can contribute to or diminish satisfaction, depending on experience and expectations. Hence, satisfaction is a result of passenger well-being.

Pleasure

Pleasure in product use is the combination of "the emotional, hedonic and practical benefits associated with products" (Jordan, 2000, p. 12). A product is beneficial from a practical point of view when it produces the expected outcomes during use. Hedonic benefits are created by a positive sensory and aesthetic experience during product use, while emotional benefits are those aspects of a product that can influence the user's mood (Jordan, 2000). Mood, especially the increase of positive affect and the reduction of negative affect, is one aspect of affective well-being. Thus, pleasurable products can contribute to well-being (Desmet and Pohlmeyer, 2013). However, product pleasure can be experienced not only during product use but also before, after, and at other times (Jordan, 1998). Thus, the concept of product pleasure takes different temporal references into account than well-being.

2.1.4 Methods for Measuring Well-being

As hypothesized that passenger well-being is based on a psychological definition of subjective well-being (c.f. Section 2.1.2), measurements for subjective well-being may also apply to passenger well-being. A wide variety of such measurements of well-being exists. Self-report measures are a traditional measurement approach (Diener, 1994). These measures can range from 1-item measures to multidimensional measures. For example, 1-item measures can be collected through ratings, non-verbal scales, or continuous dials with which participants indicate their current level of well-being (Kahneman & Krueger, 2006; Mayring, 1991). This type of measurement has the advantage of brevity at the expense of validity, reliability, and differentiation (Diener, 1984).

Multidimensional self-reports

Multidimensional measures are more complex and mirror the multidimensional nature of well-being. Numerous multidimensional scales have evolved over time and address different aspects of well-being, such as general subjective well-being, happiness, or current positive affect (Mayring, 1991) or are developed for specific target groups such as elderly people (Diener, 1984). Several reviews of scales for subjective well-being have been published (e.g., Diener, 1984; Mayring, 1991; Schumacher, Klaiberg, & Brähler, 2003). The measures vary strongly in the number of dimensions and items. Most measures discussed in the reviews have sufficient statistical quality, i.e., temporal validity and internal consistency. Shortcomings of self-ratings – although limited – include social desirability and possible distortion and bias (Diener, 1984).

Passenger well-being is likely to include aspects of current affective well-being (c.f. Section 2.1.1 and 2.1.2). To measure this aspect, adjectives lists with items on different emotional states or moods are suitable. For each item, i.e., the emotional state or mood, the current or retrospective frequency or intensity of experiencing said state is indicated (Schumacher et al., 2003). A popular measure of affective well-being is the Positive and Negative Affect Schedule (PANAS, Watson, Clark, & Tellegen, 1988). The PANAS is based on a two-factor circumplex model with positive and negative affect as dimensions (Watson & Tellegen, 1985). The PANAS was deliberately developed as a brief scale with a limited number of items that is easy to administer. It contains a scale of 10 items for each positive and negative affect (Watson et al., 1988). Despite its popularity, the PANAS has received criticism regarding unbalanced item valences and unequal measures for anxiety and anger (Daniels, 2017). Further, the discussion on the independence of positive and negative affect, which is the basis for the PANAS scale, remains unsolved (Crawford & Henry, 2004).

When turning to transportation research, the PANAS is not the only multidimensional self-rating scale utilized (c.f. Table 2.1). The used scales differ in the number of dimensions and the total number of items, which in turn impacts time for administering the scale in study settings and affects participants' fatigue. Even within the same mode of transport, different scales are used. This indicates a need to identify appropriate self-report measures for the context of automated driving.

Table 2.1 Overview of verbal self-report measures and reported reliability in exemplary transportation studies, adapted from Sauer, Mertens, Heitland et al. (2019).

Note: Numbers in brackets for dimensions and items indicate the subset of items and dimensions used in the study if the full scale is not utilized; reliability of each measure is indicated by Cronbach's α if reported.

Authors	**Self-report measure**	**Transportation mode**	**# of dimensions** **# of total items**	**Cronbach's α**
Marggraf-Micheel et al. (2010)	MDBF (Steyer, Schwenkmezger, Notz, & Eid, 1997)	Air	3 (3) 24 (12)	> .78
Winzen et al. (2014)	MDBF (Steyer et al., 1997)	Air	3 (3) 24 (12)	> .72
Quehl (2001)	EWL (adjusted) (Janke & Debus, 2003)	Air	6 (2) 161 (46)	> .85
Västfjäll, Kleiner, and Gärling (2003)	SCAS (Västfjäll, Friman, Gärling, & Kleiner, 2002)	Air	4 12	Not reported
Fairclough, van der Zwaag, Spiridon, and Westerink (2014)	UMACL (Matthews, Jones, & Chamberlain, 1990)	Car	4 (2) 48 (27)	> .78
Frison, Wintersberger, Riener, and Schartmüller (2017)	PANAS (Watson et al., 1988)	Car	2 20	> .88
Noah, Gable, Schuett, and Walker (2016)	PANAS (Watson et al., 1988)	Car	2 20	> .91

Nonself-reports

Reports on well-being levels of participants may also be completed by someone other than the participant themselves, such as by family, friends, or experts. In these nonself-reports, participants are often interviewed, and answers are analyzed content-wise by experts (e.g., Lehr, 1982). Some approaches also include non-verbal cues such as body language in the report (e.g., Noelle-Neumann, 1978). Nonself-reports face the challenge that they can lack a theoretical foundation, and coding rules can be unclear (Mayring, 1991). For this work, nonself-report measures may be less relevant, as the subjective evaluation of the passenger is central and may be more appropriately measured with self-reports (Kahneman & Krueger, 2006).

Objective measures

Objective approaches include physiological, facial, or motoric measures and may reveal additional emotional reactions that one may not admit verbally (Diener, 1994) to give more detailed insights into an emotional response. Further, non-verbal, non-invasive objective measures have the advantage for automated driving scenarios that they can be easily administered without disrupting or distracting the driver. This can be beneficial for real-world driving studies or affective computing applications requiring regular input on the current level of well-being.

In terms of physiological measures, heart rate variability (HRV) and electrodermal activity (EDA) are commonly used non-invasive vital parameters to approximate affective responses (Kreibig, 2010). Experienced affect is closely linked to facial expressions (Stöckli, Schulte-Mecklenbeck, Borer, & Samson, 2018). Thus, the analysis of experienced affect deduced by facial expressions is another promising objective approach. Further, body motion has been used successfully as an objective measure for comfort, which is linked to well-being (Vink & Hallbeck, 2012, c.f. Section 2.1.3) in automotive contexts (Lee, Grohs, & Milosic, 1995).

Heart rate variability

Variations in the beat-to-beat heart rate are seen as an indicator of the adaptability of an organism in general (Lohninger, 2017). Variations, even under constant conditions, are caused by the interplay of the parasympathetic and sympathetic nervous system. While the sympathetic nervous system is dominant in states of physical or psychological stress, the parasympathetic nervous system dominates in states of rest (Appelhans & Luecken, 2006). Thus, a relationship between subjective well-being and HRV can be expected (Geisler, Vennewald, Kubiak, & Weber, 2010). When analyzing HRV, different parameters are available, including parameters from time and frequency domains. Time domain measures indicate the HRV at predefined time intervals. In contrast, frequency domain measures apply power spectral analysis which yields four frequency components: ultra low frequency (ULF, ≤ .003 Hz), very low frequency (VLF, .003 - .04 Hz), low frequency (LF, .04 - .15 Hz), and high frequency (HF, .15 - .4 Hz) (Sammito et al., 2014; Task Force 1996).

Previous research providing evidence for the relationship between subjective well-being and HRV distinguishes between habitual and current subjective well-being. A study with students showed that positive habitual mood is partly positively correlated with HF HRV. Positive hedonic tone and positive tense arousal are significantly related ($r > .16$, $p < .05$). Energetic arousal, negative hedonic tone, tense arousal, as well as life satisfaction, show no significant relationship with HF HRV (Geisler et al., 2010). Similar results were found by Trimmel (2015). In this study, general subjective well-being was positively related to time domain parameters ($r_{RMSSD} = .23$ (Root mean square of successive differences of NN intervals), $r_{pNN50} = .27$ (the portion of successive NN intervals greater than 50ms of the total NN intervals), $p < .05$). At the same time, trait mood was only partially positively related to HRV. Good mood and relaxation were significantly positively correlated with HRV parameters from time and frequency domain ($r > .24$, $p < .05$). The highest correlations in the frequency domain are with the parameter ULF ($r > .27$, $p < .05$). Further investigation of current well-being and HRV yields inconclusive results. Wang, Lü, and Qin (2013) showed that positive affect correlates positively with HF HRV ($r = .31$, $p < .05$), while negative affect revealed no significant linear relationship ($r = -.03$, $p > .05$). Yet, a large scale study only finds negative affect to be a significant predictor of HF HRV in a regression analysis ($\beta = -.04$, $p < .01$) while positive affect is without significant influence (Sloan et al., 2017). Other studies, however, could not find a significant relationship between positive emotions (Duarte & Pinto-Gouveia, 2017) or negative affect and HF HRV (Mann, Selby, Bates, & Contrada, 2015).

In automotive contexts, HRV is used to estimate driver stress in automated driving (Heikoop, Winter, van Arem, & Stanton, 2019), to measure the affective state and be able to react on it through interfaces (Riener, Ferscha, & Aly, 2009), or to act as a proxy for discomfort caused by the driving behavior of the automated vehicle (Beggiato, Hartwich, & Krems, 2018).

Electrodermal activity

The main driver behind electrodermal activity is the sympathetic innervation of the skin's eccrine sweat glands. Depending on the sympathetic activity of the autonomous nervous system, the skin conductance changes measurably. The changes can either be of tonic nature (slow changes, i.e., skin conductance level) or phasic nature (rapid changes, i.e., skin conductance response) (Critchley, 2002). Sympathetic activation of the autonomous nervous system can be caused by emotional arousal (Bastiaansen et al., 2019).

Studies investigating the relationship between EDA and affective responses paint an ambivalent picture. On the one hand, in terms of phasic skin conductance responses, a relationship was found with arousal ($r = .81$) in a study eliciting emotion through pictures (Lang, Greenwald, Bradley, & Hamm, 1993). Further, subjective fun ($r = .694$, $p = .026$) and frustration ($r = .641$, $p = .040$) were found to correlate with skin conductance responses as well in a study on user experience in video games. However, no significant linear relationships were found with boredom, challenge, ease, engagement, or excitement (Mandryk, Inkpen, & Calvert, 2006). On the other hand, a study using affective sounds showed that skin conductance responses did not significantly vary between levels of arousal and valence within the stimuli, while the tonic component of EDA was able to significantly differentiate between the stimuli ($p \leq .033$) (Greco, Valenza, Citi, & Scilingo, 2017). In addition, a study on the relationship between induced mood and skin conductance showed that skin conductance level increases with induced mood ($F(2,66) = 18.43$, $\epsilon = .62$, $p < .01$). But it does not reveal differences between the types of induced mood, i.e., positive, neutral, or negative (Wilson, Sandler, & Larsen, 1991).

Ambivalent findings have been reported on the use of EDA to measure physiological reactions to driving situations in automated driving. Skin conductance level does not relate to subjective levels of discomfort in automated driving caused by different driving situations (Beggiato et al., 2018, 2019). Nevertheless, Morris, Erno, and Pilcher (2017) find significantly higher EDA levels for risky driving behavior compared to more cautious automated driving. Despite the ambivalent results, EDA is suggested for sleep detection (Wörle, Metz, Thiele, & Weller, 2019) or measurement of trust (Walker, Wang, Martens, & Verwey, 2019) in automated driving. For the use of EDA as a proxy for passenger well-being, further investigation of skin conductance level as a potential objective measure for passenger well-being is required.

Facial expressions

Experienced affect is closely linked with facial expressions, i.e., the movement of facial skin and tissue. Unlike conscious facial expressions, expressions elicited by emotion are controlled by the extrapyramidal motor system (Rinn, 1984). Decoding emotions from facial expressions has been pioneered by the Facial Action Coding System (FACS). FACS provides a framework linking facial movements and muscle contractions and their combination to specific emotions (Ekman, Friesen, & Hager, 2002), which is a widely utilized approach in psychology (Cohn, Ambadar, & Ekman, 2007). Automated decoding of facial expressions through software has made this measure more accessible due to ceasing expert coding (Bastiaansen et al., 2019).

The relationship between facial expressions and self-report measures has been studied in different settings. Early studies use judges to evaluate videotaped facial expressions. A study eliciting emotion from pictures shows that pleasantness is linearly related to self-rated pleasantness, and the intensity of facial expression is related to self-report intensity (Winton, Putnam, & Krauss, 1984). Further, a study using videos to elicit emotions showed that facial expressions analyzed with FACS correlate between .34 and .60 with self-report measures ($p < .05$) (Ekman, Friesen, & Ancoli, 1980). These findings were confirmed by an additional study showing that facial expression recognition matches self-reports more frequently than random probability (Rosenberg & Ekman, 1994). More recent studies in automotive settings utilize automated facial expression analysis, for example for drowsiness detection with accuracies up to 98% (Vural et al., 2009), for the prediction of accidents (Jabon, Bailenson, Pontikakis, Takayama, & Nass, 2011) or user interaction (Braun et al., 2018).

Body motion

Comfort and well-being are closely linked with each other (c.f. Section 2.1.3), and it is proposed that comfort is an influencing factor on well-being (c.f. Section 2.3.4). Thus, objective measures of comfort are possibly suitable proxies to assess well-being objectively. One of these objective measures is body motion, as uncomfortable people tend to shift their bodies to relieve discomfort (Lee et al., 1995).

In general, studies investigating the relationship between body movement and comfort or discomfort find significant relationships regardless of the exact study context. A study of sitting in general shows that different parameters of body movement are related significantly to subjective discomfort ($|r| > .140$, $p < .05$) (Søndergaard, Olesen, Søndergaard, Zee, & Pascal, 2010). A study on the comfort of wheelchairs showed that movements in the chair are significantly positively correlated with discomfort ($r = .44$, $p < .001$) and negatively correlated with comfort ($r = -.48$, $p < .001$) (Cascioli, Liu, Heusch, & McCarthy, 2016). Further, this relationship is found to be even stronger in the context of long-term driver discomfort in a driving simulator study where body movements and subjective discomfort were significantly related ($r = .927$, $p < .05$) (Sammonds, Fray, & Mansfield, 2017). In automated driving, drivers may react to discomfortable situations, e.g., unsafe driving behavior, through a push back motion that can be a characteristic type of body motion (Beggiato et al., 2018).

Implications for the measurement of passenger well-being in automated driving

To sum up, multidimensional verbal self-reports and objective physiological measures appear to be promising approaches to measure passenger well-being, if the exact conceptualization of passenger well-being includes aspects of current affective well-being. Depending on the specific context in which passenger well-being is measured, either self-reports or objective measures may be more appropriate.

2.2 Models Related to Passengers' Subjective Evaluation

To be able to consider passenger well-being in a user-centered development process of automated vehicles, an understanding of the determinants of passenger well-being, i.e., features of the automated driving experience and passenger needs, in automated driving is useful. To the author's knowledge, such a model of determinants specifically for passenger well-being in automated driving has not yet been published. Instead, models and theories on determinants influencing passengers' subjective evaluation in general and in other modes of transport are published and may be called upon as a starting point for developing a model for passenger well-being in the context of automated driving. As comfort and well-being are strongly related, and comfort is defined as a state of well-being in some cases (c.f. Section 2.1.3), models using comfort in addition to well-being as subjective evaluation criterion are discussed in the following. The identified models can be distinguished between general models aiming to explain the subjective evaluation of product use and models derived for specific transportation modes. As perception and processing of product features shall be included in the model of determinants of passenger well-being (RQ 4), a detailed view on a possible perception process is included.

2.2.1 General Models on Comfort as Subjective Evaluation

A number of general models on comfort judgments have been published and are partly interrelated. In the following, four comfort models are discussed, which originated in seat comfort but are developed to apply to general product use as well (c.f. Appendix A.3).

Comfort model by Looze et al.

Looze et al. (2003) view discomfort and comfort as independent concepts. This view is the basis for their theoretical model of comfort and discomfort. This model suggests the product, its physical and aesthetic features, the environment, and psychosocial factors are underlying factors. These factors influence comfort and discomfort based on human processing of the product and environment. For discomfort, physical processes related to biomechanical and physiological reactions dominate while comfort is derived from evaluations influenced by emotions and expectations.

Comfort model by Vink et al.

Based on this model, Vink, Looze et al. (2005) developed a simplified comfort model. This model does not differentiate between different processes for discomfort and comfort evaluations. Instead, based on physical cues, the environment these cues are experienced in, and individual differences regarding history and state, a judgment is reached. This judgment can be either comfort, no discomfort, or discomfort. Compared to the theoretical model of comfort and discomfort, this model provides more detailed information on the product features considered in product evaluation, such as visual design, smell, noise, or movements the product allows.

Comfort model by Moes

Moes (2005) suggests a comfort model based on seat comfort. It focuses on the internal biomechanical process that leads from interacting with a product to evaluations of appreciation or discomfort. The biomechanical process leads linearly to an evaluation based on four inputs: person, seat, purpose, and usage. For example, interacting with a seat causes a pressure distribution, which in turn has effects on the body in the form of compression of tissue or blood vessels. These body effects are perceived by the user and evaluated regarding appreciation or discomfort.

Comfort model by Vink and Hallbeck

Vink and Hallbeck (2012) combine the approaches by Moes (2005) and Looze et al. (2003) to derive their suggestion for a comfort model. They combine four input groups – environment, person, product, usage – which are also found in the two other models with the linear internal evaluation process proposed by Moes (2005). This internal process is extended by including expectations as an influencing factor on the perceived effects a product has. The evaluation can be either that the user feels comfort, discomfort, or nothing. If discomfort is perceived, this may lead to musculoskeletal complaints in the long term. In the short term, feelings of discomfort may affect the way a product is used through a feedback loop.

Implications for a model of determinants of passenger well-being

In sum, the models discussed in this section describe comfort/discomfort evaluations of a general nature and are not specifically targeted toward transportation. Thus, the focus rather lies on the internal biomechanical process as opposed to focusing on specific physical product features. In regards to deriving a model of determinants of passenger well-being, including both physical vehicle features and passenger needs, the discussed models give some indications, which may support modeling. Not only the physical gestalt of the product is of relevance for subjective evaluation, but also the environment in which it is used and the task which shall be completed with the product.

Further, users' expectations and the current state strongly impact the evaluation (Vink, Looze et al., 2005). Although not explicitly included, indications for passenger needs are provided. To derive a judgment of comfort, which is related to well-being, not only the physical features but also the aesthetic design are considered (Looze et al., 2003). This may point toward the need for a minimum level of aesthetic pleasing to reach a positive evaluation. However, all models lack details on how intangible product features such as aesthetics are processed. The biomechanical process may not be relevant to such aspects. Instead, other views on perception and processing provide more applicable insights (c.f. Section 2.2.3)

2.2.2 Models on Subjective Evaluation in Transportation

Published models that describe passengers' subjective evaluation of the transport experience include both well-being and comfort as evaluation criteria. Mokhtarian (2019) provides an overview of four conceptual models that describe the relationship between travel and well-being (c.f. Appendix A.4), which are strongly related to transport policy. A strong perspective of well-being in transport policy is due to the fact that ultimately transport policy aims to raise individual well-being (Ettema et al., 2010). All four models from the overview model how transport and its accompanying side effects can act as an enabler or a hindrance to well-being.

Theoretical framework by Ettema et al.

Ettema et al. (2010) suggest in their framework that travel can directly affect global subjective well-being through affective factors (safety, comfort, etc.) and instrumental factors (travel time, cost, etc.). Instrumental and affective factors, in turn, determine cognitive and affective levels of domain-specific (here: travel) subjective well-being. The level of domain-specific well-being relates to global well-being. Travel may also act as an enabler for social inclusion by providing access to activity and participation. Such access to activities can allow the progression toward personal goals, which can affect global well-being both in a hedonic and eudaimonic sense. However, social inclusion and travel options can be associated with stress, which can be detrimental to global subjective well-being.

Theoretical model of links between travel behavior and well-being by Vos et al.

The indirect path of travel affecting well-being through the access to activities described by Ettema et al. (2010) is found in the theoretical model by Vos et al. (2013) as well. In this model, the authors argue that mobility has a value in itself by offering freedom and autonomy, and thus, impacting eudaimonic well-being. Mobility can also indirectly impact both eudaimonic and hedonic well-being by enabling the experience of activities. These activities can either be activities for which destination-oriented travel is required, activities during destination-oriented travel, or traveling that constitutes an activity in itself. The authors additionally suggest that mobility itself depends on residential location choice and personal attitudes towards traveling, among other factors.

Theoretical model of transport's influence on subjective well-being by Delbosc

Delbosc (2012) suggests that transport can influence subjective well-being via three different approaches. First, as discussed in the other two models, transport can provide access. In contrast to the other models, Delbosc suggests that access to health, relationships, and employment as correlates of well-being are desired. The evaluation of access and barriers to these three personal values determine the level of satisfaction and, in turn, the overall level of well-being. Secondly, as suggested by Vos et al. (2013), mobility in itself can benefit well-being through the freedom to travel and the possibility to engage in physical activity, which, in turn, benefits health. Delbosc includes the community perspective as the third approach by considering the effects of transport on non-users as well. Transportation entails less favorable side effects such as pollution, noise, and potential impacts on physical safety. Consequently, the overall design of transport infrastructure can encourage or discourage activity, and thus, influence well-being.

Model by Reardon and Abdallah

Finally, Reardon and Abdallah (2013) present an overview of four different perspectives on how transport can impact subjective well-being: social relationships, individual factors, environment, and economy. The access and barriers to social relationships through transport suggested here correspond to similar suggestions found in the three models above. Physical activity through mode choice, psychological responses to traveling, and the level of stress and satisfaction created by transport are suggested as individual factors. The authors also take up the topic of the environment found in Delbosc's model. Reardon and Abdallah introduce a new aspect by including the economic effects of transport on subjective well-being. The authors argue that transport infrastructure influences the level of efficiency, productivity, and input volume.

The models have one central aspect in common by arguing that mobility impacts well-being by being an access provider. Access may be provided to activities, social inclusion, employment, relationships, and health. Further, the models argue that mobility itself can be a source of subjective well-being by offering a sense of control, autonomy, freedom, and prestige. Yet, according to the models, transport can also be a hindrance to well-being through negative environmental side effects and induced stress through the design of travel options and time pressure. The models offer insight on personal values or needs that may be relevant in transport contexts such as control or prestige. However, the models do not provide any insights on how design features of transportation systems such as physical features of a vehicle specifically relate to well-being. Thus, turning to additional models on subjective evaluation in transportation.

Predictive model by Vankan

Vankan (2010) suggests a predictive model for the effect of environmental features on well-being in aircraft cabins (c.f. Appendix A.5). Prediction is based on factors like pressure, temperature, climate and noise, individual passenger characteristics such as age, height, health, and behavioral factors, e.g., clothing or movement during the flight. The model predicts both subjective and objective evaluations like subjective temperature and air comfort scores or objective physiological measures based on the underlying multivariate regression. Vankan's model is limited to environmental and passenger characteristics as input and omits physical features of the aircraft and cabin. In contrast, the following models provide a broader view of influencing factors and also include physical features of the respective vehicle.

Circle of riding comfort by Mayr

Mayr (1959) proposes an overview of features essential for ride comfort using trains as an example (c.f. Appendix A.5). Ride comfort is defined as "measures which maintain and improve the well-being of a person and reduce his fatigue" (Mayr, 1959, p. 266). The model includes the psychological characteristics and physiological functions of the passenger as well as the physical features of the means of transport. According to the model, eight different categories, including physical and intangible design features and the passenger themselves, are relevant: noise, shocks and vibrations, anatomical features, aesthetic design, windows and lighting, air conditioning, sanitary installations, catering, and attendance. The first six categories apply to non-automated and automated vehicles equally. As more time can be spent on NDRTs in automated vehicles, eating and on-demand catering options may become more important and create an additional feature category.

Theory of comfort by Richards

Compared to the aforementioned models, Richards' (1980) theory of comfort includes both determinants and outcomes of comfort. Interestingly, in this model, comfort is defined as "a reaction of a person to either an environment or situation" (Richards, 1980, p. 16) and as a "state of subjective well being" (Richards, 1980, p. 16). Thus, actually equating comfort with subjective well-being. Inputs include physical (divided into dynamic, ambient, and spatial factors), social and situational aspects of the travel experience (c.f. Figure 2.2). The effect of these inputs is moderated by time, activities performed while traveling (c.f. Section 2.3.6), and passenger characteristics (c.f. Section 2.3.5). Time can act as a moderator in three ways. First, time affects the way different travel segments that take place after each other are evaluated. Segments at the end of the trip tend to affect evaluation stronger than earlier segments. Secondly, depending on the cue and specific situation, the time until a cue impacts a passenger's state and the time until a passenger's state recovers from a negative cue can differ. Lastly, time can directly affect the evaluation of a cue based on how long a passenger is exposed to it. In turn, comfort affects several output parameters, which are not discussed at this point, as this work is focused on determinants as opposed to outcomes of subjective evaluations.

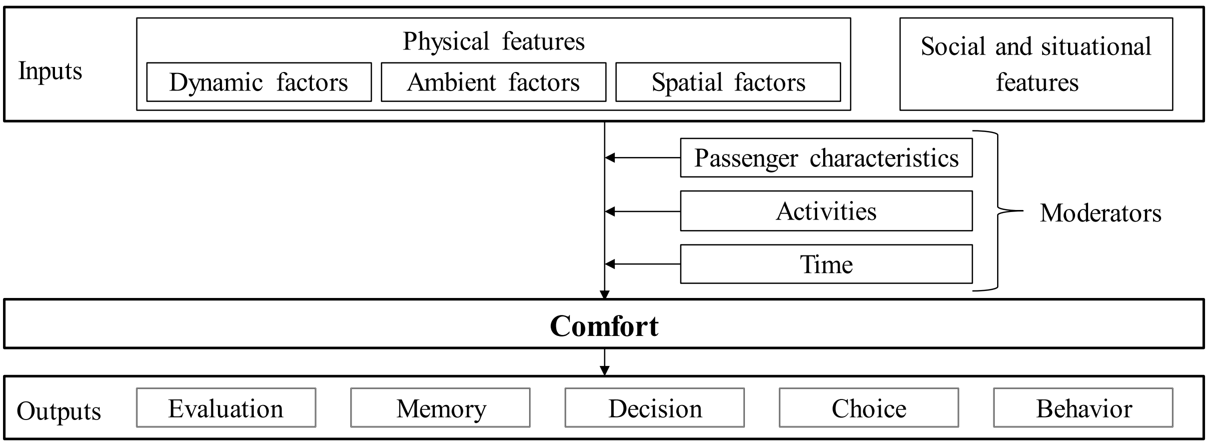


Figure 2.2 Elements of the theory of comfort, figure based on contents from Richards (1980).

This theory of comfort provides clear suggestions on physical features that may affect the level of passenger well-being. In line with the general comfort models, the theory of comfort includes passenger characteristics and activities as possible moderators. However, potential passenger needs that may be affected and details on how these physical features are perceived and processed are lacking.

Passenger comfort experience model by Ahmadpour et al.

Similar to the theory of comfort, Ahmadpour et al.'s (2014) passenger comfort experience model is based on empirical evidence in aviation. This model considers human and context features, as well as the activities performed while traveling, as inputs. Human features match the passenger characteristics suggested in Richards' theory of comfort. The context features are derived from empirical evidence and clustered into dynamic, spatial, ambient, and social and, thus, overlap with the theory of comfort. The three input groups, in turn, create physical impacts such as the pressure or temperature felt by the passenger and lead to the passenger's perception of the context. Based on physical impacts and perception, a level of comfort is derived. Ahmadpour et al. suggest eight themes to which perception can be formed and provide insights on which context features are likely to create a certain perception (c.f. Figure 2.3). For example, spatial features can affect a passenger's perception of aesthetics, proxemics, or physical well-being and contribute to peace of mind. Ambient features also influence the latter. The consideration of perception themes is an additional indication of the need to consider passenger needs in the model of determinants.

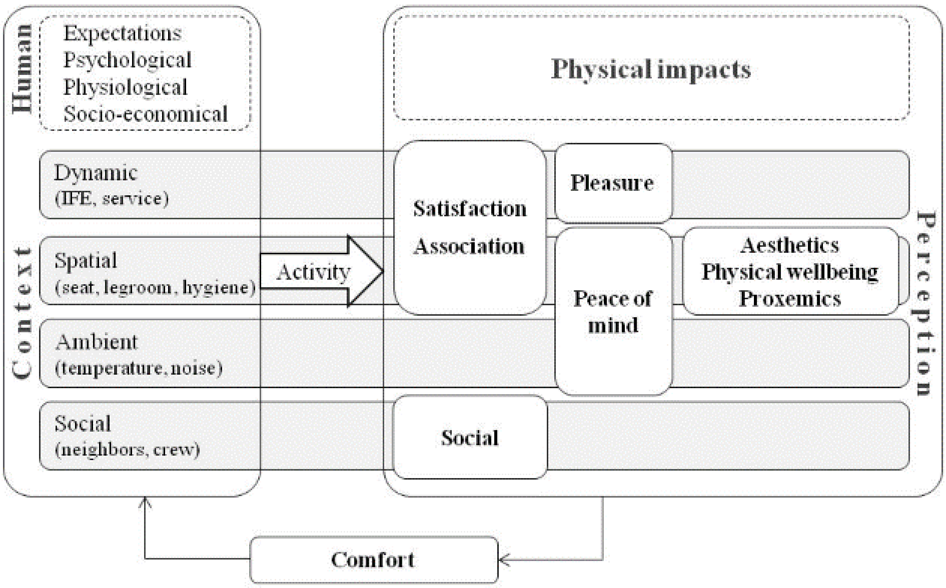


Figure 2.3 Passenger comfort experience model (Ahmadpour et al., 2014, p. 811).

Implications for a model of determinants of passenger well-being

All models specific to different transportation modes provide overviews of features that are likely to have an impact on passenger well-being. Table 2.2 summarizes the potential inputs suggested in these models. The categories are based on the theory of comfort with social and situational features split into separate groups (Richards, 1980). When reviewing this overview, it becomes evident that due to the different transportation contexts, not all features are applicable to automated driving, and in turn, features unique to automated driving are lacking. For example, pressure, sanitary installations, interaction with operators, or crowding at stations are less relevant to automated driving. Some features such as familiarity and interaction with other passengers may depend on the specific vehicle design as private use or shared use vehicle.

Technical aspects of automation are unique to automated driving. Automation is also present in aviation and railway transport, but the crucial difference is the fact that passengers in trains and aircrafts never had the option to be the operator. However, in automated driving, especially in automation up to level 4, the driver transitions between being a driver and being a passenger. Hence, the capabilities and behavior of the automation system are more present and even more crucial for the driver/passenger than in other modes of transport (c.f. Section 2.3). Thus, including an additional category of technical features is appropriate for automated driving contexts.

Moreover, the models specific to transport include indications of passenger needs that may be important for passenger well-being (Ahmadpour et al., 2014; Delbosc, 2012; Reardon & Abdallah, 2013; Vos et al., 2013). For example, the need for aesthetics is a recurring theme that is also relevant for products outside of transport (c.f. Section 2.2.1). But it remains to be validated which passenger needs apply to automated driving. Also, passenger characteristics and activities are a common aspect of the discussed models. Suggested passenger characteristics range from psychological factors to physical, physiological, and situational factors (Richards, 1980). Prior experience and resulting expectations are a major point for comfort made not only in general models (Vink & Hallbeck, 2012) but in transport context as well (Ahmadpour et al., 2014; Delbosc, 2012; Richards, 1980; Vos et al., 2013).

None of the models expand on the perception and processing of the features required for subjective evaluation in detail. A first indication of perception is included in the passenger comfort experience model (Ahmadpour et al., 2014) that suggests eight themes of perception and their allocation to feature groups. Yet, there is no specification of situational influences that may shape perception, which poses an opportunity for further research. In sum, the theory of comfort and the passenger comfort experience model provide a starting point to build and extend a model of determinants of passenger well-being in automated driving.

Table 2.2 Overview of features of the travel experience based on the models on subjective evaluation in transport.

Note: Categories are based on the theory of comfort (Richards, 1980); Categories social and situational are split into separate groups for increased clarity.

Sources: 1 Richards (1980); 2 Vankan (2010); 3 Ahmadpour et al. (2014); 4 Mayr (1959)

Physical All features related to the vehicle environment[1]			**Social** All features related to social interaction during the journey[1]	**Situational** All features that are dependent on individual circumstances[1]
Dynamic Features changing rapidly during the journey[1]	**Ambient** Features changing slowly during the journey[1]	**Spatial** Features remaining constant during the journey[1]		
Vertical, lateral, longitudinal acceleration [1] Roll, pitch, yaw rate [1] Shocks, jolts [1,3,4] Vibration [2,4] Ascents, descents [1] Change in speed [1] In-flight entertainment [3] In-flight service [3] Food [3,4]	Noise [1,2,3,4] Light [3,4] Pressure [1,2,3] Humidity [1,2] Temperature [1,2,3,4] Ventilation [1,2,4] Air recirculation [2] Air velocity [2] Smoke [1] Air quality [1,4] Odors [1]	Seat (width, adjustment, shape, and firmness) [1,3] Windows [3,4] Leg room [1,3] Ingress/egress [3] Workspace [1] Storage [3] Aesthetic design [4] Information [3] Sanitary installations [3,4]	Pre-trip interaction [1] Interaction with operators [1,3,4] Interactions with passengers [1] Crowding at station [1] Crowding in vehicle [1] Presence of travel companions [1] Familiarity with persons in adjacent seats [1,3]	Connections [4] Mobility service frequency and reliability [4] Independence of weather/climate [4] Legal obligation to provide transport mode [4]

2.2.3 Processing Vehicle Features for Subjective Evaluation

In terms of perception and processing, general comfort models and comfort models in transportation focus on the biomechanical process to evaluate bodily reactions to product use, such as using a seat or hand tool. Evaluation of intangible features is suggested to affect perception through different themes such as aesthetics, pleasure, or peace of mind (Ahmadpour et al., 2014). However, none of the models specify the processing procedure of how different features influence the passenger's evaluation and the resulting level of well-being. Yet, an understanding of perception and processing is crucial in order to determine why and when certain features are relevant for well-being. In the context of automated driving, perception and processing of vehicle features may depend on the engagement in NDRTs, among other factors, which shifts attention away from the driving experience and reduces the ability of perception and processing.

Elaboration likelihood model

The elaboration likelihood model (ELM) deals with persuasive communication and aims to model how and when stimuli are processed and subsequently cause a change of attitude (Petty & Cacioppo, 1986). The model suggests two routes to process information: the peripheral and the central route, and thus, counts as a dual process model (Klimmt, 2011). Which route is used for processing depends on the likelihood of elaboration. Elaboration is "the extent to which a person thinks about the issue-relevant arguments contained in a message" (Petty & Cacioppo, 1986, p. 128). In the context of automated driving, this definition can be adapted to be the extent to which a passenger thinks about cues created by the automated driving experience.

If elaboration likelihood is low, information is processed superficially and affectively via the peripheral route. In the case of automated driving, peripheral processing may be the affective evaluation of the overall impression of the driving experience. If elaboration likelihood is high, more information is processed (Radford & Bloch, 2011). This more extensive range of information is further processed more consciously and more fine-grained (Homburg, Schwemmle, & Kuehnl, 2015) via the central route. In the case of central route processing, passengers may take information on an atomistic level into account, such as the information displayed in user interfaces or the quality of materials.

Elaboration likelihood depends on how willing and able one is to evaluate information, which in turn depends on personal and situational factors. As information processing capacity is limited, elaboration will move on a continuum from high elaboration to low elaboration and levels in between (Petty & Cacioppo, 1986). Thus, the two routes of processing are not mutually exclusive, but rather are interrelated and can apply at the same time to varying degrees (Klimmt, 2011). Petty and Cacioppo (1986) suggest distraction, repetition, personal involvement, and responsibility, and need for cognition as key variables that influence ability and willingness.

Applying ELM to automated driving

In the case of automated driving, ability and willingness to process information from the driving experience can be influenced by the engagement in NDRTs as a representation of distraction, and individual differences such as prior experience or involvement. For example, a passenger engaging in an NDRT like watching a video, video-conferencing, or sleeping that masks environmental cues such as noise and view will have a limited ability to perceive and, in turn, process the environmental cues to derive a level of well-being. Prior experience or the passenger's interest in automated driving may influence their need for cognition and, thus, affect the level of motivation to process information. A passenger who is very interested in cars and technology may be very motivated to process all cues of the driving experience on the first automated drive. Yet, this motivation may cease with growing experience and cause a lower need for cognition.

In the case of high elaboration likelihood and cognitive processing of information, passengers may be able to describe very accurately why they experienced a certain level of well-being as experience from daily life shows. For example, unexpected and rough driving maneuvers may impair the sense of safety in the vehicle, and thus, reduce well-being. On the other hand, aesthetically pleasing design or comfortable seats may raise the level of well-being in an automated vehicle. However, it remains open to discussion if there is a hierarchy among these auxiliary passenger needs or if they can compensate each other.

Implications for a model of determinants of passenger well-being

Related work proposing models on different aspects of passengers' subjective evaluation provide different levels of detail. Recall the determinants and aspects that shall be placed in a relationship with passenger well-being in this work: physical features, perception and processing, passenger needs, and passenger characteristics (c.f. Figure 1.2). The related theory of comfort (Richards, 1980) and passenger comfort experience model (Ahmadpour et al., 2014) provide insights into physical features, passenger needs, and characteristics. Combining both models with ELM (Petty & Cacioppo, 1986) may be a solid starting base to achieve the aim of this work to build a model of determinants of passenger well-being.

2.3 Investigation of the Effect of Single Features

The previous sections provide insights into how the key elements physical features, passenger needs and characteristics, and passenger well-being may be modeled (c.f. Section 2.2). The models offer an overview of which determinants may have an impact, but they do not discuss the effect of specific forms on subjective evaluation. For example, the models suggest that lighting may have an impact (Mayr, 1959; Richards, 1980), but it is not detailed which type of lighting may be favorable for a high level of well-being. To add to the findings so far, research is discussed in the following that investigates how specific forms of different determinants may affect passengers' subjective evaluation in general and passenger well-being in particular. These studies are mostly mono-disciplinary (Vink, Overbeeke, & Desmet, 2005) by considering only a single determinant, such as the effect of light or temperature. Further, passenger well-being is an emerging field of research, and no consistent definition of passenger well-being exists (c.f. Section 2.1), which presents a challenge for the breadth of research in automated driving and the comparability of study results. Thus, research from other transport contexts and other evaluation variables such as comfort are included. The discussed related work is structured using the feature categories of the theory of comfort (c.f. Table 2.2).

2.3.1 Physical Features

Physical features are all those dynamic, ambient, and spatial features that contribute to creating the physical and intangible environment in a vehicle (Richards, 1980). Compared to ambient features, dynamic features change more frequently, while spatial features remain static throughout the journey.

Dynamic

Dynamic features include the driving dynamics of the vehicle, including acceleration and movement along all six degrees of freedom on the one hand (Richards, 1980). On the other hand, features such as entertainment or food are argued to be dynamic as well (Ahmadpour et al., 2014). As this work proposes an additional category of technical features for automated driving (c.f. Section 2.2.2), features related to a user interface are more suited for the technical category and will be discussed there.

Driving dynamics is one of the central properties in vehicle development (Atzwanger & Negele, 2006) and discussed in regards to the dimensions noise, vibration, and harshness (NVH) (Sauer, Kramer, & Ersoy, 2017). Noise covers audible frequencies (see section ambient in the following for further details). Vibration comprises tactile frequencies, and harshness represents the transient area in between. NVH is caused by structural- or airborne excitation of the vehicle and its components from roadway, imbalance, aerodynamics, or the vehicle's drive train (Sauer et al., 2017). In regards to subjective evaluation, NVH correlates with comfort (Richards, Jacobson, Barber, & Pepler, 1978). Thresholds for vibrations to maintain a minimum level of comfort and avoid impairments to physical well-being have been established (McFarland & Moore, 1957).

With increasing automation, passengers prefer a reduction in driving dynamics (Lange, Maas, Albert, Siedersberger, & Bengler, 2014). Reduced driving dynamics may also help to mitigate motion sickness caused by the engagement in NDRTs (Diels & Bos, 2016). Approaches to reduce lateral and longitudinal forces through active chassis solutions may only contribute to reduced motion sickness if visual information and the adjusted vestibular information match.

For example, an active chassis may help reduce motion sickness when reading a book inside the car but may be confusing if looking out of the window (Winner & Wachenfeld, 2015).

Ambient

Noise

Noise is closely related to driving dynamics and a part of NVH. Noise is mainly caused in two ways. Airborne noise is caused by aerodynamic interaction of the moving vehicle with the surrounding air. Structural noise is mainly caused by resonances of vehicle parts such as transmission, body structure, or interior (Gameiro da Silva, 2002). High levels of noise have an arousing effect and are negatively evaluated by passengers (Kim, Park, & Park, 2000; Penning & Quehl, 2010). Yet, evaluation of noise is a complex process and does consider not only noise levels but also spectral characteristics (de Diego, Gonzalez, Pinero, Ferrer, & Garcia-Bonito, 2001). Studies have investigated these different properties. In general, noise is evaluated differently in different modes of transport, where more regular and predictable noises are less annoying (Fields & Walker, 1982). Västfjäll et al. (2003) suggest that loudness relates to valence and sharpness to activation in the subjective evaluation of aircraft sounds. In car settings, sounds can be evaluated regarding pleasantness (height of low frequencies) and power (dynamic of low frequencies) (Bisping, 1995). In regards to NDRTs, high levels of noise can impair cognitive performance (Hygge & Knez, 2001), which is especially relevant when using automated driving time for productive tasks. Noise can also act as a feedback stimulus (Bisping, 1995), which may help passengers retain perceived control in visually demanding NDRTs.

In contrast, in-vehicle sounds caused mainly by the powertrain are often deliberately designed to provide symbolic value by creating a specific brand image and matching the product category. Generally speaking, sports cars have higher noise levels, while luxury vehicles tend to have a quieter interior (Biermayer, Thomann, & Brandl, 2001; Bijsterveld, 2015). As automated vehicles are expected to rather count as a luxury than as a sports car, quiet interiors may also be achieved by active noise canceling. Active noise canceling can be integrated into the vehicle's sound system (Chen, Samarasinghe, Abhayapala, & Zhang, 2015) and can positively affect passenger's comfort evaluations (Chen et al., 2015; de Diego et al., 2001; Gonzalez, Ferrer, Diego, Piñero, & Garcia-Bonito, 2003) and facilitate NDRTs.

Lighting

In a passenger car, two types of interior lighting are possible: functional lighting (e.g., reading lamps, light in vanity mirror) and ambient lighting used to create a positive atmosphere and sense of space (Mayer & Schwab, 2010) as well as easing the driving task at night (Bubb, 2015). A focus is placed on ambient lighting, as this is usually always on as opposed to functional light, which is only activated in specific use cases.

Ambient lighting is widely available in different car categories (Mayer & Schwab, 2010) and often uses colored light. The psychological effect of color on people is an intensively researched field (Valdez & Mehrabian, 1994), and findings most likely apply to the automotive context as well. Yet, studies in automotive reveal inconsistent results. There is disagreement in empirical study results whether ambient light affects passengers' evaluation compared to conditions without ambient light (Hassib, Braun, Pfleging, & Alt, 2019; Mandel, Senel, & Maier, 2013), or whether ambient lighting is without effects on passengers' subjective state (Caberletti, 2013). Similar contradictory results were found for the effect of the color of ambient lighting. Hassib et al. (2019) find no significant changes in passengers' arousal and valence ratings when exposed to blue or orange lighting. In contrast, Caberletti (2013) suggests that warm colors can increase the evaluation of the interior in regards to attractiveness, and green lighting causes unfavorable evaluations. The positive effect of warm colors like orange is seconded by Mandel et al. (2013) in regards to passengers' room perception and Winzen et al. (2014) in regards to preference in aviation applications.

Ambient lighting can be used beyond aesthetical purposes to provide functionalities and influence passenger behavior. For example, approaches have been made to utilize ambient light to provide information on the driven speed in order to make the driving experience more motivating and appealing (van Huysduynen, Terken, Meschtscherjakov, Eggen, & Tscheligi, 2017). In the context of automated driving, ambient lighting can also be used to provide information on the vehicle state or to visualize detected objects (Löcken, Heuten, & Boll, 2016).

Climate

The thermal conditions within the vehicle are extremely relevant for the physical well-being of the passenger and influence passengers' cognitive performance (Bubb, 2015). Thermal comfort, i.e., "satisfaction with the thermal environment" (Fanger, 1972, p. 13), is influenced by characteristics of the passenger (internal heat production, skin temperature, clothing, and sweating) as well as thermal characteristics of the environment (air temperature, radiant temperature, pressure of water vapor in ambient air and air velocity) (Fanger, 1972). In general, climate is considered as input in passengers' evaluation of comfort in aircrafts (Ahmadpour, 2014; Vink et al., 2012) and passenger cars (Norin & Wyon, 1992).

In terms of single aspects of thermal conditions, it was shown that temperature does not significantly predict passengers' well-being in aircrafts (Marggraf-Micheel et al., 2010). Yet, in driving contexts, the ambient air condition significantly influences drivers' fatigue (Makowiec-Dąbrowska et al., 2019), which is relevant for optimal conditions to conduct NDRTs. An increase in temperature can impair drivers' vigilance. A rise in temperature from 21°C to 27°C reduced vigilance by 50% (Norin & Wyon, 1992). In general, car passengers prefer lower temperatures in the head regions and higher temperatures at the feet (Amano & Imai 1971 cited from Bubb, 2015). Another aspect is air velocity. Air velocity should be kept low to avoid discomfort but needs to be high enough to achieve the targeted temperature. Generally, air velocities of 1.5-2.1 m/s but below 3 m/s are suggested. The subjective perception of air velocities is, however, culturally different (Bubb, 2015). Studies in aviation suggest that already air velocities of .8 m/s compared to velocities of .25-.30 m/s can impair passenger well-being by decreasing mood and relaxation (Marggraf-Micheel & Jäger, 2007).

Traditionally, car passengers can influence the climate predominantly via controlling air velocity and temperature via the air conditioning system (Hodder, 2013). To avoid high, discomfort-causing air velocities, other approaches to regulate the climate inside a vehicle are investigated. These include thermal preconditioning and surface heating (Wiebelt, 2019) or soft air diffusion (Mattiello, Malvicin, Mola, & Magini, 2001). These strategies may also increase in relevance for electric (automated) vehicles (Wiebelt, 2019).

Smells and odors

In-car smells are an important factor for passengers in their subjective evaluation of the driving experience (van Lente & Herman, 2001). Smells and odors within the vehicle can either be caused by unwanted outgassing of materials or be deliberately integrated by fragrancing interior materials such as leather or by integrating fragrances into the air conditioning system (Diem, 2001). The human sense of smell is strongly connected to the limbic system. Thus, smells can evoke strong affective reactions (Bubb, Vollrath, Reinprecht, Mayer, & Körber, 2015). The effect of smell strongly depends on the specific scent. For example, cinnamon and peppermint can raise alertness (Raudenbush, Grayhem, Sears, & Wilson, 2009), while lavender and rose have a soothing effect (Dmitrenko, Maggioni, Vi, & Obrist, 2017). Lemon scents showed a positive effect on positive affect and alertness (Baron & Kalsher, 1998).

In driving situations, peppermint was shown to improve drivers' alertness and reduce drowsiness (Funato et al., 2009; Mahachandra, Yassierli, & Garnaby, 2015; Raudenbush et al., 2009). Lemon scents improve drivers' positive affect and alertness (Baron & Kalsher, 1998). In manual driving, the focus lies on scents that raise alertness, stimulate, and reduce driver fatigue. In the case of highly and fully automated driving, soothing scents that reduce arousal may be applicable as well to create environments that foster different NDRTs varying from being productive to relaxing or sleeping. Yet, in the design of ambient fragrances, the olfactory adaption process and the lingering of scents need to be considered (Funato et al., 2009). Fragrancing systems can not only be used to create a pleasant environment in premium vehicles, but also to provide alarming or rewarding information (Dmitrenko, Vi, & Obrist, 2016). Approaches exist to use scents to provide notifications, such as lavender or lemon for slowing down, peppermint for low fuel level or rose for points of interest (Dmitrenko et al., 2017; Dmitrenko, Maggioni, & Obrist, 2019). Further, lemon and lavender scents were successfully utilized to complement visual information on the reliability level of an automated driving system (Wintersberger et al., 2019).

Spatial

Seats

When considering the spatial elements of a vehicle interior, the seats are a central element (Erol, Diels, Shippen, Richards, & Johnson, 2016). Sufficient seat comfort has become a basic requirement for today's cars (Kolich, 2008) and will most likely also be applicable to automated vehicles in the future. A seat can be described by its basic properties: stiffness, geometry, and contour. Further, seat materials define the breathability and styling of the seat (Kolich, 2008). A well-designed car seat can raise passengers' well-being during driving (Zenk, Franz, & Bubb, 2007). The seat is also closely linked to passengers' physical well-being due to biomechanics, especially on long trips. With constraints from the vehicle packaging, sitting in a car for a prolonged time can, in the worst case, lead to musculoskeletal disorders (Kyung, Nussbaum, & Babski-Reeves, 2008). Compared to standing, seated postures lead to increased spinal disk pressure. To counter this, car seats with lumbar support are common. Proprioceptive information helps passengers to select the best posture and is facilitated by adjustable seat settings such as backrest angles (Helander, 2003).

To avoid passive seating and unhealthy postures, active seating can be another countermeasure. First approaches show an increased muscle activity, muscle variability, and acceptance by users (Hiemstra-van Mastrigt, Kamp, van Veen, Vink, & Bosch, 2015; JLR, 2020). In addition to the basic seat properties, the seat itself can be equipped with an integrated massage system, which can have benefits for physical well-being. User studies with such massage systems show a reduced level of stress (Franz, Zenk, Vink, & Hallbeck, 2011). Further, lumbar massage was shown to increase muscle activity (Kolich, Taboun, & Mohamed, 2000), muscle oxygenation, and blood flow without impairing driver performance in prolonged driving situations (Durkin, Harvey, Hughson, & Callaghan, 2006).

In highly and fully automated driving, it may become possible to offer passengers additional seat positions such as rotating the seat or increasing the seat angles (Ive, Sirkin, Miller, Li, & Ju, 2015), which is part of many vehicle concepts for automated driving. Seat rotation is especially relevant to simplify social interaction with other passengers but depends on the length of the trip (Ive et al., 2015; Jorlöv, Bohman, Larsson, & Annika, 2017). Seat angles can help to facilitate NDRTs such as sleeping or relaxing. In any case, changes in seat positions and angles compared to traditional layouts need to be reflected in adjusted active and passive safety measures (Boin, 2018; Jin, Hou, Shen, Wu, & Yang, 2018).

Layout and Packaging

The vehicle packaging (i.e., the vehicle roominess described by head-, leg-, shoulder- and hip-room) influences the perception of the seat (Kolich, 2008). Considering vehicle packaging is not only required to fulfill basic ergonomic requirements, but packaging can also have an effect on passenger well-being. A study in aviation shows that the relationship between seat pitch in aircrafts and passengers' arousal follows an inverted U-shape (Kremser, Guenzkofer, Sedlmeier, Sabbah, & Bengler, 2012) indicating that there is an optimal point between a space being too ample and too cramped. However, to promote a positive subjective evaluation by passengers, car seats do not only have to fulfill the basic requirement of ergonomic design but also address the emotional aspect of design through aesthetics (Helander, 2003).

Aesthetics

Aesthetic design does not only apply to the seat but the vehicle overall and especially the interior. Aesthetics, in its original meaning derived from the Greek, addresses all human senses (Hekkert, 2006). A perception of aesthetics can influence passenger well-being through positive affective responses (Carbon and Jakesch, 2013; Hassenzahl, 2008). These can vary from product liking to strong reactions like enjoyment or even love (Bloch, 1995). Further, aesthetics can cause higher levels of positive valence and lower levels of arousal (Thüring and Mahlke, 2007).

Aesthetic design includes design elements, the materials utilized, and the overall quality (Bloch, 1995). Different studies suggest design elements that can positively influence passengers' subjective evaluation. For example, the anthropomorphic design of the vehicle exterior can significantly increase pleasure and arousal, depending on the specific design (Landwehr, McGill, & Herrmann, 2011). Yadav, Jain, Shukla, Avikal, and Mishra (2013) suggest that the design attributes elegant, family-feeling, modern, and youthful significantly increase satisfaction with vehicle design. Further, the spatial design and roominess created by the vehicle package shape the aesthetic judgments of the passenger (Mandel & Maier, 2016). Yet, aesthetics is not only influenced by static, spatial features but overlaps with features from other categories such as noise (Bisping, 1995) or lighting (Muramatsu, Kaede, Tanaka, & Watanuki, 2018).

Implications for a model of determinants of passenger well-being

Related work on physical features indicates that these features suggested by models in transportation research (c.f. Table 2.2) affect both comfort evaluations and the level of passenger well-being. Thus, the overview of physical features may be integrated into the model of determinants of passenger well-being in automated driving. Yet, when evaluating this assumption, it is important to bear the interrelatedness of physical features in mind. The effect of features on passenger well-being is likely to depend on the general context and configuration in which they are presented. Depending on the specific configuration of features, the evaluation and the resulting importance and desired form may differ. Further, related work shows that for some physical features, desired levels are generalizable, such as air velocity, where lower velocities are perceived as better and raise passenger well-being. Other features, such as aesthetics or smells, appear to be more subjective and may have to be customizable in order to raise well-being.

2.3.2 Technical Features

Technical features are an aspect unique to automated driving, as in automation up to level 4, the driver transitions between driver and passenger roles (c.f. Section 2.2.2). This work proposes that technical features cover the specific design of the automation and the interface between passengers and the vehicle and act as determinants of passenger well-being.

Level of automation

The effect of automation itself on passenger well-being compared to manual driving is inconclusive. It is argued that automation can increase a driver’s well-being by reducing stress and frustration (Stanton & Marsden, 1996). A study by Senn et al. (2018) shows this positive effect of automation on driver’s well-being through affect. In the case of semi-automated driving, negative affect was reduced compared to manual driving. Automation had no impact on positive affect. A simulator study by Frison et al. (2017) suggests that manual driving caused higher positive affect than automated driving. Negative affect was not influenced by the automation level. Noah et al. (2016) compare a lane departure warning system, which only warns the driver, with a lane-keeping feature, which automatically keeps the lane and constitutes a higher level of automation. Lane-keeping was linked to stronger negative affect than lane departure warning. This result complements the findings that automation reduces well-being during a driving experience. These unclear results may be an indication of the public skepticism towards automated driving (Kyriakidis, Happee, & Winter, 2015). Further, it suggests that the type of driving automation and the design of the driving experience largely influences passenger well-being.

Automated driving style

In the design of the automation system, a number of entities are involved, such as the utilized sensors, the algorithms that transform data from sensors and other hardware to actions of the vehicle (Sauer, Savinov, & Geiger, 2018). As this work considers the passenger’s level of well-being during the automated driving experience, only those automation features will be discussed that are perceivable by the passenger. This primarily concerns the driving style, i.e., driving dynamics and the maneuvers. Elbanhawi, Simic, and Jazar (2015) suggest that driving dynamics should be designed to be smooth and minimize jerk to reduce the potential for motion sickness. Further, the authors characterize maneuvering of the vehicle by the distance kept to other vehicles, the exact trajectory the car takes, and the consideration of time to execute the maneuver safely.

Bellem, Thiel, Schrauf, and Krems (2018) analyze the effect of driving style on comfort by means of three maneuvers, lane change, acceleration, and deceleration. For lane changes, the study results suggest a preference for a driving style with a stronger initial lateral jerk, while deceleration and acceleration should minimize jerk. The results indicate that the driving style of the automated vehicle does not necessarily have to mimic human driving behavior. However, to maximize a positive evaluation by passengers, manual or automatic adjustments of the driving style are suggested (Festner, Eicher, & Schramm, 2017).

User interfaces

Driving automation up to level 4 entails a transition between being a driver and a passenger. This requires providing constant information on the vehicle state and related information to the driver/passenger in addition to providing control options for the numerous functions included in today's cars, such as entertainment or ambient settings (Kern & Schmidt, 2009). Thus, automotive interfaces have an input and an output modality, which results in a number of different types of user interfaces. Classically in-car interfaces are of haptic, visual, or auditory nature (Bubb, Bengler, Breuninger, Gold, & Helmbrecht, 2015). In terms of interfaces with haptic input, a study showed that the interface attributes operation, sound, localization, touch, styling, functions, and concept influence satisfaction ratings (Gaspar, Fontul, Henriques, & Silva, 2014). Other input modalities include gestures, speech, or indirect interaction through driver state detection such as fatigue (Kern & Schmidt, 2009). Speech recognition can be utilized for novel conversational user interfaces. Such interfaces may not only receive input and provide information, but can also fill social roles (Braun, Broy, Pfleging, & Alt, 2017). Detection of the driver state opens the passenger car up to affective computing applications. Interfaces can also have a combination of multiple input and/or output modalities. A study with touch screens shows that the combination of different modes to multimodal interfaces can create a better subjective experience (Pitts, Skrypchuk, Wellings, Attridge, & Williams, 2012).

Other output channels are being investigated for their feasibility to convey information appropriately, as traditional visual information may be hard to perceive if engaged in visually demanding NDRTs. For example, olfactory feedback has been used to convey information on the reliability of vehicle automation (Wintersberger et al., 2019, c.f. Section 2.3.1). To convey information on planned maneuvers and other driving-related information via the vestibular channel, vehicle roll and pitch have been suggested (Cramer, Siedersberger, & Bengler, 2017; Lange et al., 2014; Müller, Sieber, Siedersberger, Popp, & Färber, 2017).

Not only different types of modalities for input and output but also the type and variety of information itself influence the passenger's perception. For example, novice users of automated driving systems are expected to require more information than experienced users (Reilhac, Moizard, Kaiser, & Hottelart, 2016). Providing more detailed information on the vehicle status and behavior has also been expected to minimize frustration and consequently reduce drivers' initiative to take over the driving task. Although this effect could not be established in a quantitative user study, qualitative results suggest that providing contextual information affects passengers' moods (Techer et al., 2019).

Implications for a model of determinants of passenger well-being

Increasing automation calls for an additional category of technical features to be included as input in a model of determinants of passenger well-being in automated driving. For passenger well-being, those technical features that are actually perceivable by passengers (e.g., driving style, user interfaces) play a primary role as inputs in a model of determinants of passenger well-being. Compared to features that are independent of automation (e.g., thermal conditions, seat comfort), technical features are less researched but are receiving growing interest.

With the introduction of automated driving, the definition of categories blurs. Some physical features such as interfaces become more technical by being relevant for automation (e.g., facilitating handover tasks, information on the vehicle state). Regardless of the specific assignment to a certain category, these features remain important features to be considered as determinants. Yet, in most cases, both physical and technical features were not investigated regarding passenger well-being, but rather regarding comfort or other related evaluation criteria. This calls for research investigating the effect of features specifically on passenger well-being. In addition to initiating a new feature category, automation may also cause novel physical features to be integrated into automated vehicles that need to be added as potential inputs (RQ 3).

2.3.3 Social and Situational Features

Social aspects are relevant to well-being in general, as relatedness is a central human need, and fulfillment of needs is substantial to create well-being (Deci and Ryan, 2000). Findings from a study on well-being within social groups show that both group inclusion and interpersonal relatedness as examples for social needs have a significant positive relationship with positive affect. A study on commuting behavior shows that mood improves when commuting with someone as opposed to commuting alone (Lancée et al., 2017).

Situational features cover a broad spectrum and mostly apply to other modes of transport as well. For example, waiting time and accessibility to a mobility mode such as car or bus influences mood (Ettema et al., 2011). Mood may also be influenced by the travel destination or length of travel (Lancée et al., 2017), while the influence of congestion yields ambiguous results (Lancée et al., 2017; Morris and Hirsch, 2016). Further, the brand of the automated vehicle or, in case of mobility as a service, the service brand may influence passengers' well-being, as brand prestige can significantly affect well-being perceptions (Ahn et al., 2015).

2.3.4 Passenger Needs

The analysis of determinants that factor into passengers' subjective evaluation of the automated driving experience has shown that some vehicle features may influence passenger's well-being directly while other features may also relate to passenger needs such as spatial feeling or aesthetics. As the fulfillment of needs can induce well-being (Deci & Ryan, 2000), it is worthwhile to investigate what passenger needs may be relevant in the context of automated driving.

Passenger needs suggested in transportation research and psychology

Of the investigated models in transport, only the passenger comfort experience model explicitly suggests mediating passenger needs or, as the authors coin it, perception themes. The authors include eight themes (Ahmadpour et al., 2014). The themes, in turn, aggregate underlying concepts (c.f. Table 2.3). For example, satisfaction includes trustworthiness and usability, while peace of mind comprises the feelings of security and being at ease. These underlying concepts themselves may constitute passenger needs in automated driving.

Table 2.3 Overview of perception themes from the passenger comfort experience model, adapted from Ahmadpour et al. (2014).

Perception theme	Underlying factors
Aesthetics	Style, Neatness
Association	Evocation, Symbolism
Peace of mind	Security, Tranquility, Relief, Being at ease
Physical well-being	Energy, Bodily support
Pleasure	Stimulation, Ambience, Anticipation
Proxemics	Autonomy, Control
Satisfaction	Accessibility, Adequacy, Quality, Ease of use, Trustworthiness
Social	Tolerance, Connectedness

In more general terms, theories on human psychological needs provide more universal insights. Maslow's (1954) hierarchy of needs is a well-cited overview of human needs despite limited empirical support. Maslow suggests a hierarchy of five needs: the most basic need of physical health, followed by security, self-esteem, love – belongingness, and self-actualization. Self-determination theory (c.f. Section 2.1.1) suggests three needs: competence, autonomy, and relatedness (Deci & Ryan, 2000).

Deriving passenger needs for passenger well-being in automated driving

Comparing these general human needs with the underlying factors provided by the passenger comfort experience model (c.f. Table 2.3), overlaps are evident in case of physical health or well-being, respectively, security, autonomy, and social relatedness. Physical well-being is the positive perception of one's body stimuli (Frank, 2011) and usually constitutes the absence of pain or health issues (Ahmadpour et al., 2014). Thus, it may directly relate to discomfort under the consideration that discomfort and comfort are distinct concepts and discomfort relates to biomechanical processes (c.f. Section 2.1.3). Physical well-being is one aspect of subjective well-being (Becker, 1991, c.f. Section 2.1.1). Assuming that passenger well-being may be equated with current well-being, physical well-being may be closely related. The inclusion of discomfort into the concept of physical well-being raises the question of what role comfort may play. Recall the discussion of the term comfort (c.f. Section 2.1.3). Here it was concluded that comfort is the positive subjective evaluation elicited from the currently experienced environment (Looze et al., 2003), while well-being is broader and also includes the evaluation of one's self. Based on this conclusion, comfort in terms of the evaluation of the environment may constitute a passenger need as well and can affect well-being (Knight & Haslam, 2010).

Security or safety relate to the possibility that traveling poses the risk of damage (Haverkamp & Arnold, 2015). A subjective sense of safety is necessary for product use in general (Moon, Park, & Kim, 2015) and traveling in particular (Singleton, 2018). A high level of perceived safety relates to well-being in general (Tov & Diener, 2008), and may also relate to passenger well-being. In relation, autonomy, or related the perceived level of control, is the perception that one has the ability to significantly alter events (Burger, 1989). As automated driving means that the driving task, and thus, control over the vehicle is transferred to the automation system, a perceived loss of control can be detrimental to product acceptance (Faraji-Rad, Melumad, & Venkataramni Johar, 2017) and general well-being (Burger, 1989; Chatterjee et al., 2019; Diener, 1984; Grob, 2000). Yet, increased automation through ADAS does not necessarily have to result in loss of perceived control (Biassoni, Ruscio, & Ciceri, 2016; Weyer, Fink, & Adelt, 2015). Thus, it may be beneficial to consider perceived control as a need for passenger well-being in a user-centered development process. Social relatedness is a general human need. In terms of traveling, this includes the relatedness with and tolerance of other passengers and/or attendants (Ahmadpour et al., 2014). In automated driving, depending on the service type, the need for social connection may be limited to passengers traveling together voluntarily, and social contacts outside the vehicle through NDRTs.

Further passenger needs with evidence from either general or transport-related models may be aesthetics, trust, usability, and symbolism. The role of aesthetics as a need has been highlighted by various models. Further, it is one of the key attributes in automotive design (c.f. Section 2.3.1). Trust is a strongly discussed topic in automated driving (Choi & Ji, 2015). There is a general link between trust and well-being (Hudson, 2006; Tov & Diener, 2008), but this link does not necessarily apply to all technologies (Lee, Mehler, Reimer, & Coughlin, 2015). Trust in automated driving results from the appropriate assessment that the vehicle will fulfill its purpose despite uncertainty and vulnerability (Lee & See, 2004). For optimal use of automated driving, it is vital that passengers' trust is calibrated, i.e., they do not overtrust and overrely on the automation system nor do they have disproportionally low levels of trust which will inhibit the use of automated vehicles (Helldin, Falkman, Riveiro, & Davidsson, 2013). Usability results from efficient, effective, and satisfactory product use (ISO, 1999). Engaging with technologies and products that have high usability can lead to positive affect (Hassenzahl, Diefenbach, & Göritz, 2010), positive valence and lower arousal (Thüring & Mahlke, 2007), and reduce negative affect by avoiding frustration and annoyance (Tuch, Roth, Hornbæk, Opwis, & Bargas-Avila, 2012). In the context of passenger vehicles, usability can evoke emotional reactions of car users (Williams, Attridge, & Pitts, 2011). Finally, symbolic value is a central product dimension (Creusen & Schoormans, 2005) used to communicate information on the user's self-image (Homburg et al., 2015). A direct link between symbolism and well-being is disputed (Grzeskowiak & Sirgy, 2007). However, some evidence on the positive effect of symbolism on mood (Hudders & Pandelaere, 2012) and personal expressiveness (Waterman, Schwartz, & Conti, 2008) exists.

Implications for a model of determinants of passenger well-being

Passenger needs may influence the level of passenger well-being through their fulfillment (Deci & Ryan, 2000). General comfort models, models in transportation, and human needs theories provide a starting point to collect potential passenger needs in the context of automated driving. Some needs proposed in other transportation contexts have also been frequently discussed for automated driving applications. These include, for example, physical well-being with a particular focus on motion sickness, and trust. Other passenger needs, such as social relatedness, are to be verified in the context of automated driving. As a passenger car is smaller than an aircraft and co-passengers are usually known, the need for social relatedness may be less relevant for automated driving, while trust and perceived safety may be more critical. It is also up for discussion whether there is a hierarchy among passenger needs in automated driving. Similar to Maslow's (1954) hierarchy of needs, it may apply that needs such as safety or control are basic needs that require fulfillment, whereas the need for aesthetics or symbolism may be of lesser importance.

2.3.5 Passenger Characteristics

Passenger characteristics are suggested to shape the subjective evaluation by both general comfort models and models in transport. Richards (1980) proposes psychological, physical and physiological, and situational characteristics of the passenger to influence the relationship between inputs and subjective evaluation (c.f. Table 2.4). These characteristics are adopted in the passenger experience model and specified by including expectations and socio-economical traits of the passenger as characteristics (Ahmadpour et al., 2014).

Table 2.4 Exemplary passenger characteristics suggested by Richards (1980).

Note: Situational characteristics are not explicitly discussed by Richards but may include factors such as time urgency (Novaco & Gonzalez, 2009).

Psychological	**Physical / physiological**	**Situational**
Motivation to use mode of transport Prior experience with mode of transport Attitudes, preconceptions toward mode of transport	Size Sex General health Proneness for motion sickness	Time urgency

Many of these characteristics apply to passengers in cars regardless of the automation level. As high automation presents a paradigm change, some characteristics may increase in importance in this specific type of transport. Motion sickness is a central inhibiter to the engagement in NDRTs, and countermeasures are in development (c.f. Section 2.3.1).

Role of preconceptions and culture in automated driving

Passengers' preconceptions are also central to the use of automated vehicles. One frequently discussed preconception in this context is a passenger's initial level of trust prior to using automated vehicles. A certain level of trust is mandatory for passengers to use such vehicles, activate the automation system, and receive the benefits from driving automation (Kerschbaum, Lorenz, Hergeth, & Bengler, 2015).

The preconceptions of automated vehicles, including initial levels of trust, deviate between different markets and cultures. As automated driving is a global trend, and many markets are racing to lead in this technology, it can be beneficial to consider cultural influences as well. In general terms, culture can influence product preference (Bloch, 1995) and associations with products (Creusen & Schoormans, 2005).

Further, culture has an impact on subjective well-being (Diener et al., 2003). More specifically, related to automated vehicles, cultural differences exist regarding the readiness for automated vehicles. Readiness includes legal aspects, technology, and infrastructure, as well as public acceptance of automated vehicles (Threlfall, 2018). Comparing the USA, China, and Germany as leading countries for automated vehicles (Frost & Sullivan, 2018) with different cultures and driving behaviors (Färber, 2016; Li, Braun, Butz, & Alt, 2019), the USA has the highest readiness followed by Germany and China. This ranking reflects the level of technology and consumer acceptance in the respective countries (Threlfall, 2018).

Interestingly, other studies come to a different conclusion regarding prospective users' attitudes towards automated driving. A study on future mobility behavior shows that attitudes of Chinese users are more favorable towards automated driving than those of German or US users. For example, more Chinese drivers (89%) agree to the statement that automated driving is a sensible advancement compared to German (53%) and US (50%) drivers. Also, fewer Chinese drivers (28%) are scared of driving automation than Germans (62%) or Americans (77%) (Continental, 2018). The tendency that Chinese users are more open towards automated driving than users from Germany or the USA is seconded by a study investigating users' interest and emotions towards driving automation. In China, emotions toward automated driving are dominated by optimism and curiosity. In the USA and Germany, distrust and anxiety are more present, although positive emotions prevail (AUDI AG, 2019).

Culture as an influence in the evaluation of vehicle features

Cultural differences manifested as different preconceptions are also evident in the evaluation of different vehicle features, especially in the evaluation of physical and technical vehicle features. In general, user behavior in regards to the use of in-vehicle technologies differs between US, Korean, and Austrian users (Jeon, Riener, Lee, Schuett, & Walker, 2012). Further, Chinese drivers tend to evaluate these different technologies more strongly than German drivers (Li, Wang, Guo, & Dietrich, 2018). More specifically cultural differences should be considered in the design of navigation systems (Large, Burnett, & Mohd-Hasni, 2017), in-car HMIs (Khan, Pitts, & Williams, 2016; Khan & Williams, 2014) and corresponding input modalities for in-car HMIs (Large et al., 2019; Wang, Winter, & Grost, 2015), menu structures (Olaverri-Monreal & Bengler, 2011) and their labeling (Young, Rudin-Brown, Lenné, & Williamson, 2012).

In terms of physical features, studies show that US and German drivers prefer a more pragmatic design while Indian drivers tend to appreciate hedonic design in the case of instrument clusters (Sudarshan, Wagner, Marinets, & Kauer, 2015). Further, culture also plays a role in the evaluation of center stack design (Mohamed, Shamsul, & Rahman, 2013) or anthropomorphic exterior design of the vehicle (Purucker, 2012). Yet, no cultural difference in perception of craftsmanship of vehicles has been found (Petiot, Salvo, Hossoy, Papalambros, & Gonzales, 2009).

Implications for a model of determinants of passenger well-being

Passenger characteristics can be of physical and physiological, psychological, or socio-economical nature. As automated driving is a global trend, culture may play a significant role as passenger characteristic in automated driving. Cultural differences are very apparent from related research on the evaluation of physical and technical features. Especially in HMI design, localization and consideration of cultural differences are commonly recommended. Thus, culture may be one passenger characteristic that moderates the relationship between vehicle features and passenger well-being (RQ 6).

2.3.6 Non-driving Related Tasks

Highly and fully automated driving offers the benefit of transferring responsibility for the driving task to the vehicle temporarily or completely, and thus, freeing the driver to engage in NDRTs. NDRTs, or rather activities conducted while traveling, are possible in other transport modes such as public transport or aviation, but traveling privately in a car may offer more privacy for NDRTs. Thus, the body of research on activities conducted while traveling covers both studies conducted in automated driving and work in other modes of transportation.

Effect of NDRTs on passenger well-being

In general, well-being in destination-oriented travel is not only affected by the experiences made while traveling but also the activities engaged in during that time (Vos et al., 2013). Yet, the relationship between activities during travel time and well-being is not straightforward as a study in public transport by Ettema, Friman, Gärling, Olsson, and Fujii (2012) indicates. The results of this study show that entertaining and relaxing activities are associated with lower degrees of well-being experienced while traveling, which may be explained by the tendency to engage in these activities to reduce boredom or stress. Further, the destination of travel and the corresponding mindset influence how activities impact well-being. For example, interacting with other passengers raises well-being when commuting home, but has no effect when commuting to work. Although being productive or working while traveling is a less observed activity in public transport, engaging in such activities may help free time for other activities, and thus, can raise well-being in other domains (Ettema et al., 2012). In contrast to the findings from this study, Malokin, Circella, and Mokhtarian (2019) find that transport modes that provide the opportunity to engage in working tasks while traveling increases the choice of said modes in moderate proportions. Applied to automated driving, the authors predict that automated vehicles will be more attractive than other modes due to better accessibility and the opportunity to use travel time productively.

Expected NDRTs in automated driving

Studies that investigate future users' preferences for NDRTs in automated driving suggest a wide variety of NDRTs to be requested by users. A study with mixed methods predicts that users may not only want to be productive or entertained, but also relax, or simply be idle (Pfleging, Rang, & Broy, 2016). Based on the broad variety of NDRTs expected to be available in an automated vehicle, Yang, Fleischer, and Bengler (2020) offer five NDRTs which may be prominent and require specific adaption of the vehicle interior. The authors suggest watching movies, reading, being idle/relaxing, being productive/working, and sleeping as basic areas that require different settings such as seat and lighting. Further, different seat angles may help to avoid motion sickness caused by engaging in NDRTs (Bohrmann & Bengler, 2020). The choice of NDRTs also depends on the travel length (Jorlöv et al., 2017), privacy, options to store items, and the purpose of travel (Hecht, Darlagiannis, & Bengler, 2020). Further, engagement in NDRTs can also impact the need for information (Hecht et al., 2020).

Implications for a model of determinants of passenger well-being

To sum up, research on travel in general and automated driving, in particular, shows that NDRTs are a key benefit of automated driving and can impact the level of well-being experienced while traveling. A wide variety of NDRTs is expected to be possible in automated vehicles. Yet, empirical studies do not provide a clear indication of preferred NDRTs. Rather, the choice of NDRTs depends on situational factors such as vehicle settings, layout, or travel time.

2.4 Derived Research Questions

Work related to the concept of passenger well-being yields no clear suggestion on how to define passenger well-being in automated driving contexts. Related research predominantly uses the psychological approach to subjective well-being for transportation research. This approach considers affective and cognitive evaluations in terms of experienced positive and negative affect and life satisfaction (Diener et al., 2002). Yet, it is likely that in terms of temporal reference, only current and not habitual well-being is relevant for passenger well-being. To investigate the concept of passenger well-being in automated driving further, a qualitative approach is required to identify how passengers view passenger well-being in this context. Based on related work, research question 1 is specified to the following research question:

RQ1: Does passenger well-being in automated driving relate to current subjective well-being?

Depending on the answer to RQ1, an appropriate measurement to gauge passenger well-being is required. Assuming that passenger well-being is related to well-being in a psychological sense, measurements established in psychology can be applied. Related work indicates that multidimensional self-reports and physiological measures are suitable to measure well-being in automated driving. Both objective and subjective measures are investigated, as the suitability of the measurement may vary depending on the exact circumstances. In terms of multidimensional self-reports, the measurement tool should have sufficient reliability, be easy to administer, apply to the context of automated driving and be sensitive enough to detect differences in variations of determinants of passenger well-being. Based on related work in transportation, the MDBF, EWL, SCAS, UMACL, and PANAS (c.f. Table 2.1) are multidimensional scales that are worth considering as self-reports for passenger well-being in automated driving. Objective, non-invasive measures may be useful to collect additional non-verbal aspects (Diener, 1994) and can be less obtrusive. HRV, EDA, body motion, and facial expression have been suggested as potential measures. For these objective measures, similar criteria apply as a requirement. Thus, research question 2 is extended to:

RQ2a: What multidimensional self-report is suitable to reliably, validly, and efficiently measure passenger well-being in the context of automated driving?

RQ2b: Are HRV, EDA, facial expressions, and/or body motion suitable to reliably, validly, and efficiently measure passenger well-being in the context of automated driving?

In addition to the concept of passenger well-being, a second area of related work has been investigated by reviewing models related to passengers' subjective evaluation of the driving experience to identify a starting point for a model of determinants of passenger well-being in automated driving. As determinants physical and technical features of an automated vehicle (RQ 3), the perception and processing (RQ 4), passenger needs (RQ 5), and passenger characteristics (RQ 6) are to be considered in this work.

Based on this premise, the theory of comfort (Richards, 1980) and the passenger comfort experience model (Ahmadpour et al., 2014) are identified as a suitable starting point. Both models provide an overview of physical features that apply to transportation. To be applicable to automated driving, these categories are extended by technical features. The influence of the features suggested in each category on passenger well-being is indicated by the third area of related work, research on the effect of single features. Yet, the influence of single features needs to be confirmed in the context of automated driving. As this work focuses on passenger well-being as an optimization goal in automated vehicle development, the focus lies on physical and technical features, as social and situational features are hard to predict and influence in vehicle development. Thus, research question 3 is updated to:

RQ3: What physical and technical features of an automated vehicle are relevant for passenger well-being?

The passenger comfort experience model includes a biomechanical perspective on how features of the travel experience may be processed. Yet, the processing of intangible features is omitted in this and other related models. ELM provides an approach to how processing may work to derive an evaluation of passenger well-being. It postulates that the route for processing depends on the level of elaboration, which in turn depends on motivation and ability. This leaves research question 4 unaltered and open:

RQ4: How do motivation and ability influence the perception and processing of features of an automated vehicle relevant for passenger well-being?

Both general comfort models and models in transportation provide indications that subjective evaluation not only depends on the features of a product or transportation experience but also on perceptions (Ahmadpour et al., 2014) or passenger needs. Related work on general human needs and transportation models revealed several potential passenger needs (physical well-being, safety, control, trust, usability, comfort, aesthetics, symbolism, and social relatedness) that may be consulted by passengers to determine their level of well-being.

This work focuses on the user-centered development of automated vehicles with passenger well-being as an optimization goal. Social relatedness contributes without a doubt to well-being and is likely to do so in automated driving as well. Yet, it may be put up to debate whether social relatedness is a need that can be influenced by the vehicle design itself, or whether it results from enabling technologies separate from the vehicle and situational circumstances. In contrast, additional passenger needs may apply to the context of automated driving. Thus, research question 5 is adjusted to:

RQ5a: What are relevant passenger needs in the context of automated driving?

RQ5b: How do the identified passenger needs relate to features of the vehicle and passenger well-being?

Finally, both the theory of comfort and the passenger comfort experience model suggest that passenger characteristics act as a moderator on the relationship between features and subjective evaluation. Passenger characteristics range from physical and physiological characteristics such as physique, age, proneness toward motion sickness, to psychological characteristics like prior experience, attitudes and expectations, and socio-economic characteristics. As automated driving is a global trend and will reach multiple, culturally different markets, culture as socio-economic passenger characteristic may be of especial importance. Also, car manufacturers strive towards increasingly localizing their products and considering cultural and language differences. Having an insight into how culture influences passenger well-being and its determinants will help to tailor a user-centered development process of automated vehicles to local needs and expectations. Thus, research question 6 remains:

RQ6: How does culture as an example of individual passenger characteristics influence the relationship between features of an automated vehicle, passenger needs, and passenger well-being?

The discussion of related work across three areas (work on the concept of passenger well-being, relevant models and conceptualizations of subjective evaluations, work on the effect of single features of the travel experience) and the resulting implications for a model of determinants of passenger well-being in automated driving based on the theory of comfort and passenger comfort experience model can be summarized as depicted in Figure 2.4. This figure illustrates hypotheses of how the different determinants relate to each other and passenger well-being as a consequence. This model proposal is detailed and empirically evaluated in the following.

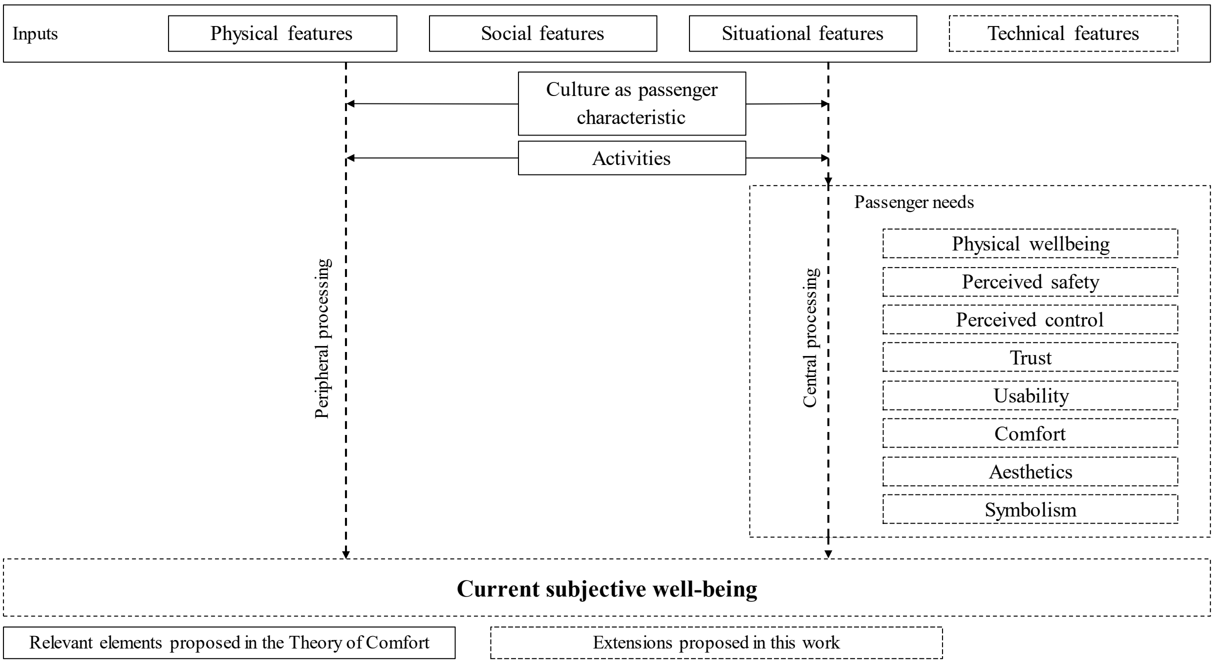


Figure 2.4 Overview of the preliminary model of determinants of passenger well-being.

Note: Figure based on the theory of comfort (Richards, 1980), passenger comfort experience model (Ahmadpour et al., 2014), and further related work.

2.5 Research Scope

In automation levels 4 and 5 (c.f. Table 1.1), the driver is relieved – at least partially – from all driving and supervision tasks. As this step from supervised to non-supervised automation offers the greatest potential for rethinking the automated vehicle design and putting passengers' well-being into focus, the research scope focusses on level 4 automated driving. Further, in level 4 automated driving, automation only works for predefined use cases. The passenger will still be required as a driver for some routes or parts of the journey. Thus, hand over scenarios are inevitable. However, this work focuses solely on the automated drive and excludes hand-over scenarios from consideration.

One key benefit of level 4 automated driving is the option to engage in NDRTs. As discussed in section 2.3.6, there is no clear evidence which NDRTs are preferred and expected by future users. Rather empirical studies indicate that automated vehicles should be able to accommodate a number of different NDRTs. Entertainment, relaxation, and working/being productive are key areas for NDRTs (Pfleging et al., 2016). In this work, the NDRTs working and relaxing are emphasized.

During automated driving, it is likely that the interior of the vehicle is predominantly perceived. Thus, a focus is placed on the vehicle interior in this work. Other aspects are considered whenever applicable. Further, most vehicle concepts for automated driving allow multiple passengers to travel together. Social and situational factors influence the relationship between passengers and, in turn, influence their well-being during the journey. Although the interrelationship between passengers opens up interesting avenues of research, the focus is placed on passengers traveling alone as 90% of commutes by car in Germany are made alone (Ziegenmeyer, 2018), and similar commuting behavior is found in other countries such as the US (Florida, 2019). In a similar vein, shared vehicles are a steadily growing trend. As this work does not consider a group of passengers traveling together, the scope includes only privately used vehicles.

3 Utilized Methods

To address the research questions raised from discussing related work, a mixed approach with qualitative and quantitative methods is required. Investigation of passenger well-being as a subjective matter calls for empirical studies with users and experts. Thus, this chapter provides an overview of the utilized statistical methods and the design of user studies.

3.1 Qualitative Methods

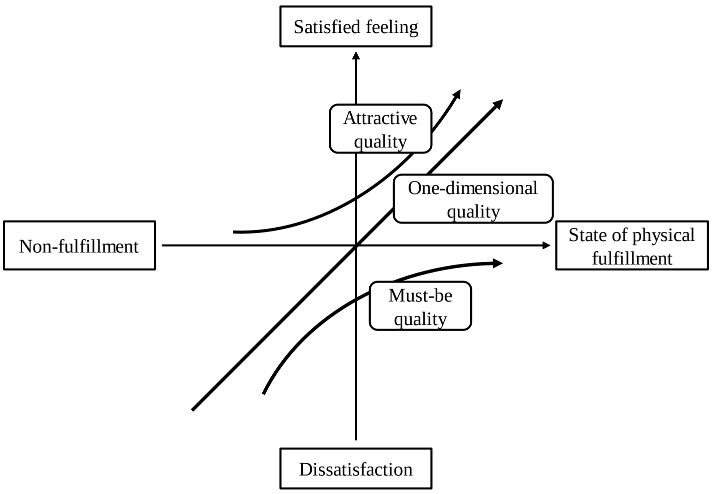
Qualitative data in this work is mainly collected by utilizing open questions to gain additional insights from participants. Further, to identify relevant vehicle features (RQ3), a suitable approach is required. A number of methods for this purpose exist (Adam, 2012; Tomiyama, Lutters, Stark, & Abramovici, 2019), of which the Kano method (Kano, Seraku, Takahashi, & Tsuji, 1984) is especially user-centered.

Open questions

Open questions are used across most user studies to collect information in an exploratory manner and/or to provide the opportunity for participants to share additional insights not considered in the survey. To analyze such data, responses from participants are clustered independently by two researchers. In a second step, the independent cluster solutions are compared and discussed by both researchers to reach a joint solution.

Kano method

The Kano method is a method in product development to gain insights into customer satisfaction by categorizing product features based on how much they contribute to satisfaction (Kano et al., 1984). The features are categorized into five categories based on the dimensions of satisfaction and physical fulfillment (c.f. Figure 3.1). To categorize product features, the Kano method utilizes one functional and one dysfunctional question per feature (Kano et al., 1984), which are both answered by participants with the same 5-point scale. As this work uses passenger well-being as the dependent variable, which is related but distinguishable from satisfaction, the questions and scale are adjusted to express the focus on well-being (c.f. Table 3.1).



- **Attractive (A):** Features that are not expected by the users, but when fulfilled create satisfaction.
- **One dimensional (O):** Features that increase satisfaction linearly with fulfillment and in the same way decrease satisfaction if not fulfilled.
- **Must be (M):** Features that are expected by the users as basic requirements and do not increase satisfaction, but can diminish satisfaction if missing.
- **Reverse (R):** Undesired features that have a reverse relationship between satisfaction and fulfillment.
- **Indifferent (I):** Features not relevant for satisfaction judgements.
- **Questionable (Q):** Contradictory ratings, feature should be reconsidered.

Figure 3.1 Underlying two dimensional model of the Kano method, figure adapted from Kano et al. (1984, p. 170), Berger et al. (1993).

Table 3.1 Original questions and scale for the Kano method (Kano et al., 1984) and adaption for well-being.

	Questions	**Scale**
Original	Functional: How would you feel if your automated vehicle had *a steering wheel*? Dysfunctional: How would you feel if your automated vehicle had *no steering wheel*?	1: like 2: acceptable 3: neutral 4: must-be 5: do not like
Adapted	Functional: How would it impact your level of well-being when traveling in your automated vehicle if it had *a steering wheel*? Dysfunctional: How would it impact your level of well-being when traveling in your automated vehicle if it had *no steering wheel*?	1: It would increase my well-being a lot 2: I take this for granted for my well-being 3: It does not matter for my well-being 4: I would barely accept this for my well-being 5: This would strongly disrupt my well-being

Categorization for each feature is derived on an individual level, depending on how each pair of functional and dysfunctional questions is answered. Pouilot offers an adjusted scheme to categorize features based on individual ratings (Berger et al., 1993). If ratings are contradictory (e.g., a feature is rated with 1 on both questions), the feature is categorized as questionable (Q) and indicates questionable appropriateness. To achieve an aggregated view on product categorization for generalization and insights into the implications of said categorization, multiple decision rules and coefficients have been established (c.f. Table 3.2).

Table 3.2 Overview of selected decision rules and coefficients to aggregate and assess aggregated categorization.

Mode rule (Berger et al., 1993)	Select categorization based on the most frequent response (mode)
Category strength (Lee & Newcomb, 1997)	Indication if classification by mode rule is unambiguous (category strength > 6%) *Category Strength = responses of highest category in % - responses of second highest category in %.*
Fong test (Fong, 1996)	Test significance of mode rule $$\lvert a - b \rvert < 1.65 \times \sqrt{\frac{(a+b)(2n-a-b)}{2n}}$$ with *a: abs. frequency of largest category, b: abs. frequency of second largest category, n: total number of responses*
Rule to reduce noise (Berger et al., 1993)	$If\ (O + A + M) > (I + R + Q),$ $then\ assign\ category\ of\ \max(O, A, M),\ else\ \max(I, R, Q)$
In case of ties (Berger et al., 1993)	$M > O > A > I$
Total strength (Lee & Newcomb, 1997)	Indication of percentage of participants that view a feature as important $Total\ strength = responses\ as\ A + responses\ as\ O + responses\ as\ M, in\ \%$
Customer satisfaction coefficients (CS) (Mkpojiogu & Hashim, 2016)	Insight if feature creates satisfaction or if it is requirement to avoid dissatisfaction $CS+ = \frac{A+O}{A+O+I+M},\ CS+ > .50$ feature contributes to satisfaction $CS- = (-1) \times \frac{O+M}{A+O+I+M},\ CS- < -.50$ feature required to avoid dissatisfaction

3.2 Quantitative Methods

For quantitative methods in this work, some general statistical assumptions are made. In general, the significance level is set to α = .05, and the central limit theorem is applied to samples or groups, respectively, which are larger than 30 (Field, 2011). Further, as this work utilizes questionnaires that collect data with Likert scales, the widespread practice to assume equidistance of ordinal Likert scales (Bortz & Schuster, 2010; Homburg, 2012) is applied as well. In this work, several bivariate and multivariate statistical methods are used to address the research hypotheses. Frequently used methods across multiple studies are introduced in the following.

Correlation

To investigate basic linear relationships between variables, correlation analysis is utilized. In cases were parametric methods can be applied, Pearson's correlation coefficient is used. To interpret correlation effect sizes, Cohen's (1988) classification with $|r| > .1$ small effects, $|r| > .3$ medium effects and $|r| > .5$ large effects is used.

Analysis of Variance

Analysis of variance (ANOVA) is used in this work for different designs, including repeated measure designs and mixed within- and between-subject designs. General underlying assumptions for ANOVA are normal distribution and homogeneity of variance. As ANOVA is robust against violations of these assumptions (Field, 2011; Keselman, Carriere, & Lix, 1993), it is assumed that ANOVA is applicable if one of the assumptions is violated. In case of violation of both assumptions, non-parametric alternatives are utilized (e.g., Wobbrock, Findlater, Gergle, & Higgins, 2011). Effect sizes of ANOVA are calculated using generalized eta squared (η_G^2) to ensure better comparability of effect sizes across designs (Olejnik & Algina, 2003). Cohen's (1988) suggestions are used to interpret the effect sizes ($\eta_G^2 > .02$ small effect; $\eta_G^2 > .13$ medium effect; $\eta_G^2 > .26$ large effect). As ANOVAs are omnibus tests, contrasts or post hoc tests are necessary for additional information if one or more differences between the groups are significant. To control for familywise error rates, Bonferroni correction is applied (Field, 2011).

Linear Regression

To analyze the hypothesized relationship between dependent and independent variables, linear regression is used. In this work, multiple regression is mainly utilized with the ordinary least square (OLS) method. For multiple regression, different methods are available: hierarchical, forced entry, and stepwise methods. Both hierarchical and forced entry methods require solid theoretical reasoning and are less suitable for exploratory analysis. Thus, this work relies on stepwise methods when using multiple linear regression for exploratory analysis. More specifically, the backward method is utilized to avoid suppressor effects, which entail missing an independent variable that acts as a significant predictor (Field, 2011).

Linear Mixed Models

In cases where assumptions of linear regression are not fulfilled, e.g., through repeated measure designs, linear mixed models (LMM) can be an alternative. By including random effects, interdependence through repeated measures can be controlled. Random effects are subject specific, while fixed effects are shared by all subjects. The simplest LMM is a random intercept model where the intercept varies randomly. For more complex modeling, random slopes or random intercepts and slopes are possible (Fitzmaurice, Laird, & Ware, 2004). Due to the restrictions of the data collected in this work, LMMs are applied with random intercepts, and the subject and stimulus are included as random effects to control for repeated measures. Further, LMMs offer the option to conduct moderator analysis by including interaction effects.

Conjoint Analysis

Conjoint analysis is based on the idea that a product is composed of different attributes. Thus, the utility of a product can be decomposed into the partworth contributed by each attribute and its levels (see Equation 3.1). Potentially, interactions between attributes can factor into the overall utility as well (Rao, 2014).

Equation 3.1 Additive model of conjoint analysis, adapted from Backhaus, Erichson, Plinke, and Weiber (2018, p. 508).

$$Utility_k = \sum_{j=1}^{J} \sum_{m=1}^{M_j} \beta_{jm} \times x_{jmk}$$

with

$Utility_k = Estimated\ utility\ for\ product\ k$

$\beta_{jm} = Partworth\ for\ level\ m\ of\ attribute\ j$

$$x_{jmk} = \begin{cases} 1, if\ product\ k\ has\ attribute\ j\ with\ level\ m \\ 0, else \end{cases}$$

Conjoint analysis is a common tool to aid in product improvement as well as in idea generation for product development (Gensler, 2003; Homburg, 2012). In automotive contexts, conjoint analysis has been applied to the design of takeover requests (Brandenburg & Epple, 2019) and vehicular assistance systems (Mihale-Wilson, Zibuschka, & Hinz, 2019) among other applications. In this work, rating based approaches are utilized to rate full profiles either as single product configurations (c.f. Chapter 8) or as paired comparisons (c.f. Chapter 9). Full profiles are able to replicate a buying decision more closely, and thus, may appear more realistic (Backhaus et al., 2018). Compared to other types of conjoint analysis, rating based approaches provide a higher level of information and are easier to design and estimate (Karniouchina, Moore, van der Rhee, & Verma, 2009). To make the number of ratings manageable for participants, fractional factorial designs are used. In cases were no orthogonal array is available, the approach by Aizaki and Nishimura (2008) is applied. In this work, conjoint analysis is conducted using ordinary least squares (OLS) regression and dummy coded variables.

Mediation Analysis

To investigate the hypothesized mediating role of passenger needs (RQ5b), mediator analysis is required. A well-used approach to mediator analysis is provided by Baron and Kenny (1986). Their approach consists of three conditions: (1) the independent variable significantly predicts the presumed mediator (X → M), (2) the presumed mediator significantly predicts the dependent variable (M → Y) and (3) if controlling (1) and (2) the relationship between independent and dependent variable is not significant anymore (X+M→Y). Shrout and Bolger (2002) argue that the association X → Y should not be a requirement, especially in cases where small effect sizes are expected. Further, Zhao, Lynch JR., and Chen (2010) argue that mediation can be established based solely on a significant indirect effect. This work follows the suggestions by Zhao et al. (2010). Mediation analysis with repeated measures utilizes LMMs. Each hypothesized mediation relationship is considered and modeled individually. In cases where the independent variable is categorical, the variable is dummy coded, and mediation analysis follows suggestions by Hayes and Preacher (2014).

3.3 General Design of User Studies

To take the subjective nature of passenger well-being and the future passengers' view into account when conducting empirical studies, user studies can be helpful. User studies conducted in this work follow the requirements and recommendations set by expert commissions and the ethic commission at RWTH Aachen University faculty of medicine (EK 086/19). As automated driving is not yet available in the market and functioning prototypes are scarce, other alternatives need to be found to conduct user studies. This work utilizes three different setups for in-vehicle user studies. Unmodified AUDI A6 vehicles were used for static interior evaluations (c.f. Chapter 4) as they are easily available and offer a low-tech setup.

To simulate level 4 automated driving, a mockup by AUDI is combined with internal and external screens for a static driving simulator setup (c.f. Figure 3.2). The mockup gives participants the feeling of sitting in a novel vehicle that is likely to have automation capabilities. It is equipped with functionalities regular production cars have, such as displays, seat functions, or ambient lighting. The driving simulator consisted of a large screen for the forward view, a corresponding instrument cluster with basic information such as speed and activation of the automation system, and a speaker for driving noise. Monitors to the side for peripheral view were used optionally. The driving simulator used videos from simulation and real-world driving events. The advantage of this setup is the high controllability of external and situational variables of the driving experience, such as route or vehicle behavior. However, it comes at the expense of an entirely realistic experience by omitting driving dynamics.

Figure 3.2 AUDI mockup from 2010 combined with external and internal screens for a static driving simulator setup.

In cases where reproducibility and control of situational influences are less critical, user studies with real-world driving experiences may be an alternative to provide a more realistic experience. Wizard of Oz setups are a common approach to counter the lack of available, reliably functioning prototypes. In such studies, participants are told that the technology they should interact with is working stand-alone, while in fact, the technology is controlled by a human operator (Dahlbäck, Jönsson, & Ahrenberg, 1993). Although the Wizard of Oz method is not yet standardized, it poses a suitable method for research in automated driving (Müller, Weinbeer, & Bengler, 2019). Therefore, for this work, a right-hand drive AUDI A8 is modified to include a mock-up driver's workplace on the left side to give the participant the impression to sit in the driver seat (c.f. Figure 3.3). The vehicle is driven from the right passenger seat. To make the experience more immersive, the vehicle driver is separated with a screen and instructed to drive defensively and strictly adhere to the traffic rules.

Figure 3.3 Interior view of the Wizard of Oz setup used for real-world driving scenarios (Sauer, Mertens, Reiche et al., 2020).

4 Passenger Well-Being in the Context of Automated Driving[3]

As the basis for a model of determinants of passenger well-being in automated driving, the concept of passenger well-being in this context needs to be clarified. To investigate if passenger well-being in automated driving relates to current subjective well-being (RQ1) as indicated by related work in other transport modes, an exploratory and qualitative user study is conducted. Such an approach allows to consider passengers' individual views on the concept of passenger well-being and underlines the concept's subjective nature.

4.1 Experimental Setup

RQ1 is addressed together with RQ2a and RQ5a in one user study. This user study combined a quantitative study with a qualitative interview. The quantitative study was used for measure evaluation (RQ2a) and the identification of passenger needs (RQ5a). It followed a design with one within- and two between-subject factors. The within-subject factor ("case") with two levels was used to evaluate subjective measures for passenger well-being and possible user needs. Participants were asked to evaluate two vehicles regarding passenger well-being and the fulfillment of potential passenger needs (c.f. Section 5.1 and 7.1). The two interiors differed in regards to four features in such a way that one interior met the participant's preferences ("best case"), and the other interior represented the opposite ("worst case"). The two between-subject factors (sequence and seat) were used to investigate sequence effects and whether the seat (driver seat or front passenger seat) where the participant was seated affects the evaluation. To control for sequence effects and identify possible anchoring effects, half of the participants started with rating the vehicle interior representing the best case, while the other half started with the worst case interior. Further, half of the participants performed the evaluations while being seated on the driver seat. The other half performed the evaluations from the front passenger seat. Overall, the quantitative study collected passenger well-being and related passenger needs as dependent variables and used the within- and between-subject factors as independent variables.

The qualitative interview was conducted to identify how passengers in an automated vehicle understand passenger well-being. The interview questions were based on suggestions by Bailom, Hinterhuber, Matzler, and Sauerwein (1996) to address RQ1 and RQ5a.

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[3] Parts of this chapter have been published in following publication: Sauer, Mertens, Heitland et al. (2019)

4.2 Procedure

To address the three different research questions in one study procedure, multiple steps are necessary (c.f. Figure 4.1). Prior to participating in the user study, participants were asked to provide their demographics (age, gender, student status) and preference for four interior features (vehicle roof (glass/regular), background music (on/off), interior lighting (on/off), additional displays (yes/no)) in a pre-study online questionnaire. The four features were chosen to have different levels of salience. The preferences were collected prior to the participation on-site to decrease potential bias of participants' ratings in regard to their stated preferences.

During the on-site user study, informed consent was obtained, followed by a baseline measurement of well-being in an adjoining room. In the following step, participants evaluated two vehicle interiors (evaluation 1 and 2) regarding their level of passenger well-being (RQ2a) and the fulfillment of passenger needs (RQ5a). The two interiors (best and worst case) were presented with two stationary production cars (c.f. Section 3.3), which were identical to the layperson apart from the four features. The participants were informed that both vehicles had automation features. They were asked to imagine the scenario that a friend had recently bought the automated vehicle and invited the participant to try it. Based on this scenario, they were asked to evaluate the vehicles using questionnaires measuring passenger well-being and the fulfillment of passenger needs. During the evaluation, the participants were alone in the car and seated either on the driver seat or the front passenger seat. They had unlimited time to complete the evaluation. On average, the participants took 10 minutes to complete one evaluation.

Following the evaluations, a qualitative interview was conducted in the adjoining room to identify participants' view on passenger well-being and related passenger needs. The pre-study questionnaire took 5-10 minutes to complete. The study on site took, on average, 45 minutes per participant. The participants were incentivized with 10€ or in the case of students with the option of credits for participating in research.

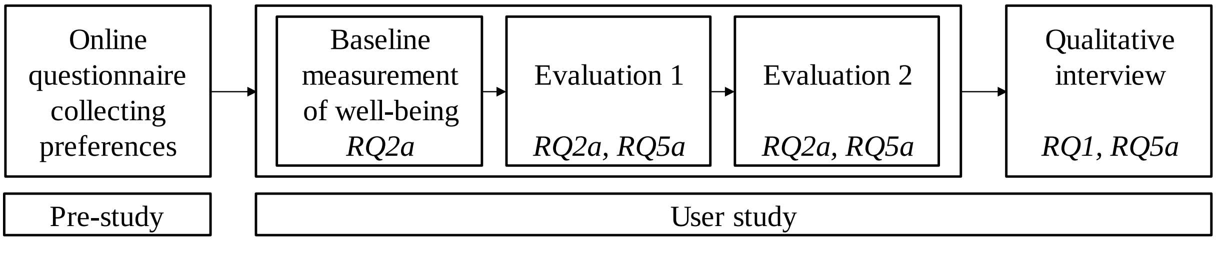


Figure 4.1 Overview of study procedure addressing RQ1, RQ2a, and RQ5a, adapted from Sauer, Mertens, Heitland et al. (2019).

4.3 Participants

Participants for the user study were recruited under consideration of requirements set by an expert commission. In total, an opportunity sample of 40 participants from the Bundeswehr University Munich, Germany (students and employees) was recruited. Of the 40 participants, 17 were female, 23 were male. The participants were aged between 19 and 62 years (M = 30.25, SD = 12.49). The sample had a moderate to high interest in cars (M = 3.55, SD = .96).

4.4 Data Collection and Analysis

Participants' interest in cars was collected on a 5-point scale (1: very low, 5: very high). Quantitative measures used to collect the dependent variables are outlined in section 5.1.3. The qualitative interview questions were constructed based on the Kano method (c.f. Section 3.1). Bailom et al. (1996) offer a set of four questions that can facilitate the identification of relevant product features for subsequent analysis with the Kano method:

1. What does a user associate with the use of the product?
2. What pain points does the user experience when using the product?
3. What are the user's criteria for a purchase decision of the product?
4. How would the user change or improve the product?

To identify what passenger well-being in automated driving may entail from a user perspective, question 1 on associations with well-being in automated driving is suitable. The question was phrased as: "Which adjectives would you use to describe your state when experiencing a high level of well-being in an automated vehicle?". A similar question was phrased to identify relevant passenger needs (RQ5a, c.f. Section 7.1.1). Two researchers analyzed the qualitative data obtained in the interviews, as outlined in section 3.1. A bilingual speaker translated the adjectives and cluster names from German to English.

4.5 Results

In total, 49 unique adjectives were used by the participants to describe their state of passenger well-being in an automated vehicle (c.f. Table 4.1). On average, the participants used 3.6 adjectives. Based on the 49 adjectives, six clusters were derived. The most frequently mentioned group relates to relaxation (8 adjectives in total, named 68 times). This cluster also contains the most frequently mentioned adjectives: relaxed (named by 24 participants, 60%), safe (named by 18 participants, 45%), and composed (named by 12 participants, 30 %).

Table 4.1 Clustered adjectives used by participants to describe their state of passenger well-being in automated driving, adapted from Sauer, Mertens, Heitland et al. (2019).
Note: Number behind adjectives indicates count, bottom row indicates totals for each cluster.

Relaxation		**Positive mood**		**Alertness**		**Control**		**Comfort**		**Prestige**	
Relaxed	24	Content	7	Concentrated	3	Sovereign	2	Comfortable	4	Unique	1
Safe	18	Good	7	Motivated	2	Confident	2	Homely	1	Luxurious	1
Composed	12	Well	3	Lively	2	Controlling	2	Domestic	1	Sporty	1
Balanced	6	Cheerful	3	Attentive	2	Familiar	2	Cozy	1	Valued	1
Calm	4	Pleased	2	Enterprising	1	Successful	1	Clean	1		
Stress-free	2	Joyful	2	Excited	1	Powerful	1	Shielded	1		
Easy	1	Happy	1	Curious	1	Determining	1				
Cared for	1	Pleasant	1	Encouraged	1	Reliable	1				
		Jolly	1	Entertained	1	Free	1				
				Awake	1	Not swamped	1				
				Rested	1						
				Alert	1						
8	68	9	27	12	17	10	14	6	9	4	4

4.6 Discussion

The adjectives participants associate with passenger well-being paint a multi-dimensional picture. The largest clusters of associated adjectives are relaxation, positive mood, and alertness. These correspond with positive affect, as the circumplex model of affect (Russell, 1980) shows. High positive and low negative affect are a key aspect of subjective well-being (Diener, 1994) and constitute current well-being. The additional clusters of adjectives emphasize the notion that participants understand passenger well-being in automated driving settings as current well-being. Apart from high positive and low negative affect, current well-being also includes the aspect of positive physical sensations (Schumacher et al., 2003). An indication that such physical sensations are relevant in automated driving is provided by adjectives such as stress-free, safe, rested, or comfortable (c.f. Table 4.1). Habitual well-being is related to life satisfaction (Diener, 1994) and aggregated emotional experiences over defined periods of time (Schumacher et al., 2003) and entails a cognitive evaluation. Yet, the adjectives used by participants to describe a state of passenger well-being provide little association with aspects of habitual well-being. Rather, the adjectives predominantly address affective aspects of well-being.

When looking at the adjective clusters in general, relaxation is a strikingly large cluster. This may be an indication that passenger well-being requires a vehicle design that fosters relaxation through safety and trust. Further, control is another cluster that may apply to vehicle design or the design of interaction with the vehicle more specifically. A feeling of comfort and prestige appears to be less relevant for a state of passenger well-being and is only mentioned sporadically by participants. This may indicate that comfort and prestige do not constitute corresponding dimensions of passenger well-being but rather indicate accompanying states through the fulfillment of individual passenger needs.

Based on these results and indications, the assumption made in RQ1 can be confirmed. Participants in this study view passenger well-being in a very similar way as current subjective well-being is defined in psychology. Positive affective states, together with positive physical sensations, are predominant in the participants' descriptions. Thus, passenger well-being in automated driving can be defined as "a positive self-evaluation of one's current affective state triggered by the travel experience" (Sauer, Mertens, Heitland et al., 2019, p. 240). This definition will be used throughout the following sections.

4.7 Limitations

The results and the derived implications for passenger well-being are subject to the constraints and limitations of the design of the user study. First of all, static production cars were used as a stimulus and consequentially as support for imagining passenger well-being in automated driving. Considering the limited availability of automated driving simulators and fully functioning prototypes, using a static vehicle is the next best option. Further, it is likely that the underlying structure of passenger well-being is independent of the specific vehicle or prototype.

The study design itself may also pose a limitation. The participants completed questionnaires on well-being and evaluation of the vehicles before conducting the interview. Filling out these questionnaires beforehand may have led to carry-over effects. Yet, this does not have to entail a reduction of validity in the results. In addition, this study was conducted in Germany. As well-being and vehicle design underlie cultural differences (c.f. Section 2.3.5), the findings of this study may not be generalizable globally. Rather, the applicability of the proposed definition needs to be confirmed for other cultures. Further, translating the adjectives and clusters to English may have caused reduced accuracy despite using a bilingual speaker.

4.8 Conclusion

Based on this user study, the following definition of passenger well-being is offered. Passenger well-being is “a positive self-evaluation of one’s current affective state triggered by the travel experience” (Sauer, Mertens, Heitland et al., 2019, p. 240). This clarifies the first element of the model of determinants of passenger well-being (c.f. Figure 4.2). To ensure cross-cultural applicability, the definition of passenger well-being needs to be confirmed in other cultures as well. Further, the results indicate a close relationship with passenger needs, such as comfort and prestige, which require further investigation. In the next step, appropriate ways to measure passenger well-being, as defined above, need to be identified. As passenger well-being relates to current subjective well-being, measures established in psychology are a promising starting point but have to fit the situation of automated driving.

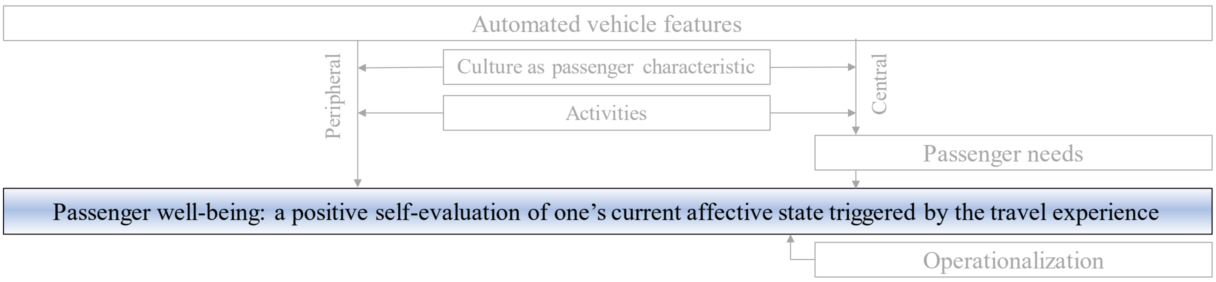


Figure 4.2 Updated overview of the proposed model of determinants of passenger well-being based on results to RQ1.

5 Measuring Passenger Well-Being in Automated Driving[4]

Providing a definition of passenger well-being in automated driving, which is related to current subjective well-being, raises the subsequent question of how passenger well-being in this specific setting may be measured (RQ2). Both subjective self-reports, as well as objective measures, are considered to be able to measure passenger well-being with as many facets as possible.

At this point, measures for passenger well-being are to be identified that can be used effectively and efficiently for subsequent user studies investigating hypothesized elements of the model of determinants of passenger well-being. To identify measures suitable for this purpose, the following criteria are set:

- Sufficient statistical quality by satisfying relevant criteria in case of self-reports
- Applicability to automated driving settings content-wise
- Economic application in user studies
- Sensitive to measure different levels of passenger well-being caused by different stimuli

5.1 Subjective Measures for Passenger Well-being

As discussed in section 2.1.4, multidimensional self-report measures may be appropriate to measure the subjective and multidimensional nature of passenger well-being. As the definition of passenger well-being includes a focus on the affective state, adjective lists to measure emotional states or moods may be especially suitable. Related work investigating well-being or affective states in transportation use different self-report measures (c.f. Table 2.1). These five different measures (EWL, MDBF, PANAS, SCAS, UMACL) provide a starting point for investigating suitable measures for automated driving contexts by applying the criteria set above.

To evaluate the measures regarding the first criterion of statistical quality, reliability measured with Cronbach's α is consulted. For the application of SCAS, no values for Cronbach's α or any other reliability measure are reported (Västfjäll et al., 2003). Thus, this measure is excluded from further consideration. All other measures display sufficient reliability with Cronbach's $\alpha > .70$ (Nunnally, 1978).

[4] Parts of this chapter have been published in following publications: Sauer, Mertens, Heitland et al. (2019); Sauer, Mertens, Nitsch et al. (2019)

The content-wise applicability of the remaining self-report measures to automated driving contexts is given by the successful application in car or aviation contexts. Aviation is related to automated driving due to the possibility of acting as a passenger. The applicability is also confirmed through a content-wise item inspection.

Passenger well-being is often collected in a repeated measure design in subsequent user studies of this work. Due to this design, an economic application of the self-report measure is mandatory. Hence, at this point, a multidimensional self-report measure is required with a minimum number of items necessary to maintain sufficient statistical quality and multidimensionality. Of the remaining four self-report measures, the EWL (Janke & Debus, 2003) is the longest with 161 items across six dimensions. Quehl (2001) suggests a shorter version, which still contains 46 items on two dimensions. The UMACL exists in two versions. The original with 48 items on four dimensions (Matthews et al., 1990) and the adjusted version with only two dimensions and 27 items (Fairclough et al., 2014). The PANAS contains 20 items distributed equally across two dimensions (Watson et al., 1988). Finally, the self-report measure MDBF has a long version with 24 items on three dimensions and an equally reliable short version with 12 items. The MDBF short version allows a quicker administration than other self-reports considered (Steyer et al., 1997).

The applicability of the MDBF for passenger well-being in automated driving is supported by the adjectives suggested by participants to describe a state of well-being (c.f. Chapter 4). Here three of the six groups correspond to the three dimensions of the MDBF (positive/negative mood, alertness/drowsiness, relaxation/unrest, c.f. Table 4.1). Thus, the MDBF meets the three preset criteria considered so far best. Indications that the MDBF is also sensitive to stimuli changes is provided by studies in aviation (Winzen et al., 2014). It remains to be confirmed whether it is sensitive in automated driving contexts as well. Based on this discussion, it is hypothesized:

H1: *The MDBF measures passenger well-being in automated driving with sufficient reliability (Cronbach's α > .70) and validity (discriminant validity).*

H2: *The MDBF is sensitive to different stimuli by measuring significant differences in passenger well-being for different stimuli with at least small effect sizes (η_G^2 > .02).*

5.1.1 Experimental Setup

The evaluation of the MDBF by investigating H1 and H2 is integrated into the same user study that was used to explore the concept of passenger well-being (c.f. Chapter 4). For the measure evaluation, especially the quantitative user study is of relevance. The experimental setup is outlined in section 4.1, and the procedure of the study is detailed in section 4.2.

5.1.2 Participants

In total, 40 participants from the Bundeswehr University Munich, Germany, were recruited. See section 4.3 for further details.

5.1.3 Data Collection and Analysis

Passenger well-being was collected with the MDBF (Short version A, Steyer et al., 1997). To be able to investigate discriminant validity, related constructs arising from the discussion on passenger needs (c.f. Section 2.3.4) were collected for each vehicle evaluation: physical well-being (dimension current physical state from Frank, 2011), comfort (single item measurement: "I find the vehicle interior comfortable", 5-point scale 1: not at all, 5: extremely), trust (Pöhler, Heine, & Deml, 2016), safety (Hayes, Perander, Smecko, & Trask, 1998), aesthetics and symbolism (both Homburg et al., 2015). An item analysis was conducted for all multi-item measures. Item 1 (deceptive) and 6 (familiarity) were excluded from the trust measure for subsequent analysis due to low item discriminability and item difficulty.

To assess reliability in the form of internal consistency and discriminant validity, Cronbach's α and Pearson correlation coefficients were calculated (H1). For assessment of the sensitivity of the MDBF (H2), mixed factorial ANOVA was calculated.

5.1.4 Results

Cronbach's α for the MDBF ranges between .90 (worst case), .92 (baseline) and .93 (best case). On the level of each dimension, Cronbach's α varies between .76 and .92, yet the overall scale always has higher internal consistency than any single dimension for each measurement point. Overall, the values for internal consistency lie above the threshold of .70 (Nunnally, 1978), and thus, indicate the reliability of the MDBF (H1).

Pearson correlation coefficients with related constructs and passenger needs are used to assess discriminant validity. Correlation shows (c.f. Table 5.1) that except for symbolism, all variables correlate significantly with passenger well-being to a varying degree (H1).

Table 5.1 Pearson correlation coefficients and p-values for passenger well-being and related concepts to investigate validity, adapted from Sauer, Mertens, Heitland et al. (2019).
Note: Grey highlight indicates p-values < .05.

	$r_{\text{passenger well-being}}$	p
Physical well-being	.596	< .001
Aesthetics	.543	< .001
Safety	.528	< .001
Distrust	-.457	< .001
Comfort	.330	.003
Trust	.268	.016
Symbolism	-.007	.948

Prior to calculating ANOVA, the effect of sequence (best or worst case as the first stimulus) was investigated and found without significant influence. Thus, a mixed factorial ANOVA with the between-subject factor seat and repeated measures as a within-subject factor (case) was calculated. There was only a significant difference between the within-subject factor case with a small effect ($F(2, 76) = 24.90$, $p < .001$, $\eta_G^2 = .033$) supporting H2. The factor seat ($F(1, 38) = .84$, $p = .364$, $\eta_G^2 = .021$) and the interaction seat x case ($F(2, 76) = 1.06$, $p = .353$, $\eta_G^2 = .001$) did not show any significant differences between the groups. The post-hoc analysis shows a significant difference between all three cases (baseline, best, and worst case). Well-being in this study was lowest in the baseline condition ($M = 4.10$, $SD = .597$), followed by the worst case condition ($M = 4.27$, $SD = .523$) and highest in the best case condition ($M = 4.50$, $SD = .641$) (c.f. Figure 5.1).

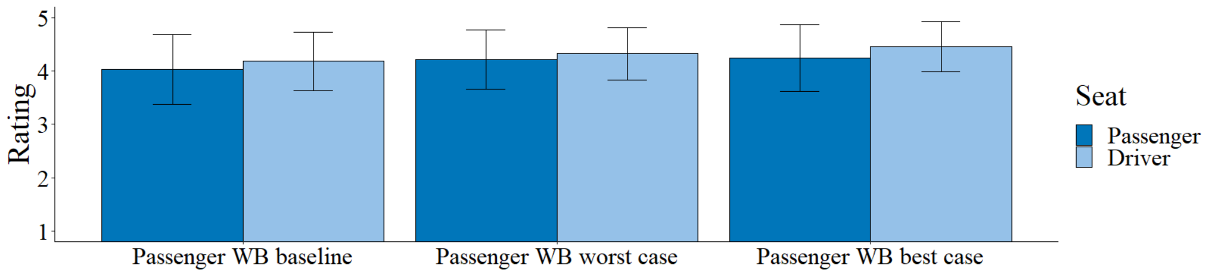


Figure 5.1 Mean ratings for passenger well-being (WB) across all repeated measures, error bar: ± 1SD, adapted from Sauer, Mertens, Heitland et al. (2019).

5.1.5 Discussion

The MDBF is a reliable measure in the context of automated driving when using internal consistency as an indicator. Cronbach's α exceeds the generally applied threshold of .70 (Homburg & Giering, 1996; Nunnally, 1978). Using the full scale, it exceeds the stricter threshold of .80 (Cohen, 1988) for all points of measurement. In this study, the MDBF's internal consistency is higher than in other related studies using the MDBF or other measures (c.f. Table 2.1).

Discriminant validity is used to evaluate the validity of the MDBF for automated driving contexts. Overall, none of the correlations suggest that passenger well-being overlaps with any of the other variables measured. Physical well-being correlates the strongest with well-being compared to the other variables. Yet, the correlation of r = .596 does not suggest that the two concepts are identical. Rather the correlation emphasizes the strong link between psychological and physical well-being (Becker, 1991, c.f. Section 2.1.1). Comfort correlates with passenger well-being on a medium level providing empirical evidence that comfort and passenger well-being are distinct concepts as suggested above (c.f. Section 2.1.3). The other significant correlations range between small to high correlation providing evidence for their role as passenger needs (c.f. Chapter 7). Based on internal consistency and discriminant validity, H1 is supported.

Turning to the sensitivity of the MDBF for automated driving contexts, results from ANOVA suggest that the MDBF is sensitive enough to detect differences in passenger well-being induced by different stimuli. Post-hoc tests suggest that the level of well-being differs significantly between all three points of measurement. For the context of automated driving, the difference between best and worst case is of particular relevance as it emphasizes the sensitivity of the MDBF in different vehicle settings. The effect is relatively small ($\eta_G^2 = .033$), but expected as the interiors differed only in regards to four attributes and varied in salience. But exactly this setting underlines the MDBF's sensitivity and supports H2. For passenger well-being, no sequence effects or influence of the driver's workplace were found.

5.1.6 Limitations

The study design for evaluating the MDBF has some drawbacks (see also section 4.7). This includes the evaluation of a static vehicle. A driving simulator or real-world driving study is likely to increase realism. Yet, increased realism will probably not change the suitability of the MDBF to measure passenger well-being, as the MDBF measures well-being in flexible vehicle environments. The same reasoning applies to changing the interior features that were manipulated to design different stimuli. Hence, the MDBF is likely to be a suitable measurement tool for stimuli derived from other features. The study was conducted in Germany, and the MDBF is a measurement tool developed in German. Thus, the generalizability of these results to other cultures may be questionable. Therefore, the identification of suitable subjective self-reports is required for other cultures.

To sum up, based on this user study, the MDBF provides sufficient reliability (internal consistency) and validity (discriminant validity) to measure passenger well-being in automated driving. Further, it is sensitive to measure differences in passenger well-being induced by different stimuli. Thus, the MDBF is used in subsequent user studies to measure well-being.

5.2 Objective Measures for Passenger Well-being

For cases in which self-reports for the measurement of passenger well-being can be obstructive to the study design or measurement context due to distraction and interruption by filling out a questionnaire, objective measures of physiological, facial, or motoric cues can be utilized. Further, these measures can add additional information on the affective state (Diener, 1994).

In section 2.1.4, four potential objective non-invasive measures for passenger well-being are identified and discussed: heart rate variability, electrodermal activity, facial expressions, and body motion. Studies investigating the relationship between objective and subjective measures and their applicability do not always reach the same conclusions on the suitability of the measures, e.g., in the case of EDA. Due to the inconclusiveness of prior research, the objective measures require an evaluation of the suitability to act as a proxy for passenger well-being in the context of automated driving. For this purpose, a user study is conducted. To judge the suitability of objective measures for this context, the criteria defined above are applied.

The four types of objective measures have been used in automated driving contexts (e.g., Beggiato et al., 2018; Braun et al., 2018; Riener et al., 2009; Walker et al., 2019) and have displayed applicability for this context. Further, all four measures are non-invasive, as they only require skin contact with the electrodes (EDA, HRV), a fixation of the sensor to the upper body (body motion) or no direct contact at all through the use of cameras (facial expression, c.f. Section 5.2.4). Thus, they may be economically used in study settings or in real-world scenarios.

In order to be applicable, objective measures need to relate to subjective measures (Looze et al., 2003). Passenger well-being is characterized by positive affect and relaxation as opposed to stress or high arousal (c.f. Section 4.6). Based on this characterization of subjective passenger well-being, the selected physiological measures, and their relationship to the autonomic nervous system, the following is hypothesized:

H1a: *RMSSD HRV as an indicator of parasympathetic activity is positively related to self-reported passenger well-being.*

H1b: *VLF HRV as an indicator of sympathetic activity is negatively related to self-reported passenger well-being.*

H1c: *HF HRV as an indicator of parasympathetic activity is positively related to self-reported passenger well-being.*

H2: *Tonic EDA as an indicator of sympathetic activity is negatively related to self-reported passenger well-being.*

H3: *Body movement is negatively related to self-reported passenger well-being.*

H4: *Valence detected through automated facial expression analysis is positively related to self-reported passenger well-being.*

Similar to subjective self-report measures, objective measures should also be sensitive enough to detect differences induced by different stimuli. Evidence for the sensitivity of some objective measures is provided by related work (c.f. Section 2.1.4). Therefore, it is hypothesized:

$H5_{a\text{-}f}$: *Parameters of HRV, tonic EDA, body motion, and valence are sensitive to different stimuli by measuring significant differences for different stimuli.*

5.2.1 Experimental Setup

To assess the suitability of the suggested objective measures to act as a proxy for subjective well-being, a driving simulator study was conducted using a static level 4 automated driving simulator with real-world driving clips (see section 3.3 for details on the simulator). The driving behavior in the simulation was safe and reliable without any take-over requests. The study followed a repeated measures design. Participants experienced different interior settings and NDRTs as stimuli to incur different levels of passenger well-being (independent variable). They were asked to evaluate their subjective level of passenger well-being for each experienced stimuli (dependent variable). Objective measures were collected during the experience (dependent variable). The stimuli were derived from five interior features (seat backrest, ambient light color, steering wheel, tablet position for NDRTs, height of center console) and the NDRT that varied systematically between two levels. Using a fractional factorial design, ten stimuli were derived (c.f. Appendix A.6). To reduce demand and fatigue for the participants, a partially balanced incomplete block design (Cochran & Cox, 1957) was used to assign six of ten stimuli in a randomized order to each participant.

5.2.2 Procedure

Upon their arrival at the study site, participants were welcomed, and informed consent was obtained. The participants then fitted the required sensors (EDA wristband and ECG sensor) following detailed instructions and completed a demographic questionnaire. A 10-minute baseline measurement outside the stimulator at a regular workspace was conducted collecting HRV, EDA, and body motion measures while the participant was sitting relaxed in a chair. Following, subjective measures were collected for the baseline measurement. Next, the participants experienced six stimuli in the simulator during which objective measures were recorded and then evaluated the experienced stimulus with a subjective questionnaire. Between each stimulus, the participants had a break for the physiological measures to normalize (c.f. Figure 5.2). After all six stimuli, a qualitative interview was conducted to gain additional insights into the participants' perspective on passenger well-being. The study procedure took, on average, 120 minutes per participant. The participants did not receive any compensation for their participation.

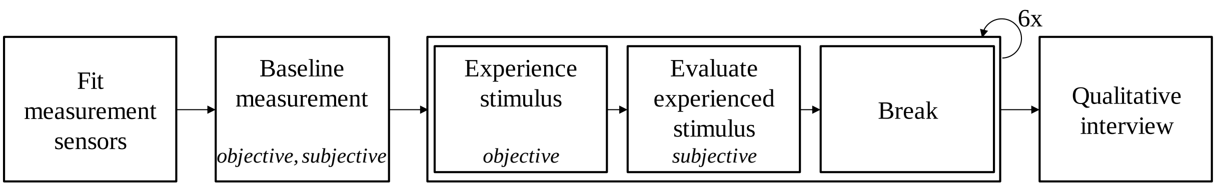


Figure 5.2 Overview of the study procedure to evaluate objective measures of passenger well-being.

5.2.3 Participants

A convenience sample of 23 participants was recruited for the study. Due to errors in recording physiological measures, three participants were excluded from the sample, leaving a sample of 20 participants (of which 10 male and 10 female). The age of the participants ranged from 23 to 42 years (M = 27.85, SD = 4.45). All participants were healthy and had no relevant primary diseases. The participants had, on average, a high interest in cars (M = 4.2, SD = .77) and intermediate prior experience with ADAS (M = 3.5, SD = 1.15).

5.2.4 Data Collection and Analysis

In this study, both objective and subjective data were collected (c.f. Figure 5.3). To measure HRV, the eMotion Faros 360 ECG monitor was used. A 1-channel, 2 electrode measurement with a sampling rate of 1000 Hz was used. Kubios HRV Premium Software with automatic artifact correction (acceptance threshold 5%) and smoothness priors method for RR interval detrending was used to extract time-domain (RMSSD) and frequency-domain (HF, VLF) results.

For the measurement of body motion, other studies have either used pressure sensors (Beggiato et al., 2018; Cascioli et al., 2016; Søndergaard et al., 2010), video recordings (Sammonds et al., 2017) or motion tracking (Beggiato et al., 2018). A disadvantage of pressure sensors is that the required integration within the seat needs to be unobtrusive. The use of pressure mats on the seat surface is an alternative. However, using separate pressure mats changes the aesthetics of the seat and may indirectly influence the level of well-being (Mandel & Maier, 2016). Video recordings require substantial effort from experts to rate the videos, and motion tracking requires technical equipment that could not be integrated into the driving simulator. Instead, in this study, the accelerometer integrated into the ECG monitor (100 Hz, dynamic range ±16g) was used to record body motion. The accelerometer is positioned close to the participant's right collarbone resulting from the required electrode position in the 1-channel ECG measurement. Body motion was range corrected (Boucsein, 1988) to control for habitual motion (Lee et al., 1995) and make the data more comparable across participants.

To record tonic EDA, the Empatica E4 wristband was used and placed on the wrist of the participant's non-dominant hand. Tonic EDA data was extracted using Ledalab (Benedek & Kaernbach, 2010a, 2010b) and range corrected (Boucsein, 1988). Facial expression was recorded with a logitech C922 camera (1920x1080 pixels, 60 fps). The camera was placed above the mock-up instrument cluster to record frontal videos of the participants (c.f. Figure 5.3). The videos were analyzed regarding the parameter valence using Affectiva Affdex SDK.

To be able to compare the objective measures with subjectively experienced well-being, the self-report MDBF, as suggested in section 5.1, was used. To reduce the demand and fatigue of the participants, only one item per dimension (positive/negative mood, alertness/drowsiness, relaxation/unrest) was selected as single-item measurement. For each dimension, the highest loading, positive item from a factor analysis provided by Steyer et al. (1997) was selected: happy, awake, and calm. Positive items were selected, as it is disputed whether positive and negative affect are independent dimensions or extreme of one continuum (Steyer et al., 1997).

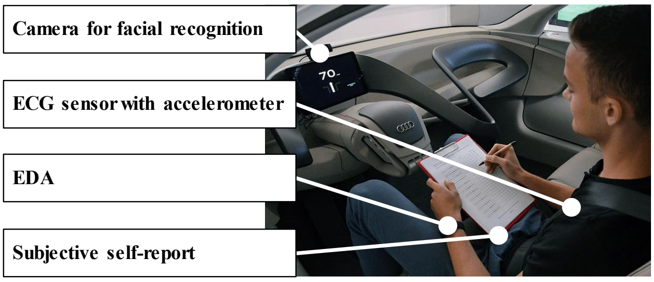


Figure 5.3 Overview of the measures used in the user study to evaluate objective measures.

To assess the required relationship between objective and subjective measures (Looze et al., 2003), Pearson correlation coefficients were calculated (H1-H4). To assess the sensitivity of each measure (H5), repeated measures ANOVA was used with the R package easyanova (Arnhold, 2013; R Core Team, 2018), which is able to consider incomplete block designs.

5.2.5 Results

In a first step, repeated measures ANOVA was calculated for all three single items (happy, awake, calm) to assess if the single items each are able to distinguish between different stimuli, as single items instead of the full self-report were utilized. ANOVAs were significant for all three items (c.f. Table 5.2). Turning to the objective measures, repeated measures ANOVA were calculated for all six objective parameters as well. For objective measures, only HRV RMSSD and body motion detected significant differences between the stimuli ($H5_{a\text{-}f}$). Conducting post-hoc tests, RMSSD significantly differs in 21 of 54 comparisons. Body motion differs in three of 54 comparisons. All three comparisons are between the baseline and a stimulus. Thus, supporting H5a and H5e.

The requirement that objective and subjective measures need to be significantly related (Looze et al., 2003) is not fulfilled for all objective measures as Pearson correlation coefficients show (c.f. Table 5.3). Interestingly, the objective measures primarily show significant relationships with the item happy (HRV RMSSD, HRV HF, and body motion). There are indications for relationships between HRV VLF and awake, and tonic EDA and calm, although not significant. The significant relationships between objective and subjective measures follow the hypothesized direction (H1a, H1c, H3 supported).

Table 5.2 Results of repeated measures ANOVA for subjective and objective well-being measures.
Note: Grey highlight indicates significant values (p < .05).

Measure	**DFn**	**DFd**	**F**	**p**
Happy	10	109	2.057	.034
Awake	10	110	3.296	< .01
Calm	10	110	2.352	.015
HRV RMSSD (H5a)	10	110	9.445	< .01
HRV VLF (H5b)	10	110	1.921	.050
HRV HF (H5c)	10	110	.583	.825
Tonic EDA (H5d)	10	110	1.163	.323
Body motion (H5e)	10	110	4.637	< .01
Facial expression (valence, H5f)	9	90	1.053	.406

Table 5.3 Pearson correlation coefficients for objective measures with each single self-report item, adapted from Sauer, Mertens, Nitsch et al. (2019).
Note: Grey highlight indicates significant values (p < .05).

	Happy		Awake		Calm	
	r	p	r	p	r	p
HRV RMSSD (H1a)	.183	.031	-.069	.416	.005	.956
HRV VLF (H1b)	-.007	.933	-.162	.056	.118	.165
HRV HF (H1c)	.205	.015	.045	.597	.001	.991
Tonic EDA (H2)	-.064	.453	-.015	.860	-.162	.055
Body motion (H3)	-.204	.016	.019	.826	-.107	.210
Facial expression (valence, H4)	.027	.772	-.063	.494	.098	.288

5.2.6 Discussion

In this user study with a static level 4 driving simulator, the suitability of objective measures to act as a proxy for passenger well-being in automated driving was investigated. The results show that RMSSD HRV and body motion fulfill the pre-set criteria. Both measures have a significant linear relationship in the hypothesized direction with the single item happy used to measure subjective passenger well-being (H1a, H3 supported). Further, they are able to measure differences between at least two stimuli (H5a, H5e supported). Yet, in the case of body motion, only differences between the baseline measurement and some of the stimuli are detected, but no differences between two simulator-stimuli. Interestingly, the stimuli that differ from the baseline measurement in case of body motion do not differ in the case of HRV RMSSD. The other objective measures indicate a tendency in their linear relationships with the single items that correspond to the hypothesized direction. Yet, these relationships are not significant, and these objective measures do not significantly vary between the stimuli. The limited evidence for the remaining objective measures reproduces some of the findings in related work.

The conclusion drawn in chapter 4 that passenger well-being is related to low arousal is underlined in this study. Here, parameters of parasympathetic activity correlate positively while sympathetic activity correlates negatively with items for subjective passenger well-being. This finding may be explained by the high reliability of a level 4 automation system used in this simulator study and the resulting low mental load while driving as the driving task and supervision are transferred (Hjälmdahl, Krupenia, & Thorslund, 2017).

Valence in facial expression has a very small, negligible relationship with all of the single items used. This negligible relationship may be explained by the fact that facial expressions rather occur in social communication. However, the participants experienced the drive in the simulator alone, and no form of social interaction took place (e.g., with a social agent during the drive, as part of an NDRT, or with the investigator). Further, affect can be experienced without displaying or changing facial expression. Vice versa, facial expression does not necessarily have to indicate experienced affect (Rinn, 1984). Thus, participants may have had little to no reason to show facial expressions. In automated driving settings where facial expressions are to be used as a proxy for affect or well-being such as in affective computing, it needs to be ensured that passengers' faces are well visible to be able to measure expressions noiselessly. In this study, participants were able to use a hand-held tablet in some stimuli to complete an NDRT. Some participants chose seat positions that resulted in the tablet-PC blocking the camera's view of the participant's face. In addition to the safety implications of hand-held devices for the design of airbags and other safety features, this behavior has implications for the design of affective computing systems as well.

5.2.7 Limitations

The design of this study includes some drawbacks. First of all, single items instead of the full self-report were used to measure subjective well-being in this study, which can cause a loss in precision. However, a study shows that the use of short measures can be permissible (Sauer, Mertens, Heyden et al., 2020). Due to the selection of the items, all three dimensions of current well-being (mood, alertness, and relaxation) were covered, and the selected items showed the capability of distinguishing between stimuli. The stimuli used in this study were deliberately chosen to not create any extreme scenario of either well- or ill-being. However, more extreme stimuli could lead to stronger relationships between subjective and objective measures. It is also important to note that this study only investigates the suitability of objective measures and not how different interior features impact passenger well-being measured objectively and/or subjectively. To be able to derive such quantitative statements, larger samples, and different statistical methods are required (c.f. Chapter 8).

Further, this study utilizes a static driving simulator instead of a naturalistic driving design. This can impact the validity of the results when applying them to naturalistic driving. Especially the measure of body motion is likely to be affected as additional vibration and movement from the vehicle will add noise to the accelerometer data. The handling of potential noise has to be investigated in this setting before using body motion as an objective approximation. The recording time of six minutes is relatively short for physiological measures. However, the recording time is sufficient to analyze EDA and the selected HRV parameters (Boucsein, 1988; Task Force, 1996).

On average, the sample is very young and has a high interest in cars. This may have influenced the absolute levels of passenger well-being experienced by the participants. However, the absolute values of well-being are irrelevant to the present research question. Rather, the relative relationship between subjective and objective measures is of relevance. Thus, the selected sample does not necessarily reduce the significance of the discussed results, but further research is advisable.

All in all, the results of this user study suggest that objective physiological (HRV RMSSD) and motoric (body motion) measures can act as a proxy for passenger well-being and complement subjective well-being by providing additional, more nuanced insights. Further, both objective measures may be suitable for affective computing applications in automated driving if corresponding sensors are integrated appropriately into the vehicle interior.

5.3 Conclusion

The aim of the two user studies discussed above is to identify a subjective self-report measure and objective proxies to measure passenger well-being in automated driving. Such measures are needed for subsequent user studies to be able to reliably, validly, and economically measure passenger well-being. Based on the finding that passenger well-being relates to current subjective well-being (c.f. Chapter 4), potential subjective and objective measures were identified from related work (c.f. Section 2.1.4) and investigated using pre-defined criteria.

The MDBF is identified as a suitable subjective self-report measure for passenger well-being in automated driving. Content-wise, the MDBF's three dimensions coincide with the largest clusters of adjectives participants used to describe their state of passenger well-being (c.f. Table 4.1). Further, the MDBF is able to fulfill the set criteria for reliability and validity. Thus, the MDBF is used as a subjective measure for passenger well-being in subsequent user studies.

As subjective measures may not always be applicable to all research settings or industry applications, objective measures are investigated. Further, such objective measures may also provide additional insights into well-being that self-reports may conceal (Diener, 1994). Similar criteria for objective measures were set, and HRV RMSSD and body motion were objective measures that showed the ability to approximate subjective well-being in the context of automated driving in the performed user study. Further, the objective measures were indeed able to provide additional nuanced insights. The post-hoc tests reveal significant differences of HRV RMSSD and body motion in different stimuli comparisons (c.f. Section 5.2.5).

Under the restrictions and limitations arising from the study designs (e.g., static driving simulator, young and experienced samples), the results suggest that the MDBF as subjective measure and HRV RMSSD and body motion as objective measures are suitable ways to operationalize passenger well-being as defined earlier (c.f. Figure 5.4).

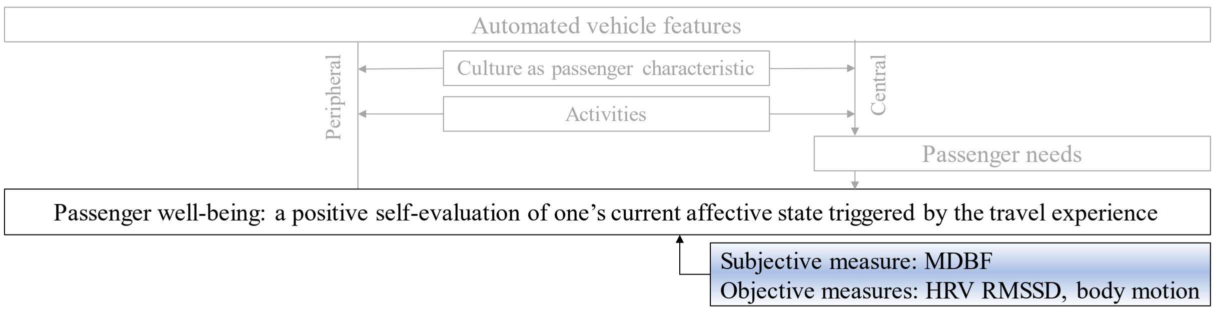


Figure 5.4 Updated overview of the proposed model of determinants of passenger well-being based on results to RQ2.

6 Physical and Technical Features of Automated Vehicles

After defining and operationalizing passenger well-being in automated driving, the next step in defining a model of determinants of passenger well-being is to identify which features of an automated vehicle are relevant for passenger well-being (RQ3). Using Richards' (1980) theory of comfort, the passenger comfort experience model (Ahmadpour et al., 2014), and other evidence from related work as a starting point, the input features suggested in these models need to be evaluated and adapted to the context of automated driving. As discussed, the focus is set on physical and technical features. To identify relevant physical and technical features in automated driving beyond those suggested in related work, a multi-step process is applied. In a first step, relevant physical and technical features of automated vehicles are identified, then rated by experts regarding the features' relevance for passenger well-being. Finally, a user study is conducted to evaluate the relevant features.

6.1 Identifying Physical and Technical Features

Highly and fully automated driving is likely to entail paradigm changes in vehicle design due to the accommodation of NDRTs. Thus, vehicle features found in traditional cars or other types of transport discussed in related work may not be sufficient. Instead, vehicle concepts for level 4 and level 5 automation presented between 2015 and 2019 are consulted to identify novel vehicle features that may appear in the future due to automation. To include a global view, 20 manufacturers from three continents and nine markets were considered (c.f. Appendix A.7). Press releases, news articles, pictures, and similar sources were used to evaluate the vehicle concepts.

When reviewing the vehicle concepts, a focus was placed on the vehicle interior (as stipulated in section 2.5), but features from other vehicle areas were added if they indicated relevance for passenger well-being. To be considered for further investigation, the feature in question has to either:

- become possible through level 4 automation (e.g., rotating seats become possible in level 4 as quick handover scenarios in level 3 become obsolete), or
- provide added benefits because of higher levels of automation (e.g., additional screens are possible in all levels of automation, but they provide added benefit if they can be utilized in NDRTs enabled by level 4 automation).

Technical feasibility was not a criterion in the selection process to avoid unneeded restrictions in feature selection caused by possible errors in the prediction of future technological advances.

Based on these criteria, 70 features of automated vehicles are identified. The 70 features (c.f. Appendix A.8) can be divided into six areas based on the categorization in Table 2.2: vehicle architecture (e.g., seats and glazing), materials (e.g., colors and materials), driving dynamics (e.g., adjustability of driving style), ambient features (e.g., noise canceling, air conditioning), driver interaction (e.g., types of interaction and interfaces) and driver health and wellness (e.g., integration of wearables, relaxation). The large number of features requires a reduction to reduce participants' fatigue in the subsequent user study. Thus, an expert survey is conducted to filter features regarding their relevance for passenger well-being.

6.2 Filtering Features for Relevance for Passenger Well-being

To identify those features that have higher relevance for passenger well-being, 15 experts from automotive manufacturers were asked to rate the relevance of each feature on a scale from 1 to 3 (1: not relevant, 2: unsure, 3: relevant). Experts were also able to make additions to the feature list. The experts were selected based on their knowledge in automated driving and resulting vehicle design requirements. For the decision to include a feature for evaluation by future users, a threshold value of 2.5 for the mean rating was set. In total, 23 features exceeded this threshold and were included in the feature set evaluated in the subsequent user study (c.f. Appendix A.8). To account for features suggested by related work as well, five additional features are included: swivel seats, massage, material sustainability and quality, and relaxation exercises.

6.3 Evaluating Features from a User Perspective

To add a user perspective to the identification of relevant physical and technical features, a user study was carried out. The study utilized the Kano method adjusted to passenger well-being as this method provides a proven approach to categorizing product features regarding their importance to create satisfaction or, in this case, passenger well-being (c.f. Section 3.1).

6.3.1 Experimental Setup

The user study followed the Kano method to evaluate the 28 features identified as relevant for passenger well-being. The study was conducted with a static level 4 driving simulator with screens displaying a simulated drive in front and side views (c.f. Section 3.3). The driving behavior in the simulation was safe and reliable without any take-over requests. The evaluation of the features with the Kano method was carried out as interview. Whenever possible, features were presented with prototypes (c.f. Appendix A.9). It was randomized whether participants answered the functional or dysfunctional questions first to avoid sequence effects.

6.3.2 Procedure

After participants arrived at the study site, they were welcomed, gave informed consent, and completed a demographical questionnaire (c.f. Figure 6.1). To ensure that all participants had the same understanding of highly automated driving, they experienced automated driving in the static driving simulator. The simulator drive lasted three minutes, after which the experimenter took a seat on the passenger seat of the simulator and joined the participant to carry out the Kano interview. The concept of passenger well-being and the 5-point scale used to rate each feature was explained to ensure understanding. The participants were instructed to evaluate each feature based on being seated in the driver's seat and given that they use the vehicle privately (i.e., traveling alone or choosing their fellow passengers, no ride-sharing). Each feature was thoroughly explained and, whenever possible, a prototype of the feature was used. On average, participation in the study lasted 45 minutes. The participation was not compensated.

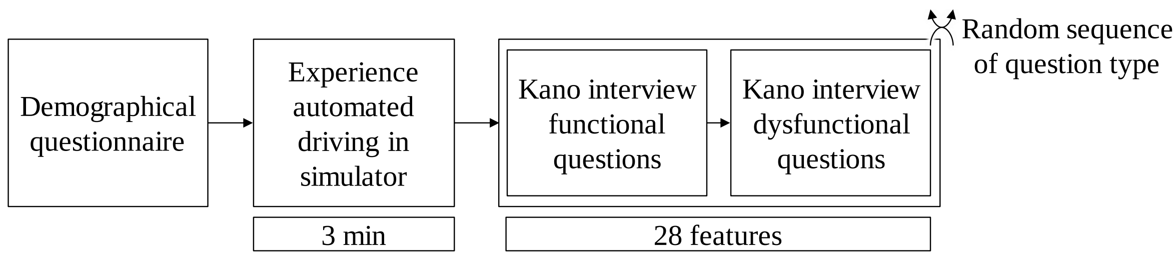


Figure 6.1 Overview of the study procedure addressing RQ3.

6.3.3 Participants

As highly automated vehicles are currently in development and not yet available in the market, it may be difficult for participants to imagine how different vehicle features affect their passenger well-being in automated driving. Thus, participants from automotive companies were recruited to increase the participants' knowledge of automated driving and their ability to estimate how different features may impact their well-being in future automated vehicles. Sixty-nine participants were recruited. Of the sample, 23 participants were female, 46 were male. On average, the participants were 34.17 years old (19-58 years, SD = 9.16). Seventeen participants stated to have a non-technical background, 52 had a technical background. The sample's interest in cars was high (M = 4.07, SD = .96) with a moderate to high level of experience with ADAS (M = 3.83, SD = .97).

6.3.4 Data Collection and Analysis

Participants' general interest in cars and their level of experience with ADAS were both collected with a 5-point Likert scale (1: very low, 5: very high). The design of the feature evaluation followed the Kano method. The phrasing of functional and dysfunctional questions and the 5-point scale used for rating were adjusted to passenger well-being (c.f. Section 3.1). The feature categorization followed the approach detailed in section 3.1. Apart from classification, category strength, total strength, Fong test, and CS+ and CS- parameters were calculated.

6.3.5 Results

The 28 features were categorized according to the mode rule if category strength and Fong test were meaningful (c.f. Section 3.1). Otherwise, the categorization was based on additional decision rules (c.f. Table 3.2). The aggregated categorization of all 28 features investigated is displayed in Table 6.1. Across the total sample, eight features were categorized as attractive (A), three as one dimensional (O), and four as must be (M) features. The remaining 13 features were viewed as indifferent (I).

To gain additional insights into the features' role in creating passenger well-being, CS+ and CS- coefficients were calculated (c.f. Figure 6.2). For CS+, the threshold is set to .50 to identify features that are particularly beneficial for passenger well-being, such as the memory function (I6) or seat massage (V7). For CS-, the threshold is set to -.50 to identify basic features that have to be present to avoid reduced passenger well-being like storage (V9). Using these thresholds, nine features are identified as drivers of passenger well-being (CS+ > .50), which can be clustered content-wise into the two groups: leisure enablers and smart functions (c.f. Figure 6.4). Six features are basic requirements for passenger well-being (CS- < .50) and are required in an automated vehicle to create a minimum level of passenger well-being (c.f. Figure 6.3).

Table 6.1 Categorization of vehicle features regarding passenger well-being using the Kano method.
Note: C: category, n.s.: not significant, sign.: significant.

Feature	C	C strength [%]	Total strength [%]	Fong test		Feature	C	C strength [%]	Total strength [%]	Fong test
Driving dynamics										
D1. Adjustable driving style	O	7.25	72.46	n.s.		D2. Active chassis	I	11.59	43.48	n.s.
Vehicle architecture										
V1. Flexible steering wheel	I	31.88	40.58	sign.		V2. Swivel seats	I	14.49	52.17	sign.
V3. Individual seats	O	7.25	59.42	n.s.		V4. Relax position	A	11.59	69.57	n.s.
V5. Foot rest	A	2.90	62.32	n.s.		V6. Arm rest	M	4.35	75.36	n.s.
V7. Massage	A	4.35	73.91	n.s.		V8. Table	I	17.39	50.72	sign.
V9. Storage	M	8.70	88.41	n.s.		V10. Privacy glass	A	1.45	53.62	n.s.
V11. Cocooning	I	53.62	10.14	sign.						
Materials										
M1. Sustainable materials	I	17.39	53.62	sign.		M2. Material quality	M	13.04	82.61	n.s.
Ambient features										
A1. Active noise canceling	I	11.59	47.83	n.s.		A2. Situational air conditioning	A	18.84	60.87	sign.
A3. Situational ambient light	I	30.43	37.68	sign.		A4. Situational reading light	I	21.74	39.13	sign.
Driver interaction										
I1. Voice control	I	24.64	53.62	sign.		I2. Own devices	I	42.03	37.68	sign.
I3. Individual displays	A	10.14	55.07	sign.		I4. Vehicle status display	M	11.59	88.41	n.s.
I5. Vehicle status ambient	I	15.94	53.62	sign.		I6. Memory function	O	5.80	71.01	n.s.
I7. Learning system	A	7.25	52.17	n.s.						
Driver health and wellness										
H1. Relaxation exercises	I	72.46	13.04	sign.		H2. Themed interiors	A	0.00	57.97	n.s.

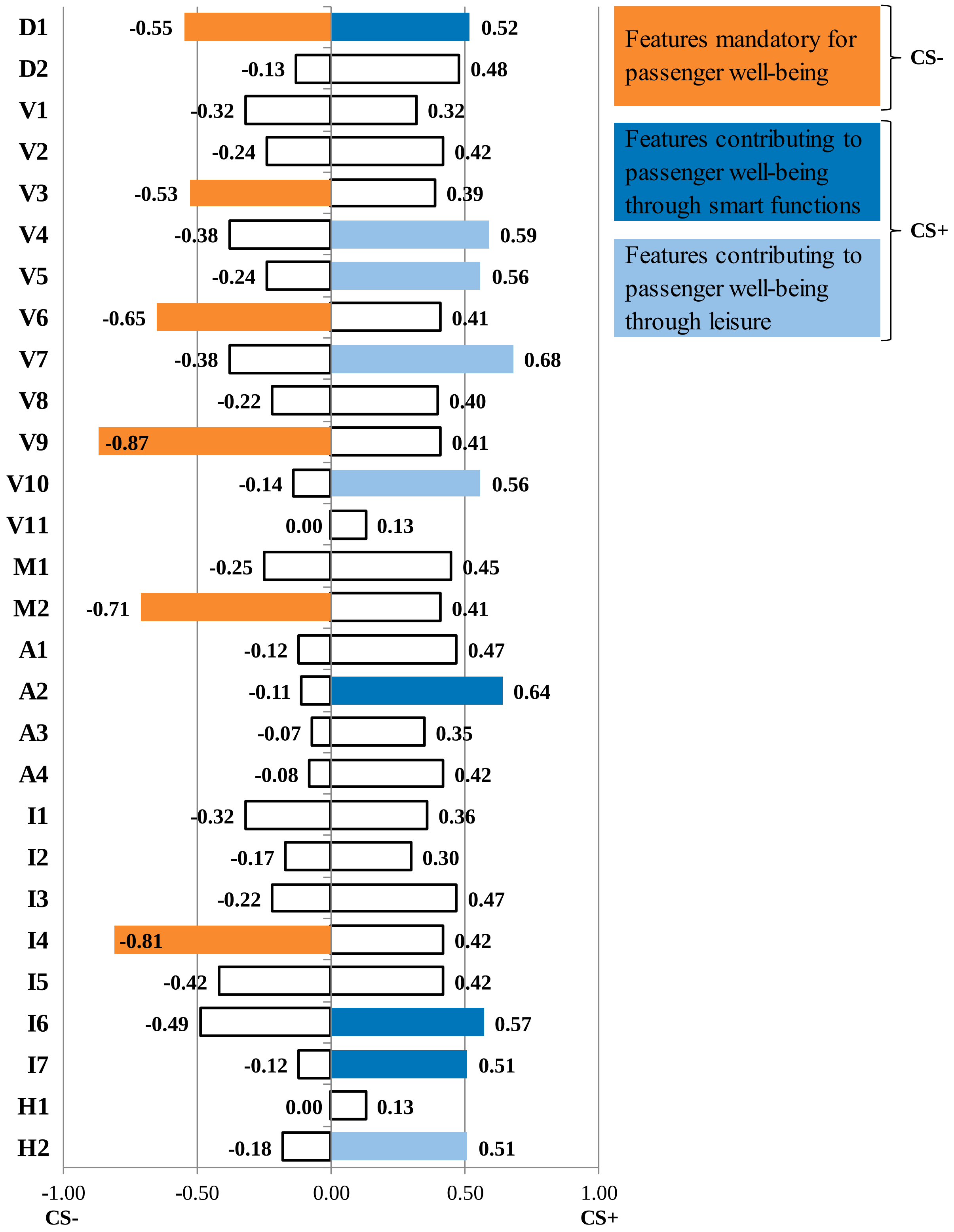


Figure 6.2 CS+ and CS- coefficients for investigated features.

Note: numbering equivalent to Table 6.1.

6.4 Discussion

The exploratory approach to review concept cars for automated driving reveals novel features beyond those proposed in related work (c.f. Table 2.2). Identified novel physical features tend to make traditional features smarter, such as situational air conditioning or lighting. In addition, some features are identified that transform the vehicle interior more towards a living room style living space. With automation, functions simplifying user interaction by making the interaction easier or providing automation-related information evolve.

In the overall categorization, participants view more than half of the features (15 of 28, 54%) as relevant for their well-being. These relevant features are distributed across all six feature groups (driving dynamics, vehicle architecture, etc.). Based on these results and the approach used, there is no indication that one feature group is viewed as more important for passenger well-being, and thus, no hierarchy of input features is evident.

Features that are rated as attractive for passenger well-being are already evident in other modes of transport or can be found in reduced form in today's production cars. For example, seats with massage functions and seat adjustments (although in a limited range for the driver) can be found in cars today. Further, cars usually have automatic air conditioning (c.f. Section 2.3.1), although it may not react to situational influences. Most of today's cars are equipped with displays. Privacy glazing, depending on legal regulations, is offered optionally. Self-learning systems and themed interiors are gaining traction in passenger cars (Automobilwoche, 2019; Mercedes-Benz, 2017). Relax positions, foot rests, and individual displays are also available to different degrees in other modes of transport such as trains or planes.

Interestingly, those features that may appear more novel and are often integrated into concept cars for automated driving are rated as non-relevant, such as active chassis, swivel seats, flexible steering wheel or noise canceling (e.g., AUDI AI-ME, see NetCarShow.com, 2019 or Nissan IDS concept, see Nissan, 2015). It is unclear if this rating is true, and these features actually are irrelevant for passenger well-being, or if the demonstration and explanation during the study were not sufficient for participants to understand these features. The latter may be less probable as the number of questionable classifications per feature is very low. Only 11 of 28 features were classified as questionable by individual participants. The highest number of questionable classifications per feature was three. Another possible explanation may be that these features can cause ambivalence. On the one hand, they facilitate NDRTs by providing more space, more natural social interaction, and a quiet ambiance. On the other hand, this facilitation comes at the expense of control. Especially for novice users, the surrender of control by not only giving up the driving task but also actively disengaging from monitoring the automation system can reduce passenger well-being. The trade-off between control and engagement in NDRTs has been addressed in research previously (Miglani, Diels, & Terken, 2016) and calls for consideration in the design of automated vehicles, especially in the first generations.

It is important to note that a feature that is classified as indifferent here does not affect the level of positive mood, relaxation, or alertness while traveling in a private-use automated vehicle. Indifferent features may, however, be applicable for other evaluations, such as the purchase decision. Some participants mentioned during the study that despite rating some features such as the sustainability of materials as indifferent, they would consider the feature in a purchasing decision. Cocooning was mentioned as more relevant if traveling in a ride-sharing vehicle.

In terms of customer satisfaction coefficients (c.f. Figure 6.2), features identified as mandatory for passenger well-being (CS- < -.50, c.f. Figure 6.2) are, to some extent, already available in vehicles today. Individual seats (V3), arm rests (V6), and storage (V9) are commonly found in passenger cars across different segments. With increasing segment, the quality of materials (M2) tends to improve. As the mockup used in the study is designed by AUDI, participants may have applied standards of the premium segment for their evaluation and thus, require sufficient material quality for their well-being in the context of premium mobility. In vehicles with ADAS typically a display with information on availability and status of ADAS is available and options to configure the behavior of the systems are offered. For example, adaptive cruise control typically allows drivers to select the target speed and headway to preceding vehicles (Vollrath, Schleicher, & Gelau, 2011). These mandatory features are visualized exemplary in Figure 6.3.

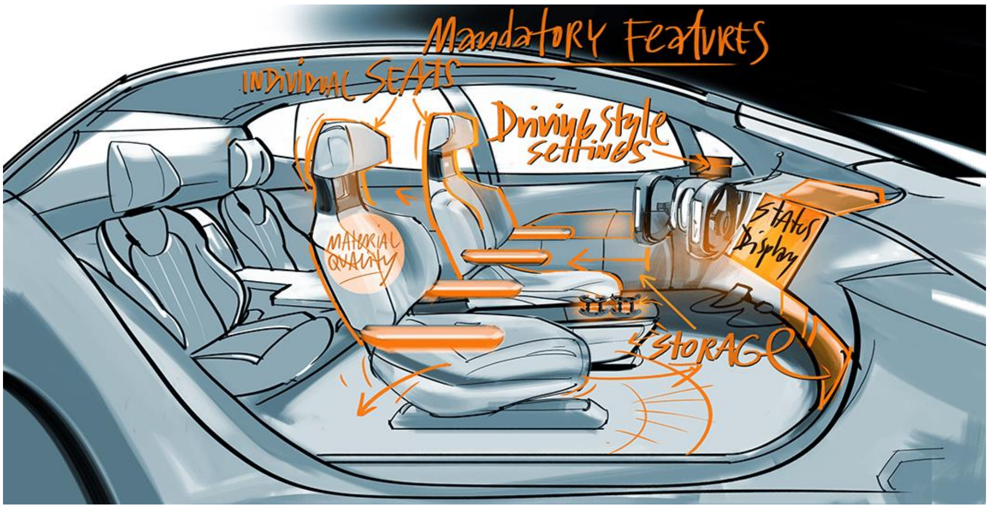


Figure 6.3 Visualization of mandatory vehicle interior features, copyright by schnellervorlauf gmbh.

The features strongly fostering passenger well-being (CS+ > .50) can be clustered into two groups: features enabling leisure and smart functions (c.f. Figure 6.4). Drawing from the features investigated, leisure can be created by a seat with massage (V7), allowing relax positions (V4) and combined with a foot rest (V5). In addition, privacy glass (V10) can help passengers to disengage from the outside world and focus on NDRTs. Such NDRTs may be facilitated by themed interiors (H2) by creating an appropriate interior ambiance. These features strongly reflect ideas of wellness, which is also suggested for future cars by manufacturers (e.g., Mercedes-Benz, 2017). Yet, participants stated that they would rather choose their own leisure activities than using in-car options such as relaxation exercises (H1).

Passenger well-being can be increased through smart functions such as adjustable driving style (D1), air conditioning that reacts to situational changes (A2), and a smart interior that remembers settings (I6) and is able to learn preferences (I7). These smart functions contribute to making user interaction more intuitive, easier, and less cumbersome.

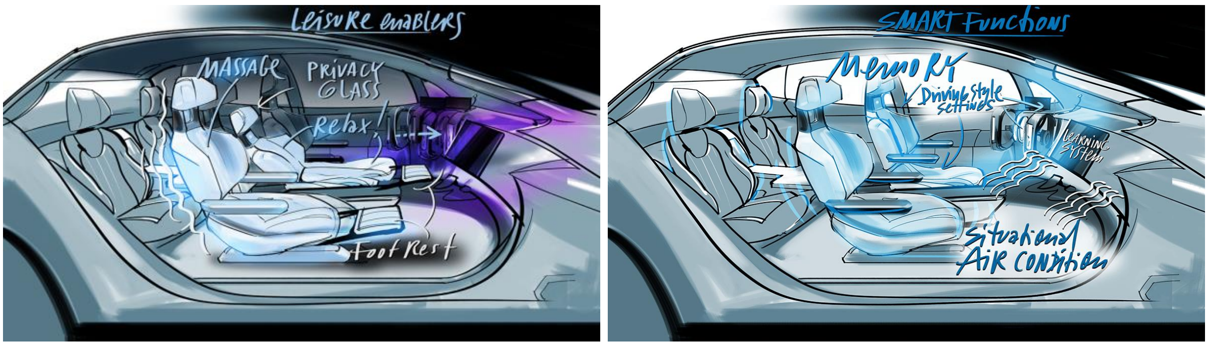


Figure 6.4 Visualization of vehicle interior features identified as leisure enablers (left), and smart functions (right), copyright by schnellervorlauf gmbh.

6.5 Limitations

When taking these results into account, it should be considered that the features could only be presented as prototypes or explained verbally (c.f. Appendix A.9). This may have impacted classification, as participants rather had a first impression instead of substantial experience with the features. Thus, rating the long-term impact of each feature on passenger well-being may have been difficult for participants. To counteract this limitation, participants were recruited from the automotive sector and thus, are expected to find the rating task easier than laypersons. Further, the market analysis of presented automated vehicle concepts may not include all physical and technical features of market-ready automated vehicles. To maintain a competitive advantage, car manufacturers may not present all the features they are developing. Additionally, features can emerge from advances in other areas such as consumer electronics or interior design. Also, these advances in related fields and the automotive industry itself can cause the feature classification to evolve (Mikulić & Prebežac, 2011) by the time level 4 automated vehicles are market-ready. Once these vehicles are available, they will likely be compared with other vehicles and related products available in the market at the same time.

6.6 Conclusion

To investigate which technical and physical features are relevant for passenger well-being (RQ3), a multi-step approach applying the Kano method was utilized. To identify novel features unique to automated driving, an exploratory approach investigating concept cars, an expert rating, and a subsequent user study was used. In total, 28 features were evaluated in the user study. These features are added to the categories of physical and technical features and function as input for the model of determinants of passenger well-being (c.f. Table 6.2).

In the study, 15 features were classified as important for passenger well-being (remaining 13 features rated as indifferent). The classification indicates that features, which are standard in today's cars, such as arm rests, storage, or information on vehicle status, are basic requirements for passenger well-being. Features creating an environment for leisure activities (e.g., seats with relax positions and massage, privacy glass) and smart functions (e.g., preference learning system, adaptive driving style) are ways to increase passenger well-being.

The results additionally indicate that the relationship between features and passenger well-being may be context-dependent. Some features like cocooning are rated irrelevant for a private use scenario while it may be important in ride-sharing situations. Other features like material quality are taken for granted in case of premium vehicles and would impair passenger well-being if missing. For volume cars, material quality may be classified differently. As automation technology will involve additional costs, it may be expected that this technology will be developed for the top of the range vehicles first before being carried over to volume cars.

For the model of determinants of passenger well-being in automated driving, the results indicate that in addition to those features identified from related work, additional features apply to automated driving (c.f. Table 6.2). The results warrant the inclusion of technical features as an own group of input features (c.f. Figure 6.5). From a vehicle development perspective, physical and technical features are predominant in the model of determinants of passenger well-being.

Table 6.2 Overview of physical and technical features based on related work and empirical findings.

Note: Italic: features from related work that are confirmed by empirical findings from the Kano study.

Sources: 1 Richards (1980); 2 Vankan (2010); 3 Ahmadpour et al. (2014); 4 Mayr (1959)

	Physical features			Technical features
	Dynamic	**Ambient**	**Spatial**	
Features from related work (Table 2.2)	Vertical, lateral, longitudinal acceleration [1] Roll, pitch, yaw rate [1] Shocks, jolts [1,3,4] Vibration [2,4] Ascents, descents [1] Change in speed [1] *In-flight entertainment* [3] In-flight service [3] Food [3,4]	Noise [1,2,3,4] Light [3,4] Pressure [1,2,3] Humidity [1,2] Temperature [1,2,3,4] Ventilation [1,2,4] Air recirculation [2] Air velocity [2] Smoke [1] Air quality [1,4] Odors [1]	*Seat* (width, *adjustment*, shape, and firmness) [1,3] Windows [3,4] Leg room [1,3] Ingress/egress [3] Workspace [1] *Storage* [3] Aesthetic design [4] Information [3] Sanitary installations [3,4]	
Additional proposed novel features	Active chassis Relaxation exercises	Active noise canceling Situational air conditioning Situational interior lighting Themed interiors	Flexible steering wheel Swivel seats Seat adjustment allowing relax positions Foot rest Arm rest Massage Privacy glass Cocooning Material type, quality	Adjustable driving style Voice control Connectivity to own devices Individual displays Vehicle status (display or ambient) Memory function Preference learning

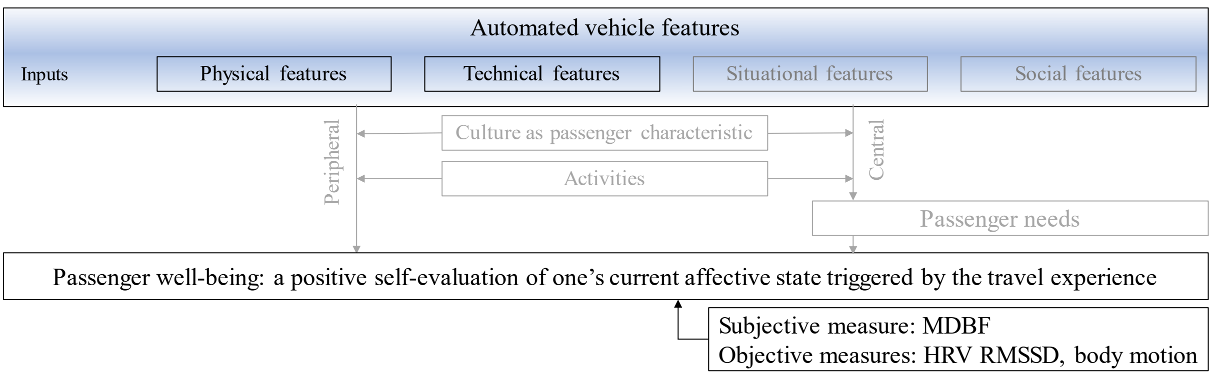


Figure 6.5 Updated overview of the proposed model of determinants of passenger well-being based on results of RQ3.

7 Perception Process of Vehicle Features[5]

Having identified what physical and technical features can apply to automated vehicles, the next step in building a model of determinants of passenger well-being is to identify how passengers perceive and process these features during automated driving using ideas from ELM (RQ4). The level of motivation and ability and the resulting likelihood of elaboration may determine if features are processed more holistically through the peripheral route, or if processing takes place cognitively with the help of passenger needs through the central route (c.f. Section 2.2.3). Based on this argumentation, RQ5 raised earlier comes into play to provide insights into which needs passengers may consult when processing centrally. Therefore, in the following RQ5 is addressed to provide a basis for investigating RQ4.

7.1 Identification of Passenger Needs

Six potential passenger needs (safety, trust, comfort, physical well-being, aesthetics, and symbolism) are suggested in related work, and the question of the relevance of theses six passenger needs in automated driving is raised in RQ5a. In line with RQ5a, the following is hypothesized:

> *H1a-f: The passenger needs safety, trust, comfort, physical well-being, aesthetics, and symbolism positively relate to passenger well-being in automated driving.*

The empirical investigation of H1a-f and the identification of additional passenger needs are integrated into the same user study as RQ1 and RQ2a (c.f. Sections 4 and 5.1) using a mixed approach with quantitative and qualitative data (c.f. Figure 4.1). Empirical data from this user study also provides insights into how these passenger needs may relate to well-being (RQ5b).

7.1.1 Study Design and Data Analysis

A multi-step study was conducted to address multiple research questions, RQ5 among them (c.f. Sections 4.1 for the study design and 4.2 for the experimental procedure). In total, 40 participants participated in the study. The sample characteristics are detailed in section 4.3. The measurement of the six passenger needs hypothesized in H1a-f is detailed in section 5.1.3. To analyze the empirical data and address H1a-f, OLS regression was calculated. To take the repeated measure design into account, OLS regressions were calculated separately for the best

[5] Parts of this chapter have been published in following publications: Sauer, Mertens, Heitland et al. (2019) and Sauer, Mertens, Reiche et al. (2020)

and worst case. The qualitative interview data relevant for RQ5 was collected by participants' answers to two questions:

- Which adjectives would you use to describe your state when experiencing a high level of well-being in an automated vehicle?
- Which adjectives would you use to describe an automated vehicle interior that created a high level of well-being for you?

The first question is primarily used to understand how participants view passenger well-being (RQ1) and was therefore analyzed in this regard in section 4. Yet, the results also provide indications for additional passenger needs. The second question was analyzed in the same way. Additionally, participants were asked to rate different potential passenger needs in their importance for passenger well-being (5-point scale, 1: very unimportant, 5: very important).

7.1.2 Results

Turning to the six hypothesized passenger needs, OLS regression ($F(3, 39) = 17.829$, $p < .001$, adj. $R^2 = .564$) shows safety, aesthetics, and symbolism significantly predict passenger well-being in the best case. In the worst case ($F(2, 39) = 17.885$, $p < .001$, adj. $R^2 = .464$), physical well-being and distrust are significant predictors of well-being (c.f. Table 7.1).

Table 7.1 OLS regression coefficients for passenger needs as predictors of passenger well-being in the best and worst case.

	Non-standardized coefficient B	**Standardized coefficient β**	**p**
Best case			
Intercept	.606		.283
Safety	.528	.462	.001
Aesthetics	.415	.493	.001
Symbolism	-.125	-.249	.044
Worst case			
Intercept	2.275		< .001
Physical well-being	.561	.610	< .001
Distrust	-.172	-.264	.032

The qualitative interview provides additional insights into further passenger needs. Clusters of adjectives used to describe a state of passenger well-being are discussed in chapter 4 (c.f. Table 4.1). In addition to the three major categories (positive mood, relaxation, and alertness), three additional categories comfort, control, and prestige were found, which may be interpreted as passenger needs as suggested in related work (c.f. Section 2.3.4).

Further, the qualitative interview revealed 81 unique adjectives used to describe a vehicle interior that fosters passenger well-being. These can be clustered into eight categories: usability, spatial feeling, comfort, atmosphere, symbolic value, safety, aesthetics, and hygiene (c.f. Appendix A.10). The results from the importance rating indicate that trust and safety are of the highest importance, while aesthetics and symbolism are less important (c.f. Figure 7.1).

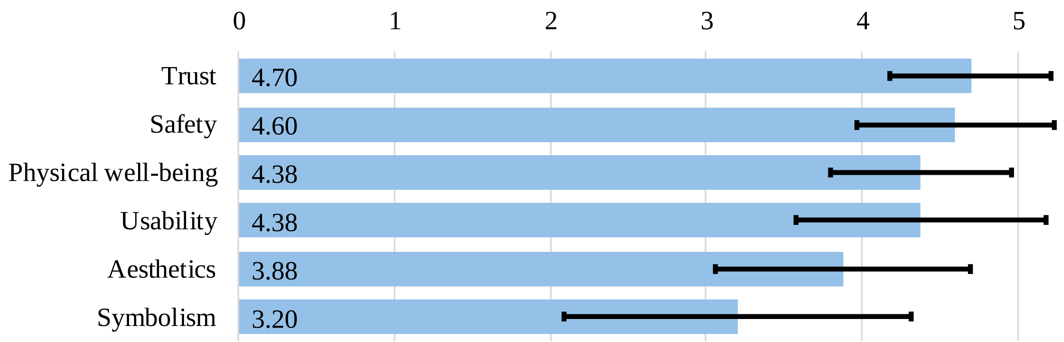


Figure 7.1 Mean importance rating of selected passenger needs for passenger well-being, error bars ± 1 SD.

7.1.3 Discussion

Regression data (c.f. Table 7.1) supports the hypothesis that safety, aesthetics, physical well-being, and trust (in the form of distrust) are passenger needs that contribute to passenger well-being (H1a-b, H1d-f). Safety and aesthetics are additionally supported by the results of the qualitative interview on adjectives for a well-being-enhancing interior (c.f. Appendix A.10). Comparing the standardized coefficients β, physical well-being has the strongest impact, followed by aesthetics, safety, and distrust. Interestingly symbolism leads to a decrease in passenger well-being. A similar negative but non-significant relationship is also found in the correlation analysis between passenger well-being and symbolism (c.f. Table 5.1), which may indicate social desirability in empirical data. In contrast, participants mention prestige as a vehicle interior characteristic that can lead to passenger well-being. The importance of symbolism for passenger well-being is further rated above the scale center ($M = 3.20 > 3.00$), providing qualitative evidence that symbolism may be an ambiguous but relevant passenger need.

The different predictors of passenger well-being in the best and worst cases indicate that the importance of passenger needs may be context-dependent. In the worst case scenario, needs related to utilitarian evaluation (trust) and physical intactness (physical well-being) appear to be dominant. In the best case scenario, utilitarian evaluations (safety) are complemented by hedonic reactions (aesthetics and symbolism). This potential hierarchy of utilitarian needs being more important than hedonic needs is supported by the importance rating (c.f. Figure 7.1), where trust, safety, physical well-being, and usability rank before aesthetics and symbolism.

Of the hypothesized needs, only comfort is not supported as passenger need by empirical data. It is not a significant predictor of passenger well-being in any of the cases. However, comfort is mentioned as a passenger need in the qualitative interview and constitutes the third largest group of adjectives used to describe a vehicle interior that creates passenger well-being. In combination with related work indicating comfort as relevant passenger need, it may be assumed that comfort is a passenger need in the context of automated driving.

To identify additional passenger needs, the adjectives used to describe passenger well-being and the vehicle interior are consulted. The results suggest usability, control, and spatial feeling as passenger needs. Usability constitutes the largest group of interior adjectives and indicates that a user-friendly, clear, and functional interior can contribute to passenger well-being. As discussed in section 2.3.4, usability can lead to positive affect (e.g., Hassenzahl et al., 2010; Thüring & Mahlke, 2007) and, thus, is considered as a relevant passenger need. Spatial feeling follows usability as the second largest group of adjectives. However, the adjectives suggest that spatial feeling is more subjective than other passenger needs. Participants' answers differ whether the vehicle interior should be open and spacious (24 responses) or rather closed and cocooned (11 responses). In literature, evidence is found that passenger well-being can be influenced by spatial feeling (e.g., Hiamtoe, Steinhardt, Köhler, & Bengler, 2012; Kremser et al., 2012; Krun, 2017). Control has been identified as a passenger need in adjectives describing passenger well-being (c.f. Chapter 4). Empirical evidence in related work also supports the idea of control being a passenger need (c.f. Section 2.3.4).

To summarize, H1a-b and H1d-e are supported. All hypothesized passenger needs except comfort and symbolism receive empirical support. Yet, comfort and symbolism as passenger needs are supported by qualitative data and related work. From qualitative data, the passenger needs control, spatial feeling, and usability are derived. Using the empirical regression data and the importance ratings, the identified passenger needs may be classified into utilitarian needs and hedonic needs. The classification follows suggestions from research on benefits created by product design (Chitturi, Raghunathan, & Mahajan, 2008). Utilitarian needs are more relevant for well-being and need to be fulfilled before hedonic needs become relevant (c.f. Figure 7.2).

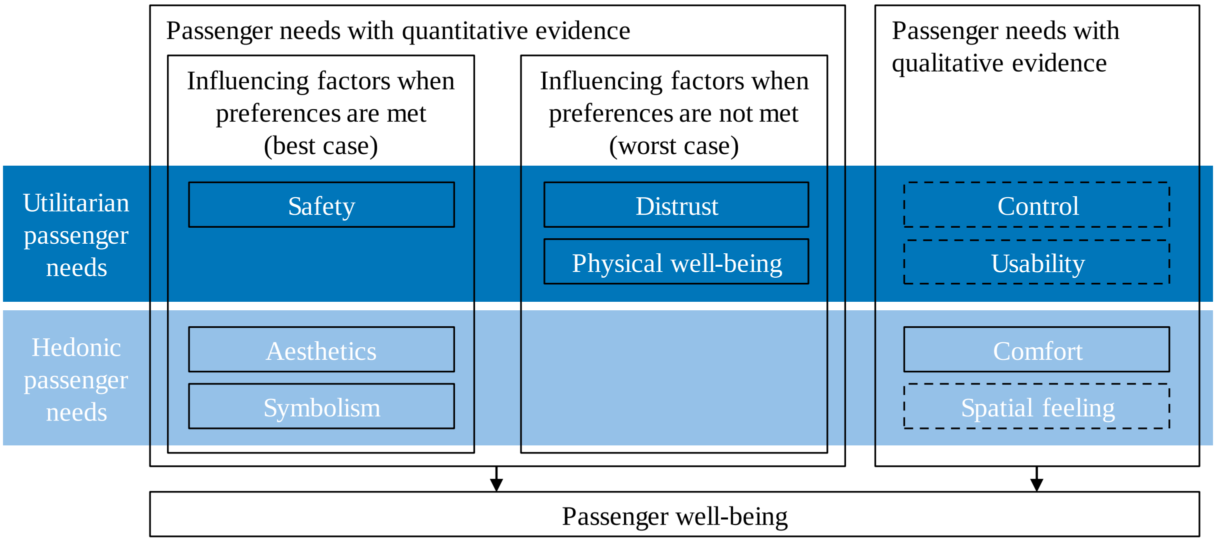


Figure 7.2 Passenger needs derived from quantitative and qualitative data, adapted from Sauer, Mertens, Heitland et al. (2019, p. 243).

Note: Solid lines indicate hypothesized passenger needs, dashed lines indicate additional passenger needs.

7.2 Investigation of Feature Processing

After identifying relevant passenger needs in automated driving, these are now used to investigate if passengers process features according to ELM (RQ4) with the help of a Wizard of Oz user study (c.f. Section 3.3). Elaboration likelihood (EL) is largely influenced by the level of motivation and ability to process features (Petty & Cacioppo, 1986). In this study, motivation and ability are manipulated to reach either higher or lower levels (c.f. Table 7.2), and thus, change the level of EL. Depending on how high EL is, the likelihood of processing vehicle features on the central route, peripheral route, or a combination of both will change (c.f. Section 2.2.3). By applying this mechanism to automated driving, the following is expected:

H1: *High EL (high motivation and ability) leads to a larger number of vehicle features perceived compared to medium EL (high motivation and low ability / low motivation and high ability) compared to low EL (low motivation and ability).*

H2: *High EL (high motivation and ability) leads to a stronger cognitive analysis of perceived vehicle features compared to medium EL (high motivation and low ability / low motivation and high ability) compared to low EL (low motivation and ability).*

H3: *Low EL (low motivation and ability) leads to more features being processed peripherally compared to medium EL (high motivation and low ability / low motivation and high ability) compared to high EL (high motivation and ability).*

H4: *High EL (high motivation and ability) leads to the consideration of a larger variety of passenger needs when determining the level of passenger well-being via central processing compared to medium EL (high motivation and low ability / low motivation and high ability) compared to low EL (low motivation and ability).*

7.2.1 Experimental Setup

For the study, a modified right-hand drive AUDI A8 detailed in section 3.3 was used. The vehicle interior largely matched the current model version (2019), with the exception of the Wizard of Oz adjustments. In addition, a fragrancing system, and additional displays for the automation status, adjustment of the driving style and NDRTs were integrated (c.f. Figure 7.3).

Figure 7.3 Wizard of Oz setup with highlighted pre-defined features for which perception is queried.

The study followed a 2x2 between-subject design with the factors motivation (low/high) and ability (low/high). The participants were assigned to one of the resulting four groups. Gender and age were considered in the assignment to achieve a preferably even distribution. The participants were not informed beforehand about the actual study purpose and to which group they were assigned. The groups or EL levels, respectively resulting from the factors motivation and ability, were used as independent variables. The number of perceived vehicle features, the level of cognitive analysis, the number and type of passenger needs considered while processing were collected as dependent variables.

7.2.2 Procedure

After obtaining informed consent, the participants completed a demographic questionnaire. They then entered the Wizard of Oz vehicle and received instructions depending on their group (c.f. Table 7.2). The route across a factory site used in this study corresponded to city traffic with a maximum speed of 30 km/h with other road users and oncoming traffic. The Wizard of Oz driver was instructed based on the driving instructions from Festner et al. (2017). The drive lasted about 10 minutes. After the drive, a manipulation check was performed by letting the participants rate how able and motivated they were to perceive the vehicle and its features. Then the participants were asked which vehicle features they perceived during the drive in an interview. This open question was complemented by a predefined list of eleven features with varying salience to ensure comparability (c.f. Figure 7.3). Further, the participants were asked how intensively they elaborated on the perceived features and which passenger needs were considered in the determination of the level of well-being for each feature. After completing the interview, participants were debriefed about the study purpose. Per participant, the study lasted, on average, 45 minutes. The participants did not receive any compensation for their participation.

Table 7.2 Priming used in the user study to create high/low levels of motivation and ability.

	Low	**High**
Motivation	Participants are told that the study investigates the suitability of standard built-in vehicle interior sensors to measure well-being in automated driving, and they do not have to do anything specific.	Participants are asked to imagine that they are planning on buying this automated vehicle. They already drove the vehicle manually. Now they want to experience the “autopilot” function. They are instructed to behave as if this were a real test drive with an actual buying decision.
Ability	Participants are instructed to perform a reading comprehension task on a tablet integrated into the center console.	Participants have no specific task but are instructed not to use any personal devices such as phones.

7.2.3 Participants

In total, 84 participants were recruited for the study and assigned to one of the four groups (c.f. Table 7.3). The participants had, on average, a high interest in cars in general. Their prior experience with ADAS was, on average, high. The majority of the participants had a technical background (61 technical, 23 non-technical).

Table 7.3 Overview of sample and group demographics.

Motivation	Ability	Gender	Age	Background	Interest in cars	Experience with ADAS
Total sample		Male: 48 Female: 36	M = 33.51 SD = 9.37	Technical: 61 Non-technical: 23	M = 4.26 SD = 0.81	M = 3.99 SD = 0.84
High	High	Male: 12 Female: 9	M = 31.10 SD = 9.11	Technical: 16 Non-technical: 5	M = 4.33 SD = 0.80	M = 4.05 SD = 0.87
High	Low	Male: 12 Female: 9	M = 33.67 SD = 9.84	Technical: 10 Non-technical: 11	M = 4.24 SD = 0.89	M = 3.86 SD = 1.01
Low	High	Male: 11 Female: 10	M = 34.33 SD = 10.16	Technical: 15 Non-technical: 6	M = 4.14 SD = 0.85	M = 4.05 SD = 0.87
Low	Low	Male: 13 Female: 8	M = 34.95 SD = 8.51	Technical: 20 Non-technical: 1	M = 4.33 SD = 0.73	M = 4.00 SD = 0.63

7.2.4 Data Collection and Analysis

Participants' general interest in cars, prior experience with ADAS, their subjective ability and motivation, and the level of cognitive analysis of each feature were collected on a 5-point scale (1: very low, 5: very high). The predefined list of eleven features (c.f. Figure 7.3) was derived from physical features suggested by prior research (c.f. Table 2.2) and mandatory and attractive features identified in chapter 6 (c.f. Table 6.2). To answer why a feature influenced their level of well-being, the participants could choose from nine passenger needs (c.f. Figure 7.2, multiple answers allowed), a general impression (used to measure peripheral processing), or indicate that the feature is not relevant for their well-being.

The collected data was analyzed using a one-factor ANOVA with the group as a between-subject factor to consider potential group differences resulting from different levels of elaboration. Depending on the hypothesis, the following dependent variables were used:

- H1: Number of perceived features per participant
- H2: Median level of cognitive analysis across all perceived features per participant
- H3: Proportion of peripheral processing per participant
- H4: Variety of needs considered to determine passenger well-being in central processing

Moreover, to assess the hypothesized trend between different levels of EL and the respective dependent variable, a Jonckheere-Terpstra-Test was calculated for each hypothesis.

7.2.5 Results

The results from one-way ANOVAs to assess if different levels of elaboration likelihood affect perception and processing are summarized in Table 7.4. Significant differences between the groups exist for H1, H2, and H4, but not for H3. In the case of H1, post-hoc tests show that the low EL group perceived significantly fewer features than all the other three groups ($p < .001$). The high EL group is not significantly different from any of the mixed groups ($p > .79$). On average, participants in the high EL group perceived 12 features, the mixed groups 11 and 10, respectively, and the low EL group about 7 features (c.f. Figure 7.4). The hypothesized trend that high EL leads to a higher number of perceived features followed by medium and low EL is supported ($J = 1733$, $p < .001$).

In the case of H2, the mixed groups have the highest levels of cognitive analysis (c.f. Figure 7.4). Post-hoc tests show that the low EL group has significantly lower cognitive elaboration than the mixed groups ($p < .01$). The high EL group does not differ from any of the other groups ($p > .21$). Moreover, the increasing trend for cognitive analysis with increasing EL is not significant ($J = 1284$, $p = .063$).

H3 shows no significant group differences. Unexpectedly, the proportion of peripheral processing is, on average, higher for high EL (7.41%) than for low EL (6.83%). The mixed groups show comparably large differences (4.81% and 8.69%, c.f. Figure 7.4). Consequently, no decreasing trend for the EL groups is evident ($J = 1119.5$, $p = .557$).

H4 shows significant group differences regarding the variety of needs considered during central processing. The variety of needs considered is largest in the case of high EL (8.0 needs considered), followed by the mixed groups (both 7.67 needs). The low EL group considered significantly fewer needs in central processing compared to the other three groups (6.1 needs, post-hoc test $p < .01$). The observed trend of increasing variety of needs with increasing EL is significant ($J = 1576$, $p < .001$).

The manipulation checks for subjective motivation ($F(3, 80) = 5.85$, $p = .001$, $\eta_G^2 = .18$) and ability ($F(3, 80) = 8.22$, $p < .001$, $\eta_G^2 = .24$) differ significantly between the groups. In both cases, the high EL group had higher ratings than the low EL group ($p < .01$).

Table 7.4 Results of ANOVAs used to evaluate differences in perception and processing stipulated in H1-H3. Note: Grey highlight indicates significant values ($p < .05$).

Hypotheses	Effect	DFn	DFd	F	p	η_G^2
H1: Perceived features	Group	3	80	15.68	<.001	.37
H2: Cognitive elaboration	Group	3	80	6.14	.001	.19
H3: Proportion of peripheral processing	Group	3	80	.64	.59	.02
H4: Variety of needs in central processing	Group	3	80	8.18	<.001	.23

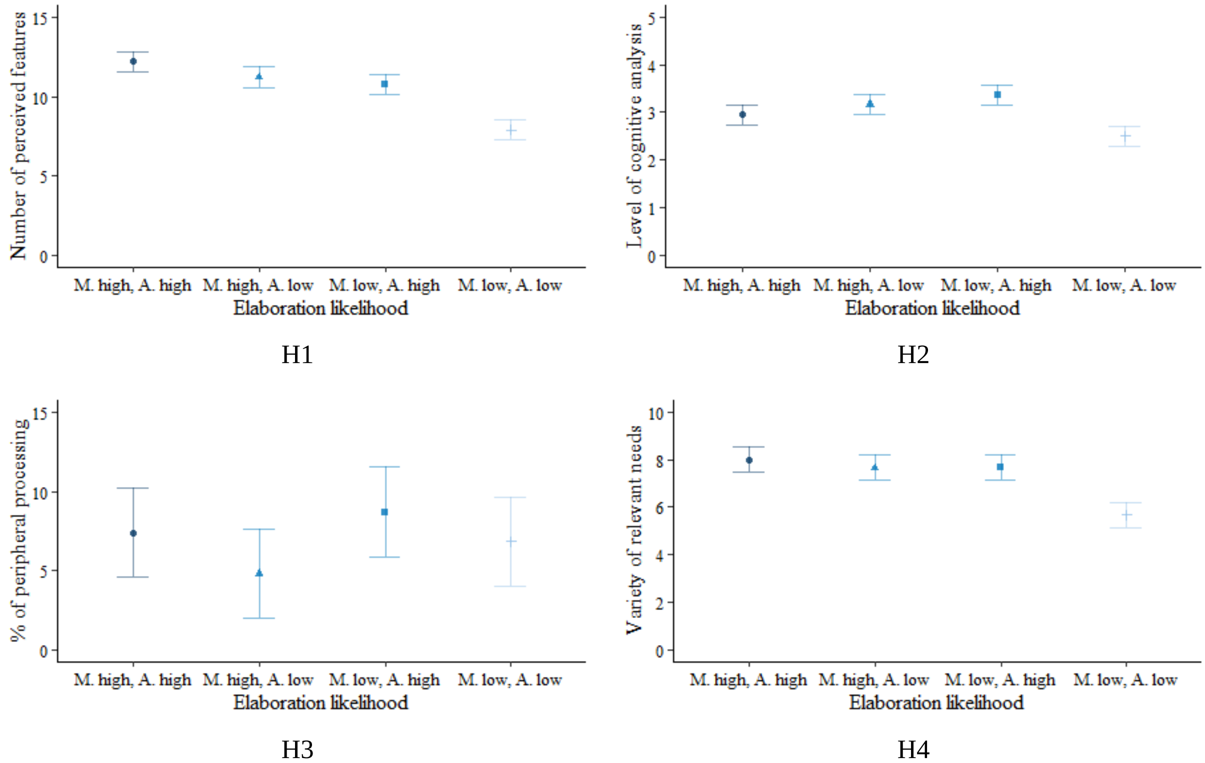


Figure 7.4 Plotted average means for corresponding hypotheses, error bars: Fisher's least significant difference (Sauer, Mertens, Reiche et al., 2020).

7.2.6 Discussion

The user study investigates if ELM with its two processing routes is applicable to automated driving and can complement models on subjective evaluation such as the theory of comfort (Richards, 1980) by shedding light on how vehicle features are processed to determine a level of passenger well-being. H1, H2, and H4 are supported in the case of hypothesized differences between high and low EL. The differences to medium EL are not significant for any of the hypotheses. Yet, the hypothesized trends caused by increasing EL is supported for H1 and H4. Further, H3 is not supported.

The results of this study provide evidence that motivation and ability influence the level of EL in automated driving. The results show that high EL and medium EL lead to significantly more features perceived (H1) and a significantly larger variety of needs considered (H4) compared to low EL. The intensity of cognitive analysis (H2) is significantly higher for medium EL groups than for low EL, which is to be expected according to ELM. However, it is counterintuitive that the cognitive analysis in the high EL group lies below the medium EL groups (c.f. Figure 7.4). ELM argues that willingness to evaluate information does not only depend on motivation and ability but also on individual factors (Petty & Cacioppo, 1986). Based on the demographic information collected in the study, the high motivation and ability group is comparable to the low motivation, high ability group that displays the highest level of cognitive analysis. There is no substantial difference, such as strong non-technical background, low interest in cars, or prior experience with ADAS, which could explain the finding. Other individual differences not collected in the demographic questionnaire or an unknown confounding factor may be cause for this finding and requires further investigation.

Furthermore, the proportion of peripheral processing does not differ between the groups (H3). Unexpectedly, high EL displays similar levels of peripheral processing to low EL. In addition, the large difference between the two mixed groups is not explainable by ELM. A possible cause for this result may be the manipulation used in the study and the recruited participants. Manipulation may not have been strong enough to achieve extreme levels of EL. Instead, mixed processing routes were used. In addition, many participants were excited to participate in the study and were curious about the vehicle. This may have interfered with manipulation.

The results do not provide clear indications if ability or motivation has a stronger impact on EL. For H1 and H3, the mixed group with high motivation indicates stronger EL, while for H2, the mixed group with high ability displays stronger EL. Yet, the difference between both mixed groups is not significant. In the case of H4, no differences are evident. In a similar vein, the differences between high EL and mixed EL are not significant, but both mixed groups differ significantly from the low EL group (H1, H2, H4). This may indicate that for low EL, both motivation and ability have to be restricted. High levels of either motivation or ability are sufficient to increase EL. This provides additional evidence that EL is not strictly high or low, but moves on a continuum in automated driving contexts (Klimmt, 2011).

Overall, the results on the number of perceived features (H1), level of cognitive analysis (H2), and variety of consulted needs in central processing (H4) provide empirical support for the applicability of ELM to automated driving. Thus, it may be assumed that peripheral and central processing take place in parallel in the evaluation of passenger well-being.

For further insights on H4, it is investigated how the level of EL shapes central processing. In total, participants could choose between five utilitarian and four hedonic needs in case of central processing. It appears that for high and medium EL, especially in cases with high motivation, all utilitarian and hedonic needs tend to be exploited when determining the features' effect on passenger well-being (c.f. Figure 7.5). With lower levels of EL, a smaller variety of needs is considered, but utilitarian needs appear to be stronger consulted than hedonic needs. Groups with low motivation tend to consult up to 100% of the preselected utilitarian needs, but the median across these two groups only consults up to 75% percent of the hedonic needs. Although this is only an indication, it strengthens the claim that utilitarian needs appear to be more dominant and need to be satisfied before turning to hedonic needs (c.f. Section 7.1).

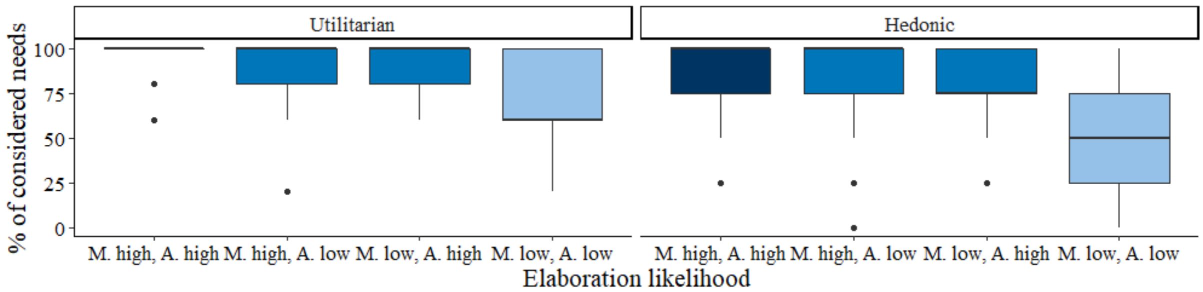


Figure 7.5 Boxplot of percentage of needs from predefined selection used by participants to determine well-being.

The study provides insights into how features are perceived and relate to different types of processing and passenger needs. In terms of perception, the predefined features appear to be perceived by more participants (c.f. Figure 7.6). This may be caused by the study design, where participants were explicitly asked about perceiving these features. Participants frequently mentioned technical features as additional features, such as interfaces and the steering wheel. The novel and atypical design of these features may have led to stronger central processing (Brunner, Ullrich, Jungen, & Esch, 2016). This may suggest that in automated driving, especially novice users pay attention to features that are novel, provide information, and convey control.

In terms of processing routes (H3), all features with the exception of storage were subject to both central and peripheral processing in this study. Yet, central processing prevails. Figure 7.7 allows conclusions to be drawn if a feature appeals stronger to utilitarian or hedonic needs under the consideration that five utilitarian and four hedonic needs were considered. Of the features considered, driving dynamics, noise, climate, and all technical features with the exception of the steering wheel and entertainment were mainly processed centrally with the help of utilitarian needs. On the other hand, smells, all spatial features, the steering wheel, and entertainment target hedonic needs more strongly. This may contribute to an understanding of how certain features are processed and why they are relevant for passenger well-being.

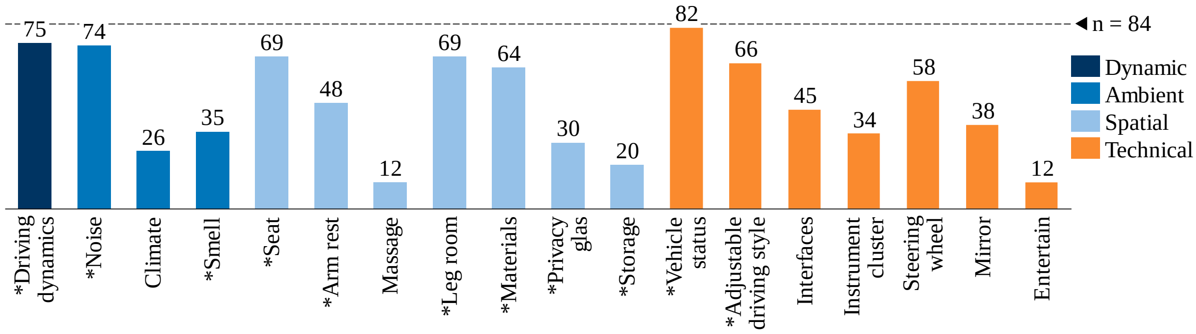


Figure 7.6 Plotted number of participants that perceived a respective feature.

Note: * indicates predefined feature.

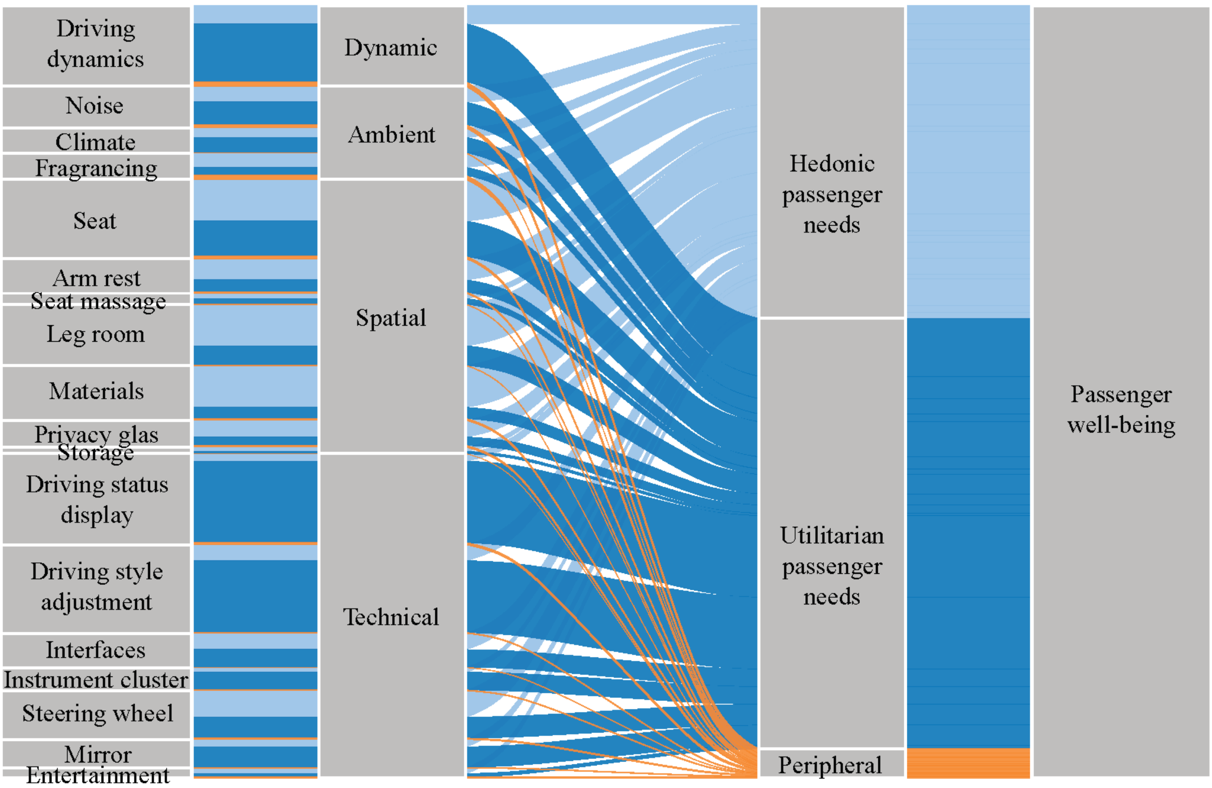


Figure 7.7 Alluvial plot of processing routes and consulted passenger needs.

Note: Width of flows represents the number of hedonic, utilitarian needs consulted in central processing or number of peripheral processing cases.

The overall frequency of passenger needs, peripheral processing, and no effect decisions for all features across all participants are consulted for a more detailed view of the passenger needs (c.f. Figure 7.8). It is evident that in the case of hedonic needs, comfort is the most frequently mentioned need. The frequency of utilitarian needs is more balanced. The dominance of comfort may be explained by the fact that comfort is a frequently used concept to evaluate vehicles and more established than spatial feeling or symbolism. Of all decisions, no effect takes only a comparably small proportion. This suggests that the features perceived frequently affect passenger well-being in automated driving. This provides empirical evidence that passenger well-being is a concept worth considering in the user centered-development of automated vehicles.

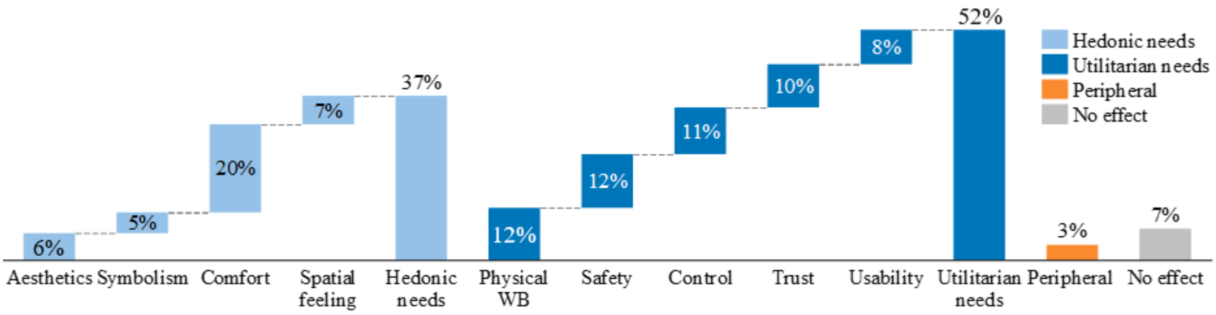


Figure 7.8 Frequency of processing routes and associated passenger needs in assessment of passenger well-being.

7.2.7 Limitations

Overall, the majority of the participants, especially in the high and mixed groups, showed high levels of EL across all aspects. This may be caused by the novelty of automated driving for the participants. Although the participants are, on average, interested in cars and experienced with ADAS, the possibility to experience automated driving is currently scarce. This may have created a bias across all groups to cause closer attention to the vehicle compared to manually driven vehicles. Manipulation may not have been strong enough to surpass this bias. With other, more extreme manipulations, significant differences between all three levels of EL may be possible, instead of only differences between high and low EL found in this study.

Further, the study design with an interview explicitly asking which passenger needs determined the feature's effect on well-being may have biased participants to stronger central processing, as is evident in the results. A revised approach may be recommended to counteract this bias. The needs from which participants were able to select were predefined. Participants had no option to add their own needs. However, in the interviews, only one participant made any additions to the list of needs. The participant suggested adding a need that captures the need for something new, surprising, that causes curiosity and is mentally engaging. This may be a helpful note for research aiming at identifying additional needs. Nonetheless, the participants' feedback provides support that the list of passenger needs presented in this work is fairly complete.

The study design itself may also present limitations. The type of vehicle used as a stimulus may impact the selection of needs and processing types. A different car with different features or a different design of the same features may provoke other responses. However, as the car used in this study is a regular vehicle, the generalizability of results may still apply. Similar effects may be caused by different routes, especially in case of driving at higher speeds, such as on highways and longer exposure to features through a prolonged driving experience.

7.3 Conclusion

This chapter aims to identify the applicability of the elaboration likelihood model for the determination of passenger well-being in automated driving. In the first step, passenger needs were identified. Empirical support for safety, distrust, physical well-being, aesthetics, and symbolism was gathered in a user study. Qualitative results suggest that control, usability, comfort, and spatial feeling may be additional needs, which with sufficient fulfillment, can contribute to passenger well-being. Further, indications for a hierarchy of needs are evident. The nine passenger needs can be split into utilitarian and hedonic needs (c.f. Figure 7.2). Utilitarian needs tend to require fulfillment similar to hygiene factors before hedonic needs increase in relevance. The model of determinants of passenger well-being may, therefore, be extended to include nine passenger needs divided into utilitarian and hedonic needs (c.f. Figure 7.10).

With the help of the identified passenger needs, the applicability of the dual processing mechanism proposed in ELM for passenger well-being in automated was investigated. Dual processing is evident from study results. Not only extremes of high or low EL are visible, but participants' EL moves on a continuum depending on ability and motivation. Motivation was manipulated with a purchase decision. Other factors may be able to influence motivation, such as the novelty of an automated vehicle causing potentially higher curiosity. Ability was manipulated by an NDRT, which is likely to apply to day-to-day use of automated vehicles and may be an important factor. Yet, individual factors may also play a role and should not be neglected.

In the majority of cases, features of the automated vehicle had an effect on passenger well-being (c.f. Figure 7.9). This stresses the relevance of this work and strengthens the claim to consider passenger well-being in user-centered vehicle development. In the case of central processing, utilitarian needs tend to be more frequently consulted than hedonic needs. However, some feature categories, such as spatial features, tend to be processed more strongly with help of hedonic needs (c.f. Figure 7.9). This finding additionally supports the assumed hierarchy of needs.

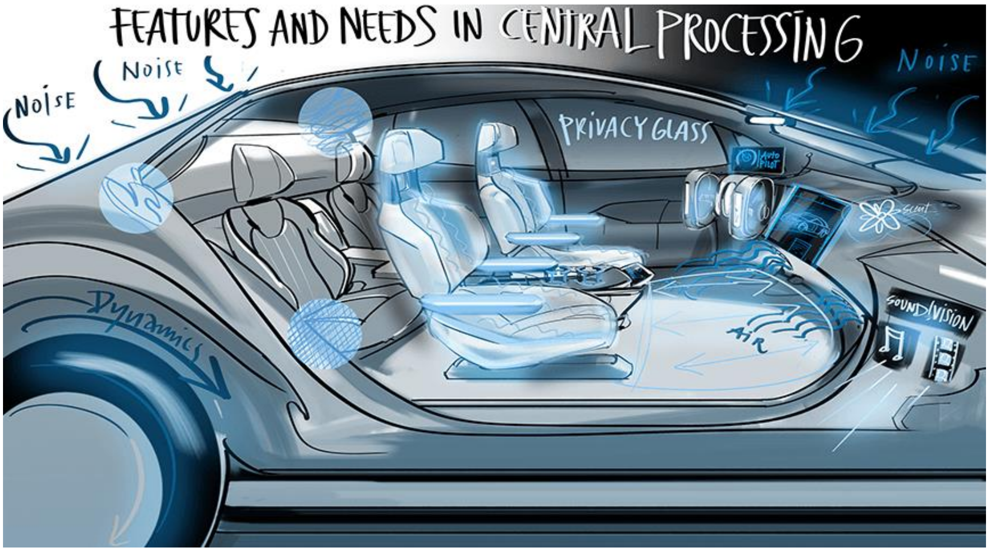


Figure 7.9 Visualization of selected vehicle features and corresponding need types (light blue: hedonic, dark blue: utilitarian) in central processing, copyright by schnellervorlauf gmbh.

Technical features were frequently perceived. This may have been fueled by their novelty and, to some extent, by the study design. Nonetheless, this supports the model extension made in chapter 6 to include technical features, such as user interfaces providing information on the vehicle status, as determinants of passenger well-being. In sum, processing as conceptualized in ELM applies to automated driving. In the case of central processing, nine passenger needs are applicable. Thus, the model of determinants of passenger well-being is extended to include two processing routes and nine passenger needs (c.f. Figure 7.10).

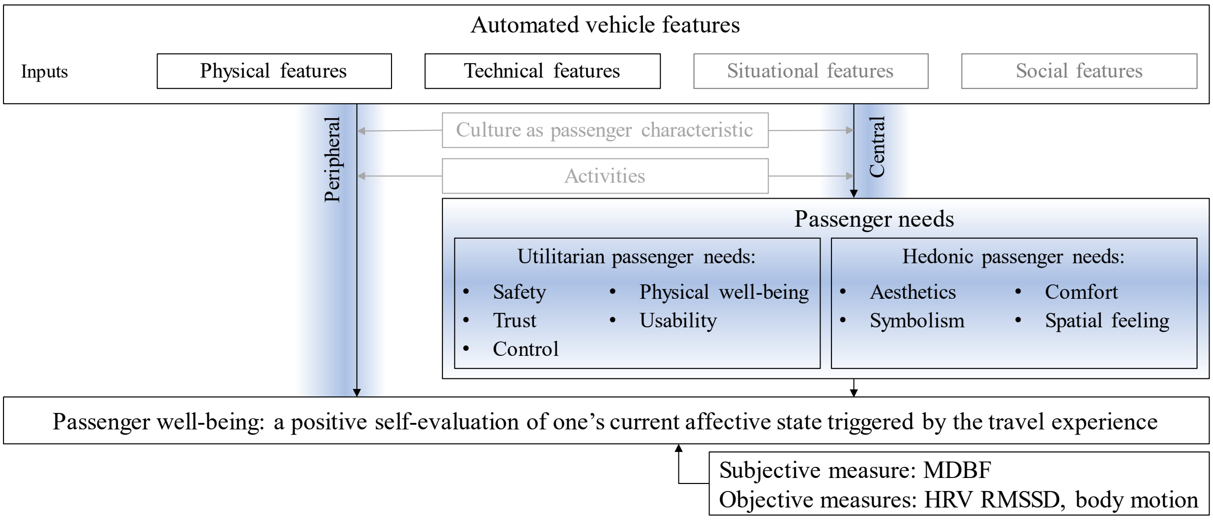


Figure 7.10 Updated overview of the proposed model of determinants of passenger well-being based on results to RQ4 and RQ5.

8 Evaluation of the Basic Model

Taking the results from empirical studies on RQ1-5 jointly into account, a basic model of determinants of passenger well-being in automated driving can be derived (c.f. Figure 7.10). This basic model considers physical and technical vehicle features as model inputs relating either directly to passenger well-being (peripheral route) or through mediating passenger needs (divided into utilitarian and hedonic needs, central route).

To provide partial empirical evidence for the basic model, a study is required considering not only single aspects of the model but the model as a whole. Conjoint analysis is a suitable method to consider the effect of multiple features jointly (c.f. Section 3.2). Further, adaptions to conjoint analysis allow the collection of multiple dependent variables, which in turn can be used to evaluate the relationship between vehicle features as model inputs, passenger needs as mediators, and well-being as the dependent variable. The user study utilizing the Kano method to identify relevant technical and physical features for automated driving yielded a large variety of features (c.f. Chapter 6). To adhere to methodological constraints, a selection of features has to be made. Thus, the evaluation study considers one NDRT attribute (relaxation/working, c.f. Section 2.5) and three vehicle features in a conjoint design to assess exemplary how vehicle features relate to passenger needs and passenger well-being. The selection of vehicle features considered in this study is based on their relevance for passenger well-being found in an expert rating (c.f. Section 6.2) and their varying level of salience and novelty.

In general, NDRTs can impair passenger well-being if a passenger cannot engage freely in a chosen task, and task execution is obstructed (Oborne, 1978a). Similar negative effects can apply if NDRTs are obligatory, and a passenger is forced to engage in certain tasks (Richards, 1980). In this case, distracting NDRTs that shift attention away from the passenger themselves can be more beneficial than NDRTs that cause the passenger to concentrate on themselves. An example of a distracting NDRT could be working or being productive, while relaxing in the form of a breathing exercise may cause a passenger to be more concentrated on themselves. Thus, it is hypothesized:

H1: Working compared to relaxing creates higher passenger well-being.

Ambient lighting is a frequent feature in vehicle interiors, which often allows the selection of different colors. The effect of ambient light on the passenger is viewed ambivalently in related work. It is put to debate if ambient light has any effect at all on affective reactions. In cases where reactions are found, the color appears to have different effects (c.f. Section 2.3.1). Further, the effect of ambient light is not only considered for passenger well-being but other passenger needs. Orange lighting is expected to improve spatial feeling compared to conditions without ambient light (Mandel et al., 2013). Further, warm colors such as yellow can cause interiors to appear more attractive, while green lighting has detrimental effects (Caberletti, 2013). Based on the previous findings, it is hypothesized:

H2: *Yellow ambient light compared to green ambient light creates higher passenger well-being (a). The passenger needs aesthetics (b), and spatial feeling (c) mediate the effect of ambient light on passenger well-being.*

Seat rotation due to increasing levels of automation is a new feature in passenger cars (c.f. Section 2.3.1). Having the freedom to utilize different seat positions may help to facilitate NDRTs, especially when interacting with preinstalled displays by optimizing viewing angles and lowering physical strain (Young, Trudeau, Odell, Marinelli, & Dennerlein, 2012). This may, in turn, impact the passenger needs usability, comfort, and physical well-being. Further, rotating the seat changes the passenger's perspective on the vehicle interior and the reachability of controls, steering wheel, and pedals. This is likely to impact several passenger needs, including control, safety, trust, and spatial feeling. Taken together, it is hypothesized:

H3: *Seat rotation (15° to center) influences passenger well-being (a). The passenger needs control (b), safety (c), trust (d), and spatial feeling (e) mediate the effect of seat rotation on passenger well-being.*

H4: *NDRTs requiring a central display moderate the effect of seat rotation (15° to center) on passenger needs usability (a) and comfort (b), and on passenger well-being (c).*

Driving noises are unavoidable when traveling by car (Chen et al., 2015). However, numerous strategies to reduce noise in the vehicle interior exist, among them active noise canceling. Reduced noises in the interior can increase passenger well-being (Penning & Quehl, 2010) by increasing passenger comfort (de Diego et al., 2001; Gonzalez et al., 2003; Kim et al., 2000) and physical well-being (Passchier-Vermeer & Passchier, 2000). Driving sounds are frequently tied to symbolic value. Depending on the vehicle category, ideal driving sounds differ. In the case of automated vehicles, a quiet, cocooned interior is expected to be standard (Jorlöv et al., 2017). Based on these results, it is hypothesized:

H5: Active noise canceling creates higher passenger well-being (a). The passenger needs comfort (b), physical well-being (c), and symbolism (d) mediate the effect of active noise canceling and passenger well-being.

8.1 Experimental Setup

For the conjoint analysis, four attributes with two levels each were used (c.f. Table 8.1). NDRTs were executed using a tablet mounted to the center console (c.f. Figure 8.1). For the noise canceling levels, the noise level in a regular car at 100 km/h (Kretzmann, 2012) and a lower but still perceivable noise level validated in a pretest were chosen. The conjoint analysis was conducted using full profiles and a rating-based approach. The profiles were rated regarding passenger well-being and the fulfillment of passenger needs. In addition, objective measures were used as response variable for each profile. Using an orthogonal fractional factorial design, eight profiles were derived (c.f. Appendix A.11). The participants experienced each of the derived profiles in a static driving simulator (c.f. Section 3.3). The simulator was equipped with a screen for the front view and two displays for the side views (c.f. Figure 8.1). The driving behavior in the simulation corresponded to level 4 automated driving. The vehicle behaved safe and reliable. The participants were not prompted with any take-over requests.

Table 8.1 Overview of attributes and levels used in user study.

NDRT	Ambient light	Seat rotation	Active noise canceling
Relaxation (Breathing exercise)	Green	0°	42 dB
Work (Reading comprehension)	Yellow	15°	68 dB

8.2 Procedure

After informed consent was obtained, and the participants were fitted with the necessary sensors for physiological data collection, a ten-minute baseline measurement of the objective measures with a subsequent subjective measurement of well-being was conducted. Prior to experiencing the first profile in the simulator, the questionnaire for the subjective rating of each profile was explained. Each profile was experienced in randomized order for five minutes in the simulator during a level 4 automated drive without any system errors or take over requests. After each drive, the experience was rated regarding the experienced level of well-being and the fulfillment of passenger needs. Participants had a break between each drive to allow physiological reactions to normalize. After the eight simulator drives, participants completed a qualitative questionnaire. Overall the study took, on average, 120 minutes per participant. Participation in the study was compensated with 20€.

Figure 8.1 Setup with the static driving simulator (left) and exemplary interior settings of the mockup (middle, right).

8.3 Participants

For this study, 61 participants were recruited with a focus on participants from all age groups (M = 47.34, SD = 18.46) to increase the generalizability of the study (c.f. Table 8.2). All participants were healthy and had no relevant primary diseases. The participants were, on average, moderately interested in cars (M = 3.51, SD = 1.03), and had little to moderate prior experience with ADAS (M = 2.44, SD = 1.25). The majority of the participants had a non-technical background (40 non-technical, 21 technical background).

Table 8.2 Overview of distribution of age and gender in the sample.

	Male	Female	Interest in cars	ADAS experience	Background
Total sample	36	25	M = 3.51, SD = 1.03	M = 2.44, SD = 1.25	NT: 40, T: 21
18-29 years	10	6	M = 3.50, SD = .97	M = 2.44, SD = 1.09	NT: 6, T: 10
30-49 years	9	6	M = 3.80, SD = .94	M = 2.87, SD = 1.41	NT: 13, T: 2
50-64 years	9	7	M = 3.44, SD = 1.09	M = 2.31, SD = 1.14	NT: 12, T: 4
65 years and older	8	6	M = 3.29, SD = 1.14	M = 2.14, SD = 1.35	NT: 9, T: 5

8.4 Data Collection and Data Analysis

For measurement of passenger well-being, the suggested physiological measures HRV RMSSD and body motion were used and analyzed according to section 5.2.4. For subjective measurement, the evaluated multidimensional state survey was utilized with a 7-point scale. Passenger needs were collected using 1-item measures to minimize participant fatigue. Interest in cars and experience with ADAS were rated on a 5-point scale (1: very low, 5: very high). In the qualitative post-study questionnaire, participants were asked what features they noticed.

Aggregated conjoint analysis was conducted with subjective and objective measures of passenger well-being as dependent variables to investigate peripheral processing. For central processing, a linear mixed model (LMM) was applied to identify which passenger needs significantly predict passenger well-being. For this purpose, a LMM with all nine passenger needs as a fixed effect was used. The stimulus profile ID and participants' ID were included as random effects. LMMs were further used to investigate the hypothesized mediating relationships as part of central processing. Each mediation was modeled individually using LMMs. To analyze the hypothesized moderating effect of NDRTs on the processing of vehicle features, LMMs with interaction effects were applied (c.f. Section 3.2).

8.5 Results

The user study provides results on the effects of vehicle features on passenger well-being using the two processing routes. Further, results on NDRTs moderating the relationship between features and passenger well-being are provided

8.5.1 Peripheral Processing of Vehicle Features

Significant results of aggregated conjoint analysis are displayed in Table 8.3, which are used to evaluate the direct effect of features on passenger well-being as assumed in peripheral processing. In the case of subjective passenger well-being, relaxing has a significant negative and activated noise canceling has a significant positive influence supporting H1 and H5a. Additional evidence for the influence of NDRTs on well-being is visible in the measure of body motion. HRV RMSSD does not yield any significant results. To give a more detailed view on the relationship between subjective and objective measures, HRV RMSSD correlates negatively with subjective passenger well-being ($r = -.155$, $p < .001$) while body motion shows no significant linear relationship with subjective passenger well-being ($r = -.012$, $p = .786$).

Table 8.3 Results of aggregated conjoint analysis for the evaluation of the preliminary model.
Note: Grey highlight indicates significant mediation effects.

	Self-rated WB (adj. R^2 = .041)			**Body motion** (adj. R^2 = .078)		
Attribute level	**Part-worth**	**Std. Error**	**p-Value**	**Part-worth**	**Std Error**	**p-Value**
Intercept	5.847	.104	< .001	.660	.030	< .001
NDRT Relax	-.202	.093	.030	-.175	.027	< .001
Seat rotation 15°	.006	.093	.947	.004	.027	.888
Ambient light green	.005	.093	.959	-.027	.027	.326
Noise Cancelling off	-.418	.093	< .001	.044	.027	.105

8.5.2 Central Processing of Vehicle Features

In this study, the utilitarian needs physical well-being, safety, and trust, and the hedonic need spatial feeling have a positive, significant relationship with passenger well-being (c.f. Table 8.4). Thus, in this study setting, only these four passenger needs significantly predict the level of subjective passenger well-being.

The applicability of central processing was assessed using mediation analysis. Empirical evidence for central processing is only evident in the case of noise canceling. The effect of noise canceling on passenger well-being is mediated by physical well-being (H5c). Other hypothesized central processing routes are not supported by mediation analysis (c.f. Table 8.5).

Table 8.4 Results of LMM to investigate the effect of passenger needs on subjective passenger well-being.
Note: Intercept of fixed effects: 1.305, Std. Error: .174, p < .001; Grey highlight indicates significant effects.

Utilitarian passenger needs				**Hedonic passenger needs**			
Fixed effects	**Estimate**	**Std. Error**	**p-Value**	**Fixed effects**	**Estimate**	**Std. Error**	**p-Value**
Physical well-being	.344	.025	< .001	Aesthetics	.023	.031	.457
Safety	.217	.034	< .001	Symbolism	.016	.024	.501
Control	.047	.026	.075	Comfort	-.046	.033	.163
Trust	.086	.036	.018	Spatial feeling	.075	.030	.014
Usability	.025	.029	.386				

Table 8.5 Results on hypothesized central processing using mediation analysis.

Note: Only causal mediation effects (ACME) displayed, bootstrapping with 1000 simulations; Grey highlight indicates significant mediation effects.

	Estimate (ACME)	95% CI Lower	95% CI Upper	p-Value
Hypothesis 2: Mediating the effect of ambient light on passenger well-being				
H2b. Aesthetics	.006	-.04	.04	.730
H2c. Spatial feeling	.005	-.04	.05	.820
Hypothesis 3: Mediating the effect of seat rotation on passenger well-being				
H3b. Perceived control	-.024	-.08	.03	.290
H3c. Perceived safety	-.046	-.13	.04	.270
H3d. Trust	-.027	-.10	.05	.420
H3e. Spatial feeling	-.038	-.09	.01	.094
Hypothesis 5: Mediating the effect of noise canceling on passenger well-being				
H5b. Comfort	-.018	-.05	.01	.240
H5c. Physical well-being	-.204	-.29	-.13	< .001
H5d. Symbolism	.003	-.02	.03	.800

8.5.3 NDRTs as Moderator

To assess the effect of NDRTs as moderator, LMMs with interaction effects were used. The results (c.f. Table 8.6) only support the hypothesized moderation in the case of seat rotation and usability (H4a).

Table 8.6 Results on hypothesized moderator effect.

Note: LMM fit by maximum likelihood, t-Tests using Satterthwaite's method; Grey highlight indicates significant effects.

Fixed effects	Estimate	Std. Error	p-Value
H4a. Seat x NDRT on usability	-.361	.140	.011
H4b. Seat x NDRT on comfort	-.180	.131	.168
H4c. Seat x NDRT on well-being	-.042	.127	.740

8.6 Discussion

This study is used to provide empirical evidence for the basic model of determinants of passenger well-being. As suggested in chapter 5, passenger well-being is measured using both subjective and objective measures for a nuanced view on the experienced level of well-being. It has been stipulated that passenger well-being is related to a state of relaxation, and consequently, subjective passenger well-being correlates positively with parasympathetic indicators (HRV RMSSD) and negatively with sympathetic indicators (body motion, c.f. Section 5.2.6). However, this assumption is not replicated in this study. Instead, subjective measures showed a negative correlation with parasympathetic indicators (HRV RMSSD) and a non-significant linear relationship with sympathetic activity (body motion) in this study. As the study setup and measurements are comparable between the two studies, one possible explanation for the different relationships in the two studies may be different sample characteristics (c.f. Table 8.7). A tendency is visible that the sample of this study was older, had a less technical background, and was slightly less interested in cars and experienced with ADAS. Two possible mechanisms come to mind that may offer insights into how different sample characteristics relate to the observed effects.

Appraisal theory suggests that emotional reactions to a stimulus or event depend on the appraisal of said event. Different underlying appraisal patterns can explain why people have different reactions to the same situation (Roseman & Smith, 2001). Assuming appraisal theory is applicable to this case, it is not clear what causes the different appraisal patterns. Based on the demographics recorded, it may be related to age, background, interest in cars, or prior experience. However, other characteristics that have not been recorded can also be the cause.

Focusing on the samples' varying level of prior experience with ADAS, habituation effects can be another possible explanation. Habituation is the processes of non-associative learning caused by frequent exposure to a particular stimulus, which in turn can decrease the intensity of the reaction to the stimulus. (Grissom & Bhatnagar, 2009). In terms of physiological measures, it is found that habituation has a more substantial effect on sympathetic activity than on parasympathetic activity (Jönsson et al., 2010). Applied to automated driving, higher exposure to ADAS may cause habituation effects, which in turn reduce sympathetic reaction to automated driving experiences. A study investigating the applicability of habituation effects to automated driving finds a similar negative relationship between the parasympathetic indicator and subjective passenger well-being, as is the case in this study (Sauer, Mertens, Heyden et al., 2020). The authors suggest that passenger well-being can also be a state of positive arousal (excitement) and does not necessarily have to be related to relaxation.

Further, the authors find indications that habituation through prior experience reduces the intensity of sympathetic activity. These possible underlying mechanisms show that the relationship between subjective and objective measures is not plain linear, but rather passenger well-being has extra dimensions in addition to arousal. Thus, physiological proxies cannot be considered isolated, but information on the context and circumstances are required. Therefore, additional research is required before physiological sensors measuring arousal can be integrated into automated driving and be used sensibly for affective computing applications and the control of passenger well-being.

Table 8.7 Comparison of sample characteristics of objective measures study and evaluation study.
Note: +: significant positive correlation, -: significant negative correlation, o: no significant correlation.

	Objective Measures Study	**Evaluation Study**
Relationship objective and subjective measures	Parasympathetic activity: + Sympathetic activity : -	Parasympathetic activity: - Sympathetic activity: o
Age	M = 27.85, SD = 4.45	M = 47.34, SD = 18.46
Background	Non-technical: 3, Technical: 17	Non-technical: 40, Technical: 21
Interest in cars in general	M = 4.20, SD = .77	M = 3.51, SD = 1.03
Experience with ADAS	M = 3.50, SD = 1.15	M = 2.44, SD = 1.25

8.6.1 Peripheral Route Processing

Conjoint analysis is used to assess the peripheral processing mechanism in this study. OLS regression is calculated across the total sample for an aggregated analysis resulting in low adjusted R^2 values. The low coefficients of determination are untypical for conjoint analysis (Gensler, 2003) and may be an indication for a heterogeneous sample that has different preferences regarding the attributes considered. An additional bias may have been caused by the fact that participants experienced each configuration without being informed about the attributes beforehand as opposed to rating each configuration in a paper-based or online questionnaire. The fact that not all estimates are significant (c.f. Table 8.3) can have similar reasons. Either the respective attributes are, in fact, not relevant for participants or preferences may have been split and canceling each other out. The fact that the non-significant attributes seat rotation and color of ambient light are less salient than the significant attributes provides evidence for the first explanation approach. Salience is also visible from the post-study questionnaire where 41 participants (67.2%) noticed noise canceling as a feature, but only 34 (55.7%) and 31 (50.8%) participants noticed ambient lighting or seat rotation respectively. The fact that color preference and seat rotation in this setting may be more subjective and depending on individual taste argues for the latter explanation. In any case, the aggregated conjoint analysis provides indications for peripheral processing by showing a direct relationship between NDRT (H1 supported) and noise canceling (H5a supported) with subjective passenger well-being.

Interestingly, NDRT is the only significant predictor of body motion (c.f. Table 8.3). Relaxation as NDRT provides a negative part-worth. As body motion is stipulated to be negatively related to passenger well-being (c.f. Section 5.3), relaxation would cause a higher level of well-being contrary to H1. As body motion shows no significant linear relationship with subjective passenger well-being, the difference in body motion caused by the NDRT may rather be explained by the nature of the NDRT itself. In the case of relaxation, passengers followed instructions on the tablet without having to interact further with it. The reading comprehension task used as working NDRT required frequent touch-interactions to enter the answer to respective multiple-choice questions. This difference in required movement may explain the change in body motion as opposed to a change in passenger well-being as an explanation.

Despite potential biases, peripheral processing has been found in cases of NDRTs and noise canceling, thus supporting H1 and H5a. Ambient light shows no significant influence in any of the aggregated conjoint analyses (H2a not supported), and thus, suggests that the color of ambient lighting does not affect passenger well-being. However, a large body of research suggests the contrary by indicating a relationship between well-being and colored lighting in other contexts (Westland, Pan, & Lee, 2017).

A reason for the non-significant effect of seat rotation (H3a not supported) may be the small angle (15°), which may have been insufficient to evoke a change in passenger well-being. In addition, driving dynamics were omitted in this study due to the static design of the driving simulator. This may have impacted the perception of seat rotation. Further, seat rotation may be more applicable to social settings and less to individual NDRTs. In future research, the effect of seat rotation on passenger well-being should not only be investigated in light of driving dynamics but also in regards to additional safety features that are required due to the novel seat arrangement (Boin, 2018; Jin et al., 2018).

8.6.2 Central Route Processing

Evidence for the stipulated passenger needs is found in this study in case of physical well-being, safety, trust, and spatial feeling, which are significant predictors of subjective passenger well-being (c.f. Table 8.4). Interestingly, more utilitarian needs were relevant than hedonic needs, which may suggest additional evidence for a hierarchy of passenger needs.

Central processing of vehicle features is considered for selected passenger needs depending on the vehicle feature. Clear evidence is provided in case of noise canceling (c.f. Table 8.5), where the effect on passenger well-being is mediated by physical well-being (H5c). Further, non-significant indications of a mediation relationship exist in case of seat rotation and spatial feeling (H3e). All other hypothesized mediations are without empirical support. The little evidence of central route processing may be caused by the fact that peripheral processing was emphasized by the study design by not informing participants beforehand about the attributes varied.

8.6.3 Moderating Effects of NDRTs

In this study, the moderating effects of NDRTs suggested by the theory of comfort and adopted in the model of determinants of passenger well-being are investigated. This study suggests a moderating effect of NDRTs on the relationship of seat rotation on usability (H4a supported). The moderating effects on comfort (H4b) and passenger well-being directly (H4c) are not supported in this study. Usability remains comparable in the case of 0° seat rotation for both NDRTs. Yet, a 15° rotation decreases usability in case of relaxation but increases usability for working tasks (c.f. Figure 8.2). The change in usability in the case of 15° seat rotation may result from the different levels of interaction required for each task. In the reading comprehension task, participants were asked to answer multiple-choice questions to different excerpts through touch interaction with a tablet mounted to the center console (c.f. Figure 8.1). A rotation toward the tablet may have made touch interaction easier. The instructions for the breathing exercise were displayed on the same tablet but did not require any interaction. Here, rotation may be detrimental to usability because the rotated seat position may have impeded supervision of the automated vehicle and reduced reachability of steering wheel and pedals.

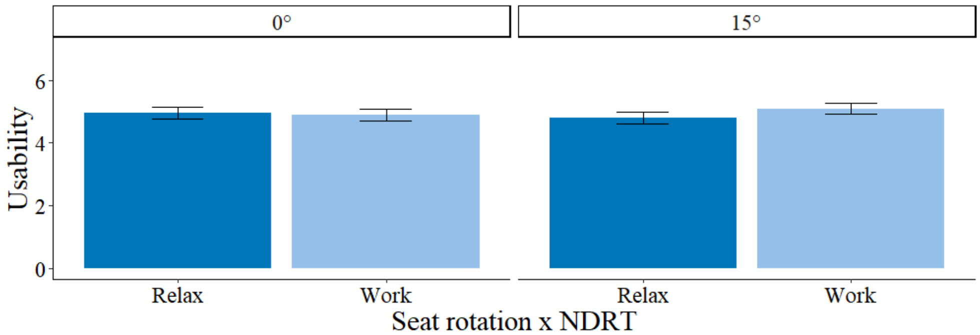


Figure 8.2 Interaction between seat rotation and NDRT on usability, error bars = ± 1 SE.

8.6.4 Limitations

This study aims to provide an empirical evaluation of the hypothesized basic model of determinants of passenger well-being. However, due to methodological constraints, vehicle features cannot be considered in their full range. Instead, selected vehicle features were considered in this study, providing partial empirical evidence for the basic model. Consequently, the relationships with passenger well-being and mediating passenger needs depend on the vehicle features considered as determinants. The use of other features in this study may have revealed other relationships for central and peripheral processing and may have affected the goodness of fit of the applied models. Further, the results of this study and the empirical support for hypotheses should be considered in light of the low coefficients of determination.

The use of a static driving simulator influences the perception of vehicle features compared to a real-world driving experience. The omitted driving dynamics may affect how participants perceived seat rotation (different force effects) or NDRTs (stronger effect of motion sickness) and evaluated them during central and peripheral processing. Further, findings on the measurement and relationship between objective and subjective passenger well-being do not replicate the findings from prior studies, and thus, call for additional research.

8.7 Conclusion

This user study provides first insights into the empirical evaluation of the basic model of determinants of passenger well-being without claiming to be all-encompassing. Despite the limitations, empirical evidence for the fundamentals of the proposed model can be provided (c.f. Figure 8.4).

Automated vehicle features show a direct effect on passenger well-being (peripheral processing) in the case of NDRTs (H1) and noise canceling (H5a). Conjoint analysis results indicate that the working task and active noise canceling is preferred (c.f. Figure 8.3). Central processing is evident for physical well-being, which mediates the effect of noise canceling on well-being. Further, exemplary evidence for the moderating effect of activities is provided for seat rotation and usability (H4a) (c.f. Figure 8.3). Results on the effect of ambient light color indicate a strong subjective preference.

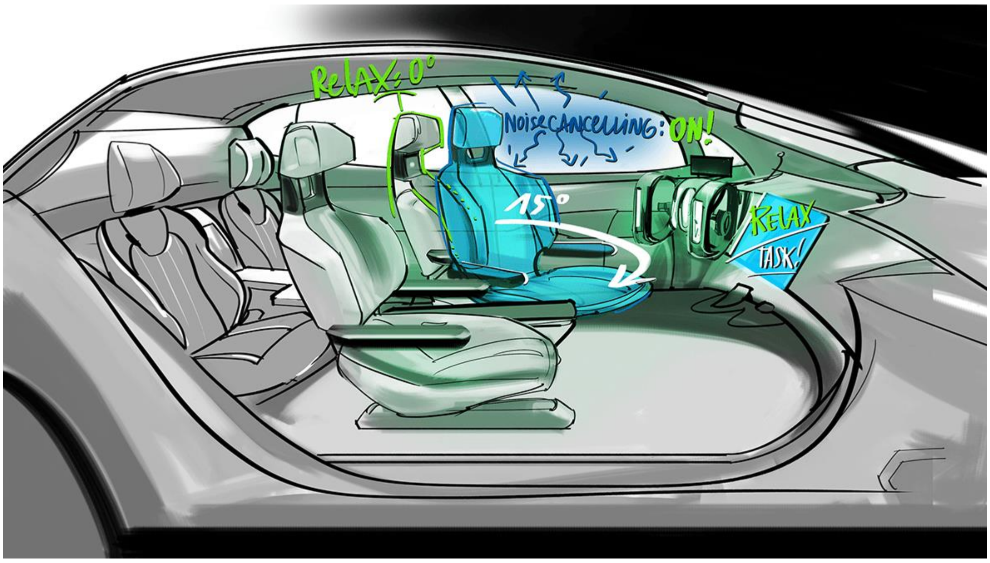


Figure 8.3 Visualization of preferences for automated interiors based on conjoint analysis results, copyright by schnellervorlauf gmbh.

This study also raises additional questions regarding the use of physiological indicators to measure passenger well-being objectively. Due to the multidimensional nature of passenger well-being and interpersonal differences, measures for arousal may not relate linearly to subjective passenger well-being. Instead, individual circumstances such as prior experience and habituation to automated driving and situational contexts have to be considered in order to be able to make statements on passenger well-being based on physiological proxies.

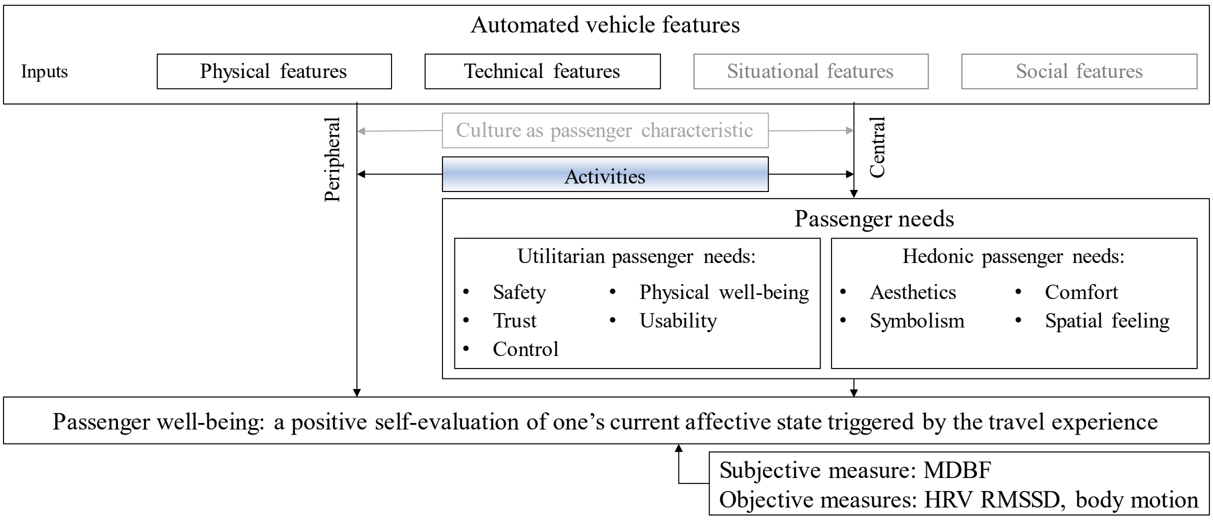


Figure 8.4 Updated overview of the proposed model of determinants of passenger well-being based on empirical evaluation study.

9 Cross-cultural Model Evaluation[6]

After establishing empirical evidence for the fundamental relationships between vehicle features, perception processing, passenger well-being, and the moderating effect of NDRTs (i.e., the basic model of determinants), it remains open how individual passenger characteristics affect these relationships. To address this question, the passenger characteristic culture and its effects (RQ6) are investigated with a two-step approach. Cultural differences between China, Germany, and the USA are considered as these markets are expected to be major markets for automated driving, and they differ regarding driving behavior (c.f. Section 2.3.5). In the first step, potential vehicle features that may be viewed differently in each culture and subsequently may have a different effect on passenger well-being are collected via an expert survey. These qualitative results are, in turn, used for quantitative partial evaluation from a user perspective by conducting an online conjoint analysis in each of the three markets.

9.1 Identifying Vehicle Features with Different Cultural Perceptions

To collect insights into which vehicle features are of especial importance for passenger well-being in each of the three markets, surveys with experts from China, Germany, and the USA are conducted. Twenty-eight experts (China: 7, Germany: 13, USA: 8) with extensive knowledge in requirements for automated vehicles in their respective markets participated in the survey. The experts had, on average, at least seven years of experience in this field (China: 7.0, Germany: 14.8, USA: 8.1) and were mainly working in R&D of automotive companies (26 experts). One expert worked in academia and one in an automotive start-up company. The survey covered different questions on passenger well-being for each respective market:

- Relevance of passenger well-being for acceptance of automated vehicles (rating on 7-point scale, 1: very unimportant, 7: very important)
- Ranking of vehicle feature categories regarding the relevance for passenger well-being
- Top 3 to top 5 features that create passenger well-being in an automated vehicle and foster identified passenger needs respectively (experts were asked to name at least 3, maximum 5 features per question)

[6] Parts of this chapter have been published in following publications: Sauer, Mertens, Groß et al. (2020); Sauer, Mertens, Groß et al. (2019)

Experts from the US rated the role of passenger well-being, on average, the highest (M = 6.13, SD = .99) followed by China (M = 5.57, SD = 1.40) and Germany (M = 4.77, SD = 1.96). A Kruskal-Wallis test (Chi-square (2) = 2.809, p = .246) shows no significant difference in the importance of passenger well-being for automated driving acceptance between the countries (c.f. Figure 9.1). Thus, passenger well-being appears to be relevant for the acceptance of automated vehicles in all markets.

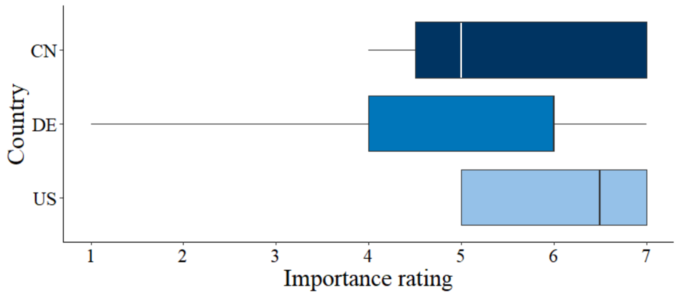


Figure 9.1 Expert rating on the importance of passenger well-being for automated driving acceptance.

Experts across all markets agree that spatial and technical features contribute strongest to passenger well-being in an automated vehicle (c.f. Figure 9.2). This strengthens the claim that in the case of automated driving, technical features influence passenger well-being and, compared to other modes of transport, have a higher relevance. The remaining physical features (dynamic, ambient) appear to play a role in passenger well-being as well. However, their importance differs between countries. According to the experts, features related stronger to the circumstances of the automated driving experience rather than the physical vehicle itself are less important. The results indicate that a user-centered development has multiple levers to influence passenger well-being in automated driving across several markets.

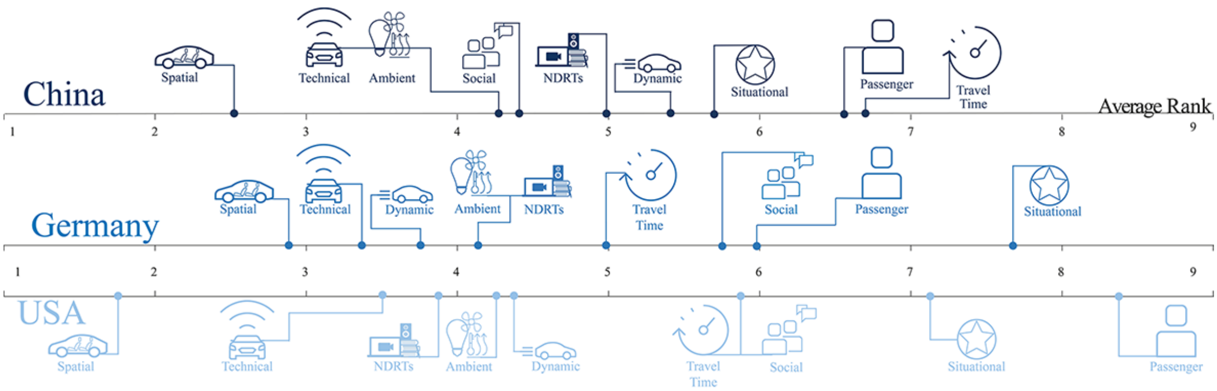


Figure 9.2 Average ranking of vehicle features regarding the importance for passenger well-being by experts (Sauer, Mertens, Groß et al., 2020).

Turning to the top features fostering passenger well-being and passenger needs, the experts' responses to this question were analyzed independently by two researchers to identify feature clusters. Clusters with less than three mentions across all three markets were excluded from further analysis. With the subsequent online study in mind, which is based on the results from the expert survey (c.f. Section 9.2), only top features fostering passenger well-being, trust, and comfort are discussed at this point.

Beginning with passenger well-being (c.f. Figure 9.3), seven groups of features are identified that are suggested to foster passenger well-being. Experts within and between markets show strong conformity regarding the high importance of *seats*. They agree that the seat has to be comfortable and adjustable. A similar agreement is found in the case of *vehicle layout* (spacious and freedom to move) and *color and trim* (high-quality materials, good haptics) although their importance differs between cultures.

In terms of *vehicle design*, Chinese experts call for a premium and well-designed vehicle, while German experts emphasize a more functional design that adapts to different NDRTs and creates a sense of safety. US experts, on the other hand, would utilize the vehicle design to allow a connection or withdrawal from the outside on demand. Further, it appears to be important for the Chinese market to allow a thorough control of the *environment* by being able to adjust the climate, sounds, lighting, smells, and to have low levels of vibrations in the vehicle. Additionally, Chinese experts view privacy glazing as a factor in passenger well-being. The ability to control the interior environment is less pronounced in Germany and the USA. Here climate control appears to be more dominant with other control options such as lighting or noise being less important.

Interestingly only German and US experts mention *user interfaces* (UI) as essential features for passenger well-being. Experts suggest that UIs are more critical in the USA than Germany, while the functionality of UIs is similar. Feedback on the vehicle, infotainment, and connectivity functions are expected. *Entertainment* functions are also only suggested by US and German experts. The experts imagine that entertainment functions in general (Germany) and good sound systems and displays in particular (USA) can contribute to well-being.

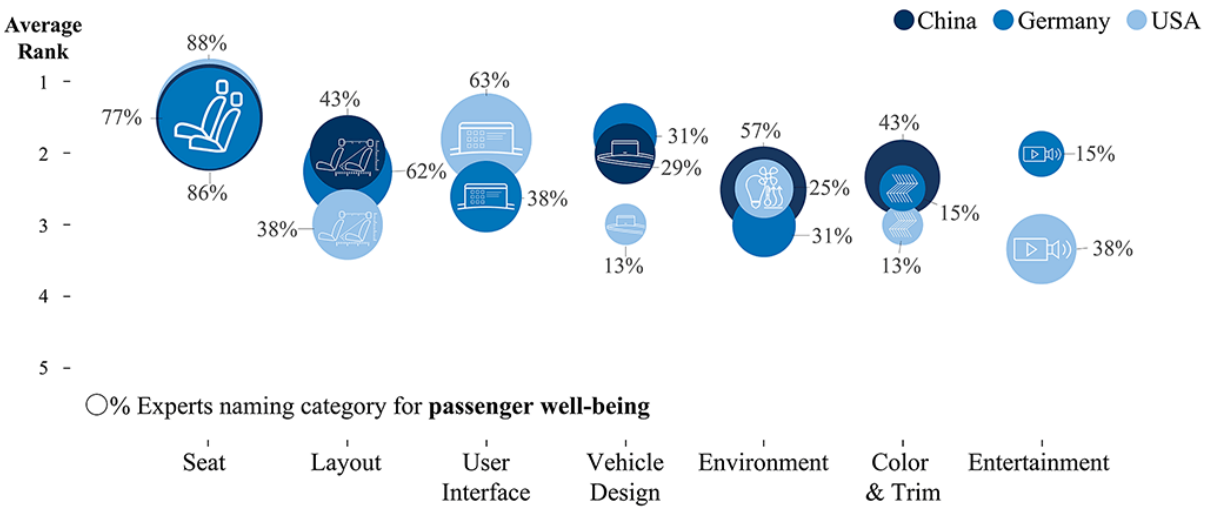


Figure 9.3 Expert assessment of interior features fostering passenger well-being in respective markets (Sauer, Mertens, Groß et al., 2020).

Based on this overview, market-specific characteristics of what makes a well-being-enhancing automated vehicle are evident. According to the expert interview, an automated vehicle interior for the Chinese market has strong hedonic characteristics. It may be described as *Luxury to go* with comfortable seats, including massage functions, a premium, and high-quality design and realization of the interior and extensive control over the vehicle interior by adjusting climate, light, sounds, smells, etc. (c.f. Figure 9.4).

Compared to this, experts paint a more pragmatic picture of what may be expected in the German market. Here a well-being-enhancing interior may be described as *Clean and functional* (c.f. Figure 9.4). Experts emphasize an ergonomic design that enables NDRTs, e.g., by providing sufficient space to move and seats that can be adjusted to support different types of tasks. Further, the passenger is informed about the vehicle status and other technical features through UIs.

The well-being enhancing vehicle interior suggested by experts for the US market lies between the two other markets and may be summarized as *Living room on wheels* (c.f. Figure 9.4). It is expected that comfortable, large seats, together with the option to withdraw from the outside world and engage in NDRTs, will foster passenger well-being. Entertainment appears to be a very important NDRT for the US market. To facilitate this, experts suggest sound systems, large displays for movies, and connectivity for external devices.

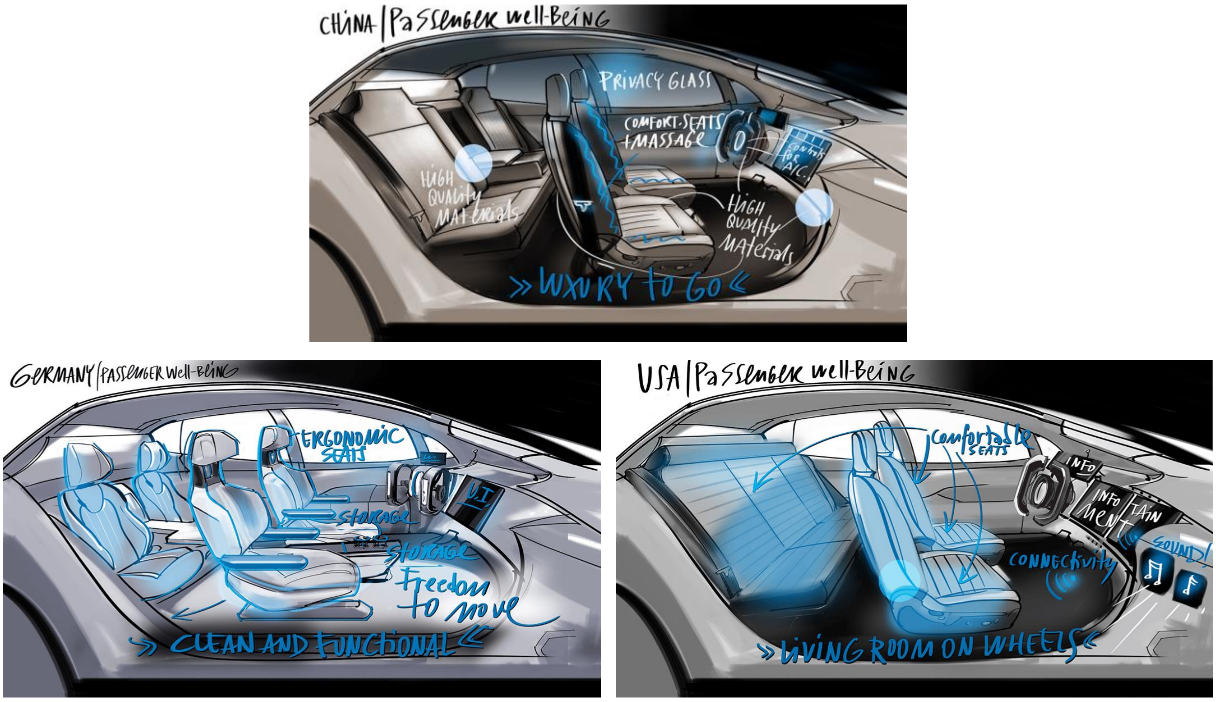


Figure 9.4 Visualizations of well-being-enhancing vehicle interiors in each market according to the experts, copyright by schnellervorlauf gmbh.

Using the experts' assessments, features for further evaluation in the subsequent user study are selected. The selection includes features that appear to have relevance in all markets and features that show cultural differences. Further, the selection is subject to the requirements of the online study. Features and their effects have to be understandable from visual and verbal explanations alone. Experts are in unison of the importance of the vehicle seat regarding seat comfort and adjustability. Due to the requirements of the online study, the feature seat adjustment is selected by considering three different types of seat adjustments to facilitate different NDRTs (manual, based on preconfigured profiles, automatic adjustment). Further, the UI in general and vehicle status information, in particular, appear to be more important for well-being in Germany and the US than in China. For this reason, the attribute UI with three levels (basic information on vehicle status, extended information, extended information with ambient light display) is included as the variety of information is expected to impact passengers' affective state (Techer et al., 2019). Further ambient light displays are a topic in automotive interface research (Löcken et al., 2016) and frequently used in automated vehicle concepts to convey information on the vehicle status peripherally (c.f. Section 6.1). In addition, both Chinese and US experts view the possibility of withdrawing from the outside environment as a factor contributing to passenger well-being. For this reason, the glazing of the side windows (transparent, privacy) is included in the study. Finally, the quality of materials is found relevant in all markets. However, it appears to be considerably more important for the Chinese market. To investigate this potential cultural difference, material quality (standard, premium) is considered as well. Based on these findings, hypotheses on the evaluation of the selected attributes in each market and cultural differences between the markets can be derived:

H1: *Seat adjustment has the highest importance for passenger well-being in all markets.*

H2: *The importance of UIs for passenger well-being is significantly higher in the US and Germany than in China.*

H3: *Privacy glass has a significantly higher utility for passenger well-being in the US and China than in Germany.*

H4a: *Premium quality provides significantly higher utility for passenger well-being in all markets than standard quality.*

H4b: *The importance of quality for passenger well-being is significantly higher in China than in Germany and the USA.*

In addition, the experts' assessment of features relevant for the needs trust and comfort are considered to identify potential relationships between vehicle features, passenger needs, and well-being in the subsequent user study in case of central processing. In the case of trust, cultural differences are more apparent in the results of the expert survey (c.f. Figure 9.5). Experts from all three markets agree on the role of *UIs* for trust-building by communicating the vehicle status and providing feedback. The UI can either be visual based or use auditory feedback through audio chimes or a dialog system. Similarities between the markets are also found in case of *color and trim,* where it is suggested that quality materials may build trust. The *design of the automated driving system* (robust, reliable automated system with calm driving style) and the option for *manual control* by overriding the automated driving system with pedals, steering wheel, or an emergency off button coincide in all markets.

In the case of China and Germany, traditional *passive safety* features such as airbags and seat belts can also increase trust in the automated vehicle. Further, in these two markets, *seats* may foster trust by providing a safe position and comfort. US experts see the opportunity to build trust in the USA by increasing familiarity with automated driving through a *demo mode*. This idea is seconded by German experts. Further, in Germany and the USA, the *vehicle design* may impact trust as well. However, in the case of Germany, emotional, trust-inducing design is preferred over the US suggestion for spacious design.

In sum, the Chinese market is expected to build trust in automated driving primarily from UIs, traditional passive safety functions, and the option of manual control. These results may be summarized as *Trust through traditional safety features.* The technological aspect is found in the case of Germany as well. Here strong attention is paid to the UIs (transparent and robust information), passive safety, and overall trust-worthy design of the vehicle and system, which may be condensed to *Trust through engineering*. In comparison, the US market is expected to build *Trust through showing*. This can be achieved through feedback from the UI using auditory and visual channels. Further, demonstrations of the automation capabilities may be a promising approach in the US for trust-building. Based on these findings and the selected attributes for the user study, it may be expected that trust mediates the effects of UI and material quality in all markets:

H5: *Trust mediates the effect of UI on passenger well-being in all markets.*

H6: *Trust mediates the effect of material quality on passenger well-being in all markets.*

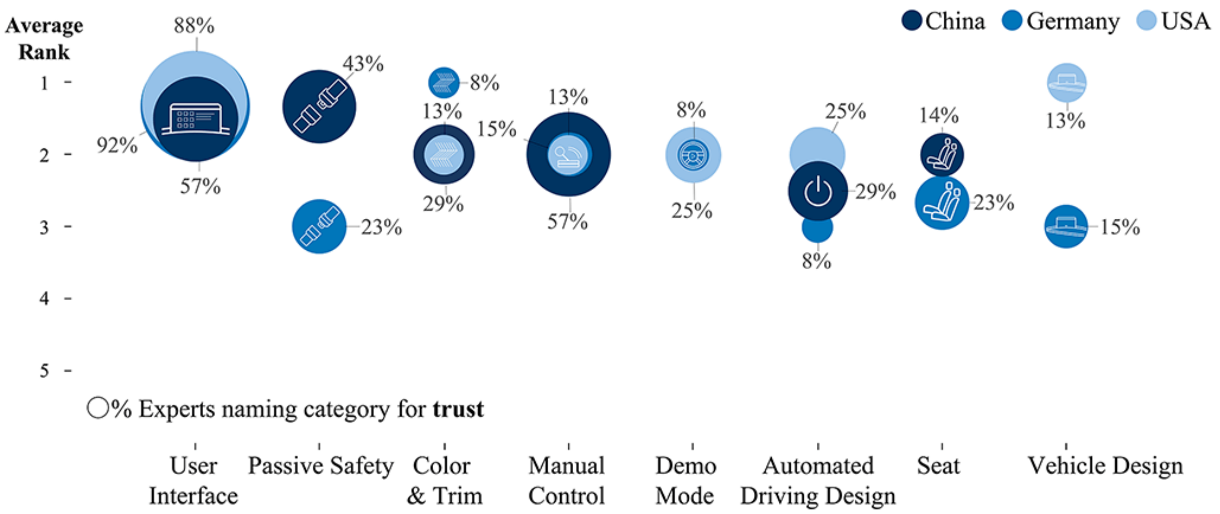


Figure 9.5 Expert assessment of interior features fostering trust in respective markets (Sauer, Mertens, Groß et al., 2020).

In case of comfort (c.f. Figure 9.6), the *seat* is once again a major feature on which experts for all markets agree. To create a comfortable interior, seat comfort appears mandatory. In addition, Chinese experts emphasize the position and adjustability. German experts add the ergonomics of the seat, arm rests, adjustability of the seat to adapt to different NDRTs. Similar agreement across markets is found in the *vehicle layout*, which once again has to be spacious and allow movement to create comfort, the *enablement of NDRTs* (primarily entertainment), and *UIs*. For UIs, the connectivity of the interfaces is emphasized across all markets. US experts also add the use of anthropomorphic agents to increase comfort.

A controlled *environment* is not only important for passenger well-being, according to the expert, but for comfort as well. Similar to the findings on passenger well-being, Chinese experts call for more detailed control of the interior (climate, sound, glazing, smells) while experts from the remaining markets focus more on climate control. Further, *noise management* is important in all markets, and experts suggest that a quiet interior fosters comfort. Bigger cultural differences are found in the case of *vehicle design*. Here, Chinese experts suggest a hedonic design that creates atmosphere, while German and US experts emphasize ergonomics in the interior design. Interestingly, Chinese experts do not mention *color and trim* of the interior to be relevant for comfort, although it has high importance to foster passenger well-being and trust in the Chinese market. German and US experts, however, suggest color and trim as a relevant feature for comfort.

To paint a more specific picture of a comfort-enhancing vehicle for each market, the suggestions from the Chinese experts on a vehicle interior with comfortable, adjustable seats, enough space, privacy glazing, and comprehensive controls for all interior settings may be aggregated to *Comfort through a controlled environment.* A comfort-enhancing interior in Germany could be described as *Comfort through ergonomics* due to the experts' suggestions to integrate comfortable, ergonomic seats that enable various NDRTs, enough space to move around, a general vehicle design that ensures an ergonomic interaction and appealing materials and haptics. Finally, in the case of the USA, the view on comfort may be summarized as *Comfort through technology.* This is evident from the US experts' call for seat comfort and a spacious interior together with infotainment functionalities, a controlled environment through noise canceling and interactions with an anthropomorphic agent. Using these findings, the following mediating relationships can be expected:

H7: *Comfort mediates the effect of seat adjustment on passenger well-being in China and Germany.*

H8: *Comfort mediates the effect of glazing on passenger well-being in China.*

H9: *Comfort mediates the effect of material quality on passenger well-being in Germany and the USA.*

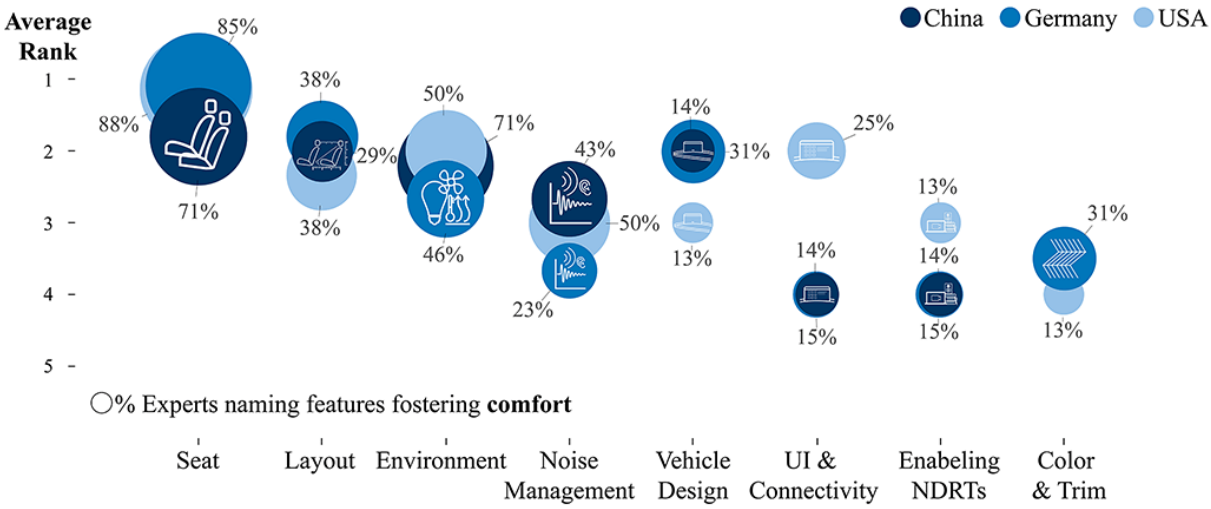


Figure 9.6 Expert assessment of interior features fostering comfort in respective markets (Sauer, Mertens, Groß et al., 2020).

The analysis of experts' responses has revealed that NDRTs and their enablement play an important role in all markets. As discussed, NDRTs during automated driving are expected to vary strongly (c.f. Section 2.3.6). Depending on the NDRT, the need for information can differ (Hecht et al., 2020). As working tends to be more visually demanding than relaxing, it may be expected that display-based information becomes less important, and peripherally perceivable information may be preferred. Following this line of argumentation, visually demanding NDRTs such as working may also change the perception of the interior and reduce visual aspects such as material quality. Thus, the following is hypothesized:

H10: Extended information with an ambient light display has significantly higher utility for passenger well-being than other levels of the attribute UI in the case of working.

H11: Quality is significantly less important in case of working than in case of relaxing.

9.2 Evaluation of Cultural Influence from the User Perspective

To assess the intercultural effect on the evaluation of the selected attributes from a user perspective and test the corresponding hypotheses, an online conjoint analysis was performed.

9.2.1 Experimental Setup

The online study investigated the four attributes identified from the expert survey (UI, glazing, seat adjustment, and quality) with two or three levels each. A rating based approach using paired comparisons and full profiles was applied. Ratings as dependent variables were collected in regards to passenger well-being, trust, and comfort to include a utilitarian and a hedonic need (c.f. Figure 7.2). To keep the workload for participants manageable, a fractional factorial design was applied (Aizaki & Nishimura, 2008) to reduce the number of possible profiles from 36 to 24 (c.f. Appendix A.12 for an overview on selected profiles). To assess the influence of different NDRTs on the evaluation of interior features (H10-H11), a between-subject design with the factor NDRT (working/relaxing) was applied. The respondents of each country were divided into two groups: one group was asked to complete the survey with regards to relaxing during the automated drive and the other in regards to working.

9.2.2 Procedure

After completing a section on demographics, respondents were asked to read a scenario describing capabilities of level 4 automated vehicles with the potential use case commuting. The scenario differed between the groups regarding the NDRT relaxing or working. Explanations of each attribute and its level followed using verbal descriptions and images (c.f. Appendix A.13). In the following, respondents rated each of the 12 paired comparisons in a randomized order on 9-point Likert scales regarding which option would increase their passenger well-being, trust, and comfort, given that all other vehicle features are identical across the options (c.f. Appendix A.14). In total, participants took 20-25 minutes to complete the survey. The survey was developed in German and translated to English by a bilingual speaker. Based on the English version, the Chinese version was translated by a professional translating service. Participants were incentivized for their participation by an online-panel service.

9.2.3 Participants

In total, 1210 participants across three markets were recruited to participate in the online study. For recruitment in each market, the following criteria were applied: representative of the population in the respective country regarding age (18 years and above) and net household income, equal gender distribution male/female, regular car use (at least 3 times per week, regardless of car ownership), only urban population to maintain comparability across the markets. The participants were randomly assigned to either the working or the relaxing group. An overview of the demographic characteristics of the sample is provided in Table 9.1.

Table 9.1 Overview of sample characteristics of the cross-cultural online study.

	China	**Germany**	**USA**
Group size	408 Work: 203, Relax: 205	405 Work: 200, Relax: 205	397 Work: 200, Relax 197
Age	M = 35.66, SD = 9.20	M = 39.83, SD = 10.88	M = 36.47, SD = 11.91
Gender	Male: 229, Female: 179 Other: 0	Male: 204, Female: 201 Other: 0	Male: 195, Female: 201 Other: 1
General interest in cars	M = 4.11, SD = .83	M = 3.61, SD = 1.06	M = 3.30, SD = 1.26
Experience with ADAS	M = 3.86, SD = .89	M = 3.29, SD = 1.06	M = 3.30, SD = 1.15
Intent to use level 4 automation	Yes: 368, No: 40	Yes: 314, No: 91	Yes: 267, No: 130

9.2.4 Data Collection and Analysis

In terms of demographic data, general interest in cars and experience with ADAS were each rated on a 5-point scale (1: very low, 5: very high). Further, the rating of paired comparisons on the three dimensions was performed on a 9-point scale. To assess the hypotheses H1-H4 and H10-H11, individual conjoint data was analyzed using OLS regression with dummy coded variables in R (R Core Team, 2018). Conjoint results on an individual level with sufficient coefficients of determination (adjusted $R^2 > .26$, Cohen, 1988) were used to perform ANOVAs to investigate cross-cultural differences. To assess H5-H9, mediation analysis was conducted using the original ratings from the paired comparisons.

9.3 Results

Results on the cross-cultural online study are organized based on the different analysis steps. Overall results and intercultural comparisons are presented in the following sections.

9.3.1 Conjoint Analysis Results

Conjoint analysis was performed on an individual level for passenger well-being across all six groups. In the first step, internal validity was considered to estimate the fit of the regression model (Skiera & Gensler, 2002). Adjusted R^2 values used to assess internal validity show large variability and an overall low fit, especially in the case of respondents from the Chinese market (c.f. Figure 9.7), which is untypical for conjoint analysis (Skiera & Gensler, 2002).

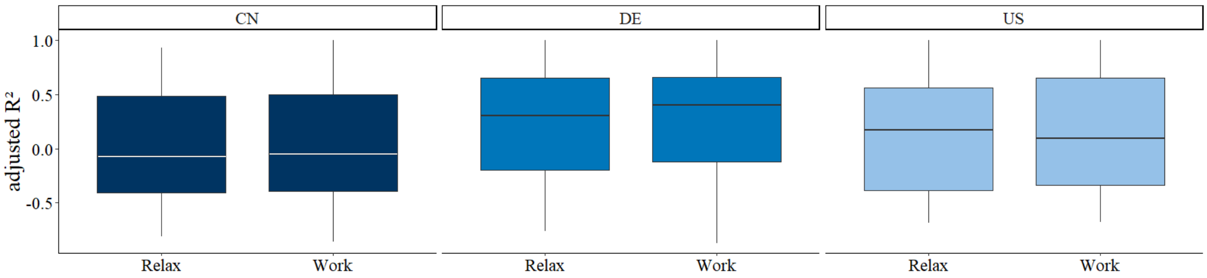


Figure 9.7 Distribution of adjusted R^2 of individual conjoint analyses for each group.

The low fit between the model and data can have different causes (Selka, Baier, & Brusch, 2012). Respondents may have viewed selected attributes as irrelevant for passenger well-being in automated driving, or lack of understanding may have caused incomprehensible ratings. Similar incomprehensible results can also be caused by a dynamic behavior of preferences (Selka et al., 2012), fatigue and boredom (DeSarbo, Fong, Liechty, & Coupland, 2005), or information overload (Jacoby, 1984). Another potential issue may have been the choice of methods. The number of paired comparisons may have been too small to derive valid assumptions (Gensler, 2003). Further, it is up to discussion if a different method, such as adaptive conjoint analysis, may be more appropriate (Selka et al., 2012). Also, the weaknesses of online studies, in general, may have taken effect in this study as well (Selka et al., 2012).

It cannot be said with certainty what reasons caused the low fit in this case. To reduce the potential heterogeneity within each group and only include responses for which the selected attributes are sufficiently meaningful, a subset was derived, including only cases with adjusted $R^2 > .26$. According to Cohen (1988) $R^2 > .26$ provides a sufficient explanation of variance. This smaller sample (c.f. Table 9.2) was used for conjoint analysis results on an aggregated level using means (c.f. Table 9.3), and for subsequent intercultural comparisons.

Table 9.2 Group sizes for intercultural comparison based on data subset with sufficient internal validity.

	China	**Germany**	**USA**
Relax	76	109	89
Work	74	115	93

Using the data subset to aggregate conjoint results, indications of differences between the markets become evident (c.f. Table 9.3 and Appendix A.15). The six groups coincide in regards to the preference for a UI with extended information combined with a light display, and premium quality. Compared to the other markets, German respondents prefer transparent glazing for both use cases. Respondents from China and the USA prefer privacy glazing regardless of the

NDRT. German and US respondents in the relax group prefer seat adjustment with preconfigured profiles over automatic adjustment, which is preferred during working in these markets. Chinese respondents prefer the option of automatic seat adjustments for both relaxing and working. Further, US respondents place the highest importance on UI, while Chinese and German participants focus most on seat adjustments. Thus, H1 is only partially supported in the case of China and Germany, while in the USA, UI is more important in both NDRTs.

Table 9.3 Overview of aggregated conjoint results based on a subset of cross-cultural study.
Note: R: Relax, W: Work; Grey highlight indicates max. partworths and max. relative importance.

	Mean adjusted partworths										**Mean relative importance**			
	UI			Glazing		Seat adjustment			Quality					
Group	Basic	Extended	Ext. + Light	Transparent	Privacy	Manual	Profiles	Automatic	Standard	Premium	UI	Glazing	Seat adjustment	Quality
CN R	.06	.13	.22	.03	.16	.10	.19	.20	.02	.20	27.6%	18.3%	32.1%	22.1%
CN W	.05	.10	.19	.02	.18	.08	.21	.21	.03	.18	24.4%	20.1%	33.8%	21.7%
DE R	.06	.14	.19	.11	.09	.14	.17	.17	.02	.19	26.6%	20.1%	32.4%	20.9%
DE W	.04	.18	.24	.13	.08	.14	.14	.18	.03	.15	28.9%	21.7%	31.6%	17.9%
US R	.05	.23	.30	.05	.08	.10	.20	.18	.02	.16	36.5%	13.7%	31.2%	18.7%
US W	.04	.21	.34	.06	.13	.13	.12	.17	.03	.12	37.9%	18.9%	28.3%	14.9%

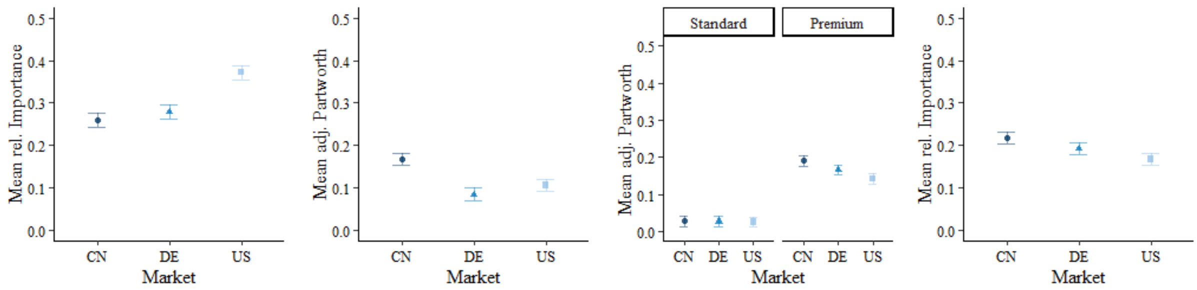
9.3.2 Intercultural Comparison

To assess intercultural differences stipulated in H1-H4, it is assumed that the six groups are homogeneous, and different NDRTs are omitted as between-subject factor. For analysis, one-way ANOVAs are calculated, and results are summarized in Table 9.4. Significant differences are evident for all hypotheses.

Table 9.4 Results of ANOVAs used to evaluate intercultural differences stipulated in H2-H4.
Note: Grey highlight indicates significant values ($p < .05$).

Hypotheses	**Effect**	**DFn**	**DFd**	**F**	**p**	η_G^2
H2: UI	Market	2	553	23.50	< .001	.08
H3: Glazing	Market	2	553	15.59	< .001	.05
H4a: Quality	Quality	1	553	287.71	< .001	.26
H4b: Quality	Market	2	553	5.85	.003	.02

Post-hoc tests for H2 show significant differences between the USA and China (p < .001) but not between Germany and China (p = .925). Thus, H2 is only partially supported, as the design of the UI is more important in the USA and Germany than in China (c.f. Figure 9.8), but not both differences are significant. H3 receives only partial support as mean adjusted partworths for privacy glass are higher in China and USA than in Germany (c.f. Figure 9.8), but the difference is only significant in the comparison between China and Germany (p < .001), but not between Germany and USA (p = .405). H4a is supported as the adjusted partworths for premium quality is significantly higher (p < .001) than the adjusted partworths for standard quality in all markets. Finally, H4b receives limited support as the relative importance of quality is highest in China (c.f. Figure 9.8), but significant differences exist only between China and the USA (p = .002) but not between China and Germany (p = .233).



H2 H3 H4a H4b

Figure 9.8 Plotted average means to corresponding hypotheses, error bars: Fisher's least significant difference.

9.3.3 Central Processing and Passenger Needs

Hypotheses H5-H9 stipulate mediating relationships between vehicle features, passenger needs, and well-being, as is the case in central processing. Results from mediation analysis are summarized in Table 9.5. Based on the results, partial support can only be provided for H5. Trust mediates the effect of UI on passenger well-being in the German sample. Indications of support but on a lower α-level is provided for H7 in the case of Germany (p = .07) and for H8 (p = .10).

9.3.4 NDRTs as Moderator

NDRTs are expected to have moderating effects on the relationship between UI type and passenger well-being and quality and passenger well-being. ANOVA results (c.f. Table 9.6) only reveal a significant difference between NDRTs for the relative importance of quality (H11). Figure 9.9 shows that the relative importance of quality is higher in the case of the NDRT relax compared to work for all markets. Significant differences between NDRTs for the adjusted partworths of extended information with an ambient light display (H10) are not visible.

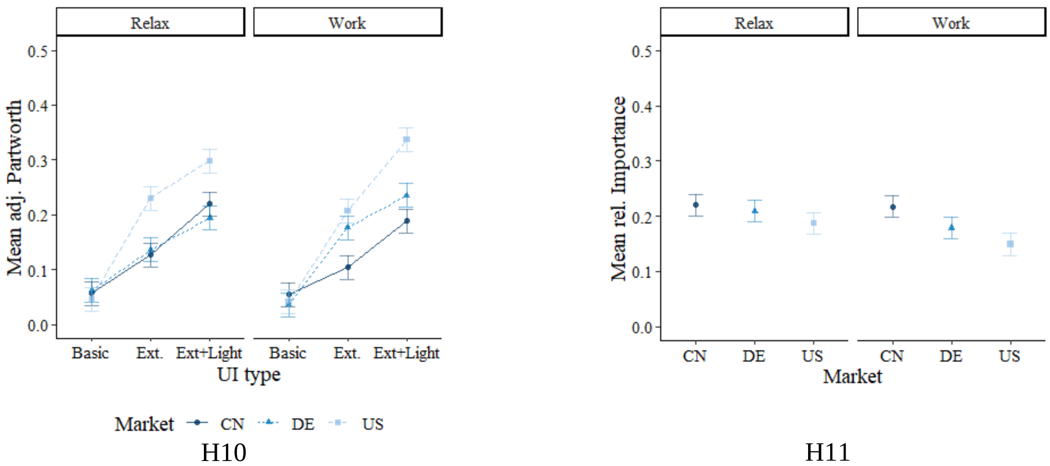


Figure 9.9 Plotted average means to corresponding hypotheses, error bars: Fisher's least significant difference.

Table 9.5 Results on hypothesized central processing in different markets using mediation analysis.

Note: Only causal mediation effects (ACME) displayed, bootstrapping with 1000 simulations; Grey highlight indicates significant mediation effects (p < .05).

	Estimate (ACME)	95% CI Lower	95% CI Upper	p-Value
H5: Trust mediates the effect of UI on passenger well-being in all markets				
China: basic info	.02	-.04	.08	.56
China: extended info	.00	-.07	.06	.58
Germany: basic info	.02	-.06	.09	.70
Germany: extended info	.08	.00	.16	.04
USA: basic info	-.03	-.11	.05	.45
USA: extended info	-.05	-.13	.04	.34
H6: Trust mediates the effect of quality on passenger well-being in all markets				
China: standard quality	.00	-.06	.05	.95
Germany: standard quality	-.02	-.08	.04	.51
USA: standard quality	.03	-.04	.10	.44
H7: Comfort mediates the effect of seat adjustment on passenger well-being in China and Germany				
China: manual	-.04	-.11	.03	.29
China: preconf. profiles	-.04	-.14	.05	.41
Germany: manual	.01	-.09	.11	.83
Germany: preconf. profiles	-.11	-.24	.01	.07
H8: Comfort mediates the effect of glazing on passenger well-being in China				
China: transparent glass	-.04	-.10	.00	.10
H9: Comfort mediates the effect of quality on passenger well-being in Germany and the USA				
Germany: standard quality	-.02	-.10	.05	.58
USA: standard quality	.02	-.05	.08	.56

Table 9.6 Results of ANOVAs used to evaluate moderating effects stipulated in H10-H11.
Note: Grey highlight indicates significant values ($p < .05$).

Hypotheses	Effect	DFn	DFd	F	p	η_G^2
H10: UI	NDRT:UI type	2	1100	1.15	.32	.00
H11: Quality	NDRT	1	554	4.97	.03	.01

9.4 Discussion

This study offers insights into market-specific requirements for automated vehicle interiors and potential cross-cultural differences. The model of determinants of passenger well-being, including culture as potential mediating passenger characteristic, is partially evaluated empirically.

9.4.1 Expert Survey

The survey with experts from three markets is not only used to derive hypotheses for the subsequent user study but provides indications for cross-cultural design requirements. For passenger well-being, spatial and technical features are most important across all markets. This provides further support for the inclusion of technical features into the model of passenger well-being determinants (c.f. Chapter 6). Additionally, according to the experts, ambient and dynamic features contribute to passenger well-being. The higher importance of ambient features in China and the USA compared to Germany seconds the need for control of the interior environment (lighting, glazing, climate, etc.) found in qualitative expert results and in the subsequent user study (see H3).

Further, qualitative results indicate that similar features are relevant to foster passenger well-being, trust, and comfort in the three markets, but the ideal design of the features differs. For example, the seat is a major feature for passenger well-being. All markets call for seats with high comfort, but additional seat requirements are market-specific, such as seat massage in China, ergonomics in Germany, or pleasant materials in the USA. This effect is also visible in the building of trust, where more market-specific strategies may be more fruitful in building trust (Hergeth, Lorenz, Krems, & Toenert, 2017). In contrast, results indicate that comfort is mainly influenced by the seat, layout, and options to control the environment of the vehicle interior across all three markets. Thus, suggesting similar design strategies for comfort across markets. Overall, the features and their design suggest a tendency toward hedonism in the case of China and a tendency toward pragmatism in Germany. The USA appears to lie in between the two other markets on a hedonic-pragmatism continuum. These tendencies are also found, for example, in a cross-cultural assessment of instrument clusters (Sudarshan et al., 2015).

In summary, the expert survey suggests that sufficient levers are available to consider passenger well-being in a user-centered approach to designing automated vehicles. To tailor automated vehicles to different cultures, features should be designed with market-preferences toward hedonism or pragmatism in mind without having to redesign the vehicles completely.

9.4.2 Cross-cultural User Study

To provide additional empirical validation of the model of determinants of passenger well-being and examine the effect of culture as passenger characteristics, an online user study using a conjoint approach is used. The results provide insights into the direct effects of features on passenger well-being (peripheral processing), indirect effects through mediating passenger needs (central processing), and the moderating effect of NDRTs.

Peripheral processing

Peripheral processing is analyzed using aggregated conjoint results. The low internal validity, causing the use of a subset for the subsequent analysis, can have multiple reasons, as discussed above (c.f. Section 9.3.1). Based on the sample subset, the following indications can be drawn (c.f. Figure 9.10). Seat adjustment is the most important feature in China and Germany for both NDRTs. However, in the case of both US groups, the UI design is more important. Thus, H1 is partly supported. In all six groups, seat adjustment and UI are more important than the remaining two features. This may be explained by the fact that UI and seat adjustment are features the passenger directly interacts with and uses to control the environment. Thus, engagement may be higher compared to material quality or glazing, which are static during automated driving.

In the case of seat adjustment, manual adjustment is dominated by the other options in all six groups. In China, regardless of the NDRT, automatic adjustment is preferred, while in Germany and the USA, preconfigured profiles for adjustment are preferred in relax NDRTs and automatic adjustment for work tasks. This parallels the findings that smart functions in automated vehicles can contribute to well-being (c.f. Chapter 6).

In all six groups, extended information with an ambient light display is the preferred level of UI. Most likely, the sample consists largely of novice users, as automated vehicles are hardly available in the market. Novice users tend to prefer more detailed information on the vehicle status (Reilhac et al., 2016). Further, ambient light displays may have been preferred due to the easy observability during NDRTs, resulting in reduced cognitive load (Löcken et al., 2013) or due to an increased hedonic experience (Karjanto et al., 2018). The hypothesized cultural difference in the importance of UI for passenger well-being (H2) is reflected in the different relative importances. However, only the USA differs significantly from China.

Compared to China and the USA, Germany prefers transparent glass over privacy glass, but only China has significantly higher utility for privacy glass than the other countries (H3 partly supported). This stresses the strong preference of the Chinese market to control the environment within the vehicle interior, as suggested by the expert results. A similar but weaker tendency is suggested by US experts, which is reflected in the conjoint results.

Premium quality provides significantly higher utility for passenger well-being than standard quality in all six groups (H4a supported). Quality is only significantly more important in China than in the USA, but not than in Germany (H4b partially supported). The partial support showing no clear difference between cultures regarding the importance of quality has been found in other studies as well (Petiot et al., 2009).

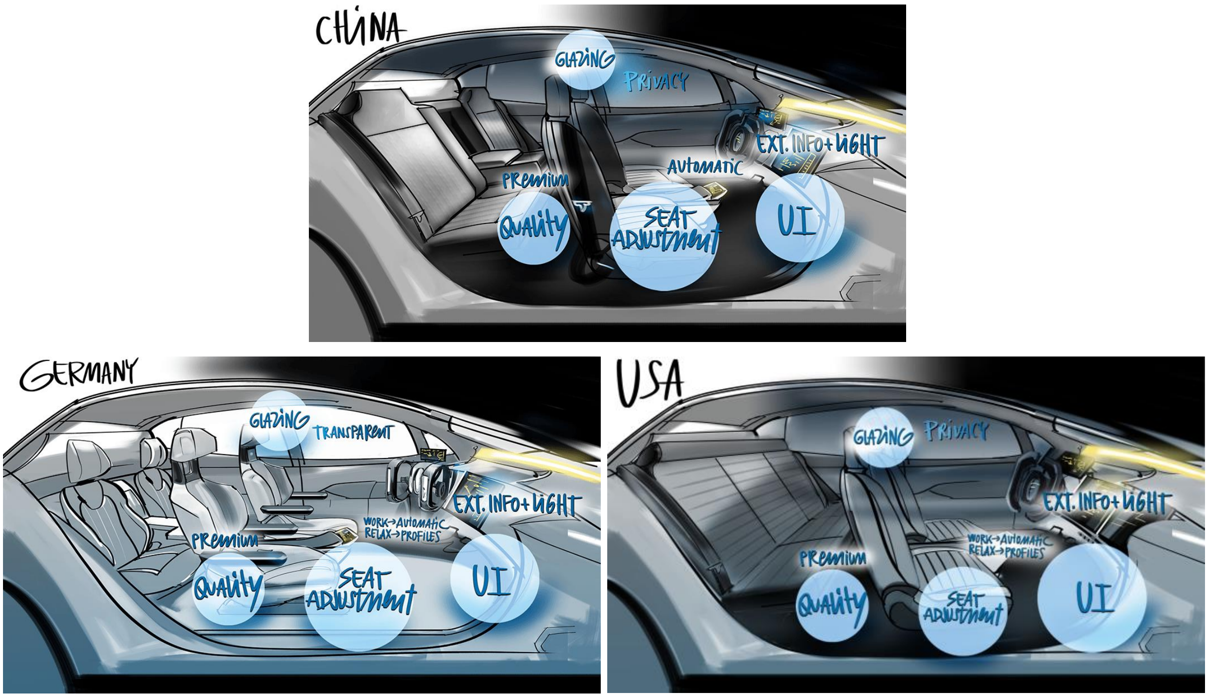


Figure 9.10 Visualization of the results for peripheral processing from the cross-cultural user study, copyright by schnellervorlauf gmbh.

Note: Size of bubbles reflects importance.

Overall, the results indicate support for cross-cultural differences in the peripheral perception of vehicle features. However, the direct effects of features on passenger well-being have to be regarded cautiously, as the conjoint results provide low validity and model fit.

Central processing

To assess cross-cultural differences in the effect of features on passenger well-being via the central route, hypotheses H5-H9 are considered. The hypothesized mediating effects of comfort and trust and potential cultural differences are derived from the expert survey. For central processing, only limited evidence is provided. Significant empirical evidence for trust mediating the effect of UI on passenger well-being is only provided in the case of Germany (H5). Further, evidence for mediation as part of central processing on a lower significance level (α = 10%) is indicated in case of comfort and seat adjustment (H7, Germany) and H8. There is no indication of mediation or central processing, respectively, in the USA. In contrast to the validation study of the basic model (c.f. Chapter 8), participants are informed about attributes and their levels in this study. Thus, the ability to cognitively evaluate these features is likely higher, which consequently should result in higher central processing. The limited evidence can have different reasons. As conjoint analysis typically collects ratings for preference (Rao, 2014) and not ratings on multiple dimensions such as passenger well-being, trust, and comfort, this may have been too demanding for participants and may have caused confusion. Alternatively, central processing may not have applied to the sample in this study setting. It is possible that participants have rated each dimension separately without linking the three ratings.

NDRTs as moderator

Based on the argumentation that working is more visually demanding than relaxing as framed in this study, it is hypothesized that NDRTs moderate the effect of UI (H10) and quality (H11) on passenger well-being. However, an effect is only visible in case of quality, indicating that quality is significantly more important for passenger well-being in case of relaxing than working. Extended information with an ambient light display provides the highest utility in all six cases. However, the difference in utility between the NDRTs is not significant. This may be caused by the fact that reasons to prefer the ambient light display (see above) dominate the influence of NDRTs. Thus, keeping the utility of this level similar in all six groups.

9.4.3 Limitations

The two-step approach used to evaluate the model of determinants of passenger well-being, specifically under consideration of culture as moderating influence (RQ6), shows some limitations in terms of methodology and results. The expert survey considers a small number of experts. Especially in the case of China and the USA, the number of experts may not be sufficient to reflect the diversity and cultural differences within a country. Further, experts were mainly employed at large car manufacturers. Experts from startups were less represented. However, due to the disruptive nature of automated driving, novel and radical ideas may evolve that change how passenger well-being is fostered by automated vehicle design. A larger number of experts from startups may be able to paint a more complete picture of design requirements for automated vehicles. It is further pointed out that both the expert and the user study focus on the interior of the vehicle. Other aspects are omitted at this point.

The limited validity of the individual conjoint analysis using OLS regression may have different reasons such as lack of understanding, choice of methods, or untypical design of the study (three-dimensional rating). As a countermeasure, aggregated conjoint analysis is based on responses providing a sufficient explanation of variance (adjusted $R^2 > .26$). Other methods for data analysis, such as latent class regression, may be able to provide better validity by considering underlying segmentations such as culture-specific characteristics in the samples (Malhotra, Agarwal, & Peterson, 1996). Further, this kind of analysis also provides information on segments within each group. Segmentation has been omitted in this data analysis in favor of concentrating on cross-cultural comparisons. However, segmentation may reveal additional insights into user behavior and passenger well-being that may be beneficial for future purposes.

Further, conjoint analysis generally assumes that attributes are compensatory (Backhaus et al., 2018). Thus, the resulting importance rating and utility depend on the combination of features considered. Different results are expected for other feature combinations and may change importance or utility in comparison. However, for empirical validation purposes, as is the case here, importance and utility are secondary, and design requirements should rather be derived from the expert survey results.

9.5 Conclusion

To assess the role of culture as passenger characteristic (RQ6) and provide additional empirical evidence for the model of determinants of passenger well-being in automated driving, a two-step approach combining an expert survey with an online user study was applied. The expert survey provides a clear indication that culture as passenger characteristic shapes how passengers of automated vehicles perceive and evaluate vehicle features. Therefore, culture as exemplary passenger characteristic is included in the model of determinants of passenger well-being (c.f. Figure 9.11). It is likely that other passenger characteristics of psychological, physical and physiological, or situational nature such as preconceptions like the initial level of trust (Kerschbaum et al., 2015) can have a moderating impact as well. However, further research to validate this assumption is required.

The effect of peripheral and central processing has been observed in the results of this study. Yet, not all assumed relationships found empirical support. The same applies to NDRTs as moderators. The results of this study should be considered in light of the discussed limitations. While the expert study provides clear design suggestions for market-specific automated vehicle interiors, the implications of the user study may be limited by the low validity and model fit of the conjoint analysis. It may be advisable to perform a similar study for validation of cross-cultural design ideas later in the development process with users that are more experienced with automated driving and may predict the effect of features on their well-being more easily.

Nonetheless, the study indicates that automated vehicle interiors do not necessarily have to be designed fundamentally differently for different markets. Yet, cross-cultural differences should be reflected in the design of selected features. This applies not only to features increasing passenger well-being but also to features used to build trust. Overall, sufficient levers are available to consider passenger well-being in a user-centered approach to designing automated vehicles.

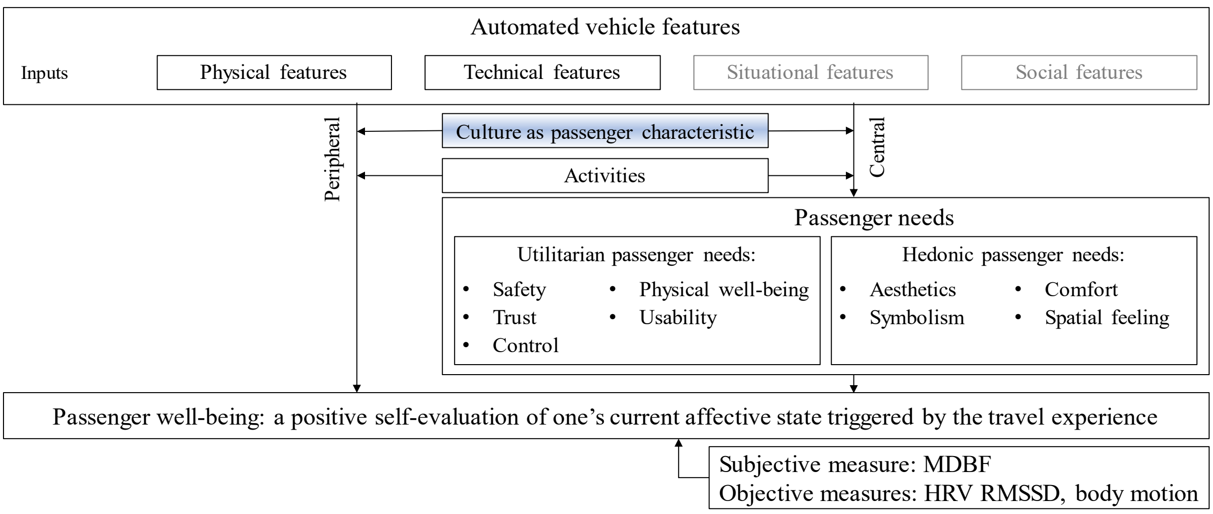


Figure 9.11 Updated overview of the proposed model of determinants of passenger well-being based on results to RQ6.

10 Conclusions

Technical advances in automation technology provide the opportunity to rethink the design of automated vehicle interiors and incorporate the advantages automation offers. With automation, the engagement in NDRTs is more extensively possible for both drivers and passengers. Consequently, many car manufacturers envision the automated vehicle to evolve from a driver-centric product to a user-centric living space. Passenger well-being is one approach to strengthen the user perspective in the development of automated vehicles. The body of research considering passenger well-being in transport, in general, and in automated driving, in particular, is growing. However, so far, an extensive framework considering the determinants of passenger well-being has been lacking. This work provides an approach to such a model by building on existing models (e.g., Ahmadpour et al., 2014; Richards, 1980) and identifying relevant vehicle features, passenger needs, processing mechanisms, and moderating variables like NDRTs and culture as passenger characteristic. The proposed model was partially validated empirically with two different user studies. To derive the model of determinants of passenger well-being, six research questions were raised and subsequently addressed in this work.

10.1 Implications for a Model of Determinants of Passenger Well-being

RQ1: Does passenger well-being in automated driving relate to current subjective well-being?

Well-being is a concept frequently called on by different disciplines. In transport research, well-being is frequently considered in its psychological conceptualization as a combination of cognitive evaluation of life (habitual well-being), high positive affect, and low negative affect (current well-being). However, a consistent definition across different studies is not used. This work argues that traveling in an automated vehicle likely impacts current well-being more strongly than habitual well-being, thus raising RQ1.

A user study provides empirical evidence that passengers in automated vehicles, in fact, use adjectives related to current subjective well-being to describe a feeling of well-being (c.f. Chapter 4). A large proportion of adjectives mentioned by participants describe a state of relaxation. Positive affect is further expressed by adjectives related to positive mood and alertness. Based on these findings, passenger well-being in automated driving is proposed as "positive self-evaluation of one's current affective state triggered by the travel experience" (Sauer, Mertens, Heitland et al., 2019, p. 240) and shows a clear differentiation of passenger well-being from related concepts (c.f. Section 2.1.3).

The proposed definition provides the foundation for developing a model of determinants of passenger well-being in automated driving. Furthermore, a distinct definition of passenger well-being in automated driving contexts may contribute to making future research results in this field more comparable.

RQ2a: What multidimensional self-report is suitable to reliably, validly, and efficiently measure passenger well-being in the context of automated driving?

A large number of multidimensional self-reports for current subjective well-being has been published over the years (Schumacher et al., 2003). Thus, it is not surprising that there appears no consensus in transport research which self-report measure to use. Even within the same mode of transportation, different measures have been utilized (c.f. Table 2.1).

To identify a suitable self-report in the context of automated driving, the variety of identified measures used in transportation research was evaluated with a set of predefined criteria regarding statistical quality and economic applicability. The MDBF was able to fulfill all pre-set criteria and was evaluated more extensively in a user study (c.f. Section 5.1). The study results attest a high reliability (Cronbach's $\alpha > .90$), sufficient discriminant validity, and the ability to measure differences induced by different stimuli. Thus, the MDBF appears to be a reliable and efficient measure for passenger well-being. Additional findings show that for situations in which the twelve items of the MDBF may still be too many and cannot be applied (e.g., in real-world driving situations), a short measure based on three items can be an alternative (Sauer, Mertens, Heyden et al., 2020).

The recommendation for the MDBF does not suggest that other self-report measures are unsuitable. Rather, the MDBF provided the best fit for the purposes of this work and was utilized for subsequent user studies to investigate determinants of passenger well-being more closely. In other settings, such as cross-cultural studies, other self-report measures may be suitable.

RQ2b: Are HRV, EDA, facial expressions, and/or body motion suitable to reliably, validly, and efficiently measure passenger well-being in the context of automated driving?

Objective measures of physiological, motoric, or facial reactions can provide additional insights into reactions to stimuli and resulting levels of well-being (Diener, 1994). Based on published research, heart rate variability, electrodermal activity, facial expressions, and body motion were identified as potential objective measures (c.f. Section 2.1.4). A user study investigating the suitability of the selected objective measures suggests that HRV RMSSD and body motion may be suitable as they significantly correlate with self-reported well-being and are sensitive enough to detect reactions to different stimuli (c.f. Section 5.2). The direction of correlation further suggests that passenger well-being positively relates to parasympathetic activity and negatively to sympathetic activity. Thus, emphasizing a state of relaxation in passenger well-being.

Despite the clear suggestions from this user study, the subsequent study used for empirical evaluation of the basic model provides contradictory results (c.f. Chapter 8). Here, self-reported well-being and HRV RMSSD correlate negatively, suggesting a state of arousal, possibly excitement. Body motion shows no significant relationship with self-reported well-being. Yet, a significant relationship with the subjective measure is required to successfully link subjective and objective measures (Looze et al., 2003). A possible explanation for the deviating results may be found in appraisal theory or habituation effects (Sauer, Mertens, Heyden et al., 2020). Based on the results of this work, the identification of the underlying mechanism is not possible. Additional research clarifying the relationship between objective and subjective measures of passenger well-being under different circumstances is mandatory. Only then can objective measures be used reliably to approximate passenger well-being and be utilized for research or for affective computing applications in automated driving.

RQ3: What physical and technical features of an automated vehicle are relevant for passenger well-being?

Physical features are one of the feature groups suggested to impact passengers' subjective evaluation of the travel experience. A number of these features and their effect on subjective evaluation have already been identified and discussed in prior research (e.g., Ahmadpour et al., 2014; Mayr, 1959; Richards, 1980) and present a compilation of physical features with potential relevance in automated driving. Moreover, this work argues that automated driving compared to other modes of transport has the unique characteristic that the driver shifts between the role of driver and passenger. Thus, technical features, which provide information on the vehicle state and offer control, such as user interfaces or driving controls, may be more important for passenger well-being in automated driving than in other modes of transport. Overall, the applicability of physical features proposed for other modes of transport has to be confirmed for automated driving, and physical and technical features novel to automated driving need to be explored.

A study with a multi-step approach identified potential physical and technical features that may be novel to automated driving from concept cars and evaluated them regarding their relevance for passenger well-being with an expert survey. The resulting features with sufficient relevance were assessed in a user study with the help of the Kano method (c.f. Chapter 6). The study suggests three categories of features with particular importance for passenger well-being in automated driving. Mandatory features, such as individual seats with arm rests, storage, vehicle status displays, and adjustability of the driving style, are required to avoid impairment of passenger well-being. These features are largely found in manually driven cars or other modes of transportation as well. Passenger well-being can be increased by leisure enablers such as seats with relax positions and massage functions, or privacy glazing and by smart functions that make interaction with the automated vehicle more intuitive and less cumbersome.

Interestingly, unique features that may be introduced through higher levels of automation, such as swivel seats, flexible steering wheel, or an active chassis were rated irrelevant for passenger well-being. This may be explained by the fact that these features facilitate NDRTs, which in turn diminish the subjective level of control. This may create trade-off decisions that affect passenger well-being. Features possibly affected by this trade-off decision should be reevaluated with more experienced users. Overall, the results from prior research are extended to include physical and technical features unique to automated driving (c.f. Table 6.2). This extended feature list acts as a list of determinants in the model of determinants of passenger well-being.

RQ4: How do motivation and ability influence the perception and processing of features of an automated vehicle relevant for passenger well-being?

Models describing the subjective evaluation of products or experiences published so far, concentrate on the relationship between features and evaluation. The processing mechanism is mainly neglected or limited to biomechanical processes. Yet, passenger well-being does not only result from physical, bodily reactions but from affective reactions as well. These processes may be influenced by the level of motivation to process automated vehicle features and the ability to do so, as suggested in the elaboration likelihood model (Petty & Cacioppo, 1986).

To assess the applicability of ELM to explain the perception and processing mechanism in automated driving, a user study utilizing a Wizard of Oz setup was conducted (c.f. Section 7.2). Study results indicate that ability and motivation drive elaboration likelihood in automated driving, i.e., the likelihood of thinking about and dealing with features of the automated driving experience. Depending on elaboration likelihood, different processing routes were detectable, providing evidence for the dual processing approach suggested by ELM. Overall, central processing dominated peripheral processing, which may be owed to the study design. Yet, peripheral processing was still evident. Further, higher levels of motivation and ability causing higher elaboration likelihood lead to a higher number of perceived features, impact the level of cognitive analysis, and increase the variety of passenger needs consulted in central processing to determine the level of well-being.

Applying the study results to the model of determinants of passenger well-being, it is suggested that features can either have a direct effect through peripheral processing, or the effect may be mediated by passenger needs in central processing. There is no clear allocation of features to one of the processing routes. How features are processed depends on the specific circumstances. Thus, dual processing, as suggested in ELM, is included in the model of determinants.

RQ5: What are relevant passenger needs in the context of automated driving, and how do they relate to features of the vehicle and passenger well-being?

Passenger needs can be derived from transport research and research on general human needs. Combining these sources, a number of possible passenger needs relevant in automated driving, in general, and central processing of vehicle features, in particular, can be derived. To assess the applicability of passenger needs suggested in research and to identify other relevant needs in automated driving, qualitative and quantitative approaches were used. Overall, nine passenger needs were identified that play a role in passenger well-being in automated driving (c.f. Section 7.1). These needs can be divided into utilitarian (physical well-being, trust, safety, comfort, usability) and hedonic needs (aesthetics, spatial feeling, symbolism, comfort). Empirical evidence across different user studies suggests that utilitarian needs are viewed as more important by passengers than hedonic needs. Also, utilitarian needs were more frequently considered than hedonic needs when determining the level of passenger well-being. One possible explanation may be that utilitarian needs need to be fulfilled to a minimum degree, similar to hygiene factors before hedonic needs become relevant and different need fulfillments can compensate each other. Interestingly, empirical results indicate that utilitarian needs are consulted fairly equally in the determination of passenger well-being, while comfort dominates clearly in the case of hedonic needs. This may be due to the fact that comfort is a more established measure in automotive evaluations compared to aesthetics, symbolism, or spatial feeling.

It is not conclusively clarified if the nine passenger needs suggested in this work are exhaustive. Very little feedback was given by participants that the list of needs is incomplete, but there were suggestions to add a need that addresses curiosity and mental engagement. This may be an indication that a state of flow (Csikszentmihalyi, 1999) is desirable in automated driving. For the model of determinants of passenger well-being proposed by this work, the nine passenger needs and their allocation to one of the two groups are included on the central processing route.

RQ6: How does culture as an example of individual passenger characteristics influence the relationship between features of an automated vehicle, passenger needs, and passenger well-being?

Well-being, in general, is closely linked to individual factors and circumstances such as culture (Diener & Suh, 2000). Culture also impacts the way products are perceived and evaluated (Creusen & Schoormans, 2005). Thus, culture may determine how features of automated vehicles are perceived and subsequently impact passenger well-being. Studies with experts and users in the markets China, Germany, and the USA suggest that culture shapes the perception of vehicle features and influences what features are relevant to fulfill certain passenger needs to in turn foster passenger well-being (c.f. Chapter 9). For example, increasing trust in automated vehicles may work best in the USA by demonstrating the capabilities of the vehicle to passengers. In China, trust may be built more efficiently by visibly integrating passive and active safety features. Based on the findings from these studies, automated vehicles do not have to be designed fundamentally different for each market. However, some features should be designed market specifically, such as material quality or glazing. Culture as an example for passenger characteristics with its moderating effect on perception is included in the model of determinants of passenger well-being

The empirical validations undertaken in this work provide only partial validations due to the complexity of the model caused by the large number of vehicle features. Both validation studies find evidence for the effects of vehicle features on passenger well-being through dual processing and mediation of passenger needs. Further, the moderating effects of NDRTs and culture as passenger characteristics are found. Yet, the findings from empirical validation studies are limited by their low validity (see discussion in sections 8.6 and 9.4). Thus, further empirical validation studies, possibly using other approaches and methods, are required.

Based on the findings for each research question and the overarching discussion, final conclusions on the hypothesized model of determinants of passenger well-being in automated driving can be drawn. The final proposal for the model of determinants of passenger well-being is summarized in Figure 10.1.

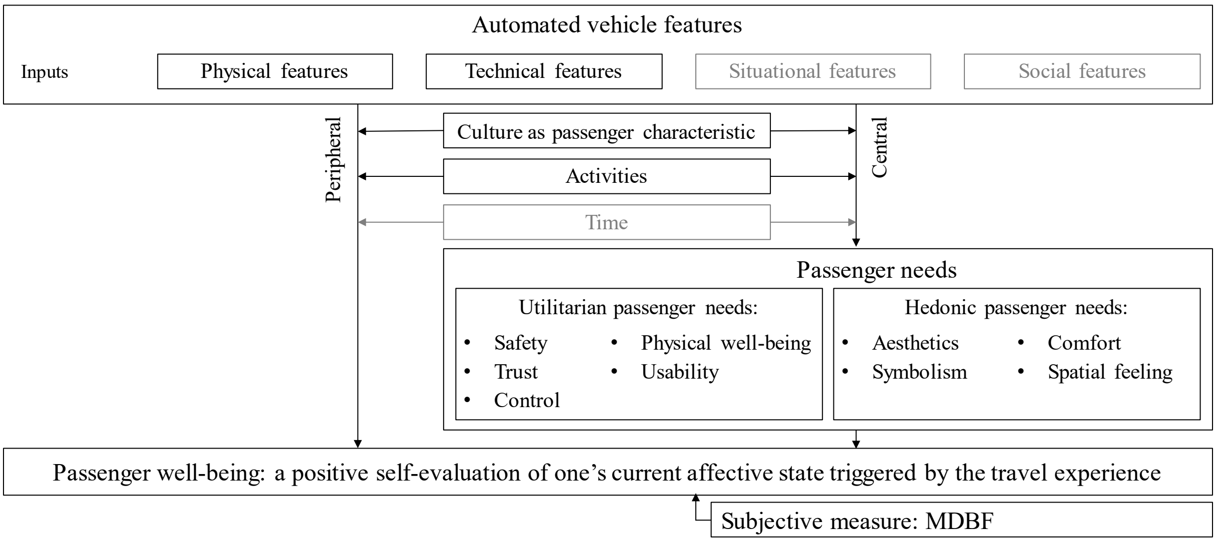


Figure 10.1 Final proposed model of determinants of passenger well-being in automated driving.

10.2 Implications for Future Research

This work examines different elements of the model of determinants of passenger well-being. The effect of each element could not be examined exhaustively in this work, and thus, opportunities for future research remain. The model draws strongly from prior research, such as the theory of comfort (Richards, 1980). Yet, not all determinants hypothesized in prior research are considered in this work. Situational and social features were deliberately excluded as they can hardly be influenced in a user-centered development process. Yet, they may remain important inputs deserving of future research. Similarly, time as a moderator has not been considered in this work. Additional passenger characteristics should also be investigated for a more complete view of the determinants of passenger well-being.

For those features that were considered in this work avenues for future research remain. The question of which objective measures are suitable for measurement of passenger well-being in automated driving could not be answered conclusively in this work. Further investigation, especially under consideration of situational circumstances and possible underlying mechanisms, such as appraisal theory or habituation effects, is advisable. New findings can contribute to a wider variety of valid and reliable measures of passenger well-being for research and may enable complex affective computing applications in automated vehicles.

This work contributes to the existing body of research, among other things, by considering and confirming cultural influences on passenger well-being. Although this work suggests that cultural differences in the markets considered are existent but not extreme, different culturally motivated nuances in the understanding of passenger well-being and its determinants may exist. This should be considered in future research.

Additionally, the model of determinants of passenger well-being proposed in this work is developed with empirical evidence. Empirical validation of the complete model has not been undertaken due to the complexity and the large number of determinants acting as potential independent variables. Instead, this work offers partial empirical validations of the basic model (c.f. Chapter 8) and the full model, including cultural effects (c.f. Chapter 9). However, the explanatory power of the validation studies depends on the determinants included and methods utilized. Thus, further research, including a larger number of determinants, is required. Both validation studies in this work omitted the effect of dynamic features, which could pose as interesting research topics. The validation studies conducted in this work displayed low validity limiting their explanatory power. Other methodological approaches are, thus, advised to ensure sufficient validity.

The model proposed in this work exclusively considers determinants and provides an extensive framework for factors influencing passenger well-being in automated driving. Yet, for a more holistic view on passenger well-being, its consequences are relevant as well. Future research investigating consequences can build on the consequences suggested in the theory of comfort (Richards, 1980) and may profit from existing findings such that pleasurable products are used more often (Jordan, 1998), and affect experienced during use may shape future product decisions (Steg, 2005) and drive product loyalty (Chiu, Cheng, Huang, & Chen, 2013).

10.3 Implications for Passenger Well-being in User-centered Development

Passenger well-being is increasingly gaining relevance in the user-centered design and development of vehicles (Addam, Knye, & Matusiewicz, 2018). This work provides extensive insights into the concept of passenger well-being specifically for automated driving and its determinants, which may provide a supporting framework for the development process of automated vehicles. The framework may assist in trade-off decisions during component development and provide guidelines for the user-centered design of components. Some findings may also apply to vehicles with lower automation levels, and thus, may be beneficial for the development of these vehicles as well.

In the development process, different circumstances, use cases for automated driving, and the individual characteristics of future users should be considered. In the case of user characteristics, one factor may be the level of experience with automated driving and the initial level of trust. Depending on these factors, vehicle features may differ in relevance. A user-friendly design addressing these differences between users can increase the acceptance of automated vehicles. This may be especially important for early generations of automated vehicles where market-diffusion of the product is uneven, and products have to appeal to users with different levels of trust and experience (Mahajan, Muller, & Bass, 1990).

In addition, methodological learnings from this work may be beneficial for a user-centered approach to developing automated vehicles. This work utilizes different methods to identify how passenger well-being may be increased. A mixed method approach using both experts’ and future users' opinions can be advisable for research during vehicle development to avoid the issue that future users may not be able to express their true preferences and needs due to lacking knowledge on the potential of future technologies (Füller & Matzler, 2007).

Findings from this work provide suggestions for user studies conducted during vehicle development. Users should be able to experience the features in question ideally through prototypes (e.g., as done in studies detailed in sections 6.3 and 7.2). Further, studies using interviews for collecting data may provide the advantage of gaining additional insights and explaining features and effects more thoroughly than possible in pen and paper or online studies. This may be beneficial for cases where users are asked to evaluate features they have no or limited experience with, which may apply especially for radical innovations.

In cases where pen and paper or online studies are favored, such as conjoint analysis, training the participants is advisable for complex stimuli or cases where participants may have little prior experience with consumer choices (Jaeger, Hedderley, & MacFie, 2001). This work has utilized two types of stimuli for conjoint analysis: allowing the participants to experience a prototype (c.f. Section 8.1) or realistic images of features (c.f. Section 9.2). For conjoint analysis, realistic images may be sufficient to represent stimuli (Jaeger et al., 2001).

10.4 Implications for the Design of Automated Vehicles

Apart from evidence required to build a model of determinants of passenger well-being, this work provides insights into how an automated vehicle can be designed to increase passenger well-being (c.f. Figure 10.2). As this work focuses on privately used vehicles, other implications may apply to other use cases, such as shared vehicles.

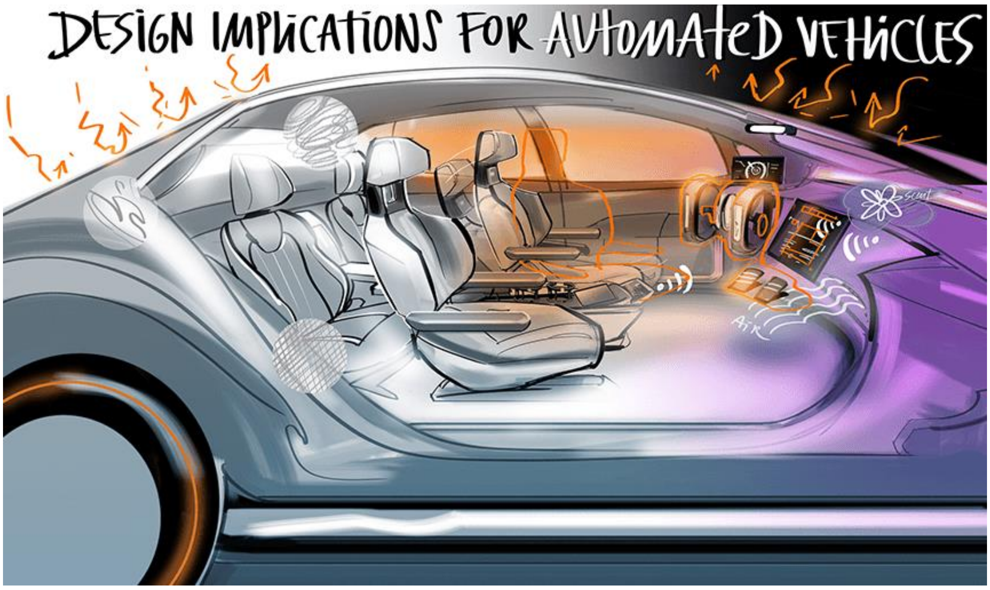


Figure 10.2 Visualization of design implications for automated vehicles, features that should emphasize user control are highlighted, copyright by schnellervorlauf gmbh.

In general, future users evaluate automated vehicles using currently available vehicles as a benchmark. Thus, features common in current vehicles are expected in future vehicles as a basic requirement. This includes mandatory features detailed in section 6.4, such as comfortable, individual seats, sufficient storage, and a minimum level of information on the automation status and control of the automation behavior. In level 4, driving controls still have to be integrated into the vehicle. Based on the study results, it is suggested that the retraction of driving controls, especially of the steering wheel, should be controlled by the driver. The controllability by the driver/passenger should also apply to novel features such as swivel seats, cocooning functions, or active chassis. This may increase the sense of control and safety.

Passenger needs other than control and safety require fulfillment as well. Based on the findings on passenger needs (c.f. Section 7.1), utilitarian needs should be sufficiently satisfied. This can be achieved through several features such as calm driving dynamics and the option to adjust the driving style (c.f. Figure 7.7). Further, interfaces providing clear and transparent information on the vehicle status can contribute as well. Hedonic needs require satisfaction as well to foster passenger well-being. Apart from a general appealing design and materials, sufficient space and comfortable seats are frequently suggested features. Additionally, passenger well-being may also benefit from creating different holistic interior experiences tailored to enabling different types of NDRTs. In case of relaxing, this may be achieved by adjustable seats, which can be set to a relax position, noise canceling and coordinated lighting, background music, and air conditioning (c.f. Section 6.3).

Moreover, passenger well-being should not only be considered as a means to an end. Passenger well-being in automated driving may also be used for affective computing, and the adjustment of systems and interfaces to the passenger's current condition (Li et al., 2019). This may present new avenues for vehicle design, allowing stronger customizability not only to an individual passenger but also to individual conditions or situations and, in turn, making the use of automated vehicles potentially less cumbersome and more enjoyable. However, a solid understanding of objective measures of passenger well-being is a prerequisite.

To tailor automated vehicles to market-specific requirements, the design does not have to be fundamentally changed. Rather, those features that have high importance for a specific market should be adjusted. Based on the studies in China, Germany, and the USA in this work, market-specific features could be material quality in China, a focus on ergonomic and pragmatic design in Germany, and a technology-centric, hands-on approach to automated vehicles in the USA.

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VI Figures

Figure 1.1 Examples of automated driving concepts that evolve the interior to a living space. 12

Figure 1.2 Overview of the chapter outline and corresponding research questions to build a model of determinants of passenger well-being. 16

Figure 2.1 Overview of selected conceptualizations of subjective well-being. 18

Figure 2.2 Elements of the theory of comfort, figure based on contents from Richards (1980). 34

Figure 2.3 Passenger comfort experience model (Ahmadpour et al., 2014, p. 811). 35

Figure 2.4 Overview of the preliminary model of determinants of passenger well-being. 60

Figure 3.1 Underlying two dimensional model of the Kano method, figure adapted from Kano et al. (1984, p. 170), Berger et al. (1993). 63

Figure 3.2 AUDI mockup from 2010 combined with external and internal screens for a static driving simulator setup. 68

Figure 3.3 Interior view of the Wizard of Oz setup used for real-world driving scenarios (Sauer, Mertens, Reiche et al., 2020). 68

Figure 4.1 Overview of study procedure addressing RQ1, RQ2a, and RQ5a, adapted from Sauer, Mertens, Heitland et al. (2019). 70

Figure 4.2 Updated overview of the proposed model of determinants of passenger well-being based on results to RQ1. 74

Figure 5.1 Mean ratings for passenger well-being (WB) across all repeated measures, error bar: ± 1SD, adapted from Sauer, Mertens, Heitland et al. (2019). 78

Figure 5.2 Overview of the study procedure to evaluate objective measures of passenger well-being. 82

Figure 5.3 Overview of the measures used in the user study to evaluate objective measures. 84

Figure 5.4 Updated overview of the proposed model of determinants of passenger well-being based on results to RQ2. 88

Figure 6.1 Overview of the study procedure addressing RQ3. 91

Figure 6.2 CS+ and CS- coefficients for investigated features. 94

Figure 6.3 Visualization of mandatory vehicle interior features, copyright by schnellervorlauf gmbh. 96

Figure 6.4 Visualization of vehicle interior features identified as leisure enablers (left), and smart functions (right), copyright by schnellervorlauf gmbh. 97

Figure 6.5 Updated overview of the proposed model of determinants of passenger well-being based on results of RQ3. 99

Figure 7.1 Mean importance rating of selected passenger needs for passenger well-being, error bars ± 1 SD. 102

Figure 7.2 Passenger needs derived from quantitative and qualitative data, adapted from Sauer, Mertens, Heitland et al. (2019, p. 243). 104

Figure 7.3 Wizard of Oz setup with highlighted pre-defined features for which perception is queried. 105

Figure 7.4 Plotted average means for corresponding hypotheses, error bars: Fisher's least significant difference (Sauer, Mertens, Reiche et al., 2020). 109

Figure 7.5 Boxplot of percentage of needs from predefined selection used by participants to determine well-being. 111

Figure 7.6 Plotted number of participants that perceived a respective feature. 112

Figure 7.7 Alluvial plot of processing routes and consulted passenger needs. 112

Figure 7.8 Frequency of processing routes and associated passenger needs in assessment of passenger well-being. 113

Figure 7.9 Visualization of selected vehicle features and corresponding need types (light blue: hedonic, dark blue: utilitarian) in central processing, copyright by schnellervorlauf gmbh. 115

Figure 7.10 Updated overview of the proposed model of determinants of passenger well-being based on results to RQ4 and RQ5. 115

Figure 8.1 Setup with the static driving simulator (left) and exemplary interior settings of the mockup (middle, right). 119

Figure 8.2 Interaction between seat rotation and NDRT on usability, error bars = ± 1 SE. .. 126

Figure 8.3 Visualization of preferences for automated interiors based on conjoint analysis results, copyright by schnellervorlauf gmbh. 128

Figure 8.4 Updated overview of the proposed model of determinants of passenger well-being based on empirical evaluation study. 128

Figure 9.1 Expert rating on the importance of passenger well-being for automated driving acceptance. 130

Figure 9.2 Average ranking of vehicle features regarding the importance for passenger well-being by experts (Sauer, Mertens, Groß et al., 2020). 130

Figure 9.3 Expert assessment of interior features fostering passenger well-being in respective markets (Sauer, Mertens, Groß et al., 2020). 132

Figure 9.4 Visualizations of well-being-enhancing vehicle interiors in each market according to the experts, copyright by schnellervorlauf gmbh. 133

Figure 9.5 Expert assessment of interior features fostering trust in respective markets (Sauer, Mertens, Groß et al., 2020). 135

Figure 9.6 Expert assessment of interior features fostering comfort in respective markets (Sauer, Mertens, Groß et al., 2020). 137

Figure 9.7 Distribution of adjusted R^2 of individual conjoint analyses for each group. 140

Figure 9.8 Plotted average means to corresponding hypotheses, error bars: Fisher's least significant difference. 142

Figure 9.9 Plotted average means to corresponding hypotheses, error bars: Fisher's least significant difference. 143

Figure 9.10 Visualization of the results for peripheral processing from the cross-cultural user study, copyright by schnellervorlauf gmbh. 146

Figure 9.11 Updated overview of the proposed model of determinants of passenger well-being based on results to RQ6. 149

Figure 10.1 Final proposed model of determinants of passenger well-being in automated driving. 156

Figure 10.2 Visualization of design implications for automated vehicles, features that should emphasize user control are highlighted, copyright by schnellervorlauf gmbh. 159

VII Tables

Table 1.1 Overview of vehicle automation levels based on SAE standard J3016. 13

Table 2.1 Overview of verbal self-report measures and reported reliability in exemplary transportation studies, adapted from Sauer, Mertens, Heitland et al. (2019). 24

Table 2.2 Overview of features of the travel experience based on the models on subjective evaluation in transport. 37

Table 2.3 Overview of perception themes from the passenger comfort experience model, adapted from Ahmadpour et al. (2014). 50

Table 2.4 Exemplary passenger characteristics suggested by Richards (1980). 53

Table 3.1 Original questions and scale for the Kano method (Kano et al., 1984) and adaption for well-being. 63

Table 3.2 Overview of selected decision rules and coefficients to aggregate and assess aggregated categorization. 64

Table 4.1 Clustered adjectives used by participants to describe their state of passenger well-being in automated driving, adapted from Sauer, Mertens, Heitland et al. (2019). 72

Table 5.1 Pearson correlation coefficients and p-values for passenger well-being and related concepts to investigate validity, adapted from Sauer, Mertens, Heitland et al. (2019).... 78

Table 5.2 Results of repeated measures ANOVA for subjective and objective well-being measures. 85

Table 5.3 Pearson correlation coefficients for objective measures with each single self-report item, adapted from Sauer, Mertens, Nitsch et al. (2019). 85

Table 6.1 Categorization of vehicle features regarding passenger well-being using the Kano method. 93

Table 6.2 Overview of physical and technical features based on related work and empirical findings. 99

Table 7.1 OLS regression coefficients for passenger needs as predictors of passenger well-being in the best and worst case. 101

Table 7.2 Priming used in the user study to create high/low levels of motivation and ability. 106

Table 7.3 Overview of sample and group demographics. 107

Table 7.4 Results of ANOVAs used to evaluate differences in perception and processing stipulated in H1-H3. 109

Table 8.1 Overview of attributes and levels used in user study. 118

Table 8.2 Overview of distribution of age and gender in the sample. 119

Table 8.3 Results of aggregated conjoint analysis for the evaluation of the preliminary model. 121

Table 8.4 Results of LMM to investigate the effect of passenger needs on subjective passenger well-being. 121

Table 8.5 Results on hypothesized central processing using mediation analysis. 122

Table 8.6 Results on hypothesized moderator effect. 122

Table 8.7 Comparison of sample characteristics of objective measures study and evaluation study. 124

Table 9.1 Overview of sample characteristics of the cross-cultural online study. 139

Table 9.2 Group sizes for intercultural comparison based on data subset with sufficient internal validity. 140

Table 9.3 Overview of aggregated conjoint results based on a subset of cross-cultural study. 141

Table 9.4 Results of ANOVAs used to evaluate intercultural differences stipulated in H2-H4. 141

Table 9.5 Results on hypothesized central processing in different markets using mediation analysis. 143

Table 9.6 Results of ANOVAs used to evaluate moderating effects stipulated in H10-H11. 144

VIII Appendix

A.1. Definitions of Well-being from a Psychological Perspective

Authors	Definition
Bradburn, 1969, p. 9	“A person's position on the dimension of psychological well-being is seen as a resultant of the individual's position on two independent dimensions - one of positive affect and the other of negative affect. The model specifies that an individual will be high in psychological well-being in the degree to which he has an excess of positive over negative affect and will be low in well-being in the degree to which negative affect predominates over positive.”
Brey, 2015, p. 367	“Well-being is a state of persons which designates that they are happy or flourishing and that their life is going well for them.”
Diener et al., 2002, p. 63	“Subjective well-being is defined as a person’s cognitive and affective evaluations of his or her life. These evaluations include emotional reactions to events as well as cognitive judgments of satisfaction and fulfillment. Thus, subjective well-being is a broad concept that includes experiencing pleasant emotions, low levels of negative moods, and high life satisfaction.”
Diener, Suh, & Oishi, 1997, p. 25	“Subjective well-being (SWB) refers to how people evaluate their lives, and includes variables such as life satisfaction and marital satisfaction, lack of depression and anxiety, and positive moods and emotions.”
Diener et al., 1999, p. 277	“Subjective well-being is a broad category of phenomena that includes people's emotional responses, domain satisfactions, and global judgments of life satisfaction.”
Eid & Diener, 2004, p. 245	“SWB refers to people’s multidimensional evaluations of their lives, including cognitive judgments of life satisfaction as well as affective evaluations of moods and emotions.”
Keyes, 1998, p. 121	“The psychological tradition operationalizes well-being as the subjective evaluation of life via satisfaction and affect […] or personal functioning […]. According to this view, emotional well-being is an excess of positive over negative feelings; personal psychological functioning is the presence of more positive than negative perceived self-attributes such as personal growth.”
Lundqvist, 2011, p. 111	“The term subjective well-being (SWB) applies to affective and judgmental elements of well-being.”
Lyubomirsky, 2007, p. 32	“I use the term happiness to refer to the experience of joy, contentment or positive well-being, combined with a sense that one’s life is good, meaningful and worthwhile”
Ryan & Deci, 2001, p. 142	“The concept of well-being refers to optimal psychological functioning and experience“
Ryff, 1989, p. 1071	Characteristics of psychological well-being: Self-acceptance, positive relations with others, autonomy, environmental mastery, purpose in life, personal growth

Authors	Definition
Wright, Emich, & Klotz, 2017, pp. 47–48	“As we define it, psychological well-being has three primary defining characteristics. First, it is a phenomenological event. People are psychologically well when they subjectively believe themselves to be so. Second, it involves how we feel, experience, and process various forms or patterns of emotional feelings. In particular, psychologically well individuals are more prone to experience positive emotions and less prone to experience negative emotions. Third, psychological well-being is best considered as a global judgment. This means that psychological well-being refers to one's life in the aggregate, that is, considered as a whole.”

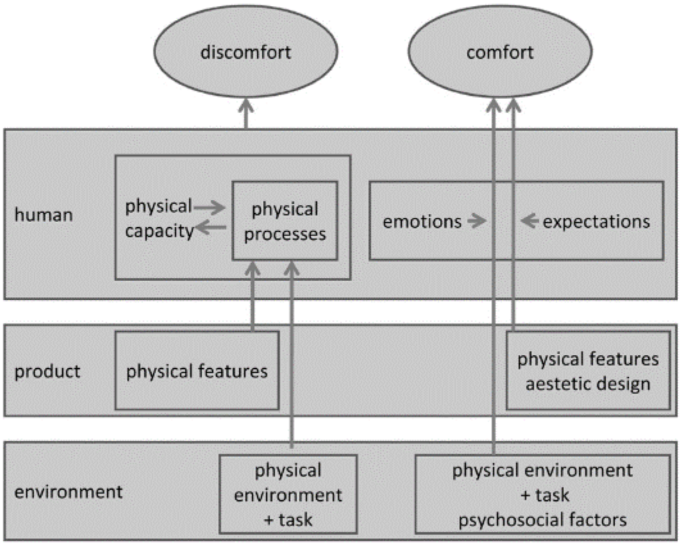
A.2. Definitions of Well-being in Transportation

Authors	Transportation mode	Definition	Type
Ahn et al., 2015, S123	Air	"An individual's well-being perception is defined as a 'consumer's perception of the extent to which a brand (a consumer good or service) contributes to positive affect in various life domains creating an overall perception of the quality-of-life impact of that brand' (Grzeskowiak & Sirgy, 2007, p. 291)."	Psychological
Hinninghofen & Enck, 2006	Air	Not provided but focus on health-related effects	Health
Kremser et al., 2012	Air	Not provided but operationalized as 1-item for overall well-being	-
Marggraf-Micheel et al., 2010	Air	Not provided, but operationalized as physical and psychological well-being	Psychological
Winzen et al., 2014, p. 466	Air	"subjective well-being in terms of psychological and physiological aspects"	Psychological
Ma et al., 2018, p. 16	Bike sharing	"Subjective well-being is defined as 'a broad category of phenomena that includes people's emotional responses, domain satisfactions, and global judgments of life satisfaction' (Diener et al., 1999)."	Psychological
Zhang et al., 2017, p. 203	Bike sharing	"Subjective well-being is defined as 'a broad category of phenomena that includes people's emotional responses, domain satisfactions and global judgments of life satisfaction' (Diener et al., 1999)."	Psychological
Senn et al., 2018, p. 1581	Car	"Subjective well-being (SWB) describes one's well-being through the global evaluation of life satisfaction (LS), positive affect (PA), and negative affect (NA) (Diener, 1984)"	Psychological
Silla & Gamero, 2018, p. 85	Car	No definition provided but: "Burnout and general health were selected as indicators of drivers' well-being at work."	Health
Sirgy et al., 2006	Car	"Consumer well being (CWB) with personal transportation: The extent to which personal transportation vehicle satisfies human developmental needs"	Psychological
Reardon & Abdallah, 2013, p. 637	General transportation	"well-being is defined as the good feelings day to day and overall, coupled with positive psychological functioning (which includes creative thinking, productivity, and good interpersonal relationships and resilience — all elements of flourishing), and the ability to fulfill individual needs and engage with society (Foresight Mental Capital and Well-being, 2008, pp. 61–63)"	Psychological

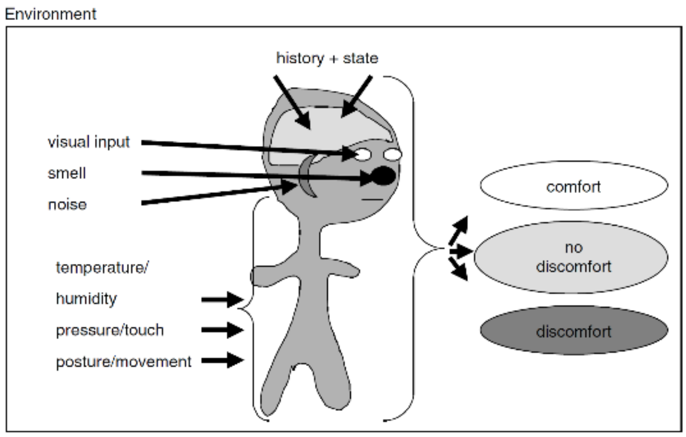
A.3. General Models on Comfort as Subjective Evaluation

Theoretical model of comfort and discomfort by Looze et al. (2003)

Figure from Vink & Hallbeck, 2012, p. 274

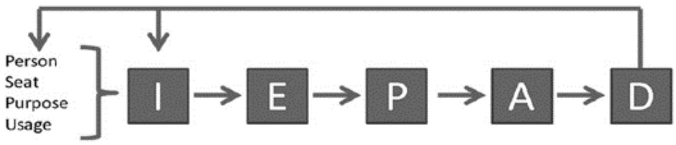


Comfort model by Vink, Looze et al. (2005)

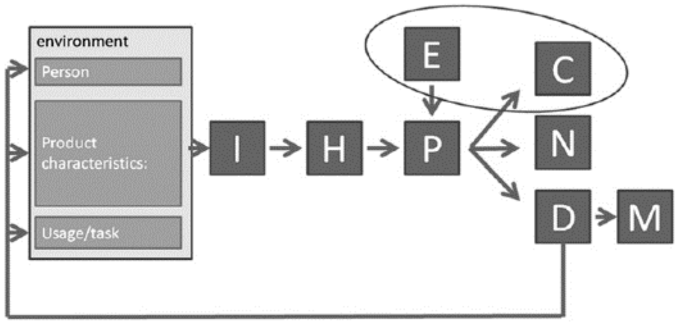


Comfort model by Moes (2005)

Figure from Vink & Hallbeck, 2012, p. 274

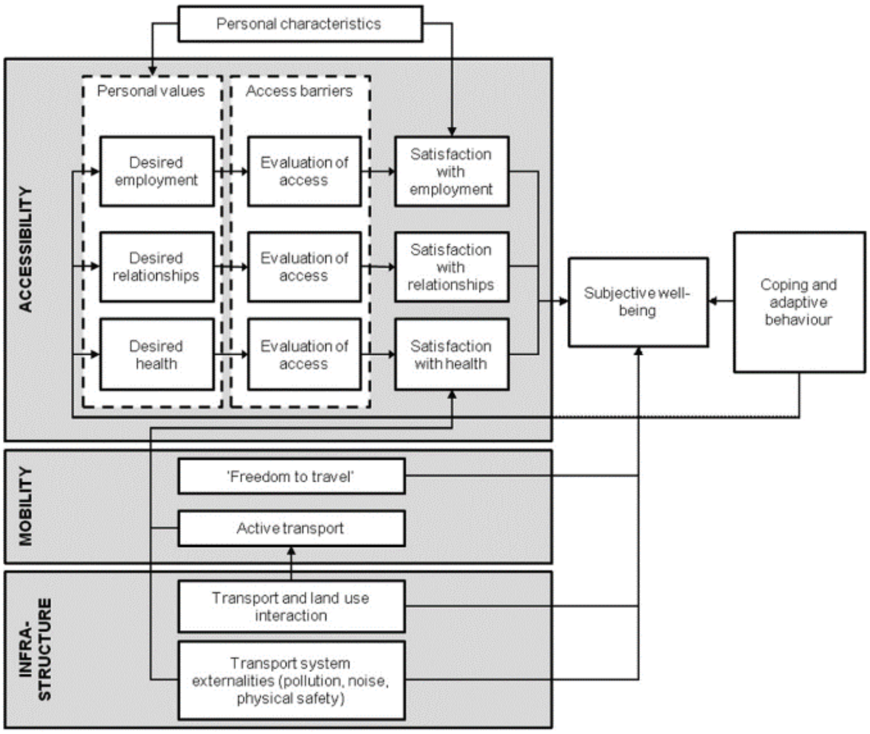
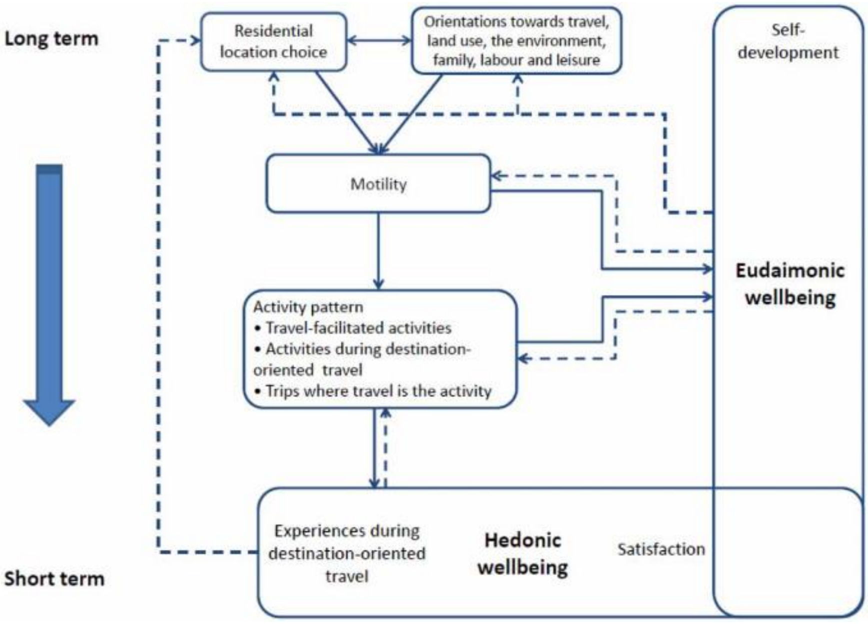


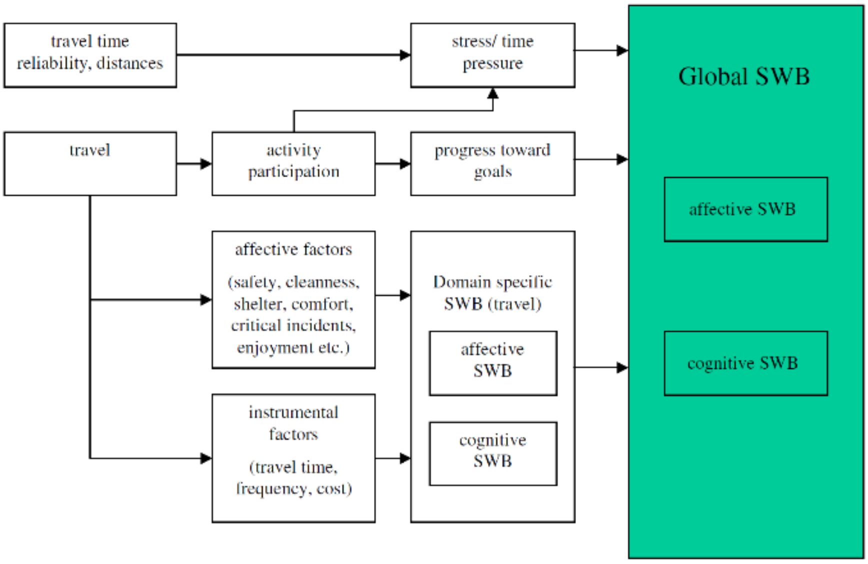
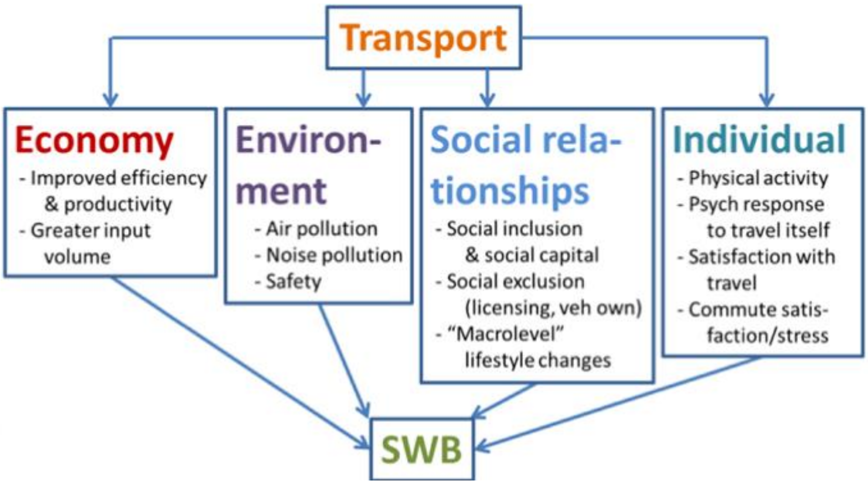
Comfort model by Vink & Hallbeck, 2012, p. 275



A.4. Models on the Influence of Transportation on Well-being

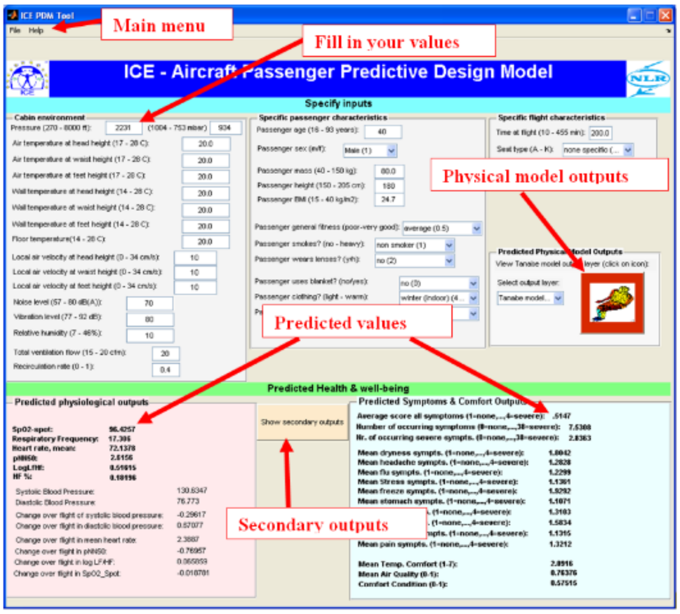
Model overview provided by Mokhtarian (2019)

Theoretical model of transport's influence on subjective well-being by Delbosc, 2012, p. 29	
Theoretical model of links between travel behaviour and well-being by Vos et al., 2013, p. 435	

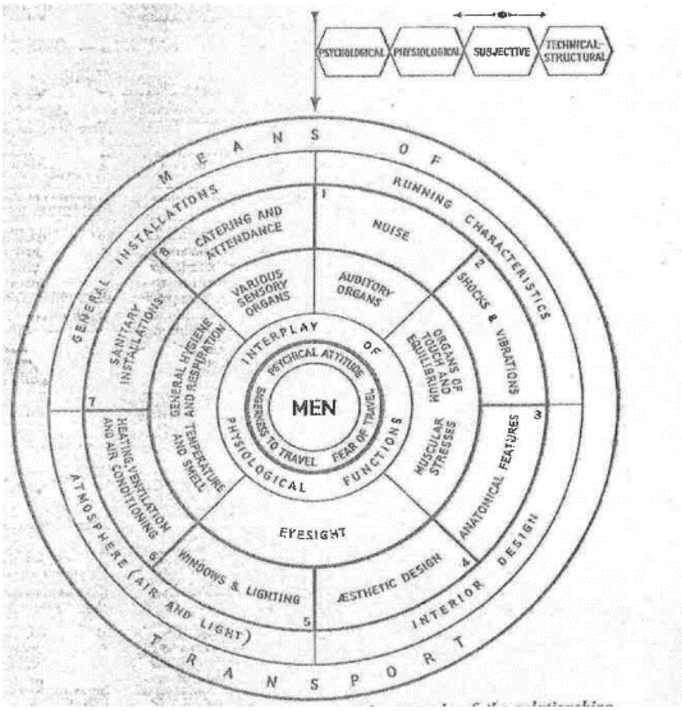
Theoretical framework by Ettema et al., 2010, p. 728	
Model by Reardon & Abdallah, 2013; Figure by Mokhtarian, 2019, p. 499	

A.5. Models on Subjective Evaluation in Transport

Model for predicting well-being in aircraft cabins by Vankan, 2010, p. 9



Circle of riding comfort by Mayr, 1959, p. 267



A.6. Stimuli Used to Evaluate the Suitability of Objective Measures for Passenger Well-being

Overview from Sauer, Mertens, Nitsch et al. (2019).

Stimulus	NDRT	Backrest	Ambient light	Steering wheel	Tablet position	Center console
1	Working	Upright	Blue	Collapsed	Hand-held	High
2	Relaxing	Reclined	Blue	Collapsed	Mounted	Low
3	Working	Reclined	Blue	Moveable	Hand-held	Low
4	Working	Upright	Yellow	Moveable	Mounted	Low
5	Relaxing	Reclined	Yellow	Moveable	Hand-held	High
6	Relaxing	Upright	Blue	Moveable	Mounted	Low
7	Relaxing	Upright	Yellow	Collapsed	Hand-held	Low
8	Working	Reclined	Yellow	Collapsed	Mounted	High
9	Working	Reclined	Yellow	Moveable	Hand-held	High
10	Working	Upright	Yellow	Collapsed	Mounted	Low

A.7. Manufacturers Considered for Identifying Potential Features from Automated Vehicle Concepts

Region	Country	Manufacturers
Asia	China	Byton, Nio
	Japan	Nissan, Toyota
	South Korea	Kia
Europe	France	Citroen, Renault
	Germany	Audi, BMW, Mercedes-Benz, Smart, VW
	Sweden	Volvo
	Switzerland	Rinspeed
	United Kingdom	Aston Martin Lagonda, Bentley, Mini, Rolls-Royce
North America	USA	Chevrolet, Chrysler

A.8. Overview of Identified Features and Mean Rating of Relevance

Mean rating performed by 15 experts on a 1-3 scale (1: not relevant for passenger well-being, 2: unsure, 3: relevant for passenger well-being);

In Grey: Features selected for user study (mean rating > 2.5)

* Features added to user study based on evidence from prior studies.

Feature	Explanation	Mean rating
Driving dynamics		
Adjustable driving style	Driving style in automated mode can be adjusted within technical and legal constraints by the driver	2.73
Learning driving style	Automated vehicle adapts preferred driving style from the driving sections driven manually	1.73
Active chassis	Lateral forces are reduced through active chassis when automated mode is active	2.53
Vehicle architecture		
Flexible steering wheel	When in automated mode, the steering wheel can be moved away for more space	2.60
Swivel seats*	Front seats can rotate ±15°	1.73
Rotating seats	Front seats can rotate ±180°	2.00
Individual seats	All seats in the vehicle are individual seats which can be adjusted accordingly	2.80
Bench	All seat rows have bench seats instead of individual seats	1.27
Relax position	Seats can be adjusted to a relax position with larger back rest angles	2.67
Foot rest	Seat includes a foot rest	2.73
Arm rest	Seat includes an arm rest	3.00
Massage*	Seats with massage function which can be adjusted in intensity and massage program	-
Table	A foldable table is available in automated mode	2.73
Storage	Storage for personal items in different areas of the vehicle	2.93
Glass roof	Large-scale glass roof	2.27
Switchable glass roof	Glass roof with switchable glass to adjust transparency	2.20
Privacy glass	Side windows with switchable glass to switch between transparent and privacy glass	2.73
Foldable head rests	Head rests of front seats are foldable	1.80
Cocooning	Option to unfold privacy screen	2.60
Brand	Brand of the vehicle	1.79

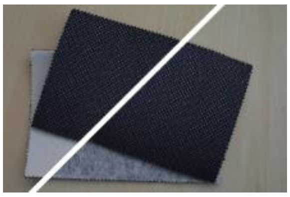
Materials		
Light interior colors	Materials used in the interior are in light colors	2.27
Dark interior colors	Materials used in the interior are in dark colors	1.80
Plants	Real life plants integrated into the vehicle interior	1.40
Sustainable materials*	Sustainable materials such as textiles made from recycled materials are used in the interior. The sustainability aspect does not impair quality or haptics	2.40
Material quality*	The materials used in the interior are of high quality and have visual and haptic appeal	-
Ambient features		
Active noise canceling	Reducing interior noise volume through active noise canceling system utilizing the onboard sound system	2.60
Interior fragrance	Option to scent interior with different fragrances	1.67
Ambient light roof	Additional ambient lighting integrated into vehicle roof	2.40
Situational air conditioning	Automatic control of air conditioning (temperature, air flow) based on situational factors such as weather or physiological indicators of users	2.67
Situational settings of ambient light	Ambient light (color, brightness) is controlled based on situational factors such as NDRTs, time of day	2.53
Situational settings of reading light	Brightness of reading light is controlled based on situational factors such as NDRTs, route (e.g., tunnels)	2.60
Driver interaction		
Haptic interaction	Users can interact with the vehicle through haptic controls	2.00
Touchpanels	Users can interact with the vehicle through touch panels	2.33
Touchpanels with haptic feedback	Users can interact with the vehicle through touch panels with haptic feedback	2.33
Gestures	Users can interact with the vehicle through gestures	1.86
Voice control	Users can interact with the vehicle through natural voice control	2.87
Brain computer interface	Users can interact with the vehicle through a brain computer interface	1.50
Interaction via eye tracking	Users can interact with the vehicle through gaze via eye tracking	2.07
Facial recognition	Users can interact with the vehicle through facial recognition such as emotion detection	1.87
Own devices	Users can interact with the vehicle through their own devices using an app	2.73
Pillar to pillar display	Display across the complete width of the vehicle cockpit	2.07
Display in sun visor	Display integrated into both sun visors in the front of the vehicle	1.27
Head up display	Head up display across the whole windscreen	2.14
Display in foot space	Displays integrated into foot space of front seats	1.07

Displays in door panels	Displays integrated into door panels of all vehicle doors	1.60
Displays in side windows	Transparent displays integrated into side windows	1.67
Displays in rear panel	Display integrated into rear panel of vehicle and accessible if no rear seat passengers are in the vehicle	1.47
Displays in head rests	Displays integrated into head rests of front seats for rear seat passenger	2.50
Individual displays	Individual displays for each passenger integrated into interior	2.60
Holograms	Users can interact with the vehicle through holograms	2.27
Projections	Users can interact with the vehicle through projections	2.33
Virtual reality	Users can utilize virtual reality for interactions and NDRTs	2.13
Augmented reality	Information is displayed using augmented reality	2.13
Vehicle status display	Vehicle status, esp. in automated mode, is displayed in a central display	2.80
Vehicle status ambient	Vehicle status, esp. in automated mode, is conveyed through an ambient light display	2.53
Vehicle status morphing	Vehicle status, esp. in automated mode, is conveyed through morphing surfaces	1.73
Empathic assistant	Users can interact with an empathic voice assistant	2.27
Anthropomorphic interaction	The interaction with the vehicle is designed using anthropomorphic traits	1.64
Memory function	Users can save all interior settings in a memory function	2.93
Learning system	The vehicle is able to learn users' preferences such as routes, interior settings or similar	2.87
Emergency off	Driver can use the emergency off to force the vehicle to stop safely when in automated mode	2.47
Driver health and wellness		
Integration of wearables	Information about driver status is derived from driver's wearable and displayed in the vehicle	1.86
Visualization of driver state through heart rate	Information about driver status is derived from integrated heart rate sensors and displayed in the vehicle	1.67
Visualization of driver state through cameras	Information about driver status is derived from integrated cameras and displayed in the vehicle	2.20
Visualization of driver state through respiration	Information about driver status is derived from integrated respiration sensors and displayed in the vehicle	1.50
Visualization of driver state through brain waves	Information about driver status is derived from integrated brain wave sensors and displayed in the vehicle	1.57
Visualization of driver state through body temperature	Information about driver status is derived from integrated body temperature sensors and displayed in the vehicle	1.73

Visualization of driver state through eye tracking	Information about driver status is derived from eye tracking and displayed in the vehicle	2.13
Visualization of driver state through iris recognition	Information about driver status is derived from iris recognition sensors and displayed in the vehicle	1.71
Visualization of driver state through muscle tension	Information about driver status is derived from muscle tension sensors and displayed in the vehicle	1.60
Relaxation exercises*	A menu with different relaxation exercises (e.g., meditation, biofeedback, yoga) is included in the vehicle and can be accessed by the driver when driving automated	2.33
Themed interiors	Depending on primary themes (e.g., work, leisure, relax) the interior settings such as seats, air conditioning, music, lighting, fragrances, etc., are adjusted to create an environment that facilitates primary theme	2.80

A.9. Overview of Prototypes Used to Visualize Features for User Study

D1. Adjustable driving style	 Screenshot of prototype interface	D2. Active chassis	Verbal explanation using the experience in the static driving simulator as extreme for an active chassis as compared to today's chassis
V1. Flexible steering wheel	Steering wheel with flexible depth adjustment and foldable rim	V2. Swivel seats	
V3. Individual seats	 Seat bench in rear as example for dysfunctional question	V4. Relax position	
V5. Foot rest		V6. Arm rest	
V7. Massage	Experience of seat massage integrated into front seats of mockup	V8. Table	
V9. Storage	Storage integrated into table (V8)	V10. Privacy glass	
V11. Cocooning			

M1. Sustainable materials	 Example of textiles made from unrecycled (left, virgin PET) and recycled materials (right, PET bottles)	M2. Material quality	 Example for low quality materials
A1. Active noise canceling	Verbal explanation using different noise levels in the driving simulator as an example	A2. Situational air conditioning	Verbal explanation based on feature definition in Table above
A3. Situational settings of ambient light		A4. Situational settings of reading light	
I1. Voice control	Verbal explanation using ambience light setting as example	I2. Own devices	 Screenshot of prototype interface on private device
I3. Individual displays	Verbal explanation using spare tablet as additional display mounted on dashboard on the passenger side	I4. Vehicle status display	 Screenshot from instrument panel with information on vehicle status
I5. Vehicle status ambient	Verbal explanation using ambient light (c.f. feature A3) as example	I6. Memory function	 Screenshot of prototype interface
I7. Learning system	 Screenshot of prototype interface		

H1. Relaxation exercises	 Exemplary breathing exercise using application from Calm (2019)

H2. Themed interiors	 Themed interior with lighting, sounds, and fragrance, additional verbal explanations on coordinating air conditioning

A.10. Overview of Adjectives Used to Describe a Vehicle Interior that Creates Passenger Well-being

Overview adapted from Sauer, Mertens, Heitland et al. (2019), adj: adjectives.

Usability		Spatial feeling		Comfort		Atmosphere		Symbolic value		Safety		Aesthetics		Hygiene	
Clear	12	Spacious	7	Comfortable	13	Modern	6	High quality	7	Safe	7	Appealing	3	Clean	4
Functional	11	Light	7	Convenient	7	Tidy	4	Sporty	4	Sturdy	1	Aesthetic	2	Smells	1
Intuitive	7	Cozy	5	Warm	4	Simple	2	Fine	3	Solid	1	Chic	2	Fragrant	1
Structured	4	Big	4	Soft	2	Technical	2	Elegant	2	Powerful	1	Beautiful	2	Neat	1
Easy	3	Good view	3	Tempered	2	Ambience	1	Superior	2	Persuasive	1	Pleasant	2		
Ergonomic	2	Open	2	Quiet	1	Neutral	1	Classy	2	Robust	1	Harmonious	1		
Comprehensible	2	Small	2	Cool	1	Not bright	1	Impressive	1	Secure	1	Subtle	1		
Reliable	2	Generous	1			Not cluttered	1	Reputable	1	Soothing	1				
Practical	2	Pleasant	1			Homogeneous	1								
Useable	1	Compact	1			Calm	1								
User friendly	1	Dark	1			Factual	1								
Self-explanatory	1	Closed	1			Relaxed	1								
Informative	1	Snug	1			Innovative	1								
Supportive	1					High-tech	1								
Predictable	1					New	1								
Familiar	1					Tasteful	1								
Flexible	1														
Versatile	1														
18 adj.	54	13 adj.	36	7 adj.	30	16	26	8	22	8	14	7 adj.	13	4 adj.	7

A.11. Profiles Used in Evaluation of the Preliminary Model

Profile	NDRT	Noise canceling	Seat rotation	Ambient lighting
1	Relax	42 dB	15°	Yellow
2	Relax	42 dB	0°	Green
3	Work	68 dB	0°	Green
4	Relax	68 dB	15°	Green
5	Relax	68 dB	0°	Yellow
6	Work	42 dB	0°	Yellow
7	Work	42 dB	15°	Green
8	Work	68 dB	15°	Yellow

A.12. Profiles Used in Cross-cultural Conjoint Analysis

	Display	Glazing	Seat adjustment	Material quality
1	Extended information + light display	Privacy	Pre-configured profiles	Premium
2	Basic information	Privacy	Manual	Standard
3	Extended information	Privacy	Pre-configured profiles	Standard
4	Extended information + light display	Privacy	Automatic	Premium
5	Extended information + light display	Transparent	Manual	Premium
6	Extended information	Transparent	Manual	Premium
7	Basic information	Privacy	Pre-configured profiles	Premium
8	Extended information + light display	Transparent	Pre-configured profiles	Standard
9	Extended information	Transparent	Manual	Standard
10	Extended information	Privacy	Automatic	Premium
11	Basic information	Transparent	Manual	Standard
12	Extended information + light display	Transparent	Automatic	Premium
13	Extended information + light display	Privacy	Pre-configured profiles	Standard
14	Extended information + light display	Transparent	Automatic	Standard
15	Basic information	Transparent	Pre-configured profiles	Premium
16	Extended information	Privacy	Manual	Premium
17	Basic information	Privacy	Manual	Premium
18	Basic information	Privacy	Automatic	Standard
19	Extended information	Transparent	Pre-configured profiles	Standard
20	Basic information	Transparent	Automatic	Premium
21	Extended information + light display	Privacy	Manual	Standard
22	Extended information	Transparent	Pre-configured profiles	Premium
23	Extended information	Privacy	Automatic	Standard
24	Basic information	Transparent	Automatic	Standard

A.13. Attribute Explanations Used in Cross-cultural Conjoint Analysis

Display with information on car status

A central display shows information on the car status when the car is in Autopilot. The information displayed varies regarding the amount of information and its presentation.

Basic information:

The central display shows the following basic information:

- Activation Autopilot (On/Off)
- Current speed
- Remaining range
- Remaining time until reaching destination

Extended information:

The central display shows extended information in addition to the basic information:

+ Remaining time in Autopilot

+ Next manoeuver of the car (e.g., lane change, overtaking)

Extended information with ambient light display:

The central display shows extended information.

Additionally, an upcoming request for you to take-over the driving task is visually announced through a color change of the ambient light display below the windshield.

Glazing of side windows

All side windows of the car are made of switchable glass. With switchable glass, the transparency of the side windows can change between transparent and privacy glass in Autopilot. When you are driving the car yourself (Autopilot inactive), all side windows are transparent.

Side windows with transparent glass:

- When driving in Autopilot, all side windows are transparent
- You can clearly see outside of the vehicle
- The interior of the car is fully visible from outside.

Side windows with privacy glass:

- When driving in Autopilot, all side windows are switched to privacy glass
- You can see outside of the vehicle with only minor restrictions
- The interior of the car is hardly visible from outside.

Seat adjustments for non-driving related tasks

You can engage in non-driving related tasks once Autopilot is activated. Please imagine that you use time in Autopilot to do some small work tasks such as reading and answering your emails/to relax by meditating or following a guided breathing exercise. You can adjust your seat when working/relaxing. There are three options to adjust the seat.

Manual adjustment:

- You can adjust the seat manually using the electric seat controls.

Adjustment via pre-configured profiles:

- You can configure different seat positions for different use cases beforehand and save them as different profiles.
- In Autopilot, you can choose one of the predefined configurations, and the seat automatically adjusts.

Automatic adjustment:

- The car can detect which non-driving related tasks you are engaging in while in Autopilot through sensors in the interior.
- Based on preconfigured seat settings, the seat is automatically adjusted accordingly.

Material quality

The materials used in the interior, such as seat covers, decorative inlays, and surfaces, can either be in standard or premium quality.

Standard quality:

- Simple materials are used in the interior.
- The materials are plain and can have minor flaws.
- The seat covers are made of fabric.
- Most surfaces in the interior are made of plastic.

Premium quality:

- Premium materials are used in the interior.
- The materials are of high quality and exclusive.
- The seats and surfaces are upholstered with leather.

A.14. Exemplary Paired Comparison Rated in Cross-cultural Conjoint Analysis

Please assume that you are **driving in your automated car with active Autopilot**. While in Autopilot, you are **relaxing** by meditating or following a guided breathing exercise.

Please indicate which feature combination creates the highest level of well-being, trust, and comfort for you.
Please provide a value on the respective scale for each of the 3 criteria.

Please assume that the two options only differ regarding the specified features. All other features are identical for both options.

Option 1	Option 2
Display: Basic information	Display: Extended information with ambient light display
Glazing: Side windows with privacy glass	Glazing: Side windows with transparent glass
Seat adjustment: Manual adjustment	Seat adjustment: Automatic adjustment
Material quality: Standard quality	Material quality: Standard quality

	1	2	3	4	My well-being is equal in both options 5	6	7	8	9	
I have the highest well-being in **option 1**	○	○	○	○	○	○	○	○	○	I have the highest well-being in **option 2**

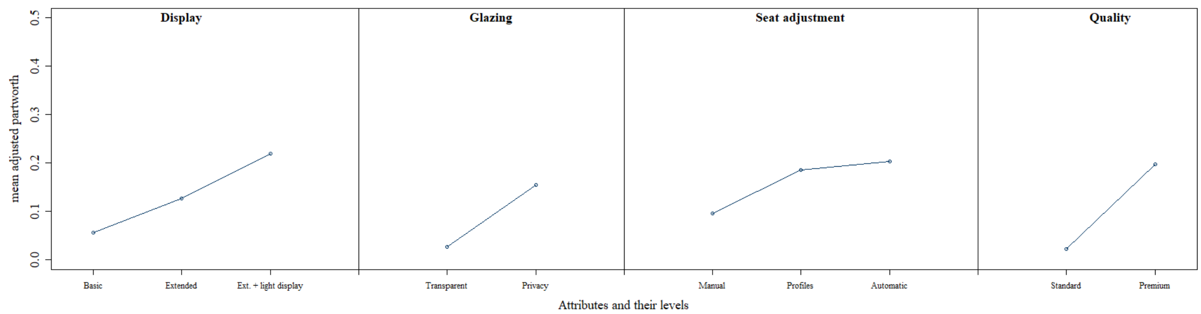
	1	2	3	4	I trust both options equally 5	6	7	8	9	
I trust a car with features from **option 1** the most	○	○	○	○	○	○	○	○	○	I trust a car with features from **option 2** the most

	1	2	3	4	Both options are equally comfortable 5	6	7	8	9	
Option 1 is most comfortable	○	○	○	○	○	○	○	○	○	**Option 2** is most comfortable

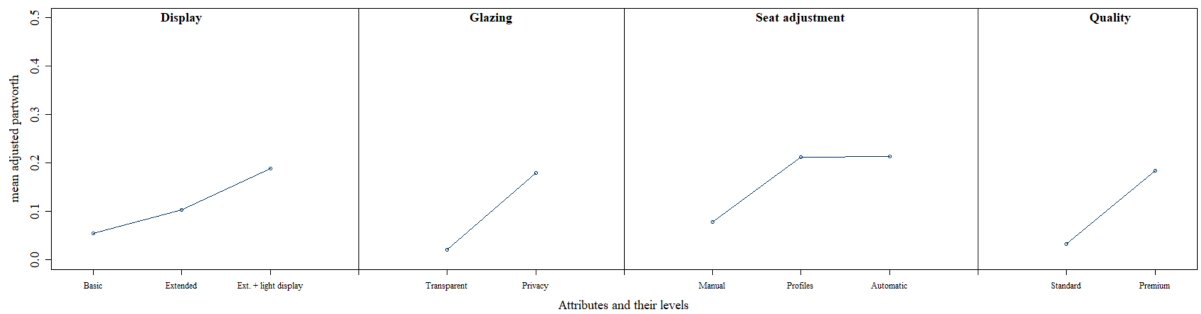
A.15. Partworth Diagrams for Cross-Cultural Conjoint Analysis

Based on aggregated results with subsetted data.

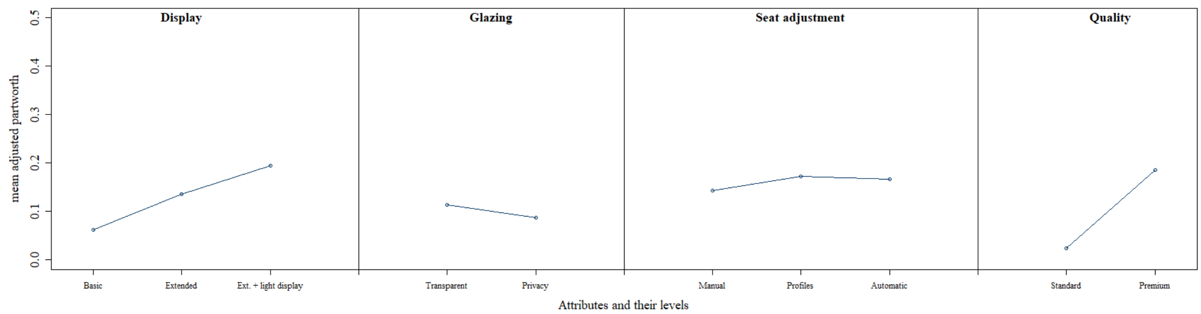
Mean partworths across subsample: NDRT relax in CN



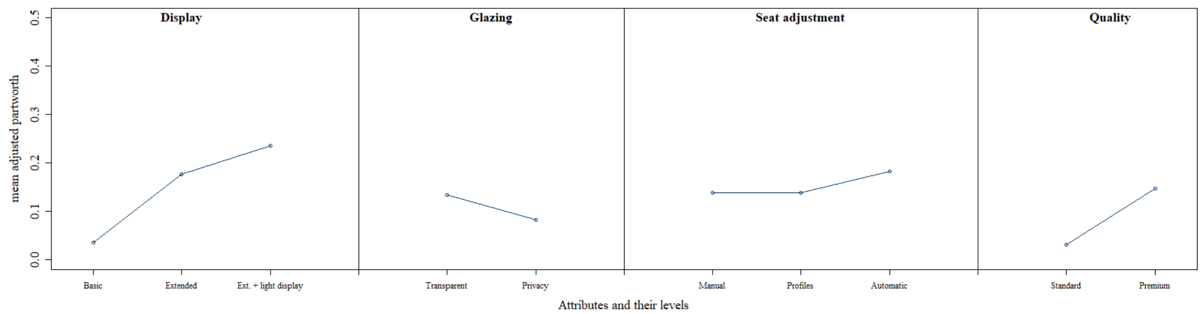
Mean partworths across subsample: NDRT work in CN

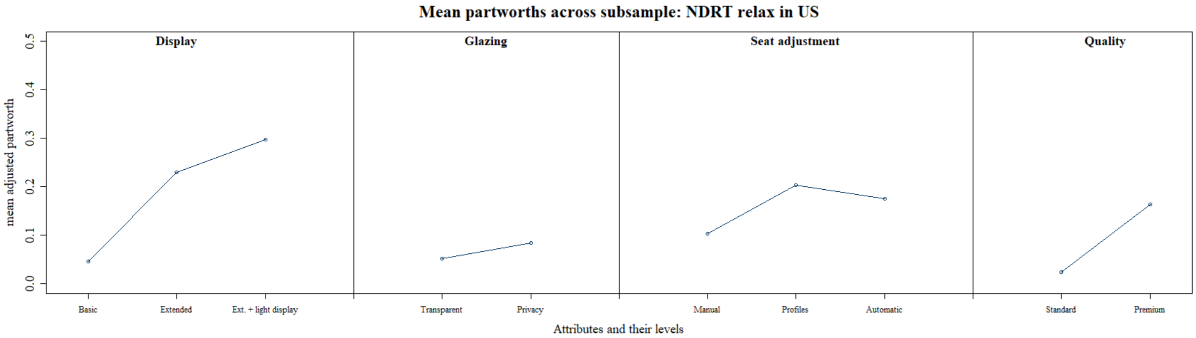


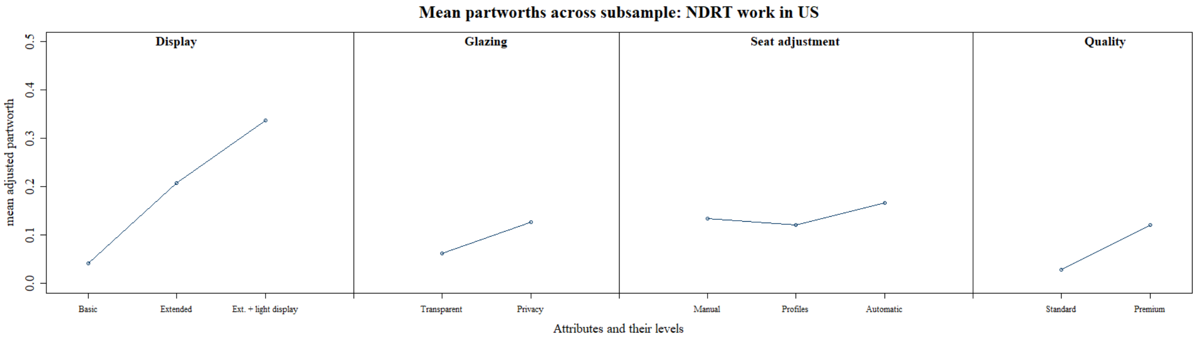
Mean partworths across subsample: NDRT relax in DE



Mean partworths across subsample: NDRT work in DE




Mean partworths across subsample: NDRT relax in US
Display
Glazing
Seat adjustment
Quality
mean adjusted partworth
0.0
0.1
0.2
0.3
0.4
0.5
Basic
Extended
Ext. + light display
Transparent
Privacy
Manual
Profiles
Automatic
Standard
Premium
Attributes and their levels


Mean partworths across subsample: NDRT work in US
Display
Glazing
Seat adjustment
Quality
mean adjusted partworth
0.0
0.1
0.2
0.3
0.4
0.5
Basic
Extended
Ext. + light display
Transparent
Privacy
Manual
Profiles
Automatic
Standard
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Attributes and their levels