Is more automation always better? An empirical study of customers' willingness to use autonomous vehicle functions

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Abstract: Sometime, many (maybe all) vehicles on our streets will drive autonomously – or at least have autonomous functions. However, in the short run, consumers' preferences regarding the automation of pivotal vehicle functions are not entirely clear. This paper accordingly investigates consumers' willingness to use three levels of automation (none, partial, and full) of potentially autonomous vehicle functions (safety, parking prediction, and remote diagnostics). The results show that consumers' willingness to use autonomous vehicle functions is generally the highest for moderately autonomous functions and that the willingness to use these functions decreases above a certain level of autonomy. This paper also finds that this effect is moderated by gender and depends on individual involvement level with respect to autonomous vehicle functions, that is, highly involved consumers are more likely to appreciate autonomous vehicle functions compared with low-involved consumers.

Keywords: autonomous vehicles; autonomous vehicle functions; choice-based conjoint analysis; consumer preferences; involvement; level of automation; safety; parking prediction; remote diagnostics; willingness to use; WTU.

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1 Introduction

Several car producers and some IT companies have already presented prototypes of autonomous vehicles (AVs), and the first commercially available driverless cars are expected to be on roads within the next years (Driverless Car Market Watch, 2017; Krueger et al., 2016; Wadud et al., 2016). For instance, BMW announced market entry of its autonomous iNext model for the year 2021 (Lambert, 2016), and Toyota intends to make its first autonomous car, the teammate, available in showrooms by 2020 (Becca, 2015). AVs are expected to increase road safety, reduce travel costs and time, and generally change mobility and transportation paradigms significantly, while making daily transportation routines more sustainable (Becker and Axhausen, 2017; Hohenberger et al., 2016; National Highway Traffic Safety Administration, 2013). Dovetailing with this, a market study conducted by IHS Markit projects that AVs sales will increase to more than 33 million annually by 2040 (IHS Markit, 2018). This suggests that automation has the potential to revolutionise the automotive industry and reshape the market (König and Neumayr, 2017).

AVs are vehicles that are equipped with fully autonomous functions[1] that replace the driver and take over critical decisions. Conversely, when no automation is present, the driver is responsible for all functions of the vehicle. Accordingly, partially AVs lie in between: the driver cedes some degree of control over selected functions to the car while retaining control over others.[2] While fully AVs are not yet on the road, numerous automated functions are already commercially available to consumers. For instance, Swan (2015) and Viereckl et al. (2015) identified several automated and smart vehicle functions currently in progress among developers, for example, safety, mobility management, home integration, fatigue detection, stress management, and real-time parking assistance. The appraisal and acceptance of such functions and features might provide insight into consumers' attitudes toward fully AVs and might help elicit beneficial vehicle designs.

Given the nascent status of extant literature on AVs, only a few studies have attempted to evaluate consumers' willingness to use (WTU) different levels of overall vehicle automation, and these few have given little attention to distinguishing between individual vehicle functions. The crucial question of how consumers perceive different levels of automation for particular AV functions is therefore still open. The study at hand accordingly aims to address this research gap by investigating the acceptance of some autonomous functions as opposed to addressing overall vehicle automation. Notably, existing studies have primarily relied on direct surveys, in which respondents report their preferences directly. This study applies a more realistic approach that reflects actual buying situations. By employing a choice-based conjoint (CBC) analysis – a widely used technique in research on consumer preferences – this study attempts to investigate consumers' WTU different automation levels of three prominent autonomous functions: safety, the ability to find and pay for a parking space, referred to herein as parking prediction, and remote diagnostics. Additionally, this paper investigates the role of individual involvement with respect to AV functions. Involvement represents individual differences in the way consumers receive and process marketing communications regarding a certain product category (Laurent and Kapferer, 1985), and it is usually measured via individual judgement criteria, e.g., degree of excitement and importance (Zaichkowsky, 1994). Consequently, the level of involvement influences consumers' purchasing decisions (Laurent and Kapferer, 1985). Thus, analysing the influence of involvement regarding AV functions on the WTU them is of great importance for marketing and advertising strategies in the automotive industry. In addition, we will also have a look at the effect the gender of the respondents may have.

The remainder of this paper is structured as follows: after a review of related work, as well as a more detailed description of this paper's contribution to this field of research in

Section 2, the design of the empirical study is described in Section 3, and results are presented and analysed in Section 4. Section 5 then provides a discussion of the implications for theory and practice. The paper concludes in Section 6 with a summary, some limitations, and an outlook on promising directions for future research.

2 Background

Academic research on AVs is still in the early stages (König and Neumayr, 2017), having emerged substantially in 2013 (Haboucha et al., 2017). While most extant research to date has focussed on investigating the technical features and feasibility of AVs (Haboucha et al., 2017), relatively little attention has been devoted to the analysis of AVs from a consumer perspective (for a recent literature review, see Becker and Axhausen, 2017). A somewhat larger set of consumer-oriented studies explores consumers' choices among various levels of vehicle automation. However, these studies estimated consumers' preferences for automation as a general driving mode without focusing on individual functions. In the following, we first review these studies' findings to examine whether there is a relationship between consumers' acceptance and level of autonomy in general, that is, we address the question of whether more automation always means higher appreciation. Subsequently, we hypothesise any such relationship for AV functions.

In this research line, scholars usually have employed direct survey methods and used various measures such as willingness to pay (WTP). For instance, Bansal et al. (2016) and Bansal and Kockelman (2017) observed that consumers were willing to pay more than double to add full automation to a vehicle compared to adding only partial automation. In a discrete choice experiment, Daziano et al. (2017) included varying levels of automation as an attribute and found that consumers were willing to pay, on average, about \$3,500 to add partial automation and about \$4,900 to add full automation. Although all authors detected substantial heterogeneity in their WTP measurements, including many consumers who did not want to pay any amount for automation, a clear monotonic relationship can be observed on average: the higher the level of added automation, the higher the WTP.

Accordingly, an important question is whether the same monotonic relationship can be observed between different levels of autonomy and the corresponding WTU. Daziano et al. (2017) found that respondents preferred full automation over both partial automation and no automation and preferred partial automation over no automation. In contrast, Kyriakidis et al. (2015) reported that respondents preferred manual driving as the most enjoyable mode and fully automated driving as the least enjoyable. Schoettle and Sivak (2015) also reported similar results: the mode 'no self-driving' was stated as the most preferred level of automation (43.8%), followed by partial self-driving (40.6%) and, finally, full automation as the least preferred level (15.6%). Schoettle and Sivak explained these findings as reflecting the fear that consumers might have with regard to using full automation: 96% of the respondents expressed a desire to have gas and brake pedals, as well as a steering wheel, in fully automated vehicles. Also, König and Neumayr (2017) observed that users expressed fear of surrendering control to a technology, citing safety concerns.

These attitudes represent potential adoption barriers in the consumer market for AVs. In fact, adoption barriers might occur as a result of interactions between consumers and the new technology, in which the user tends to observe gains and losses (Jiang et al., 2000; König and Neumayr, 2017). On one hand, AV functions are projected to provide riders with more safety, comfort, and free time. Thus, perceived ease of use and usefulness positively influence consumers' intentions to use this new technology (Davis et al., 1989). On the other hand, as the level of autonomy increases, the vehicle executes more of the critical decisions. In such situations, drivers have expressed a lack of trust in machines making decisions on their behalf (Rupp and King, 2010), and due to this lack of trust, as well as the lack of control, consumers might feel uncomfortable about using full automation (Khan et al., 2012).

Keeping this in mind, it is hypothesised that beyond a certain level of automation, the WTU autonomous functions actually decreases. Thus, some kind of optimal level of autonomy might exist. The findings of Abraham et al. (2017) support this assumption: after asking respondents to state their preferred maximum level of automation, they found that respondents are most likely to use partially AVs, followed by fully automated vehicles, then those with no automation.

This study extends the current literature in this field by investigating consumer preferences for different levels of automation (no automation, partial automation, and full automation) for (potentially) AV functions. In their literature review on the acceptance of automated vehicles, Becker and Axhausen (2017) pointed to the need for future research to focus on highly demanded vehicles' features. In addition, the present study further contributes to the latest extant research by examining an important marketing concept: the effect of the level of consumer involvement as described above with respect to AV functions on consumers' WTU them.

3 Study design

3.1 Methodology

As fully automated cars are not yet on the market, it is necessary to apply a consumer-oriented empirical approach that allows for a detailed assessment of the perceived benefits of (potentially) AV functions. Our study therefore employed conjoint analysis as it is the most widely used technique in marketing research concerning consumer choices and preferences, and it is well-suited to new-product-development studies (Curry, 1996; Green et al., 2001). Conjoint analysis is a multivariate technique developed to understand how consumers value different attributes or functions (e.g., size or colour) of a certain product or service; each attribute is defined in terms of levels, known as *attribute levels* (e.g., 'large', 'medium', and 'small', for the attribute 'size') (Green et al., 2001; Hair, 2010). In conjoint experiments respondents are shown a number of *profiles* (also known as *treatments*), e.g., in the form of real or hypothetical products or services, and are asked to make trade-off decisions among the presented profiles (Green et al., 2001). Each conjoint profile represents a possible combination of levels of each attribute (Hair, 2010). The conjoint procedure enables the assignment of a numerical value to each attribute level, also known as *part-worth utility*, such that the overall perceived utility (preference value) of the profile equals the sum of the individual part-worth utilities (Breidert et al., 2006; Hair, 2010). Moreover, the importance of each attribute, relative to the other attributes, can be computed by considering the difference each attribute makes in the total perceived utility of a profile, given that the sum of all attribute importance values for each respondent is 100% of the total value (Stöckigt et al., 2018).

Among other conjoint methods, CBC analysis is the most preferred method (Orme, 2009). With CBC, instead of ranking (i.e., the most preferred profile on the first position, the next preferred profile on the second position, etc.) or rating (e.g., 1 = not attractive at all and 10 = very attractive), respondents express their preferences by selecting their most preferred profile from among several alternatives (profiles) (Breidert et al., 2006; Orme, 2009). In addition, CBC includes a 'none' option, giving respondents the opportunity to answer that all presented choices (profiles) are unattractive (DeSarbo et al., 1995; Johnson and Orme, 1996). Thus, the CBC approach represents a realistic choice experiment that mirrors actual decision situations (Chakraborty et al., 2002; DeSarbo et al., 1995; Johnson and Orme, 1996). A CBC analysis was thus selected for this study to investigate how consumers value different levels of automation (no automation, partial automation, and full automation) for respective vehicle functions.

3.2 Attributes and attribute levels

3.2.1 Autonomous vehicle functions

A pre-test was used to determine which AV functions consumers perceive as most useful, and these were selected for inclusion in the discrete choice experiment. Six functions were initially presented: safety, stress and fatigue management, vehicle management, remote diagnostics, parking prediction, and mobility management. In this pre-test, respondents were shown a short statement characterising each of the functions and were asked to rate the perceived usefulness of each on a two-item ('the function described above makes it easier for me to handle specific situations' and 'the function described above is overall useful to me'), seven-point Likert-type scale (1 = I do not agree at all and 7 = I fully agree; Davis et al., 1989).

The 95 participating respondents indicated that they perceived parking prediction [mean (M) = 5.36, Cronbach's alpha[3] (α) = 0.92)[4]], safety (M = 5.01, α = 0.86), and remote diagnostics (M = 4.92, α = 0.93) as the most useful AV functions. Based on the highest scored means, these three functions were included for further analysis. Finally, three levels of automation were implemented: no automation, partial automation, and full automation. The subsequent CBC analysis allows the determination of the perceived utility of each of these levels of automation for (potentially) AV functions.

3.2.2 Conventional vehicle attributes

The decision to purchase or use a specific vehicle depends not only on its (potentially) autonomous functions but also on its conventional attributes (i.e., non-autonomous attributes). To ensure a more realistic decision scenario, the attributes brand, body style, and engine power were also included in the discrete choice experiment. Brand is an important criterion in car-buying decisions for most consumers (Alamgir et al., 2011). Brand attribute levels were set as Audi, BMW, and Mercedes because all three German brands primarily produce for the premium segment and this selection ensures the credibility of the scenario given that AVs are primarily marketed toward the upper- and upper-middle-class consumer segment (Klifa, 2018). This setting also circumvents country-of-origin effects, which otherwise would be likely to occur, as country of origin also affects consumers' purchase decisions in the automobile context (Sohail and Sahin, 2010). Concerning the body style, saloon cars, estate cars, and sport-utility vehicles (SUVs) were chosen because these are the best-selling body styles in the premium segment (Gibbs, 2018). Finally, engine power was included, which is a particularly relevant feature for buyers of luxury-class vehicles (Löffler, 2015). Attribute levels were categorised as low, medium, and high based on calculated horsepower (hp) averages.

Table 1 shows all attributes and attribute levels used in the CBC model. The decision to include no more than six attributes follows the recommendations for this type of model (Green and Srinivasan, 1990).

Table 1 Overview of attributes and attribute levels included in the CBC

Choice-based conjoint-analysis	*(Potentially) autonomous vehicle functions*		
	Safety	*Parking prediction*	*Remote diagnostics*
	No automation	No automation	No automation
	Partial automation	Partial automation	Partial automation
	Full automation	Full automation	Full automation
	Conventional vehicle attributes		
	Brand	*Body style*	*Engine power in hp*
	Audi	Saloon car	160
	BMW	Estate car	260
	Mercedes	SUV	360

3.3 Survey

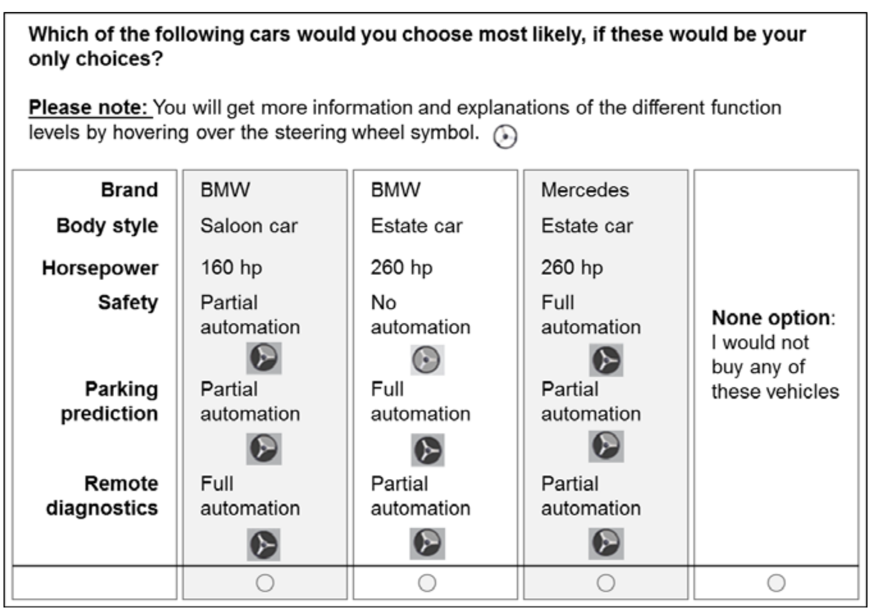
The survey consisted of three parts. In the first part, the respondents indicated their gender, age, and whether they had a driving license. The second part of the survey contained the CBC experiment. A detailed explanation of the (potentially) AV functions and their varying levels was first presented to the respondents (see Table 2). As an example, the attribute level 'no automation' in combination with the attribute 'safety' indicates that the vehicle does not have the ability to warn or protect the driver from potentially dangerous situations.[5] Partial automation (with the attribute safety) refers to the vehicle's ability to perceive its environment and warn the driver proactively about potentially dangerous situations. Finally, a fully automated safety function indicates that the vehicle detects potentially dangerous situations and automatically initiates necessary manoeuvres to avoid accidents.

Following the explanation of the given context, the respondents were presented with 12 choice sets and two holdout tasks[6], each consisting of three vehicle profiles plus the 'none option'. Choice tasks were generated and randomised using the balanced-overlap method.[7] The respondents had to decide in favour of exactly one vehicle profile or select the 'none option' separately for each of the given choice sets. Every vehicle profile consisted of all six attributes, each at a single level. For instance, as shown in Figure 1, a vehicle profile could include the following attribute levels: BMW (attribute brand), saloon car (body style), 160 hp (horsepower), partial automation (safety), partial automation (parking prediction), and full automation (remote diagnostics). In the final part of the survey, the respondents were asked to state their involvement regarding AV functions via a six-item, seven-point semantic-differential scale[8], including importance, interest, relevance, excitement, meaning, and attractiveness, with higher scores indicating higher involvement (Zaichkowsky, 1994).

Table 2 Autonomous vehicle functions and their varying levels of autonomy presented to the respondents in the survey

	No automation	*Partial automation*	*Full automation*
Safety	The vehicle cannot warn or protect the driver from potentially dangerous situations.	The vehicle perceives its environment and warns the driver proactively about potentially dangerous situations.	The vehicle anticipates dangerous situations and automatically initiates the needed manoeuvres to avoid accidents.
Parking prediction	The vehicle cannot support the driver in finding, reserving, or paying for a parking space.	The vehicle senses situations in which the driver is looking for a parking space and proactively informs the driver about free parking spaces, reservation possibilities, and prices.	The vehicle senses situations in which the driver is looking for a parking space and automatically drives to, reserves, and pays for the available parking space.
Remote diagnostics	The vehicle cannot diagnose or repair defects in the vehicle.	The vehicle senses defects in the vehicle and proactively informs the driver about them.	The vehicle senses defects in the vehicle and, if a repair is possible via a software update, repairs itself automatically. Otherwise, the vehicle automatically schedules a workshop appointment.

Figure 1 Example of a choice set presented to the respondents in the survey



4 Analysis

A web-based survey was distributed online through German-speaking automotive forums in 2016. A total of 1,093 respondents completed the survey, but 127 did not have driving licenses and were excluded, as they do not represent the target sample group (namely potential consumers). To further ensure data quality, 161 respondents who completed the survey either too slowly (took more than 15 minutes) or too quickly (took less than four minutes) were excluded because in these cases, the respondents might not have been fully or continuously engaged with the choice (and holdout) sets. Finally, 104 respondents were excluded based on low indicated involvement (cut-off mean value set at 3.5), as in these cases, the credibility of the given answers is in question (internal consistency of the seven involvement items, $\alpha = 0.8$; M = 4.9; SD = 1.18). Accordingly, the final sample contained 701 respondents, between 18 and 70 years of age, with an average age of about 25 years (SD = 7.11). The gender breakdown was approximately 54.4% ($n = 381$) male and 45.6% ($n = 320$) female.

Lighthouse Studio 9 software was used to create the survey design and to collect and analyse the data. IBM SPSS 21 was used for further analysis. The part-worth utility values (or ‘part-worth utilities’ for short) of each attribute were estimated by using the hierarchical Bayes (HB) method,[9] which allows utilities to be estimated at individual levels and has been shown to yield accurate results with CBC and to enhance the predictive validity of the data (Andrews et al., 2002; Hair, 2010; Wellman and Vidican, 2008). Table 3 shows that the attribute ‘safety’ has the highest *relative importance* (32.58%), followed by remote diagnostics (21.54%), and finally parking prediction (17.63%). The differences between the three conventional attributes are relatively low: the relative importance of body style, engine power, and brand is 10.53%, 9.83%, and 7.89%, respectively. The sum of the relative importance of the potentially autonomous attributes (71.75%) is considerably higher than that of the conventional attributes (28.25%). This can be viewed as a first indicator of the impact that AV functions might have.

Table 3 Relative importance of vehicle attributes

Attributes	*Conventional vehicle attributes*			*(Potentially) autonomous vehicle functions*		
	Brand	*Body style*	*Engine power*	*Safety*	*Parking prediction*	*Remote diagnostics*
Relative importance	7.89%	10.53%	9.83%	32.58%	17.63%	21.54%

The HB model estimations of the part-worth utilities (PW) are shown in Table 4 and illustrated as inverted U-shaped curves in Figures 2, 3, and 4 for the (potentially) AV functions of safety, parking prediction, and remote diagnostics, respectively.

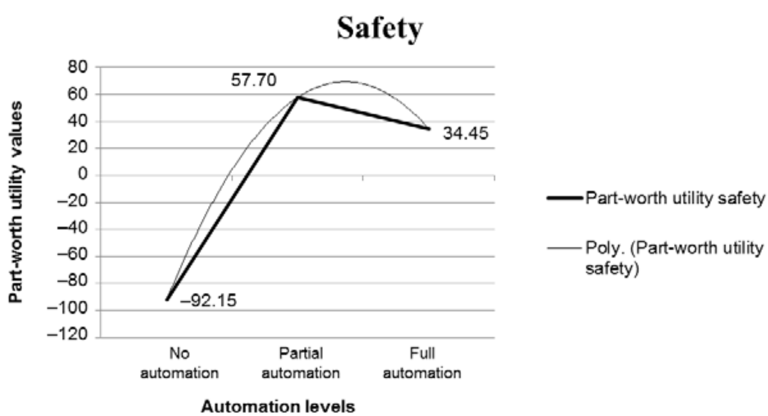
Conjoint utilities are interval values. Part-worth utilities are computed using dummy coding in a way that results in utilities that are scaled to sum to zero within each attribute, allowing the remaining levels, within the same attribute, to be estimated. A negative part-worth utility value, however, does not mean that the given attribute level has a ‘negative utility’, or appears unattractive per se; rather, it means that this level is on average less preferred than the other two attributes (Chapman, 2013; Orme, 2010; Schaupp and Bélanger, 2005).

Table 4 Choice-based conjoint analysis with hierarchical Bayesian (HB) estimates

Attribute	*Attribute level*	*PW*	*SD*
Brand	Audi	8.61	25.55
	BMW	–0.44	24.01
	Mercedes	–8.17	24.36
Body style	Saloon car	3.34	31.21
	Estate car	7.35	27.19
	SUV	–10.69	38.63
Engine power	160 hp	–24.78	35.51
	260 hp	6.40	12.50
	360 hp	18.38	28.31
Safety	No automation	–92.15	63.47
	Partial automation	57.70	35.13
	Full automation	34.45	74.50
Parking prediction	No automation	–31.40	48.13
	Partial automation	33.48	25.12
	Full automation	–2.08	51.55
Remote diagnostics	No automation	–46.01	47.54
	Partial automation	44.06	31.53
	Full automation	1.95	57.77
None option		20.11	113.25

Note: N = 701; PW = Mean part-worth utility; SD = standard deviation.

Figure 2 Part-worth utility values for safety



For safety, partial automation with a part-worth utility value of 57.70 appears to be the most preferred choice. The differences between the second choice – fully automated, with a part-worth utility value of 34.45 – and the least-preferred choice – no automation, with a part-worth utility value of –92.15 – are substantial. The results for parking prediction are similar. The part-worth utility value of 33.48 indicates that consumers prefer a vehicle with a partially automated parking prediction function. Both the full-automation and no-automation choices have lower part-worth utility values (–2.08 and –31.40, respectively). Partial automation, again, was the preferred level of automation for remote diagnostics, with a part-worth utility value of 44.06. As the level of automation increases to full, the part-worth utility value declines to 1.95. The no-automation option, as for the other three attribute, was the least-preferred level of automation (–46.01). The part-worth utilities reveal that the differences between the autonomous levels depend on the respective function. For instance, the value of the full autonomous level for the attribute of safety is relatively high and positive, whereas the value of the full autonomous level of parking prediction is negative, while that of remote diagnostics is only slightly above zero. It is worth mentioning that all statements about the part-worth utilities refer to the corresponding mean values for the whole sample. At the individual level, a large heterogeneity can be observed, as indicated by the relatively large standard deviations of the part-worth utilities. Apparently, individuals might have varying functional profiles. Nevertheless, on average, a clear inverted U-shape can be observed for all investigated AV functions.

Figure 3 Part-worth utility values for parking prediction

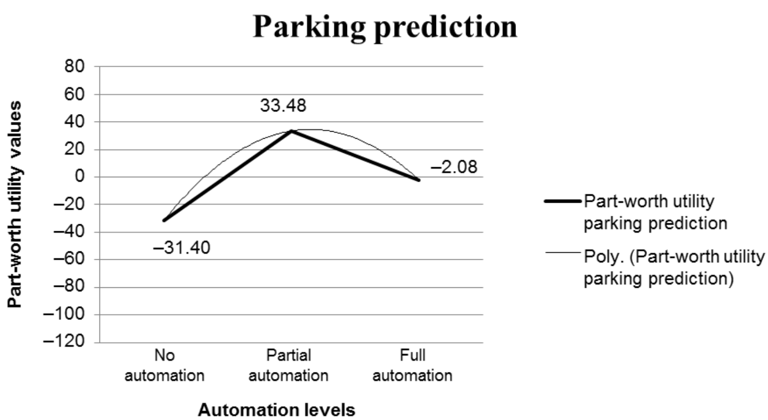
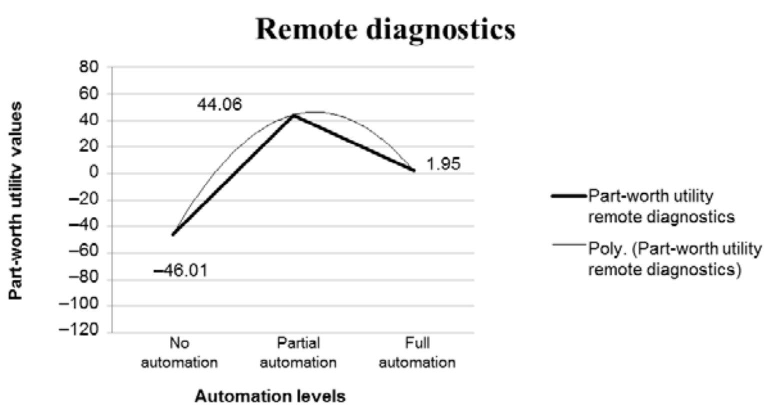


Figure 4 Part-worth utility values for remote diagnostics



To check whether these differences in the part-worth utilities might be even more relevant for highly involved customers, the 701 responses were split into a low-involvement group (360 respondents) and a high-involvement group (341 respondents) along the median (cut-off value = 5.17).[10] As shown in Table 5, both groups consider the presented (potentially) autonomous functions as relatively more important than the conventional attributes. For the high-involvement group, the relative importance of safety and parking prediction is higher than it is for the low-involvement group. In contrast, remote diagnostics was perceived as more important by the low-involvement group than by the high-involvement group.

Table 5 Relative importance of attributes among the high- and low-involvement groups

Attribute	*High involvement (N = 341)*		*Low involvement (N = 360)*	
	Relative importance	*SD*	*Relative importance*	*SD*
Brand	7.70%	4.95	8.79%	6.91
Body style	9.34%	6.78	11.40%	8.06
Engine power	9.07%	7.06	10.60%	8.68
Safety	35.03%	11.17	30.29%	11.47
Parking prediction	18.26%	8.86	16.67%	8.66
Remote diagnostics	20.61%	7.33	22.26%	9.11

Note: SD = standard deviation.

The attribute levels for the high-involvement and low-involvement groups are presented in Table 6 and illustrated in Figures 5, 6, and 7 and 8, 9, and 10, respectively, as inverted U-shaped paths, just as for the complete sample.

Highly involved respondents prefer the high level of automation for the attribute of safety, followed by partial automation, and finally low automation. In contrast, respondents classified as low involvement are likely to prefer partial automation, followed by full automation, then no automation. Regarding the attribute of remote diagnostics, both groups revealed similar results, resembling those from the full sample in Table 4. The high- and low-involvement groups prefer partial automation, followed by full automation, then no automation. Regarding parking prediction, in contrast with the complete sample and the high-involvement group, the low-involvement group is likely to select no automation as the second choice after partial automation. Finally, the non-purchase option for the low-involvement group is considerably higher than for the high-involvement group. The results indicate an even greater difference in the part-worth utilities of different autonomous functions for highly involved customers. Again, it is important to mention that all statements about part-worth utilities refer to the corresponding mean values. Concerning the heterogeneity within the two groups, the high involvement group responded observably more homogeneous than the low involvement group, as indicated by the lower standard deviations of the part-worth utilities for that group.

Finally, a gender effect analysis was carried out in order to check for possible influences on the attributes at hand. For the parking prediction and remote diagnostics attributes, the results did not reveal any considerable differences between females and males. However, the analysis of the effect of gender on the safety attribute shows interesting results, as shown in Figures 11 and 12. Compared to females, males have a clear higher tendency to prefer the full automation level of the safety function. Previous research has revealed similar results concerning overall acceptance of automated cars. For instance, Hohenberger et al. (2016) found that women exhibit lower WTU automated cars since they are more likely to anticipate anxiety toward the respective technologies.

Table 6 Part-worth utility values for the high- and the low-involvement groups

Attribute	*Attribute level*	*High involvement (N = 341)*		*Low involvement (N = 360)*	
		PW	*SD*	*PW*	*SD*
Brand	Audi	5.02	24.08	11.68	26.67
	BMW	–3.59	23.44	3.55	26.17
	Mercedes	–1.43	22.42	–15.23	26.44
Body style	Saloon car	5.08	28.74	3.01	31.58
	Estate car	2.94	25.12	10.28	30.00
	SUV	–8.03	32.75	–13.28	41.08
Engine power	160 hp	–24.62	30.35	–23.51	39.05
	260 hp	6.83	13.27	3.50	16.71
	360 hp	17.78	22.97	20.00	30.66
Safety	No automation	–114.43	47.06	–71.77	69.02
	Partial automation	54.84	36.07	60.34	35.14
	Full automation	59.59	60.53	11.43	77.71
Parking prediction	No automation	–48.92	42.78	–13.40	45.67
	Partial automation	33.52	25.23	31.14	25.70
	Full automation	15.40	44.87	–17.74	52.58
Remote diagnostics	No automation	–58.88	38.39	–33.67	51.10
	Partial automation	38.83	27.83	48.74	36.04
	Full automation	20.05	44.98	–15.07	62.68
Non-buy option		7.06	106.02	34.98	110.97

Note: PW = mean part-worth utility; SD = standard deviation.

Figure 5 Part-worth utility values for safety for the high-involvement group

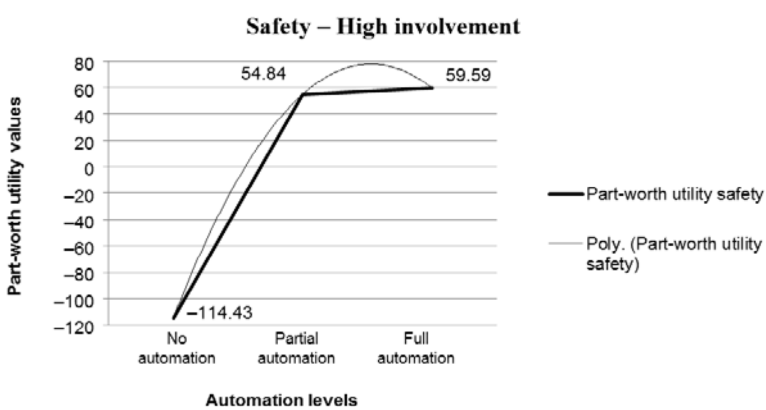


Figure 6 Part-worth utility values for parking prediction for the high-involvement group

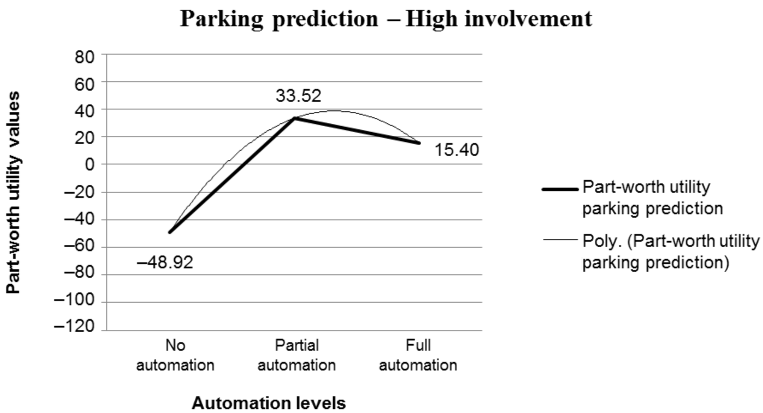


Figure 7 Part-worth utility values for remote diagnostics for the high-involvement group

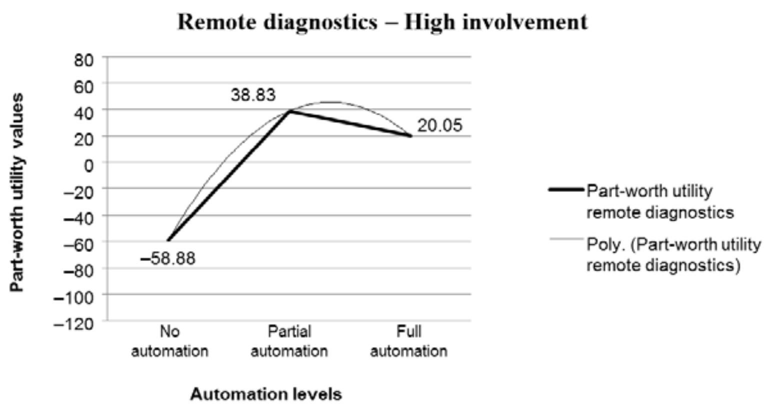


Figure 8 Part-worth utility values for safety for the low-involvement group

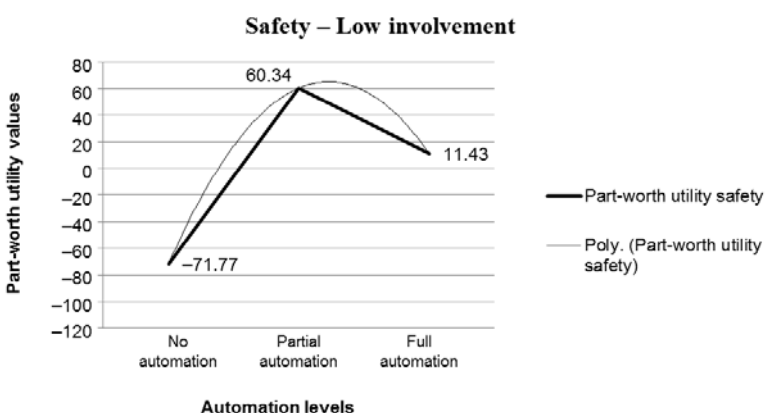


Figure 9 Part-worth utility values for parking prediction for the low-involvement group

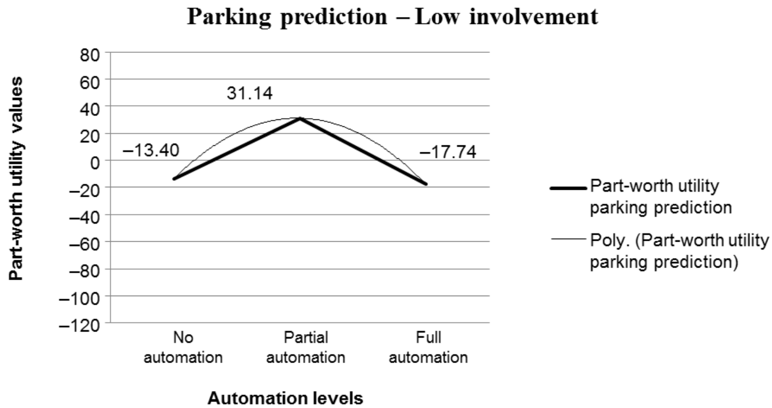


Figure 10 Part-worth utility values for remote diagnostics for the low-involvement group

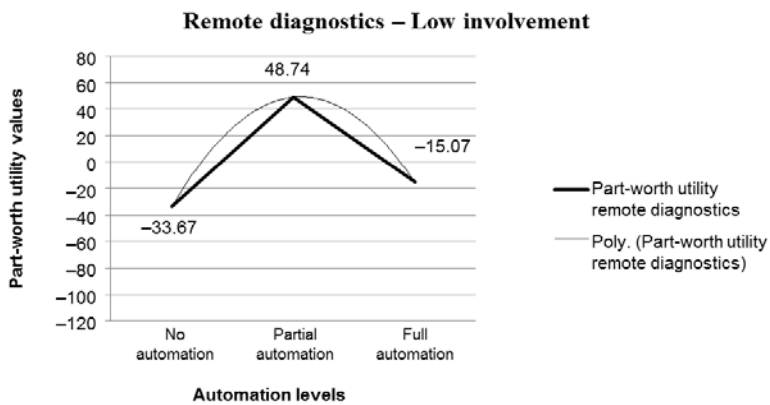


Figure 11 Part-worth utility values for safety for females

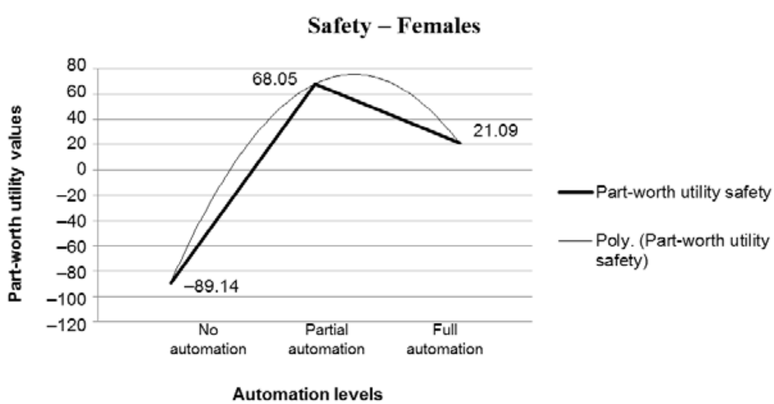
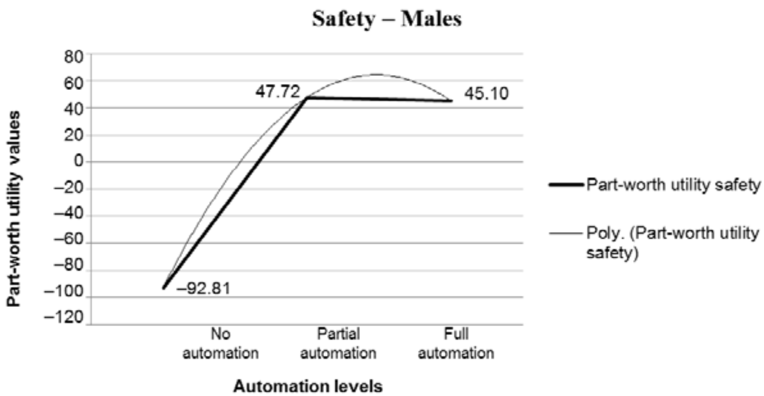


Figure 12 Part-worth utility values for safety for males



5 Discussion

From Table 3, it can be derived that the combined relative importance of the potentially AV functions, safety, parking prediction, and remote diagnostics (71.75%), is more than 2.5 times the combined relative importance of the conventional attributes of brand, body style, and performance (28.25%). This result demonstrates that the three potentially autonomous functions included in the survey are considerably more important to consumers compared to the included conventional vehicle attributes. This is consistent with the a study by McKinsey (2014) according to which 28% of new-car buyers are likely to make purchase decisions on a car based on connectivity features rather than on conventional features such as engine power. This finding poses important managerial implications for car manufacturers. Despite high investment costs associated with developing new technologies, our results strongly recommend continuous development and provision of automated functions to meet drivers' needs.

Among the potentially autonomous functions, safety, unsurprisingly, garnered the highest relative importance (32.58%), followed by remote diagnostics (21.54%) and parking prediction (17.63%). Safety has been widely reported as both a top concern and a strength in AVs (Daziano et al., 2017) and has been highlighted as the most attractive feature of self-driving cars (Howard and Dai, 2014). Parking prediction and remote diagnostics, although yielding substantial relative importance values, can be considered to be less sensitive functions compared with safety. This might suggest that the safety attribute should be examined exclusively apart from other 'less sensitive' features, such as parking prediction, and from 'more entertainment-oriented' features such as home integration. For all three attributes, the results suggest that the relationship between level of automation and perceived utility function can be described by an inverted U-shaped curve. Thus, the presented results confirm our hypothesis that an optimal level of automation exists.

Moving along the part-worth utility curves, there is a robust benefit increase between the no-automation and partial-automation levels for the three AV functions considered here. Regarding the partial-automation safety level, consumers can rely on the car to warn them about potentially dangerous situations, thereby generating safer conditions.

The partially automated remote diagnostics level delivers to the driver information about possible defects in the car. Finally, the partially automated parking prediction level informs the driver about available parking spaces and prices. These functions all provide the driver with informational support, which saves time and increases comfort (Bohn et al., 2004; Hahn, 1996; Rogers, 2003). Such benefits likely lead to consumers' preference for partial automation over no automation.

The downward slope of the curves reflects a decrease in perceived benefit from partial automation to full automation, at least for parking prediction and remote diagnostics. Fully automated functions not only share information with the driver but also automatically make decisions and take actions. According to self-determination theory, exercising decisions is a basic psychological need (Ryan and Deci, 2001, 2006). This need may explain why respondents have a tendency to reject situations in which the car automatically makes important decisions and acts on them. However, consumers are more likely to cede control to the vehicle to make decisions in emergency situations or when the driver purposely chooses to do so (König and Neumayr, 2017).

Another reason for rejecting highly autonomous functions could be perceived risk. Consumers may lack confidence in fully automated functions. Empirical studies have confirmed the existence of a positive correlation between degree of autonomy and perceived risk (Rijsdijk and Hultink, 2003, 2009; Rijsdijk et al., 2007). The roles of data transmission and privacy have also been highlighted in extant AVs literature as major concerns (Howard and Dai, 2014; Kyriakidis et al., 2015). Data collocation and storage, and the risk of losing control of sensitive personal information, may represent a portion of perceived risk of autonomous features (Sheng et al., 2008). This issue is prevalent in Germany (where this study was conducted and the sample collected). The previously mentioned study by McKinsey (2014) showed that more than 50% of respondents were unwilling to use connected cars because of data privacy issues. With the recently implemented EU General Data Protection Regulation (GDPR)[11], consumers' sensitivity in this regard will probably increase.

In comparing the part-worth utilities of the high- and low-involvement groups, three key findings can be noted. First, within the high-involvement group, a complete absence of automation for all functions elicits a considerably larger negative effect on the overall assessment of a vehicle than for the low-involvement group. Second, within the high-involvement group, the preference for partial autonomy for safety and remote diagnostics is considerably lower than in the low-involvement group. Finally, within the high involvement group, the preference for full automation of all functions is considerably higher than in the low-involvement group.

Barriers to adoption have been explained as perceived complexity, lack of knowledge of the new technology, and lack of experience or understanding of how to use it (Havlena and DeSarbo, 1991; Rijsdijk and Hultink, 2013). Previous research has indicated that high product involvement implies strong perception of the differences between various attributes and their relative importance (Howard and Sheth, 1969; Zaichkowsky, 1985). This notion can explain the strong variation in preferences between the two groups, which is assumed to be common with regard to highly innovative products (Claudy et al., 2015). Consumers in the low-involvement group might find it difficult to develop an understanding of the functionality of AV functions and thus might tend to avoid using them (Rijsdijk and Hultink, 2013). Daziano et al. (2017) found that individuals with greater knowledge regarding AVs abilities are less likely to express safety concerns and that they have a greater WTP more for fully autonomous cars. Our results suggest that consumers' WTU different levels of autonomous functions is influenced by individual involvement level and that greater individual involvement is correlated with higher perceived benefit from AV functions. This finding represents an additional central result of the present study and has not been investigated in previous research regarding AV functions. Accordingly, getting consumers involved with and knowledgeable about AV functions should be a major concern for car producers and marketers, especially during the awareness and the consideration phases. TV and online ads can help raise involvement levels in general at the early stages of the customer's journey. Nevertheless, it might be necessary to address detailed technical information with highly involved customers using other touch points, e.g., test drives, sales conversations, and newsletters, where it is more likely that segment-specific messages can be delivered.

Finally, females and males share the highest utilities regarding the safety function for the partial level of automation. Despite this similarity, for the second choice, males are significantly more likely to select the full level of automation for the safety function. Previous research has found that men have a higher WTU fully automated vehicles (e.g., Hohenberger et al., 2016; Payre et al., 2014). Of particular interest, gender differences are mediated by affective reactions, that is, females feel more anxious toward automated cars than males (Hohenberger et al., 2016). This might explain the gender-based variation in our results, exclusively regarding the safety functions, where females may exhibit greater reluctance toward using the full automated level.

6 Conclusions and outlook

The increasing importance of AVs makes the examination of consumers' preferences regarding the acceptability and usefulness of their autonomous functions an important topic of investigation for researchers, practitioners, and policy makers. Given the nascent status of the literature on AVs, most studies published so far have been concerned with consumer preferences for various levels of overall vehicle automation rather than for specific autonomous functions. This study sheds further light on consumer preferences in the automotive industry by analysing the relationship between levels of autonomy (no automation, partial automation, and full automation), presented in terms of different potential AV functions (safety, parking prediction, and remote diagnostics), and users' WTU them. Furthermore, for the first time in this product category, an important marketing concept was investigated: the relevance of the level of involvement in attitudes toward AVs functions. The study employed a CBC analysis approach, which has repeatedly proven its methodological power in empirical new-product research. Taken together, one key finding of this paper is that the increase and decrease of the part-worth utility values along the perceived utilities differs in intensity between the three potentially autonomous functions. This leads to the conclusion that car makers, as well as further research, should investigate in-depth the preference for and the usefulness of specific autonomous functions rather than looking only at overall AVs. Otherwise, the effects of specific autonomous functions may be overlooked.

The results reveal that autonomous functions contribute to consumers' buying decisions more than conventional attributes (by a factor of 2.5). As hypothesised, consumers prefer a moderate level of automation regarding the functions considered herein. Thus, an optimal value of automation can be assumed. However, the optimal level is highly dependent upon the respective function and whether a customer is highly involved with the product category or not. There appear to be functions, like safety, to which the statement ‘the more autonomous, the better’ applies.

Future research could be devoted to the question of what exactly determines this optimum and, with respect to the data-privacy issues mentioned above, whether this optimum remains stable over time. Drivers seemingly favour functions that sense, collect, and analyse information, then warn and inform them, but they do not favour functions that make decisions automatically on their behalf. This finding implies that autonomous functions can satisfy consumers’ needs. Nevertheless, a high level of automation does not seem to provide compelling value. In this regard, loss of control, lack of self-determination, and perceived risk – both safety and informational – are factors that have been suggested to explain the observed benefit reduction. Whether these are the relevant factors responsible for the lower attractiveness of fully automated functions could be examined in further research studies. Moreover, insights into how to overcome adoption barriers to fully automated functions are needed. As fully AVs might lead to more safety and greater efficiency on our streets in the future, strategies to market such vehicles successfully are essential and should be investigated further.

Regarding the level of involvement, we can conclude that highly involved consumers are more likely to appreciate highly autonomous functions compared with less involved consumers. This observation represents a central finding of this paper and suggests important managerial implications: car producers must develop strategies that increase consumers’ knowledge of and trust in automated functions as well as ways to train consumers in their use. Interestingly, consumers in the high-involvement group demonstrated great WTU safety functions, as an exception to other functions, at the highest automation level. Again, this result suggests that the safety attribute should be examined in greater depth.

The present study’s restrictions and limitations include the CBC study design, which allows for investigation of only a limited number of attributes. Thus, while the survey considers relevant characteristics, it does not include all the choices that consumers might face in their purchase decisions. Consequently, future research should include the consideration of more functions. Another limitation of the CBC study design concerns the survey presentation of the (potentially) AV functions and their varying levels of autonomy to the respondents.[12] It can be argued that the attributes were presented in a way that induced respondents to favour the intermediate solution among the three (partial automation against no or full automation). If this were the case, the resulting inverted U-shaped curves might be partly due to this presentation effect and might not necessarily reflect real consumer preferences, which might limit the meaningfulness of the results. Accordingly, replications of the present study should work with more attribute levels along a continuum to control for this aspect.

As this study includes many rather young respondents, another limitation of the present study is that there was no chance to verify whether age is a relevant moderator of the presented effects. The average age in this study was 25 years (SD = 7), which represents the largest current consumer segment. This age group exhibits the highest level of desire to buy AVs, when compared with other groups, and they believe such vehicle technologies offer remarkable benefits (Brown et al., 2014). Nevertheless, future research should further investigate the preferences of other age groups to check for moderating effects of age.

Last, but not least, it would be interesting to compare attitudes in Germany with those in other leading auto markets, particularly in China, the USA, and Japan, as the present study was not able to test whether country is a relevant moderator due to the fact that all respondents were from Germany. The theory of cultural differences introduced by Hofstede (1983) might be a helpful tool for decision analysis in these countries when delving deeper into, for example, risk aversion and risk taking as a determining factor.

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Notes

1 The term 'autonomous functions' is used by Gordon and Lidberg (2015) in reviewing the evolution of intelligent vehicles and supporting technologies. Also, Hahn (1996) identified 'safety' and 'comfort' as major benefits of autonomous vehicle functions. Both attributes will be referred to in the empirical part of the present study either explicitly ('safety') or implicitly ('comfort').

2 For a differentiation among several levels of vehicles automation, see the suggestions by the National Highway Traffic Safety Administration (2013) or by the Society of Automotive Engineers (SAE) International (On-Road Automated Driving ORAD Committee, 2016).

3 Cronbach's alpha is a reliability coefficient that measures the internal consistency of a scale (how closely the set of items/multiple questions are related; Tavakol and Dennick, 2011).

4 For Cronbach's alpha, the lower limit commonly recommended is 0.70 (Hair, 2010; Robinson et al., 1991).

5 Examples for dangerous situations are traffic jams on the highway or sudden lane changing of a car ahead.

6 Holdout tasks are extra profiles generated to test the reliability and validity of the model estimates, but they are not used in the part-worth estimation (Hair, 2010).

7 The balanced-overlap method is a randomized method used to construct profiles and display choice tasks (Chrzan and Orme, 2000).

8 The semantic differential scale is a survey design that uses an opposing pair of words, e.g., young-old or masculine-feminine (Mooi and Sarstedt 2011).

9 For more details on hierarchical Bayes estimation, see Hair (2010) and Orme (2000).

10 Respondents with an involvement value of exactly 5.17 were assigned to the low-involvement group. This assignment explains the unequal sub-sample sizes.

11 For details, see https://ec.europa.eu/commission/priorities/justice-and-fundamental-rights/data-protection/2018-reform-eu-data-protection-rules_en.

12 We thank one of the reviewers of this paper for pointing out this limitation.