# "What-are-you-looking-at?" – Implicit Behavioural Measurement Indicating Technology Acceptance in the Field of Automated Driving

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## ABSTRACT

Automated driving functions are gradually entering individual mobility markets. First studies on consumer acceptance show that parts of the classical innovation acceptance models can be applied to autonomous driving, but others do not work in this context. As it is expected that perception and evaluation of automated driving functions are correlated with the behaviour of the driver, we investigated if eye-tracking data as an implicit behavioural measurement could indicate the acceptance of automated driving. We developed and conducted a user experience study with a pre- and a post-questionnaire, a standardized test track, and 98 test drivers with eye-tracking glasses using level 2 driver assistant systems either with a Mercedes-Benz E-Class or S-Class. The study refers to the Consumer Acceptance of Technology model and adds eye distraction from forward road scenes as antecedent indicator while activating the automated "Lane Keeping"-function in separated one minute slots. Results of structural equation modelling show that despite a lack of significance, our general line of argument is largely confirmed according to which a longer eyes-off-road-time indicates a higher acceptance of automated driving technology. It is assumed that the effects could become more apparent when participants use the automated driving function within a longer period.

## KEYWORDS

Automated Driving, Eye-tracking, Implicit Behavioural Measurement,
Technology Acceptance, User Experience

## INTRODUCTION

"Autonomous Driving" is currently one of the "hot topics" on mobility markets (Bertrandias et al. 2018). Original equipment manufacturer (OEM) deal with the development of innovative functionalities, politicians discuss about legal issues and science investigates the driver's intention of using this technology. The investigation of these intentions is essential because it provides important insights into the acceptance of this technology. In the field of technology acceptance different theoretical models were developed (e.g. Davis et al. 1989; Kulviwat et al. 2007) as well as reviewed and evolved during the last decades (e.g. Nasco et al. 2008; Hong et al. 2013). However, most studies investigating the acceptance of automated driving are based on standardized questions in the context of scenario descriptions or simulated driving with regard to an automated vehicle so that only explicit measurements are included in the model (e.g. Buckley et al. 2018; Planing 2014; Nielsen/Haustein 2018; Rödel et al. 2014; Waytz et al. 2014; Bansal/Kockelman 2016; König/Neumayr 2017; Haboucha et al. 2017). Yet, the automated driving technology is developed incrementally – series vehicles today only reached autonomous level 2 from 5 (SAE International 2018) – but the full disruptive version of a driverless car is already in the head of consumers. In a level 2 vehicle, drivers can take their hands off the wheel for a certain period of time. However, they are still responsible for the entire driving process and can take control of the vehicle again at any time (see Table 1).

| Driving function | Description of autonomous level 2 functions in today series vehicles |
|---|---|
| Lane Keeping | … assists the driver in keeping the vehicle in its lane. |
| Lane Changing | … assists the driver in lane changing, e.g. in an overtaking manoeuvre. |
| Automatic Distance Keeping | … keeps the vehicle within a safe distance from vehicles ahead. |
| Automatic Speed Control | … ensures that vehicle speed does not exceed a legally enforced speed. |
| Automated Parking | … assists the driver in moving the vehicle into a parking spot. |
| Automated Braking | … prevents dangerous situations by informing the driver of an upcoming collision and by braking automatically in an emergency situation. |

**Table 1: Overview of available automated driving functions. Adapted from Selinka/Kuhn 2018.**

Since the autonomous car is already in the head of the driver, the technology acceptance models could be supplemented by implicit behavioural measured variables to overcome the weaknesses of an exclusively explicit measurement through standardized questioning. With implicit behavioural measured variables we mean above all variables that measure the behaviour of drivers with level 2 automated vehicles using implicit methods like eye-tracking. Especially the parameter "eyes-off-road-time" is of interest, which specifies how long a driver keeps his eyes away from the road. A longer eyes-off-road-time could indicate a higher technology acceptance, since the driver already turns his attention away from the road when driving with a level 2 (and not fully autonomous) vehicle. Our research question can therefore be formulated as: To what extent do implicit behavioural measured variables indicate the acceptance of automated driving, a technology where the fully disruptive innovation (level 5) is already known?

To address this question, we conducted a user experience study with level 2 automated vehicles in which the test drivers were equipped with an eye-tracking glasses system (Tobii glasses 2, 50 Hz sampling rate) to measure their eye-distraction from forward road scenes.

## THEORETICAL BACKGROUND AND STATE OF RESEARCH

The evaluation of technology acceptance for automated driving is essentially based on the Technology Acceptance Model (TAM) and the Consumer Acceptance of Technology (CAT) model as its further development (e.g. Buckley et al. 2018; Köpsel et al. 2018). The TAM identifies two central factors that influence the "Attitude Toward Adoption", i.e. the attitude toward the use of the technology, and by the end the "Adoption Intention" of the technology: "Perceived Usefulness" (PU) and "Perceived Ease of Use" (PEoU). PU refers to the degree to which a person believes that using a particular technology is helpful and enhances performance (Davis et al. 1989). PEoU is an individual assessment in terms of the effort required to use the technology (Davis et al. 1989). Buckley et al. conducted a study where they applied the TAM to assess driver's intended use of automated driving technology after undertaking a driving simulation task (Buckley et al. 2018). The TAM variables of PU and PEoU explained 41% of the variance in intentions (Buckley et al. 2018).

The CAT model adopts the core idea of the TAM and adds "Relative Advantage" (RA) to the cognitive dimension of PU and PEoU. RA refers to the degree to which a technology is perceived as superior to its predecessor (Kulviwat et al. 2007). This aspect is particularly important in the context of automated driving, as the functions are intended to support the driver in comparison to a "conventional car". In addition to the cognitive dimension, the model also includes an affective dimension, which comprises "Pleasure" (e.g. happiness), "Arousal" (e.g. relaxation) and "Dominance" (e.g. control) (Kulviwat et al. 2007). These three variables define a person's feelings that, in turn, influence the "Attitude Toward Adoption", and by the end the "Adoption Intention" of the technology. A study published by Köpsel et al. examined the CAT model in the context of a user experience setting. Over 200 test drivers activated automated driving functions following a standardized test track on public roads using either a Mercedes-Benz E-Class or a Tesla Model S with level 2 automated driving functions (Köpsel et al. 2018). Questionnaires before and after the driving experience included items on attractiveness of innovation (Boyd/Mason 1999), self-efficacy (Jones 1986; Meuter et al. 2005) and standardized dimensions of expectations. The cognitive determinants of the CAT model showed high explanation of variance in test driver's intention of using automated driving functions. While the cognitive part of the CAT model has been confirmed, there were no effects of affective determinants on the "Attitude Toward Adoption" and thus on the "Adoption Intention" (Köpsel et al. 2018). Furthermore, the authors emphasized that it was very difficult to transfer the dimensions of the cognitive part into the context of automated driving (Köpsel et al. 2018).

Against this background, the present paper builds upon the "reduced" version of the CAT model including the cognitive part in terms of RA, PU and PEoU. The focus is not so much on a further empirical test of the already known line of argument, whereby the variables of the cognitive dimension influence the "Attitude Toward Adoption", which in turn affects the "Adoption Intention". Rather, we refer to one of the few studies that used eye-tracking as implicit behavioural measurement for the evaluation of technology acceptance in terms of TAM (Molina et al. 2013). Molina et al. investigated the usage of mobile devices in teaching-learning contexts. The eye-tracking system was mainly used to distinguish between visualization behaviours of different types of devices – the relationship between the eye-tracking parameters and the variables of the TAM was not analysed (Molina et al. 2013). Given that, further studies on implicit behavioural measurements in the area of technology acceptance are required, especially in the field of automated vehicles. The benefit – in considering implicit behavioural measurements – is an understanding of technology acceptance that takes into account that the final stage of development is already known. Furthermore, the study by Köpsel et al. highlighted the context-dependency of item formulations with regard to the affective dimension of the CAT model (Köpsel et al. 2018), which makes it necessary to use measurements that are context-independent. This context-independency is also met by implicit behavioural measurements in terms of eye-tracking.

## RESEARCH APPROACH AND METHODOLOGY

We conducted a user experience study with a total of 98 test drivers recruited through local press releases using either a Mercedes-Benz E-Class or S-Class equipped with identical level 2 automated driving systems. Each participant got a general introduction to the automated driving system while sitting in one of these test vehicles. The test drivers were also informed that they were responsible for the entire driving process and had to respect traffic regulations. The participants were equipped with eye-tracking glasses (Tobii glasses 2, 50 Hz sampling rate) for measuring glance behaviour. The following main drive took place on a standardized test track in Stuttgart/Germany in December 2017 (see Figure A1). The driving experience had an average time of approx. 40 minutes and was framed by two questionnaires before (expectations) and after (experience/evaluation) the test. We reached an age distribution corresponding to the German population (see Table 2). A $\chi^2$-test showed no significant differences between the age structure of our sample and the population in Germany. With a gender split of 63% to 37% we had a disproportionally high share of male participants.

| Age | Distribution in our study | Distribution in Germany |
|---|---|---|
| 18-29 years | 19.4% | 17.0% |
| 30-39 years | 10.2% | 14.7% |
| 40-49 years | 20.4% | 16.7% |
| 50-59 years | 20.4% | 18.9% |
| 60-69 years | 13.3% | 13.8% |
| 70 years and older | 16.3% | 18.8% |

**Table 2: Age distribution of test drivers.**

The eye-tracking technology is mainly used in distraction studies with regard to the active usage of human-machine interfaces in vehicle cockpits (Kraft et al. 2018). In this context, the project of the National Highway Traffic Safety Administration (NHTSA) is of particular importance aiming to fight driver distraction caused by In-Vehicle Electronic Devices (NHTSA 2010). According to the findings of this project, driver distraction can be measured by assessing the driver's glance behaviour, i.e. the driver's eye-distraction from forward road scenes when using/ looking at an in- vehicle display is evaluated (eyes-off-road-time). As studies show a general positive relationship between driver's eye-distraction/eyes-off-road-time and their degree of habituation and relaxation in driving conditions (Kraft et al. 2018), we assume that this correlation might be transferred to the acceptance of automated driving technology. The assumption that driving while automated driving functions are activated is: A more "relaxing" driving behaviour in terms of a longer eyes-off-road-time indicates a higher acceptance of automated driving technology. Based on this assumption, we derive the following three hypotheses concerning the cognitive part of the "reduced" CAT model:

| **Cognition** | **Hypotheses with regard to "eyes-off-road" parameter** |
|---|---|
| RA | H1. Test drivers with longer eyes-off-road-time evaluate automated driving functions with a higher relative advantage. |
| PU | H2. Test drivers with longer eyes-off-road-time evaluate automated driving functions with a higher perceived usefulness. |
| PEoU | H3. Test drivers with longer eyes-off-road-time evaluate automated driving functions with a higher perceived ease of use. |

**Table 3: Hypotheses.**

Empirical examination of these hypotheses required the definition of two "Areas of Interests" (AOIs). AOI1 comprised all glances on the road (eyes-on-road) while AOI2 comprised all other glances, e.g. to the interior space of the vehicle (eyes-off-road) (see Figure 1). We investigated the raw eye-tracking video material in Tobii Pro Lab and defined here in a first step the two event types AOI1 and AOI2. We then analysed each video with reduced speed and manually marked the driver's glances starting with the AOI "eyes- off-road". The program calculated the difference between the time-stamps for every pair of AOI so that we could get the total duration for each driver's eyes-off-road-time (in sec). It must be noted that this study refers to the driver's eyes-off-road-time while activating the "Lane Keeping"-function in separated one minute slots at fixed locations on the test track.


"eyes-on-road" (circle symbolizes driver's eye glance)


"eyes-off-road" (circle symbolizes driver's eye glance)

**Figure 1: Eye-tracking recordings at "Lane Keeping".**

Figure 2 illustrates the model as tested in this study. The items for the "reduced" version of the CAT model were mainly adapted from prior studies and appropriately modified to suit the purposes of the study. A list of the CAT items and scale types is presented in Table A1.

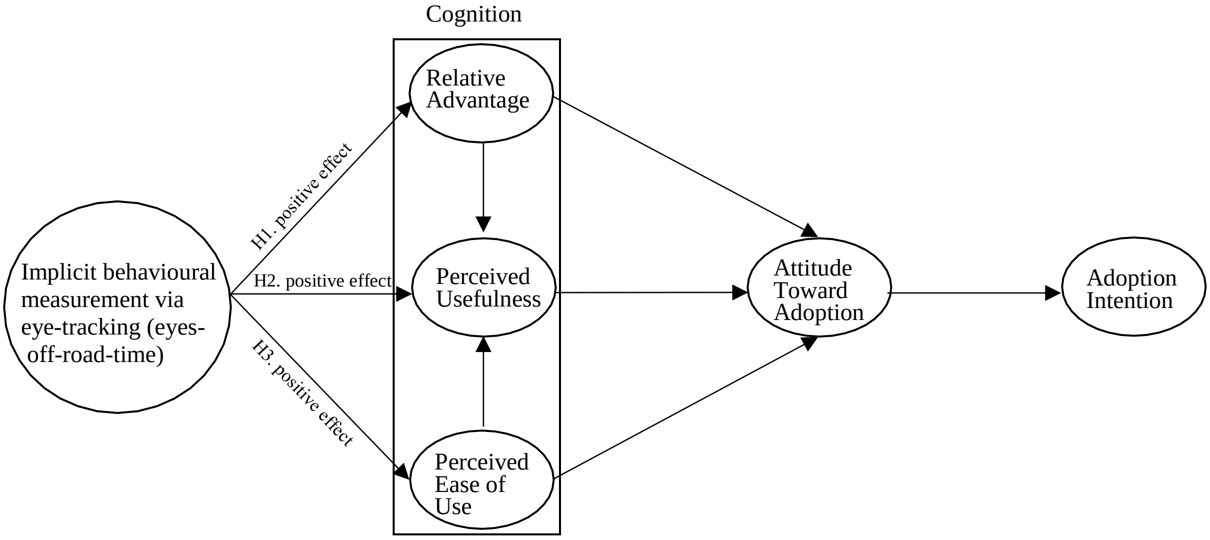


**Figure 2: Conceptual Model.**

## DATA ANALYSIS AND RESULTS

Because of the exploratory character of this study, the model and hypotheses are examined by a consistent partial least squares-based structural equation modelling approach (Dijkstra/Henseler 2015). The data is analysed in SmartPLS 3[1] (Ringle et al. 2015), employing a path weighting scheme and consistent bootstrapping method. In this context, we draw on 5,000 bootstrap samples and applied no sign change option.

Firstly, we evaluate the three reflectively measured models of RA, PEoU and Attitude Toward Adoption (see Table 4) concerning reliability and validity. Assessment of *convergent validity* leads to the exclusion of four items from the initial structural equation model as their loadings are clearly below the threshold value of 0.70 (Hair et al. 2017). The loadings of the remaining items are above 0.70 or slightly lower. Table 4 summarizes the final set of indicators and their loadings, respectively. A further criterion for convergent validity is the average variance extracted (AVE) which should be at 0.50 or higher (Henseler et al. 2015). In this study, the AVE scores exceed the minimum requirement of 0.50 so that on average all reflective constructs explain more than 50% of the variance of their indicators (see Table A2). As far as *discriminant validity* is concerned, we evaluate the Fornell-Larcker criterion which states that

[1] Outliers in the eye-tracking parameter (n=3) were detected by visual inspection of boxplots and excluded before running the analysis. Occasional missing values were replaced with the mean value. Results were estimated after six iterations.

a latent variable should share more variance with its associated indicators than with any other construct (Hair et al. 2017). Accordingly, the square roots of the AVE should be larger than the interconstruct correlations. This condition is met, since all AVE measures prove to be greater than the interconstruct correlations suggesting that the reflectively measured models are empirically distinct from each other (see Table A3). In addition, the indicator loadings are higher compared to their cross loadings (Hair et al. 2017) (see Table A4). Finally, the HTMT-values for all reflectively measured models are significantly below the more rigorous threshold value of 0.85 with the 95% bias-corrected confidence intervals not including the value of 1 (see Table A5), which provides further confidence for discriminant validity (Hair et al. 2017). For *reliability* assessment, we evaluate Cronbach's α, Composite Reliability and Dijkstra-Henseler's $\rho_A$ (threshold value = 0.70). These three measures vary between 0.76 and 0.92 (see Table A2), thus suggesting a satisfactory level of internal consistency (Henseler et al. 2015).

| **Measurement** | | **Loading** |
|---|---|---|
| **Implicit behavioural measurement** | | |
| Eyes-off-road-time *single-item* | 1. Total Duration of "eyes-off-road" while activating the "Lane Keeping"-function *in sec* | 1.0 |
| **Cognition** | | |
| Relative Advantage of automated driving functions *reflective* | Based on your experience with the test vehicle, how do you evaluate the following autonomous driving functions? | |
| | 1. … Distance alert assistant | 0.70 |
| | 2. … Automated braking assistant | 0.61 |
| | 3. … Speed adaption assistant *7 point scale from very negative to very positive* | 0.82 |
| Perceived Usefulness of automated driving functions *single-item* | 1. In my daily life, automated driving functions will be… *7 point scale from very useless to very useful* | 1.0 |
| Perceived Ease of Use of automated driving functions *reflective* | 1. This technology looks easy to learn. | 0.96 |
| | 2. This technology looks easy to master. | 0.71 |
| | 3. The implicit knowledge of this technology looks easy to figure out by myself. *7 point scale from very useless to very useful* | 0.63 |
| **Attitude Toward Adoption** | | |
| Attitude toward the use of automated driving functions *reflective* | Overall, how would you describe your experience? For me, using the automated driving functions is: | |
| | 1. … bad/good | 0.94 |
| | 2. … negative/positive | 0.85 |
| | 3. … unfavourable/favourable | 0.90 |
| | 4. … unpleasant/pleasant *7 point scale within a semantic differential* | 0.71 |
| **Adoption Intention** | | |
| Intention to adopt automated driving functions *single-item* | 1. Assuming you have access to such a technology in the future, what is the probability that you would use it? *7 point scale from unlikely to likely* | 1.0 |

**Table 4: Loadings of the final set of indicators.**

After confirming reliability and validity with regard to the reflective measurement models, we evaluate the results of the structural model. *Multicollinearity* assessment by means of variance inflation factor (VIF) demonstrates that the results are not biased, since the VIF values range between 1.0 and 1.15 (see Table A6), thus not exceeding the threshold value of 5 (Hair et al. 2017). The results of testing the model and its hypotheses are summarized in Figure 3.

Examination of the explanatory power shows a substantial adjusted $R^2$ value of 0.57 for our ultimate endogenous variable Adoption Intention. Focusing on the predictive power of the eye-tracking parameter, we find rather weak adjusted $R^2$ values. However, this weak predictive power can be explained by the lacking statistical significance of eyes-off-road-time, thus leading to a rejection of all three hypotheses. Notwithstanding the absence of statistical significance, it must be noted that the effects are largely in line with our expectations (see Figure 2).

In assessing the impact of a particular predictor latent variable, the effect size $f^2$ is calculated. A recommended guideline is that values of 0.02, 0.15 and 0.35 represent a small, medium or large effect at the structural level (Hair et al. 2017). The path between eyes-off-road-time and RA indicates a small effect size ($f^2 = 0.02$) so that the removal of the path from the structural model would have a small effect on RA. Similarly, the removal of the path between eyes-off-road-time and PEoU suggests a small effect size ($f^2 = 0.02$). Finally, the path between eyes-off-road-time and PU is clearly smaller than 0.2.

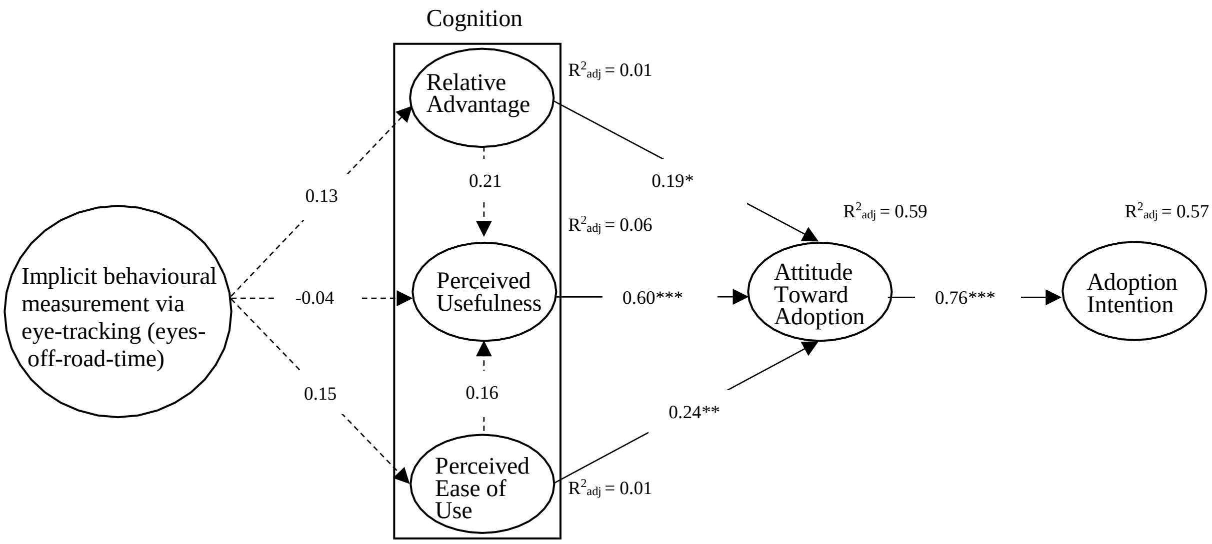


**Figure 3: Results of structural equation modelling using a partial least squares-based approach.**
*Note:* ***p ≤ 0.01; **p ≤ 0.05; *p ≤ 0.10; dashed paths refer to non-significant relationships.

## DISCUSSION, LIMITATIONS AND FURTHER RESEARCH

The objective of this study is the evaluation of automated driving technology using implicit behavioural measurement in terms of the eye-tracking parameter “eyes-off-road-time”. In summary, our general line of argument is – despite a lack of significance – largely confirmed according to which a longer eyes-off-road-time indicates a higher acceptance of automated driving technology. However, the absence of significance could be primarily a consequence of our operationalization, since eyes-off-road-time refers to a period of only one minute. It is assumed that the effects could become more apparent when test drivers use the automated driving function within a longer timeframe. Furthermore, it should also be kept in mind that this study refers to level 2 automated vehicles. Drivers are obligated to keep their concentration on the road. In the next stage of development, drivers have more freedoms, since level 3 automated vehicles allow them to turn their attention away from forward road scenes for a longer time. Accordingly, it can be expected that the eyes-off-road-time parameter provides in this context more reliable information with regard to the evaluation of technology acceptance. If our line of argument is further confirmed, it will be necessary that the OEMs develop measures to bring "technology enthusiasts", who already fully trust the technology, back onto the road. The findings could also be integrated into the marketing process in order to address precisely this target group. It is also possible to include in future studies further automated driving technologies (e.g., automated braking assistant, automatic speed control) to obtain a more comprehensive picture of technology acceptance. Finally, a balanced relation between male and female participants would be desirable as well.

Overall, the present study argues to include implicit behavioural measured variables when evaluating technology acceptance of automated driving, since this is a technology where the fully disruptive innovation (level 5) is already in the head of consumers. The implicit behavioural measured variables also meet the requirement of context-independency, a demand formulated by Köpsel et al. for the evaluation of technology acceptance in the field of automated driving (Köpsel et al. 2018). The effects that tend to be observed in this study now need to be examined further using level 3 automated vehicles, which in turn provides a deeper understanding of technology acceptance.

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## APPENDIX

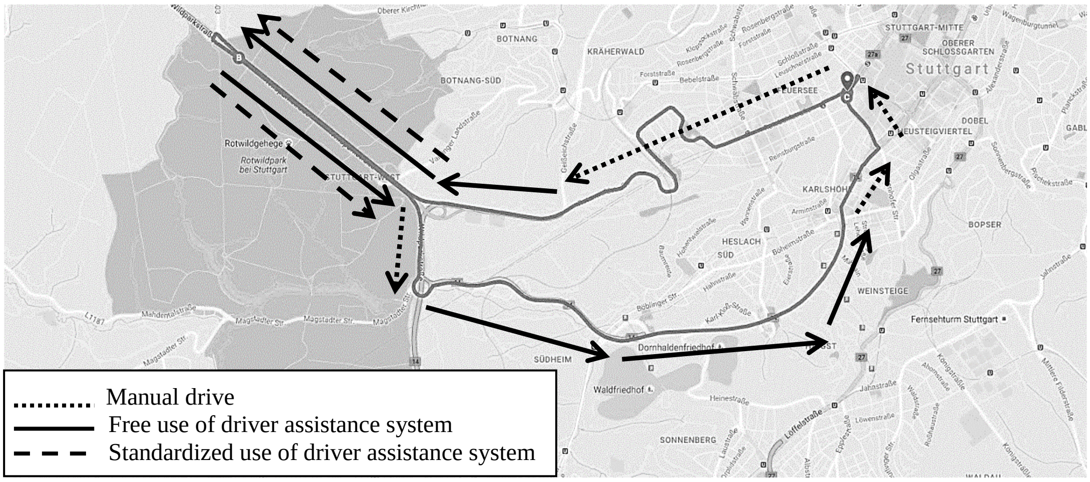


**Figure A1: Test track in Stuttgart/Germany.**

| **Measurement** | | **Source** |
|---|---|---|
| **Cognition** | | |
| Relative Advantage of automated driving functions | Based on your experience with the test vehicle, how do you evaluate the following autonomous driving functions?<br>… Distance alert assistant<br>… Automated braking assistant<br>…. Speed adaption assistant<br>… Automated parking assistant<br>… Lane keeping assistant<br>… Lane change assistant<br>*7 point scale from very negative to very positive* | |
| Perceived Usefulness of automated driving functions | In my daily life, automated driving functions will be…<br>*7 point scale from very useless to very useful* | Kulviwat et al. 2007 |
| Perceived Ease of Use of automated driving functions | This technology looks easy to learn.<br>This technology looks easy to master.<br>The implicit knowledge of this technology looks easy to figure out by myself.<br>It seems convenient for me to use this technology.<br>*7 point scale from very useless to very useful* | Hong et al. 2013 |

| | | |
|---|---|---|
| **Attitude Toward Adoption** | | |
| Attitude toward the use of automated driving functions | Overall, how would you describe your experience? For me, using the automated driving functions is:<br>… bad/good<br>… negative/positive<br>… unfavourable/favourable<br>… unpleasant/pleasant<br>*7 point scale within a semantic differential* | Kulviwat et al. 2007 |
| **Adoption Intention** | | |
| Intention to adopt automated driving functions | Assuming you have access to such a technology in the future, what is the probability that you would use it?<br>*7 point scale from unlikely to likely* | Kulviwat et al. 2007 |

**Table A1: Item summary.**

| | AVE | Cronbach's α | Composite Reliability | Dijkstra-Henseler's $\rho_A$ |
|---|---|---|---|---|
| Adoption Intention | 1 | 1 | 1 | 1 |
| Attitude Toward Adoption | 0.73 | 0.92 | 0.92 | 0.92 |
| Off-road-time | 1 | 1 | 1 | 1 |
| Perceived Ease of Use | 0.61 | 0.80 | 0.82 | 0.86 |
| Perceived Usefulness | 1 | 1 | 1 | 1 |
| Relative Advantage | 0.51 | 0.76 | 0.76 | 0.77 |

**Table A2: Criteria for assessing convergent validity and reliability.**
*Note:* AVE refers to convergent validity. Cronbach's α, Composite Reliability and Dijkstra-Henseler's $\rho_A$ refer to reliability.

| | Adoption Intention | Attitude Toward Adoption | Off-road-time | Perceived Ease of Use | Perceived Usefulness | Relative Advantage |
|---|---|---|---|---|---|---|
| Adoption Intention | **1** | | | | | |
| Attitude Toward Adoption | 0.76 | **0.86** | | | | |
| Off-road-time | 0.01 | -0.03 | **1** | | | |
| Perceived Ease of Use | 0.31 | 0.43 | 0.15 | **0.78** | | |
| Perceived Usefulness | 0.77 | 0.70 | 0.01 | 0.21 | **1** | |
| Relative Advantage | 0.35 | 0.41 | 0.13 | 0.31 | 0.25 | **0.72** |

**Table A3: Fornell-Larcker criterion for assessing discriminant validity.**
*Note:* Diagonal elements in bold represent the square roots of the shared variance between the constructs and their indicators (AVE); off-diagonal elements represent the correlations among the constructs (interconstruct correlation).

| | Adoption Intention | Attitude Toward Adoption | Off-road-time | Perceived Ease of Use | Perceived Usefulness | Relative Advantage |
|---|---|---|---|---|---|---|
| Eyes-off-road-time | 0.01 | -0.03 | 1 | 0.15 | 0.01 | 0.13 |
| Adoption Intention | 1 | 0.76 | 0.01 | 0.31 | 0.77 | 0.35 |
| Attitude 1 | 0.71 | **0.94** | -0.04 | 0.50 | 0.65 | 0.31 |
| Attitude 2 | 0.62 | **0.85** | -0.04 | 0.37 | 0.60 | 0.43 |
| Attitude 3 | 0.70 | **0.90** | -0.00 | 0.31 | 0.65 | 0.36 |
| Attitude 4 | 0.56 | **0.71** | -0.00 | 0.26 | 0.49 | 0.33 |
| Assistant 1 | 0.21 | 0.32 | 0.17 | 0.20 | 0.15 | **0.70** |
| Assistant 2 | 0.20 | 0.26 | 0.06 | 0.21 | 0.15 | **0.61** |
| Assistant 3 | 0.34 | 0.31 | 0.04 | 0.25 | 0.22 | **0.82** |
| Ease of use 1 | 0.32 | 0.41 | 0.10 | **0.96** | 0.25 | 0.26 |
| Ease of use 2 | 0.21 | 0.29 | 0.12 | **0.71** | 0.14 | 0.27 |
| Ease of use 3 | 0.18 | 0.29 | 0.14 | **0.63** | 0.08 | 0.19 |
| Perceived Usefulness | 0.77 | 0.70 | 0.01 | 0.21 | 1 | 0.25 |

**Table A4: Cross loadings for assessing discriminant validity.**
*Note:* The indicator loadings in bold are consistently higher on the construct with which they are associated than on any other construct as referred to the cross loadings.

| | Adoption Intention | Attitude Toward Adoption | Off-road-time | Perceived Ease of Use | Perceived Usefulness |
|---|---|---|---|---|---|
| Attitude Toward Adoption | 0.76 [0.62; 0.86] | | | | |
| Off-road-time | 0.01 [0.00; 0.01] | 0.03 [0.00; 0.03] | | | |
| Perceived Ease of Use | 0.32 [0.09; 0.54] | 0.43 [0.22; 0.62] | 0.16 [0.04; 0.32] | | |
| Perceived Usefulness | 0.77 [0.62; 0.87] | 0.70 [0.58; 0.79] | 0.01 [0.00; 0.01] | 0.21 [0.05; 0.42] | |
| Relative Advantage | 0.34 [0.12; 0.56] | 0.41 [0.17; 0.62] | 0.13 [0.04; 0.24] | 0.32 [0.11; 0.57] | 0.24 [0.05; 0.48] |

**Table A5: HTMT-values and 95% bias-corrected confidence intervals for assessing discriminant validity.**
*Note:* 95% bias-corrected confidence intervals are reported in parentheses. Confidence intervals base on 5,000 bootstrap samples.

| | Adoption Intention | Attitude Toward Adoption | Off-road-time | Perceived Ease of Use | Perceived Usefulness | Relative Advantage |
|---|---|---|---|---|---|---|
| Attitude Toward Adoption | 1.0 | | | | | |
| Off-road-time | | | | 1.0 | 1.03 | 1.0 |
| Perceived Ease of Use | | 1.13 | | | 1.12 | |
| Perceived Usefulness | | 1.09 | | | | |
| Relative Advantage | | 1.15 | | | 1.11 | |

**Table A6: Inner VIF-values for assessing multicollinearity.**