Predicting driver intentions: a study on users’ intention to use

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Abstract

Future driver assistance systems (ADAS) need driver intention prediction. This can help to configure ADAS by (de)activating them in context specific situations where the driver intends to perform a certain action. User’s acceptance of such systems is crucial for their usage. In the present study, an algorithm predicted lane change intentions by combining head movement and surrounding information. An automatic turn indicator function made the prediction visible and was used to examine acceptance of such a system. Twenty-one participants drove ten passing manoeuvres, in two manoeuvres activating the indicator manually and in eight manoeuvres with automatically activated indicator. System acceptance was assessed with the Van der Laan-Scale and a questionnaire on Unified Theory of Acceptance and Use of Technology. Additionally, we investigated the activation moment of the indicator as an objective performance measure. Acceptance measures showed intermediate judgements and a low usage intention, each with ample standard deviations. Social influence was the strongest predictor of usage intention whereas performance expectancy and effort expectancy hardly contributed to the explained variance of usage intention. It is concluded that the intention prediction is evaluated mainly sceptically, while also including excited judgements. This result is discussed with regard to the function using it.

Introduction and Review of Literature

Many driver assistance systems are only relevant with certain manoeuvres or in certain situations, e.g. congestion assistance, traffic light assist or blind spot warning. With interconnection and purposeful (de-)activation of different assistance systems, the workload for the driver could be reduced. To allow for this, it is necessary to detect the user intentions as early as possible and to predict his behaviour. This should ensure that information, warnings and especially system interventions do not come into conflict with driver intentions.

According to Michon (1985) the driving task can be subdivided into three hierarchical and interconnected levels in accordance with the respective control processes. The highest level is the Strategic Level which contains the superior
planning of a trip based on knowledge, such as route choice or travel time estimation. The level below is the Manoeuvring Level, which comprises rule-based actions regarding interactions with other road users, collision avoidance and adherence to traffic rules. Examples for such actions are turning, lane changing or overtaking. The lowest level is called the Control Level, which is executed highly automated and unconsciously. It involves all basic actions of car handling, such as steering, braking and accelerating. Driver intentions are especially relevant for the two upper levels of the driving task (Kopf, 2005) whereas the control level doesn’t require conscious intentions and decisions. Nevertheless, the actions on this level are crucial as indicators for driver behaviour prediction, because driver intent constitutes an unobservable state which only can be estimated on the basis of driver behaviour. Therefore in this paper driver intention detection and behaviour prediction are used synonymously.

Previous approaches of intention detection and behaviour prediction primarily concentrated on the control level and on driver state independent of the driving situation, for example fatigue (e.g. Bekiaris, 2002; Bellet et al., 2009) or attention (e.g. Rauch et al., 2009). But there are well-investigated situations at the manoeuvring level, for example lane changes. Lee et al. (2004) investigated more than 8600 lane changes from a naturalistic driving study. Based on this they propose to classify lane changes into subtypes according to their cause, for example slow lead vehicle, added lane, enter, obstacle or merging vehicle. Additionally for 500 of the lane changes Lee et al. did a detailed analysis of braking, steering, indicating and gaze behaviour as well as data about the vehicles’ surroundings. Regarding intention detection these analyses provide important basic insights for the subdivision of lane change types, the relevance of different measurement parameters and the operational sequence of a manoeuvre. Beggiato et al. (2016) also investigated lane changes but specifically in urban traffic. It was shown that gaze patterns play an important role for the detection of certain lane change types. E.g. for lane changes with slow lead vehicle, certain mirror glance patterns were found to be early and robust predictors, but this didn’t apply to lane changes due to an added lane. This shows that intention detection on the manoeuvring level should happen situation specific. Nevertheless, Beggiato et al. state that gaze patterns are too ambiguous to serve as the only predictors for intention detection. For example, gaze patterns before some lane changes and turning manoeuvres at crossroads were sometimes similar. Hence for reliable prediction of lane changes, the integration of vehicle parameters as well as data from the vehicles’ surroundings is necessary. Therefore the approach of the current study uses basic driver behaviour parameters on Michon’s Control Level like gaze patterns to detect driver intentions on the manoeuvring level even before they are put into practice.

But in order to use information about drivers’ behaviour for intention detection, a constant observance and recording for example with camera or eye-tracking systems is necessary. Additionally, the intention detection process is invisible to the driver and its result is only perceptible via the automated (de-)activation of a dependent assistance system. In this case the driver doesn’t necessarily understand the reason for (de-)activation. This raises the question of the current study if such a system is accepted by drivers. According to Adell (2014), user’s acceptance of advanced driver assistance systems is crucial for their usage. She defines acceptance as “the degree to
which an individual intends to use a system and, when available, to incorporate the system in his/her driving.’ (p. 31). According to this definition, acceptance is a behavioural intention to use a system and real usage if the system is available. For investigating the determining factors of this behavioural intention Adell (2014) proposes to use the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003). In this theory, behavioural intention is determined by three factors: performance expectancy, effort expectancy and social influence. Venkatesh et al. define performance expectancy as ‘the degree to which an individual believes that using the system will help him/her to attain gains’ (p. 447), effort expectancy as ‘the degree of ease associated with the use of the system’ (p. 450) and social influence as ‘the degree to which an individual perceives that important others believe he or she should use the new system’ (p. 451). Furthermore, in the model behavioural intention determines usage together with facilitating conditions. Additionally, the UTAUT contains four moderating variables which are sex, age, experience and voluntariness of use.

Only a few expectations regarding system acceptance can be made in advance, because at the moment there is no system on the market to compare with. Effort expectancy is expected to be low, because the intention detection is derived out of natural gaze behaviour. Out of the assumptions of the UTAUT model it can be derived that the performance expectancy and social influence should determine behavioural intention in a positive way, whereas the relation with effort expectancy should be negative. Furthermore it is expected that performance expectancy of the participants correlates with actual performance of the intention detection.

Method

Participants

A total of 23 participants took part in the test drive, but two of them had to be excluded from the analysis due to damaged driving data files. The remaining 21 participants were aged between 25 and 38 years (M = 31.6, SD = 3.5). Nine of them were female. They drove between 1200 and 50000 km per year (M = 13176 km, SD = 10832, Med = 10000 km). Due to legal and insurance regulations regarding the test car, all participants had to be employees or students of university and to possess a driving licence. They got no compensation.

Materials and procedure

The test vehicle was a VW Touran equipped with radar sensors (front, rear & blind spot), cameras (front, rear, blind spot), Differential GPS and CAN-recording for environment recognition and positioning. Driver behaviour was recorded with an inside camera and a head tracking API, with which the gaze direction of the driver could be estimated (for details see Pech, Lindner & Wanielik, 2014). The information about number of lanes, and the motion of the test vehicle in relation to other traffic were merged with the driver’s gaze patterns to a real time probability estimation of an upcoming lane change (for details see Leonhardt et al., in press). To make this estimation visible to the participant, an automated indicator function was implicated to a Samsung Galaxy S3 Smartphone which was attached to the central instrument
behind the steering wheel. By that the car’s indicator was overlaid and replaced by the smartphone indicator application (see Figure 1)

![Driver camera and smartphone application for automated indicator function in the test vehicle](image)

Figure 1. Driver camera and smartphone application for automated indicator function in the test vehicle

A mostly straight part of a public, but quiet street served as test track. The lane markings of the track were partially missing and there were changing amounts of parking cars at the roadside. Despite this drawback, the street was chosen because it was in close proximity to the university campus where the participants came from and it had a dead end which served as starting point. A first car accelerated to a speed of 30 km/h. The participant was driving the test vehicle equipped with the intention detection/automated indicator. When the first vehicle reached a marked point, the participant started too and followed the first car at a speed of 50 km/h. Participants were instructed to overtake if possible, taking account of speed limit and oncoming traffic. After 540 m a parking bay was used to turn and drive back, repeating the follow-and-overtake manoeuvre. Hence the participants drove laps, each consisting of two overtaking manoeuvres at most. Each participant drove 5 laps resulting in a maximum of ten overtaking manoeuvres. If in a lap the traffic situation didn’t allow for at least one overtaking manoeuvre, this lap was repeated immediately. Figure 2 shows a sketch of the test procedure including an overview about independent and dependent variables.

**Design**

Two independent variables were manipulated in a within-subjects design: information about the intention detection system (none/informed) and indicator activation (manual/automatic). At first the participants were not informed about the intention detection. They were told that the purpose of the study was testing the car software. They were instructed to drive the way they always did. After the third lap it was explained to the participants, that the intention detection tries to predict an upcoming lane change by merging gaze patterns and car environment information announcing the detection by indicator activation. During the first two laps participated activated the indicator by hand and the intention prediction was not visible to them (but nevertheless recorded). Dependent variables were the acceptance concepts Usefulness,
Satisfaction and Usage Intention together with indicator activation time as a performance measure. Because of occasional surrounding traffic and parking cars on the roadside, at times participants had to drive unplanned evasive manoeuvres while approaching the standardized overtaking manoeuvre of interest. The tested intention detection algorithm wasn’t trained for this kind of situations resulting in random activation of the automated indicator. Due to this and the very short track length, a comprehensive count of false alarms was not possible.

After every lap with automated indicator signal, the Van-der-Laan scale (Van der Laan, Heino & de Waard, 1997; German version) was used as an economic and general acceptance assessment tool. This scale assesses system acceptance on the two dimensions Usefulness and Satisfying. It contains of nine bipolar ratings in a semantic differential from -2 (e.g. ‘bad’) to 2 (e.g. ‘good’). To get a more detailed understanding of system acceptance, the UTAUT model was assessed additionally after the first and the last lap with automated indicator activation. Because in the current study only a prototype of an intention detection system was available for testing with a restricted user group, the UTAUT concepts usage and facilitating conditions could not be varied and therefore not be investigated. Also of the
moderating factors only gender could be included. Figure 3 shows a schematic picture of the UTAUT model including all determining and moderating relations.

The Items of the UTAUT-Scales behavioural intention to use the system (BI), performance expectancy (PE), effort expectancy (EE) and social influence (SI) in Adells’ (2014) adaptation to the driving context were translated to the German language. Each UTAUT Scale consisted of five statements, (e.g. PE1 ‘I would find the system useful in my driving.’) which were rated on a five-point Likert Scale from ‘strongly disagree’ (1) to ‘strongly agree’ (5).

The performance of the intention detection was defined as the first indicator activation before an overtaking manoeuvre. Only indicator activation within a maximum time window of eight seconds before lane change was regarded as corresponding to the overtaking manoeuvre because the earliest moment participants activated the indicator was 6.9 seconds before a lane change. Due to missing lane markings on parts of the street, a deviation of the participant’s lateral position on the street of one standard deviation from the mean value of all lateral positions of this participant was defined as the lane change moment. This criterion classified trials without overtaking most correctly. Additionally, for seven manoeuvres the lane change moment had to be set using the mean lateral position in the respective lap instead of the mean overall lateral position, because during those manoeuvres parking cars at the roadside narrowed the street considerably.

![Figure 3. Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003); only the factors marked with grey filling are included in the current study.](image)
Results

*Van der Laan Scale*

On average, participants showed intermediate judgements regarding usefulness and satisfaction with the intention detection as revealed by automated indicating. But the range of judgements was tremendous, indicating a notable disagreement amongst the participants (see also Figure 4). Table 1 shows the mean scores and standard deviations of the ratings in detail.

![Figure 4. Box Plot of the acceptance ratings in the Van-der-Laan-Scale over driven laps with automated indicator activation.](image)

*UTAUT*

The UTAUT model was only assessed after the uninformed lap and the informed lap 2. The mean performance expectancy and social influence ratings were intermediate. The effort expectancy of the participants was rather high. This result contradicts the expectation made before. The core acceptance measure of the UTAUT is Usage Intention, which obtained low mean ratings. But again all standard deviations were large. The detailed values are shown in Table 1.

Table 1. Mean Scores and standard deviations of acceptance ratings after the three laps with automated indicator activation.

<table>
<thead>
<tr>
<th></th>
<th>uninformed lap</th>
<th>informed lap 1</th>
<th>informed lap 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
<td>M</td>
</tr>
<tr>
<td>Usefulness</td>
<td>0.28</td>
<td>0.87</td>
<td>0.26</td>
</tr>
<tr>
<td>Satisfying</td>
<td>0.04</td>
<td>0.89</td>
<td>-</td>
</tr>
<tr>
<td>performance expectancy</td>
<td>2.40</td>
<td>0.97</td>
<td>-</td>
</tr>
<tr>
<td>effort expectancy</td>
<td>3.87</td>
<td>0.81</td>
<td>-</td>
</tr>
<tr>
<td>social influence</td>
<td>2.58</td>
<td>0.85</td>
<td>-</td>
</tr>
<tr>
<td>behavioural intention</td>
<td>2.03</td>
<td>1.16</td>
<td>-</td>
</tr>
</tbody>
</table>

Note: upper two rows: Van-der-Laan Scale (rating -2 to +2), last four rows: UTAUT (rating 1 to 5). N=21.
Behavioural intention is determined by three factors: performance expectancy, effort expectancy and social influence. A regression analysis was calculated to test the assumption of the UTAUT model that behavioural intention is determined by performance expectancy, effort expectancy and social influence. The data of the first assessment violated the data requirements for a regression analysis in several points. Therefore, the regression was only calculated with the data assessed after the informed lap 2. Figure 5 shows some distribution information and the resulting regression scores.

The beta values of predictors were pointing in the expected direction. Social influence was the strongest predictor of usage intention. Its beta value was more than four times higher than the values of performance expectancy and effort expectancy. The value of their coefficients resulted on comparable levels. The standard errors of the unstandardized regression coefficients of performance expectancy and effort expectancy were larger than those coefficients, indicating an unprecise estimation. Moreover, only the beta value of Social Influence was significant. In total, the regression model explained 46% of the variance ($R^2 = .461, F(3,17) = 4.85, p = .013$). This result was against expectation of the UTAUT model. To account for this result, we tested if the Social Influence mediates the influence of Performance and Effort Expectancy on Behavioural Intention in a mediator analysis (Preacher & Hayes, 2008). Performance Expectancy showed substantial bivariate correlations with Social Norms ($r = .48, p = .033$) and Behavioural Intention ($r = .41, p = .068$) whereas the respective correlations of Effort Expectancy were smaller ($r = .40, p = .07; r = .22, p = .341$). When Social Influence is added as a mediator to the regression, only the correlation of Performance Expectancy with Behaviour Intention decreased significantly (to $r = .12, p = .542$). The respective 95%-Bias Corrected Confidence Interval (BCCI) ranged from .05 to .85 indicating a significant indirect effect. The correlation of Effort Expectancy with Behaviour Intention
showed no significant decrease (to \( r = -0.07, p = 0.765; \) BCCI .17 to .81). The inclusion of gender as moderating variable did not add substantially to the explained variation of the model (\( R^2 = .496, \) \( F(7,13) = 1.83, p = .165 \)) and no moderating factor was significant (\( p \) between .430 and .837).

**Performance**

The mean detection time before an overtaking maneuver, when the automated indicator was activated, was 4.85 seconds (SD = 1.22). On average that was more than one second before the mean activation time by hand (Mdiff = 1.32s, SD = 1.08). Additionally, the mean detection time correlated with the rating on the performance expectancy scale (\( r = -0.42, p = 0.057 \)) even though it didn’t become significant. Included into the regression model of the UTAUT measures as supplementary predicting variable, detection time did not add to the explained variance of the model (\( R^2 = .464, \) \( F(4,16) = 3.46, p = .032 \)).

**Discussion**

On average the intention detection, which was made visible with an automated indicator function, is rated as intermediate useful and satisfying. This judgement remains stable, at least over the few usage experiences reported here. But according to Adell’s definition, the crucial element of acceptance is usage intention. However, this turns out to be rather low. The UTAUT model suggests three influencing factors to explain behavioural usage intention. Two of them, performance expectancy and effort expectancy, don’t show substantial explanatory power to predict behavioural intention. Instead, social influence is the best predictor of the intention to use the intention detection investigated in the current study. This is surprising, especially because actual performance of the intention detection is, as expected, coherent with performance expectancy. Furthermore, effort expectancy turns out to be unexpectedly high, which should diminish the behavioural intention as suggested by the UTAUT. The reason for their weak impact on behavioural intention can only be supposed. One possible explanation could be conceptual blending (Turner & Fauconnier, 2002), a theory on the emergence of new concepts in situations where no established mental patterns are available. An intention detection system is a new and unknown concept so far. There can’t be an existing social opinion about the system. Blending theory suggests that in such a case conceptual material from other mental spaces is selected and merged into a new concept or understanding. In this way own precariousness against the system could be blended in, filling the empty space of absent public opinion while Performance and Effort Expectancy can be judged more directly out of the first experience with the system. The mediator analysis supports this assumption at least for Performance Expectancy. But to substantiate this assumption and clarifying its reasons further research is needed.

It can be concluded that the Intention detection is judged mainly sceptical. But the judgements are far from being consistent between people. All results show almost enthusiastic ratings as well as complete rejection of the intention detection system.

This leads to further questions. The first one is if the intention detection is too notional. Participants were asked to rate a highly abstract system which was only
experienced with an artificial indicator function, which isn’t useful itself. It is not clear to what extend people are able to differentiate their judgement between the intention detection and the visualization function used, even when asked to do so. Also the potential use of an intention detection system could be insufficiently imaginable to some people. A second, but similar question concerns the extent to which the functioning is understandable to different people. Perhaps the unexpected high ratings of effort expectancy indicate a lack of understanding about the systems functioning. This is underpinned by statements of some participants that they did an extra pronounced head movement for a mirror glance but the indicator wasn’t activated. Knowing the system in greater detail it is clear that it uses natural glance patterns over time for prediction. But at least some participants seemed to build simple heuristics on the systems functioning and acting according to them. From diffusion theory it is long known, that especially with complex innovations in the first knowledge phase people require a fundamental understanding of its functioning (Rogers, 1995). Therefore by making the system’s principle of operation transparent to participants before testing could help to get more valid results. Beyond that, in further research it should be investigated if imperfect or intransparent automation functions can trigger superstitious behaviour. Also other behavioural adaptations are possible. Therefore long-time experiences with such systems are necessary. Additionally some shortcomings of the current study need to be addressed in further research. With lane change behaviour only a very limited set of situations and manoeuvres were tested here. Furthermore it was only tested in an artificial repeated situation and a small set of highly educated people, which also limits the generalizability of the results.

Nevertheless in the current study for the first time an intention detection system for behavioural prediction on the manoeuvring level was systematically tested for acceptance. With this a first step towards a context specific coordination of advanced driver assistance systems is done. With the obtained knowledge the system can be further developed in a user centred process. Especially when developing an automated function using the intention detection algorithm, e.g. blind spot warning, it seems to be important to thoroughly compile user expectations regarding performance and to make system functioning transparent before testing. In this way future intention detection systems can contribute to more security in driving.

References


