

Effects of Driver Characteristics and Driver State on Predicting Turning Maneuvers in Urban Areas: Is There a Need for Individualized Parametrization?

Matthias Graichen and Verena Nitsch

Abstract In future, advanced driver assistance systems (ADAS) may be able to adapt to the needs of the driver, thus reducing the risk of information overload in complex traffic situations. One way of achieving this may include the use of predictive algorithms that anticipate the driver's intention to perform a certain traffic maneuver based on vehicle data, such as acceleration and deceleration parameters. In order to explore whether the predictive quality of such algorithms may be mitigated by individual driver-specific parameters such as driver characteristics (i.e. emotional driving [ED] and uncritical self-awareness [US]) as well as driver state (specifically stress), an empirical test-track study was conducted with N = 40 participants. The results indicate that maximum longitudinal and lateral acceleration vary significantly depending on driver characteristics. Moreover, analyses of the collected data suggest that incorporating psychological aspects into driver models can promote new insights into driving behavior.

Keywords Maneuver prediction • Driver intention • Driver model • Driver characteristics • Driver state • Driver behavior • Driver assistance • Urban • Intersection

M. Graichen (✉) · V. Nitsch
Human Factors Institute, Universität der Bundeswehr München,
Werner-Heisenberg-Weg 39, 85579 Neubiberg, Germany
e-mail: Matthias.Graichen@unibw.de

V. Nitsch
e-mail: Verena.Nitsch@unibw.de

1 Introduction

Efforts in design and development of advanced driver assistance systems (ADAS) focus currently on challenges of urbanization, which is expected to increase significantly over the next few decades [1–3]. Inner-city traffic in metropolitan areas exhibit great complexity and diversity, not only with respect to the various road design features (e.g. architecture, type of traffic regulation, number of turning lanes, etc.) and other environmental aspects (visibility; e.g. [4]), but mainly in terms of number, types and dynamics of different traffic participants. Since the driver is necessarily confronted by a large amount of information in these complex traffic situations, it is of paramount importance to minimize the amount of information that is transmitted to the driver by the ADAS in order to ensure high levels of user acceptance and thereby also frequent voluntary usage of these assistive systems [5]. This can be achieved by reducing unnecessary warnings and making them adaptive to drivers' intentions and maneuver-planning [6]. This appears particularly necessary in highly complex traffic situations that include approaching and passing through intersections.

Urban intersections are a major accident hotspot: 25 % of accidents with personal injuries occur at intersections, 16 % while turning [7]. Here, the driver has to detect, identify and assess a large amount of visual stimuli correctly and within a brief time span [8], while scanning areas with decreasing distal proximity to the car at the beginning of the approaching phase and immediate proximity after reaching the intersection and performing the actual driving maneuver [9]. During this time, adaptive ADAS would only provide information about potential crossing cyclists or pedestrians if it was predicted with high certainty that the intention of the driver was to turn—but not in the case of drivers passing without turning, as no critical interaction with the other traffic participants is to be expected in this case. Numerous studies have demonstrated the potential of using vehicle data for predicting (turning) maneuvers (for a general overview see [10]).

As part of the on-going efforts to enhance the performance and adaptability of ADAS, (sensory) perception, evaluation and prediction of traffic situations and driving maneuvers play an important role. The present study aimed to explore the extent to which the predictive quality of vehicle data-based algorithms might be mitigated by specific driver characteristics that are assumed to influence the driving behavior during the approach to the intersection. For this purpose, a prediction algorithm for turning maneuvers based on Bayesian networks is used [11]. A model is stipulated based on two essential parameters: (1) speed models, e.g. acquired through (a) clustering of (desired) speed profiles of different drivers approaching intersections, or (b) obtained from path curvature, and (2) a maximum acceleration parameter (longitudinal acceleration after performing the turning maneuver for 1a, or lateral acceleration when during the turning process for 1b). Using the intelligent driver model (originating from traffic flow modeling), potential speed profiles for the maneuver types 'going straight', 'stopping', 'turning (right)' and 'turning (right), but stopping' can be modelled on the basis of any previously shown speed

data of the driver (alternatively, speed profiles can also be modeled using modelled curvature data, without any driving data). When taking into account the last shown speed data point of the driver, the probability for any of these maneuvers can be computed.

The relationship of these parameters to psychological aspects lies within the initialization by the (individual) driver and corresponding driver operations (e.g. pedal activity and acceleration). These may be influenced by individual preferences and characteristics (as can be inferred from literature, e.g. [12, 13]). The following analyses investigate speed, acceleration and the underlying operational processes of the driver with respect to individual driver characteristics and driver state (in particular stress), which serve as input for the stated algorithm.

2 Method

2.1 *Sampling and Participants*

In order to measure and control for relevant driver characteristics, a pre-sampling process was applied. As a first step, participants possessing a valid driver's license could apply for the study by completing a validated online questionnaire about driving-related personality (VIP [14]), driving style (adapted from [15]), driving experience and demographic information. In a second step, potential participants out of 186 applications were selected based on extreme (high or low) scores on the VIP subscales emotional driving (ED) and uncritical self-awareness (US). These subscales were chosen, as their items concerned contents relevant to speed behavior and its sensitivity to driver state. In addition, only participants were included if they had indicated a certain amount of driving experience. Specifically, in reference to [16], participants were selected if they had acquired their driver's license before 2014 and had driven more than 30,000 km overall or more than 25,000 km in the last 12 months.

The resulting sample consisted of 40 participants (8 female), with a mean age of 36.78 years (Min = 20, Max = 61, SD = 13.14). They were assigned to one of four groups according to their scores on the ED and US subscales (N = 10 in each group). Participants had an average total driving experience of 354,625 km (SD = 287,244).

2.2 *Research Design*

The study was conducted as a 2 (approaching speed) * 3 (driving maneuver) * 4 (driver characteristic) repeated-measures mixed design with two consecutive runs (labelled as 'time') on a closed test track. Approaching speed was manipulated

within-subjects with intersection approaching speeds of 50 or 70 km/h (labelled as ‘apprspeed’). Approaching intersections with 70 km/h was considered an upper limit in the context of driving in urban areas, but also appeared to alter the driver state by inducing stressful experiences when participants were reminded repeatedly and in short intervals to maintain that speed after each turning and when driving through curves. The within-condition of approaching speed was systematically varied, meaning that half of each group was instructed to approach the intersection with 50 km/h in the first two runs and 70 km/h in the second two runs, and vice versa. Each participant performed three types of driving maneuvers (left or right turn, or going straight). The sequence of maneuver types had to be held constant due to the structural requirements of the test track. Overall, there were twelve intersection maneuvers for each participant, with four runs for each direction and one repetition at each level of approaching speed. Finally, the factor driver characteristic was manipulated between-subjects, with participants being assigned to one of four groups based on their scores on the VIP subscales ED and US (labelled as ‘VIP’).

2.3 Measurements and Hypotheses

In order to check for efficacy of stress induction and accompanying changes in driver state through approaching speed requirements, the two scales ‘threat’ and ‘challenge’ from the PASA questionnaire [17] were used, which measure (cognitive) primary appraisal of stressful situations.

Since the present study aimed to explore the extent to which driver characteristics and driver state can predict turning maneuvers during the approach phase, dependent variables were selected that focused on longitudinal driving behavior as no lateral movements are to be expected to indicate turning maneuvers before entering the intersection. The dependent variables of interest in the present study are speed, speed profiles, and therewith-associated values for deceleration or acceleration, and—pertaining to these variables—pedal activity (e.g. releasing of acceleration pedal, pressing of braking pedal, or length of no-pedal-activity). The latter analysis can also serve as assessment of the general predictive potential for predicting turning maneuvers.

Table 1 lists a summary of the investigated hypotheses. The first hypothesis is exploratory, while hypotheses two to four relate to different phases of pedal activity (H2—releasing accelerator pedal, H3—no pedal-activity, and H4—pressing brake pedal).

Table 1 Summary of hypotheses

H1:	It is expected that drivers with high ED-scores intend generally to drive with higher speed and/or try to maintain speed longer and will decrease at lower time-to-intersection (TTI)/distance-to-intersection (DTI) compared to drivers with low ED-scores
H2:	Drivers with high ED-scores control actively their speed longer by means of pedal activity, and thereby will release the accelerator pedal at lower TTI/DTI (a), and will drive faster at this position (b)
H3:	Drivers with high ED-scores will avoid longer phases without pedal activity, thereby duration or driven distance without pedal activity will be shorter (a), and the loss of speed will be lower (b)
H4:	When pressing the brake pedal the position of TTI or DTI will be lower for drivers with high ED-scores (a), and the corresponding speed at this position will be higher (b). Speed values when entering the sequence of braking are expected to be higher (c). Consequently, speed loss is expected to be higher (d), as high-ED drivers need to decelerate more to reach a comfortable speed level for turning. Based on the general necessity for decreasing speed before turning maneuvers (contrary to the intention of drivers with high ED-score to maintain speed), maximum values of deceleration values (e) are expected to be higher before entering the intersection
H5:	Due to the intention of maintaining higher speeds, drivers with high ED-scores will experience greater lateral acceleration while turning
H6:	Due to the intention of maintaining higher speeds, it is expected that drivers with high ED-scores will show greater maximum acceleration values after performing the turning maneuver to reach faster preferred levels of higher speed

2.4 Driving Scenario

The study was conducted on a closed-off test track (see Figs. 1, 2 and 3). The route was designed with the same four rounds: approaching the intersection from a western starting point (1), right turn maneuver (2), following the circuit and re-approaching the intersection from east (3), left turn maneuver (4), following the circuit and re-approaching the intersection from east (5), and finally going straight over the intersection (6) back to the starting point.

**Fig. 1** View from north-west (right turn maneuver before scenery-vehicle)



Fig. 2 View from east (left turn maneuver behind scenery-vehicle)

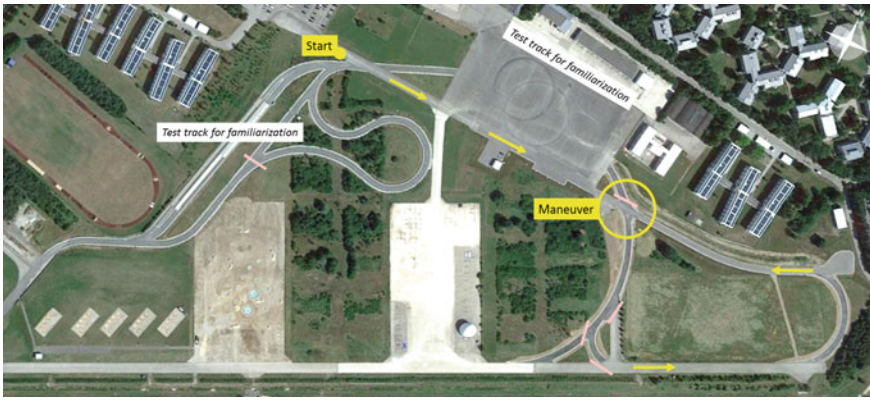


Fig. 3 Satellite view on test track (*Origin* Google Earth). Free area in the *middle* and *curvy roads* on the left side were used for familiarization

2.5 Procedure

Upon arrival, participants completed questionnaires pertaining to demographics, personality (BFI-10 [18]), sensation seeking (BSSS [19]) and traffic-related locus of control (T-LOC [20]). A cover story (“Adjusting of vehicle chassis for urban intersections”) was used in order to avoid undue influence of participants’ expectations. Participants familiarized themselves with the vehicle and test track circuit by performing a series of basic driving maneuvers (cautious, as well as strong acceleration and deceleration; driving through a constricted alley, slalom course, and curves; left and right turning maneuvers). The experimenter was seated on the right rear seat of the vehicle.

Each run began at the same starting point, at which participants were instructed regarding the approaching speed requirements. After the first of each approaching speed condition, participants completed the PASA questionnaire in order to

evaluate the experience of situationally-induced stress. At the end of the session, participants were informed about the true purpose of the study and received monetary compensation for participation. Overall, the experiment took each participant about 45 min.

2.6 Data Processing

All data from CAN-interface GPS-data, and questionnaires were stored in a PostgreSQL database [21]. To access the data from the database for further processing, a comprehensive framework was programmed in R. Approximate “arrival measures” with respect to DTI and TTI were computed in three steps: (1) Detecting the GPS-coordinates for (artificial) positions-of-interest as reference points (here: latest meaningful position before entering the intersection, likely to stopping line), (2) computing the linear (spherical) distance between these coordinates and the actual GPS-position of the driver at each timestamp (using R package ‘geosphere’), and (3) computing the arrival measure by subtracting the driven distance/time from the driven distance/time when reaching the minimum GPS-distance from step 2.

2.7 Manipulation Check

In order to ascertain whether changes in approaching speed requirements affected stress levels, PASA reliability and scores were examined for each speed condition. After excluding item two of the PASA questionnaire (“This situation is important to me”) due to response ambiguity, Cronbach’s alpha indicated high reliability (0.72) in runs with approaching speed of 70 km/h, and moderate reliability in the 50 km/h condition (0.6) (for interpretation of Cronbach’s alpha according to common practice see e.g. [22]). Means for scales ‘threat’ and ‘challenge’, and scores for primary appraisal were significantly higher in conditions with high approaching speed to the intersection (see Table 2). As there was no sequential effect of driving with 50 or 70 km/h at first, the results indicate that stress induction was successful.

Table 2 Scale characteristics for primary appraisal of PASA

	$M_{50\text{kmh}}$ (SD)	$M_{70\text{kmh}}$ (SD)	$t_{df = 39}$	p	d
Threat	4.8 (1.65)	6.03 (3.0)	-2.37	.011	-0.37
Challenge ^a	6.1 (3.22)	7.5 (3.1)	-1.93	.03	-0.31
Primary Appraisal ^a	10.9 (4.09)	13.53 (5.06)	-2.61	.006	-0.41

^aWithout item two

3 Results

Present analyses focus on the relationship between VIP and vehicle data, while analyses of the questionnaire for driving style, BFI-10, BSSQ or T-LOC are not reported at this point. In the following, participants with high or low scores in VIP subscales will be labeled according to their initials, e.g. high ED or low US. For the investigation of approaching behavior with respect to group assignments, objective data and subjective data were merged. All variables have been tested for univariate outliers using z-scores according to the thresholds proposed by [23]. To test for statistical significance of dependent variables (dv), linear mixed models (see Eq. 1) were performed using R-packages afex, lsmeans and multcomp. Tests were computed with an alpha of 5 %.

$$dv \sim VIP * appr\ speed * time + Error(id / (appr\ speed * time)). \quad (1)$$

All tests were performed using both TTI and DTI. Data from maneuvers of left and right turning were separated (no going straight maneuvers were analyzed at this point). For analyses and preceding visual exploration of key parameters of pedal activity, sequential data were computed and sorted (using R packages ‘TraMineR’, and ‘TraMineRextras’) by minimum position of braking activity, see Fig. 4. All

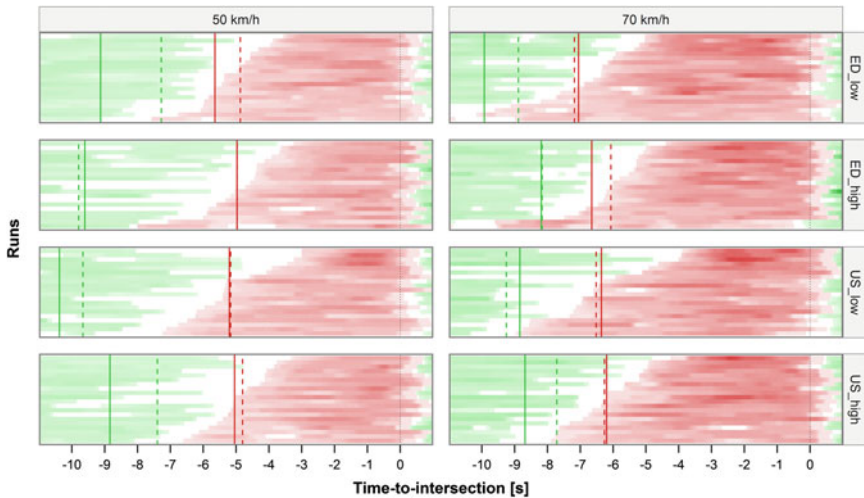


Fig. 4 Pedal sequences for right turning. Rows represent runs. Colours represent type of pedal activity (green—acceleration, red—braking, white—no pedal activity). Gradient represents intensity of pedal activity (high gradient—high intensity). Coloured, vertical lines represent first (dashed) or second (solid) run in blocks of approaching speed

Table 3 Model statistics for VIP from linear mixed models

	DTI				TTI			
	Left		Right		Left		Right	
	<i>F</i>	<i>p</i>	<i>F</i>	<i>p</i>	<i>F</i>	<i>p</i>	<i>F</i>	<i>p</i>
accprel_pos	2.08	.12	2.08	.12	3.00	.05**	0.57	.64
accprel_speed	2.62	.07**	3.88	.02*	2.37	.09**	3.55	.03*
wopedal_length	1.47	.25	1.29	.3	1.37	.27	1.53	.23
wopedal_speedloss	0.24	.87	0.72	.55	0.55	.65	1.29	.3
brake_pos	1.19	.33	0.65	.59	1.54	.22	0.92	.44
brake_length	0.29	.83	0.61	.61	0.4	.76	0.78	.51
brake_speed	1.91	.15	1.24	.31	1.91	.15	1.23	.32
brake_speedloss	0.98	.42	0.34	.8	0.97	.42	0.57	.64
max_decel	1.88	.15	0.62	.61	1.88	.15	0.62	.61
max_latacc	12.10	<.001*	5.80	.003*	12.13	<.001*	6.72	.001*
max_lonacc	1.84	.16	2.33	.09**	1.77	.17	2.43	.09**

* $p < 0.05$

** $p < 0.1$

visualizations were compiled using R-package ‘ggplot2’. A summary of statistical key values for the model component ‘VIP’ can be seen in Table 3. Due to outliers, within-group degrees of freedom vary between 25 and 35.

3.1 Speed Profiles (H1)

As this hypothesis was intended for exploration, no differentiation between consecutive runs of the same participants and no additional adjustments for t-testing (e.g. repeated measures) between VIP groups were performed. There were mostly no deviations from normal distribution (tested using Shapiro-Wilk test) throughout the trend of speed data against DTI, but in speed data against TTI. As no significant differences between speed profiles of groups with low or high scores in US could be found, no further analyses were performed here in the context of exploration.

Participants with high scores in ED drove slightly faster, particularly when approaching the intersection followed by a left turning maneuver. A significance level of 5 % was surpassed at DTIs between −10.1 and −3.3 m before reaching the (artificial) stopping line. Corresponding values for TTI can be seen in Fig. 5.

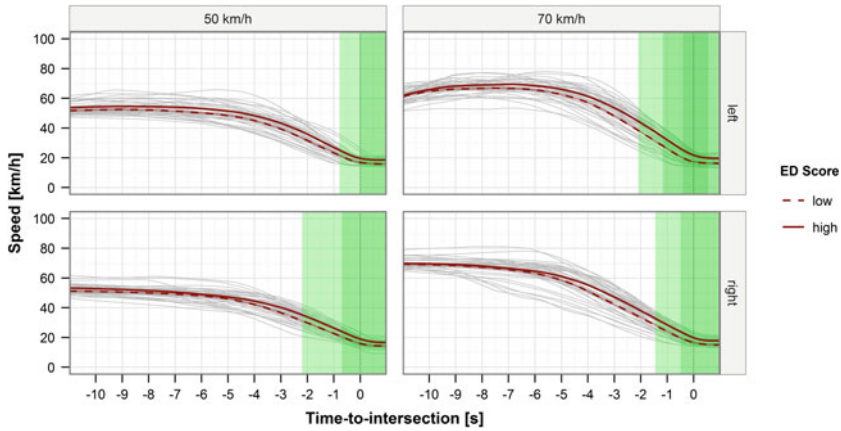


Fig. 5 Speed profiles and areas of significance ($\sim$ green, saturation $\sim p < [0.1; 0.05; 0.01]$)

3.2 Pedal Activity (H2–H4)

The results of the tests of hypotheses H2 to H4 are summarized in the following:

H2:	(a) No significant differences in positions of releasing acceleration pedal (labelled as 'accprel_pod') could be found in terms of DTI in left and right turning maneuvers. In terms of TTI, values almost reach significance in left turning maneuvers
	(b) Speed values (labelled as 'accprel_speed') between groups were significantly different when approaching intersection with 70 km/h and turning right (see right column in Fig. 5), slightly significant in cases of left turning
H3:	(a) In phases without pedal activity (between releasing accelerator pedal and pressing brake pedal), there were no significant differences in length of phases (labelled as 'wopedal_length') measured as time (using TTI) and driven distance (using DTI)
	(b) There were also no significant differences in speed loss (labelled as 'wopedal_speedloss')
H4:	(a) There were no significant differences between minimum positions of pressing brake pedal (labelled as 'brake_pos')
	(b) There were no significant differences in length of braking activity (labelled as 'brake_length')
	(c) There were no significant differences in speed values (labelled as 'brake_speed') at minimum position of pressing brake pedal
	(d) There were no significant differences in speed loss (labelled as 'brake_speedloss')
	(e) There were no significant differences in maximum deceleration values

3.3 Driving Through Intersection and Re-Accelerating (H5–H6)

In the following, the results of the analyses pertaining to hypotheses H5 and H6 are summarized:

H5:	In all conditions (left and right turning) related to both measures DTI and TTI (see Fig. 6) values of maximum lateral acceleration are significantly different between groups
H6:	No significant differences in maximum longitudinal acceleration could be found in left turn maneuvers. In right turn maneuvers (see Fig. 7) values almost reach significance, in relation to measures of both DTI and TTI

Fig. 6 Maximum lateral acceleration while turning left (means—coloured lines in background)

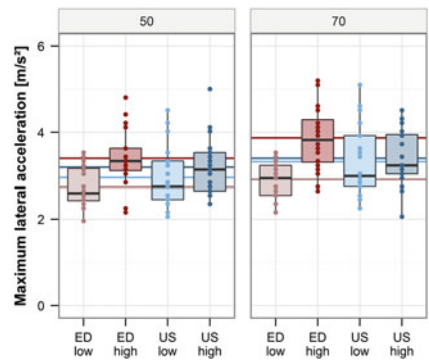
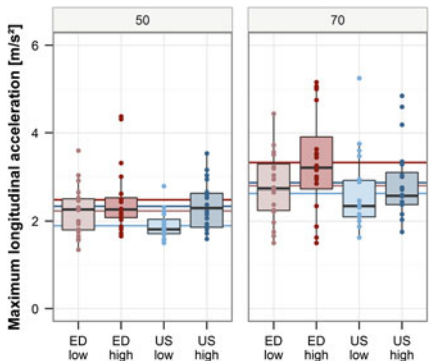


Fig. 7 Maximum longitudinal acceleration after turning right (means—coloured lines in background)



4 Discussion

The present study focused on the effect of driver characteristics and driver state on different parameters when approaching intersections and their potential of mitigating prediction algorithms. Most hypotheses regarding driver operations underlying to speed behavior were not confirmed by the empirical data. Only values for speed when releasing the accelerator pedal, values for maximum lateral acceleration while turning ($p < 0.001$) and values for maximum longitudinal acceleration after turning ($p < 0.1$) show significant differences. The last two variables represent essential parameters to create speed models for the used prediction model of [11]. Therefore, it can be stated that conventional parameters used in prediction algorithms for turning maneuvers can be significantly differentiated between groups of drivers based on driver characteristics as indicated by the VIP.

Regarding the initial research question (“Is there a need for individual parametrization of prediction algorithms?”), the present statistical results do not indicate that the consideration of detailed individual differentiations is necessary, but relating to the essential parameters of [11], there were significant differences in maximum longitudinal and lateral acceleration. Thus, in future work, it is planned to extend the model (Bayesian network) of [11] by additional nodes (e.g. VIP), as is suggested in Fig. 8. The integration of knowledge about individual characteristics is also supported by the grouping results of exploratory cluster analysis of speed profiles (Figs. 9 and 10), which shows good differentiation between ED. Regarding driver state more elaboration is necessary.

Furthermore, the present article elaborates sophisticated methods of analyzing and visually exploring driving behavior in complex driving situations using colored sequence tiles and gradient, which allows for differentiated insights into data and could be transferred to the analyses of other critical situations in urban areas. Additionally, driving behavior was dissected in different phases on the basis of elementary driver operations such as pedal activity. For example, visualizations

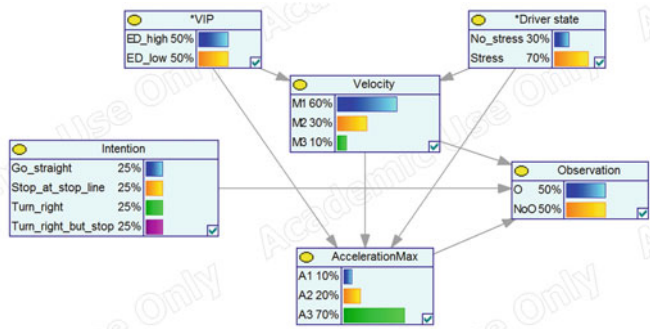


Fig. 8 Extended prediction model (built with GeNIe by BayesFusion). New nodes (*) for ‘VIP’ (as measure for driver behavior) and ‘Driver state’ added

Fig. 9 Clustered groups (using k-means) for left turning and approaching speed of 50 kmh. Most speed profiles of drivers with low ED-scores were assigned to group 1

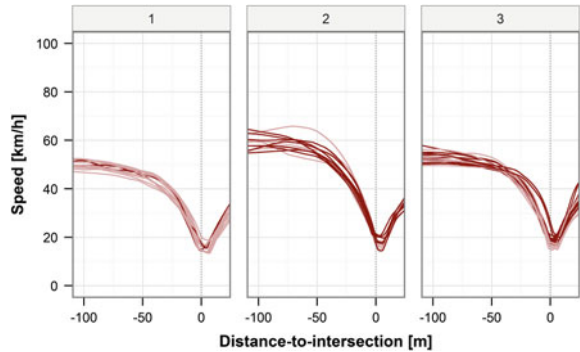
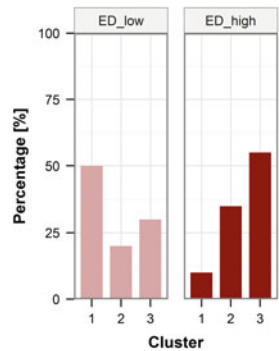


Fig. 10 Percentage of speed profiles in each cluster group for each ED score



from present data show (see Fig. 4), that approaching intersections begin with cautious release of the accelerator pedal (0), up to the complete release of the accelerator pedal (1). This is followed by a phase without pedal activity (2), and pressing the braking pedal (3) until reaching the intersection. This basic (and plausible) sequence might hold true in situations without preceding vehicles or with distant preceding vehicles as well as high familiarity with the route and thereby habituation to comfortable speed according to individual preferences. Otherwise, the number of changes in pedal activity are expected to be higher and the length of phases without pedal activity to be shorter. Also, lack of familiarity with the route might lead to early releasing of the brake pedal to allow for coasting at lower than usual speeds.

In conclusion, statistical analyses only partially show significant differences in underlying operations for “designing” driving behavior, but machine learning techniques can take complete profiles into account and even integrate into algorithms, thereby enhancing the prediction model with psychological aspects and thus promote new insights.

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