Lane Change Decision Making for Automated Driving

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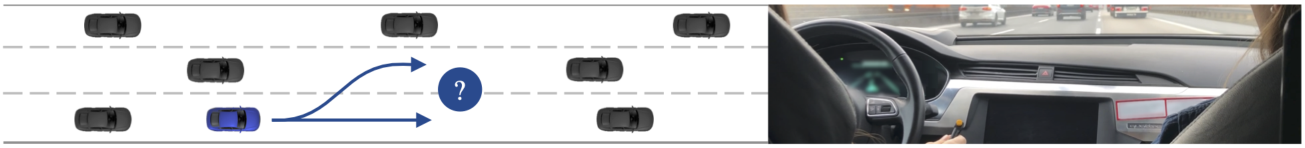

Figure 1: Identification of factors influencing lane change decisions during automated driving under real driving condition.

ABSTRACT

For the success of automated vehicles, in addition to legal, safety, and technical aspects, user acceptance and trust in automation systems are considered to have a significant impact. The driving style can decisively influence these factors. Besides driving dynamics, such as velocity and accelerations, tactical decisions (e.g. for lane changes) also define the driving style on highways. In order to get a better understanding of lane change behavior expected by passengers during automated driving, participants ($N = 35$) determined and initiated the desired point in time to perform lane changes in a study under real highway driving conditions. Subsequently, a logistic regression analysis could determine the probability of a lane change considering different environmental variables as predictors. Thus, the most important factors influencing lane change decisions could be identified. The results indicate that for lane changes from the right to the middle lane as well as from the middle to the right lane, the preceding and approaching vehicle on the target lane as well as the preceding vehicle on the current lane have a significant influence on the lane change decision. In addition, vehicles entering the highway and presence of more than one preceding vehicle on the right lane were revealed as significant predictors for the lane change decision to the right. Contrarily, for the lane change decision to the left, the relative velocity to the preceding vehicle as well as a speed limit equal to the target velocity have decisive influence. The results give a first important insight for a user-centered automated lane change behavior. Following, individual aspects of these results can be considered to be evaluated more specifically.

CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in HCI**; **HCI design and evaluation methods**; **User studies**; • **Applied computing** → *Transportation.*

KEYWORDS

Lane change behavior, automated driving, user-centered design

ACM Reference Format:

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1 INTRODUCTION

Mobility is changing towards a more efficient, resource-saving, and user-oriented transportation. The development of automated driving plays a major role in this [46]. The potential and expectations of automated driving is high: it should make driving safer, more environmentally friendly, comfortable [17, 31], relieve the increasing traffic load [31], and create access to mobility for all ages [13]. Nevertheless, studies reveal that a majority of people have feelings of skepticism and unease when it comes to automated driving (e.g [6]). In addition to legal and safety aspects, a fundamental prerequisite for the success of automated vehicles is the fulfillment of customer expectations, user acceptance, and usability of respective implementations [17]. The change from active driver to passenger raises new research questions in the field of human-vehicle interaction [41]. So far, work in this domain has mainly focused on concepts for interaction between driver and automation (e. g. [1]), control transitions, and take-over requests (e. g. [22, 26]), or the design of human machine interfaces (e. g. [1, 16, 37]). Beyond that, the way the vehicle behaves and its so called “driving style” is considered to have an important influence on trust, acceptance, and experience of automated driving [3, 10, 14].

Automated driving on highways is a first step for this new technology due to manageable complexity as well as structured nature of the traffic situations [5]. Main driving maneuvers for automated driving on highways are lane following and lane change [28]. A previous driving study investigating conditionally automated highway driving pointed out that passengers have a strong feeling of trust and safety in automated driving, which is even higher when only one lane is used and no lane changes (LC) are performed [8]. However, 97% of participants stated they would overall prefer an automated system with LCs on highways [8]. Thus, LCs are expected by passengers during conditionally automated driving, but also have a strong impact on trust and feeling of safety in the system.

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Consequently, the design and implementation of LCs is essential for the development of automated vehicles, designed to meet users expectations and needs.

Prior studies considering LCs during automated driving have mainly focused on driving metrics of LCs, such as design of acceleration, jerk, and duration of the LC [4, 14, 19, 28]. Lange [28] identified that LCs should be asymmetrical, and thus have an asymmetric lateral acceleration (cf. Figure 2). In addition, Festner et al. [14] showed that LCs with a maximum lateral acceleration of 0.8 m/s^2 were preferred independently if performing any non driving related task or not. This is enhanced by findings of [28], which revealed that a maximum lateral acceleration of 1.0 m/s^2 at 60 *km/h* should not be exceeded during LCs. Wei et al. [47] claim that a cooperative driving style of automated vehicles increases comfort and safety. This raises the research question about drivers' expectations on tactical decisions, i.e. when automated vehicles should initiate LCs. In contrast to preferred driving dynamics of passengers and drivers, there is only little knowledge about favored tactical decisions of the automation system with respect to LC decisions. A simulator study indicated that participants perceived less discomfort and higher safety during a more defensive driving style with a distance of 130 *m* (velocity not mentioned in [39]) to the preceding vehicle at LC initiation [39]. Besides, a more dynamic driving style, which accepted a smaller time gap and higher deceleration of approaching vehicles on the target lane for LC to the left, was preferred over a more cautious driving style in real driving [8]. To implement different automated driving styles passengers might prefer, Kuderer et al. [27] developed a learning from demonstration approach that learns individual model parameters of the highway planning algorithm based on different observed manual driving data. They concluded that distances to other vehicles, distance to the desired lane as well as velocities and accelerations are relevant features of highway driving. Kuderer et al. [27] proofed technical feasibility, but lack of evaluating the acceptance of the resulting automated driving style, as other studies already showed that passengers would not necessarily prefer their manual driving style for automated vehicles [41].

Several models already exist to describe and understand human LC behavior. Erdmann [11] divided the LC into four types according to its underlying motivation: LC to follow the planned route (strategic LC), LC to allow other vehicles to perform a LC (cooperative LC), LC to increase velocity (tactical LC), and LC to comply with the obligation to use the right lane (mandatory LC). Besides the motivation, which is described by desirability and necessity, Gipps [18] also mentioned the feasibility, which is defined by risk of collision, as a further important factor affecting LC decisions. He defines existence of permanent obstructions, transit lanes, and heavy vehicles as well as driving route, physical possibility, drivers' intended turning movement, and velocity of surrounding vehicles as the most crucial influencing factors. The driver model MOBIL also differentiates into necessary, discretionary, and possible LCs and predicts LC behavior only based on accelerations and velocities of surrounding vehicles [23]. For this purpose, the LC decision is made by considering the values of utility and risk of different lanes.

Technical LC decision models for automated driving are mostly built on rule-based approaches [35, 44] or on methods of artificial intelligence and machine learning [29, 33, 47]. Ulbrich and Maurer [44], for example, similar to the previous mentioned model of Gipps [18], subdivided the decision-making process into release and motivation of a LC. The motivation is defined by factors such as obstacles, desire to overtake, and the rule to use the right lane. The time to a theoretical collision determines the release parameter. A consideration of both determined values for motivation and release finally result in a decision [44]. Yang et al. [49] recommend an adaptation of duration and time gap of automated LCs to road type and underlying motivation (necessary or discretionary).

The results of various research studies indicated that an individualizing of driving behavior should be considered [14, 19, 31]. Keyvan-Ekbatani et al. [24] defined four different driving strategies on highways (*speed leading*, *speed leading with overtaking*, *lane leading*, and *traffic leading*) by observing manual LC behaviors. Rossner and Bullinger [39] defined a dynamic, an everyday, and a comfortable automated driving style, which differed in the duration and starting time of LCs. Cramer et al. [8] made a distinction based on the approaching vehicles on the target lane and defined a dynamic and cautious automated driving style.

So far, there is very little knowledge about a preferred tactical LC behavior during automated driving. Therefore, this is the topic of the study presented in this paper which used an exploratory approach. In order to determine the influencing factors for LC decisions, participants define the appropriate time and, thus, initiate LCs during conditionally automated highway driving under real driving conditions. Furthermore, it should be evaluated to what extent and how strongly the individual factors influence LC decisions and if different preferred driving strategies considering LCs exist.

2 METHOD

2.1 Test Vehicle and Automation System

The test vehicle was an Audi A7, year of construction 2010. It was equipped with additional sensors for environment perception as well as a differential global positioning system (dGPS; [21]). A visibility range of approximately 200 *m* to the front and rear was achieved by the sensors. A prototypical automation system that simulated SAE-level 3 [40] was implemented in the test vehicle which completely performed the lateral and longitudinal vehicle guidance. Hence, participants could take their hands off the steering wheel when the automation system was active, but had to be ready for taking over vehicle guidance after a certain time. The target velocity was set to 120 *km/h* or equal to the current speed limit.

The technical implementation of the automated driving function was realized using the software framework ADTF (Automotive Data and Time-Triggered Framework, C++ based). The trajectory planning on the operational layer (according to [30]) was based on the approach of Werling et al. [48] including adaptions by Heil et al. [20]. The decisions on the tactical layer of the automation system (according to [30]) was not made by the automation system, but was triggered by the participants (cf. Section 2.2).

Based on prior results [28], LC dynamic was defined by a maximum lateral acceleration of 0.75 m/s^2 and jerk of 0.8 m/s^3 for both LC right and left. Figure 2 shows exemplary the trajectory of a LC at straight and free course. However, the planning algorithm was implemented adaptively to external environmental parameters, such as road curvature. Therefore, lateral offset and acceleration could vary slightly from the values in Figure 2 during the test drive.

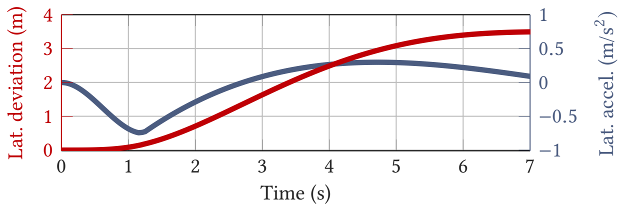


Figure 2: Course of lateral deviation and acceleration at LCs.

2.2 Test Setup and Procedure

Participants were seated on the driver's seat and were accompanied by two experimenters. One always sat on the passenger's seat and was only acting as a safety driver. This task was supported via a monitor containing information about the automation system, a second interior mirror as well as driving school mirrors and pedals to be able to intervene in vehicle guidance in risky driving situations. Using a controller, this experimenter was able to give approval for LCs, adapt target velocity, or trigger LCs. The participant's task during automated driving was to observe surrounding traffic and to determine the most suitable time for a LC. The test vehicle only drove on the right and middle lane of the highway due to safety reasons. Thus, the study investigated LCs to the middle and to the right lane. To initiate LCs, participants were holding a push button (Figure 1). If the participant thought it is a suitable time for a LC, he/she pressed the button and if approval of the safety driver was given, the LC was directly initiated. After finishing the LC, the participant rated the time of the LC as suitable or unsuitable. The second experimenter was seated in the back row and was responsible for questioning and providing participants with instructions.

The driving study was conducted in German language in December 2019 and was approximately 90 minutes per participant. They received important information about the study at the time the appointment was arranged to ensure the participant is able to finally consent on the study. On the study day, after receiving a verbal briefing on how to handle the test vehicle, participants drove manually on the highway and activated the automation system afterwards by pressing the automation button in the center console. The first drive (approx. 13 *km*) served as a settling-in phase to get familiar with the automation system and to practice announcement and initiation of LCs. After a stop the main part of the study followed, which covered a distance of approximately 53 *km*. To evaluate the influencing factors for initiating a LC in the specific situation, the Thinking Aloud Method was used [12]. Therefore, participants were instructed to speak out loud all their thoughts considering the decision whether to trigger a LC or not.

To assess well-being and the extent to which this changed as a result of automated driving, participants filled out the short version A of the German multidimensional state survey (MDBF; [43]) before and after the test drive and also after the settling-in phase. In the final survey, participants rated trust in the automation [25], perceived LC dynamics, preferred driving strategy for an automation system, and specified main reasons for or against a LC.

2.3 Processing and Evaluation of the Data

In addition to subjective data, which were gathered using questionnaires and Thinking Aloud method, objective data for subsequent recorded during the study. Subsequently, relevant situations were labeled using a graphical user interface in ADTF. Two situations were crucial: the times when a suitable LC was initiated and when participants did not want to perform a LC. For the positive event (*LC*), the actual starting time of the LC, triggered by the participant, was used. In order to additionally collect sufficient negative cases (*no LC*) and to keep the evaluation within a reasonable time frame, situations in a fixed interval of 60 seconds were defined as negative cases. If participants initiated a LC close to a negative case (± 3 seconds), the situation was excluded from the evaluation. Furthermore, it was relevant to define different values of environmental variables for the respective situation. Speed limits were determined using recorded GPS-positions. The subsequent assignment of various data was done by exact time stamps which were available for respective recorded situations and various measured data. In addition to recorded data, variables that could not be collected simultaneously during the study but were crucial for the regression models had to be labeled. For this purpose, type of vehicle and existence of a highway entry with or without a joining vehicle were identified based on video recordings. Finally, relevant variables were specified and calculated. Many participants noticed that frequent changing of lanes is disturbing, thus a variable indicating the time since the last LC was defined. In order to outline the influence of the speed limit, a binary variable was established, which specified whether the speed limit was equal to the target velocity or not. The type of vehicle was defined on based on whether it has to comply with a speed limit on the highway (e.g. truck, car with trailer, bus, or caravan) or not (e.g. car, van). In the vehicle coordinate system, the x-axis is in the longitudinal direction of the vehicle and the y-axis in the lateral direction.

LCs which were subsequently rated unsuitable, were not included in the final data set. Moreover, certain situations were handled as exceptions and excluded. These included LCs due to upcoming highway exits that were taken, situations during traffic jams and daytime construction sites. Video recordings of six participants were not available due to technical problems. Therefore, data of 29 participants was used to build the regression models. An overview of the different variables is shown in Table 1. Furthermore, this data set was used in [36] and thereby compared to LC data of manual driving.

2.4 Sample

36 participants took part in this driving study. One had to be excluded from data evaluation due to bad automation performance induced by bad weather. The sample ($N = 35$) had a mean age of 33.7 years ($SD = 10.9$, $MIN = 21$, $MAX = 62$) and was a variation of professional background and gender (22.9% technical female, 31.4% technical male, 25.7% non-technical female, 20.0 % non-technical male). The median mileage per year was 10,001-15,000 *km* with on average 47.2% highway driving, followed by driving on rural roads (27.1 %) and in cities (28.7 %). All participants had used adaptive cruise control, 80.0% lane keeping assistance, and 48.6% partially automated driving systems (e.g. traffic jam assistance) before.

Table 1: Overview of the independent variables (predictors for the regression models)

Variable	Definition	Value range	Unit	Symbol
Relative velocity to target velocity	target velocity - velocity(ego)	$[0, 33.\bar{3}]$	*m/s*	$v_{targ.,ego}$
Existence of vehicle x	indicates if vehicle x is ± 200 *m* behind or in front of ego vehicle	0 = not existent 1 = existent	-	*V(x)*
Longitudinal distance to vehicle x	$\text{position}_x(V(x))$ - $\text{position}_x(\text{ego})$	[-200, 0] vehicle x behind ego vehicle [0, 200] vehicle x in front ego vehicle	*m*	$d_{V(x),ego}$
Relative longitudinal velocity to vehicle x	$\text{velocity}_x(V(x))$ - $\text{velocity}_x(\text{ego})$	< 0 vehicle x slower than ego vehicle > 0 vehicle x faster than ego vehicle	*m/s*	$v_{V(x),ego}$
Type of vehicle x	indicates if the type of vehicle x is speed limited on the highway	0 = not limited 1 = limited	-	$Type_{V(x)}$
Highway entry	indicates existence of highway entry	0 = no entry 1 = entry without joining vehicle 2 = entry with joining vehicle	-	$Entry_{wo}$ $Entry_w$ $Entry_w$
Speed limit	indicates if the speed limit is equal to the target velocity	0 = no 1 = yes	-	$v_{targ.=lim.}$
Time since last LC	indicates the time since the last LC	> 0	*ms*	$t_{last\text{-}LC}$

3 RESULTS

The data is analyzed and findings are reported according to recommendations in [15]. For subjective data, rating scales were assumed as interval scaled variables because answer scales were equidistant [9]. Normal distribution was assumed for sample sizes $N > 30$ [15].

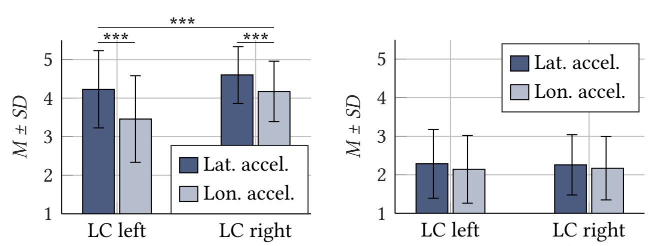
3.1 General Assessment of Automation System

3.1.1 Well-being and Trust. The MDBF questionnaire [43] is divided in three subscales *good-bad mood*, *calm-nervous*, and *awake-tired*. Results are presented in Table 2 for each time of measurement. An ANOVA with repeated measures indicated a significant difference between the times for subscales *calm-nervous* ($F(1.26) = 5.85$, $p = .014$, $\eta_p^2 = 0.15$) and *awake-tired* ($F(1.18) = 5.53$, $p = .019$, $\eta_p^2 = 0.14$), but not for *good-bad mood* ($F(1.12) = 0.20$, $p = .683$, $\eta_p^2 = .01$). Participants stated that they were significantly calmer after than before the drive ($M_{\text{t3-t1}} = 0.35$, $p = .020$) or after the settling-in phase ($M_{\text{t3-t2}} = 0.16$, $p = .008$). Moreover, participants were significantly more awake after than before the test drive ($M_{\text{t3-t1}} = -0.34$, $p = .049$). To evaluate trust in automation, three subscales *understandability/predictability* ($M = 4.17$, $SD = 0.62$), *reliability/competence* ($M = 3.68$, $SD = 0.61$), and *trust in automation* ($M = 3.97$, $SD = 0.74$) of [25] were used (scale: 1 $\widehat{=}$ strongly disagree - 5 $\widehat{=}$ strongly agree). Results of subscale means reveal on average a high trust in this automation.

Table 2: Evaluation of the MDBF [43] before *t1* and after the study *t3* as well as after settling-in phase *t2* (scale: 1 to 5)

	t1, *M*(*SD*)	*t2*, *M*(*SD*)	*t3*, *M*(*SD*)
Good ($\widehat{=}$ 5) - bad ($\widehat{=}$ 1) mood	4.58 (0.12)	4.63 (0.06)	4.64 (0.07)
Awake ($\widehat{=}$ 5) - tired ($\widehat{=}$ 1)	4.04 (0.14)	4.35 (0.09)	4.38 (0.09)
Calm ($\widehat{=}$ 5) - nervous ($\widehat{=}$ 1)	3.89 (0.11)	4.08 (0.12)	4.24 (0.09)

3.1.2 Lane Change Dynamics. On several five-point semantic differentials, participants rated LC accelerations (1 $\widehat{=}$ unsuitable, low - 5 $\widehat{=}$ suitable, high) and LC executions in general (1 $\widehat{=}$ unpleasant, uncomfortable, artificial - 5 $\widehat{=}$ pleasant, comfortable, natural) according to [28]. The mean values indicate that execution of LCs are overall pleasant ($M = 4.54$, $SD = 0.56$), natural ($M = 4.09$, $SD = 0.89$), and comfortable ($M = 4.57$, $SD = 0.78$). Considering the ratings how suitable accelerations were perceived, a 2 (lateral/longitudinal) x 2 (LC left/right) ANOVA revealed a significant main effect for acceleration ($F(1) = 14.67$, $p < .001$, $\eta_p^2 = 0.31$) as well as LC direction ($F(1) = 18.19$, $p < .001$, $\eta_p^2 = 0.35$), but no significant interaction effect ($p = .063$) (Figure 3a). Post hoc-tests showed that LC right is more suitable than LC left ($M_{\text{right-left}} = 0.62$, $p < .001$), and also that lateral acceleration is more suitable than longitudinal ($M_{\text{lat-lon}} = 0.56$, $p < .001$). The intensity of accelerations was assessed as rather weak and rather equal for the different aspects (Figure 3b).



(a) Scale: 1 $\widehat{=}$ unsuitable - 5 $\widehat{=}$ suitable (b) Scale: 1 $\widehat{=}$ low - 5 $\widehat{=}$ high

Figure 3: Evaluation of suitability (a) and intensity (b) of longitudinal and lateral acceleration of LCs left and right

3.2 Driving Strategy

The evaluation of Thinking Aloud statements indicated that participants mostly differed in one need. This concerned approaching traffic as a factor influencing the LC decision to the right. Participants who pursued a more cooperative driving strategy, initiated LCs to the right due to an increased number of faster approaching vehicles. This was based on the need to avoid being an obstacle for approaching vehicles and to clear the lane for them. Hence, in situations where the right lane was free, but no traffic was coming from behind, it was more expected that no LC to the right should be performed. Contrary, the more speed-driven driving strategy was due to the need to maintain target velocity as long as possible and to avoid frequent braking. Therefore, participants would not change to the right lane when there was a lot of traffic from behind, in order to avoid being unable to change back to the middle lane due to much traffic. It should be mentioned that the two driving strategies are not mutually exclusive. Consequently, there were also participants who were influenced differently by approaching traffic in different situations. In order to substantiate those driving strategies with quantitative data provided by the participants, we assigned each participant to one driving strategy based on their statements. In the case participants followed both driving strategies, the strategy was chosen, which they demonstrated more frequently and clearly. For participants who followed the more cooperative driving strategy (*median* = 5, $N = 15$) it is more important that the automated vehicle does not negatively influence driving behavior of other vehicles (scale: 1 ≙ does absolutely not apply - 5 ≙ does absolutely apply) than for participants who followed the speed-driven driving strategy (*median* = 4, $N = 14$; Mann-Whitney test: $U = 55.50$, $p = .029$, $r = .44$). The other comparisons considering the compliance to use the right lane, a traffic leading or lane leading driving strategy, the desire to maintain a constant velocity, and the disturbance of frequent LCs showed no significant differences ($p > .05$).

3.3 Factors Influencing Lane Change Decisions

3.3.1 Qualitative Data. In an open formulated question in the final survey, participants mentioned significant influencing factors for deciding whether to perform a LC to the left or right or not. The answers were categorized and serve as a basis for the following regression models. The results are presented in Figure 4. The velocity of the preceding vehicle, increase of ego velocity, vehicles on the highway entry, vehicles on the left lane, and pre-/ absence as well as the velocity of approaching vehicles on the target lane are important factors for LCs to the left. Contrarily, pre-/ absence, velocity as well as distance to the preceding vehicle on the target lane, vehicles on the highway entry, approaching vehicles, and distance to the approaching vehicle on the target lane are crucial for LC decisions to the right.

3.3.2 Regression Models. Using objective data, binary logistic regression analysis were conducted. The dependent variable is represented by a binary variable with values *LC* and *no LC*. The influence of predictor variables with categorical as well as metrical levels were considered. As this was exploratory work due to no prior research, the backward method of regression was selected [15].

The regression models were built separately for both LC directions in two steps. First, a general model was set up in which the existence of surrounding vehicles were included as dichotomous variables. In order to be able to specify the influence of distance, relative velocity, or type of surrounding vehicles on the LC decision, certain scenarios were considered in a second step. These were chosen based on the results of the model built in the first step. To classify surrounding vehicles, a specific name depending on their lane and whether they are in front of or behind the ego vehicle was selected (Figure 5).

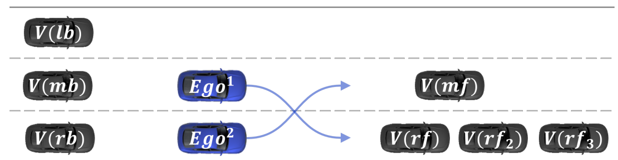
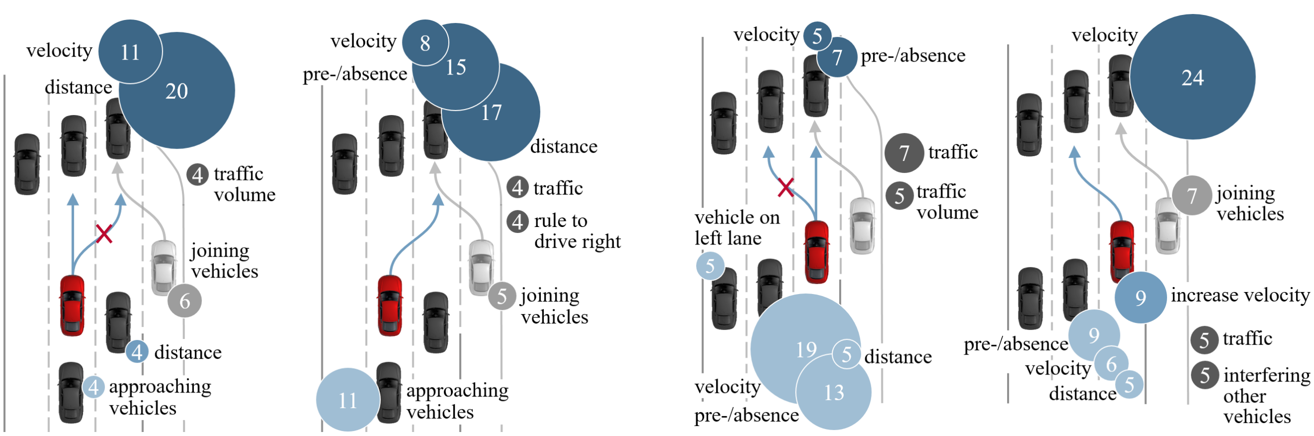


Figure 5: Nomenclature of surrounding vehicles according to lane (r(ight) / *m*(iddle) / l(eft)) and position of the vehicle (b(ehind) / f(ront)) relative to the Ego ([1] LC right, [2] LC left)

Lane Change to the Right. The following regression models estimate the probability for initiating a LC from the middle lane (ego lane) to the right lane (target lane) in different situations. Overall, 740 situations for the LC to the right could be used for evaluation. 218 were positive (*LC*) and 522 negative cases (*no LC*) (Table 3).

Table 3: Number of cases for each LC regression model

Model	Number of situations	LC	no LC
Model 1 (LC right)	740	218	522
Model 1a (LC right)	541	99	442
Model 1b (LC right)	444	64	380
Model 2 (LC left)	438	257	181
Model 2a (LC left)	228	123	105
Model 2b (LC left)	205	86	119



(a) Influencing factors against (left) or for (right) LCs to the right

(b) Influencing factors against (left) or for (right) LCs to the left

Figure 4: Visualization of absolute mentions ($N > 3$) of significant influencing factors for or against LCs

The resulting regression model 1 included the existence of a vehicle in front of the ego vehicle (*V(mf)*), of a vehicle behind (*V(rb)*) and in front of (*V(rf)*) the ego vehicle on the target lane, a vehicle in front of this (*V(rf$_2$)*) and of a highway entry as well as the relative velocity to the target velocity ($v_{targ.,ego}$) and the existence of a speed limit equal to the target velocity ($v_{targ.=lim.}$). All included predictors have significant influence except speed limit ($v_{targ.=lim.}$) and the existence of highway entry (cf. Table 4).

Table 4: Results of the logistic regression model 1 (LC right)

	B (*SE*)	*p*	*Exp(B)*	95 % *CI Exp(B)* Lower	Upper
Variables in the equation					
Constant	1.87 (0.58)	< .01	6.51		
V(mf)	-0.73 (0.26)	< .01	0.48	0.29	0.81
V(rf)	-2.75 (0.33)	< .001	0.06	0.03	0.12
V(rb)	1.25 (0.46)	< .01	3.49	1.41	8.68
V(rf$_2$)	-1.83 (0.28)	< .001	0.16	0.09	0.28
$v_{targ.,ego}$	-0.19 (0.05)	< .001	0.83	0.75	0.92
$v_{targ.,=lim.}$	-0.60 (0.35)	.090	0.55	0.28	1.10
$Entry_w$	-0.71 (0.63)	.259	0.49	0.14	1.69
$Entry_{wo}$	-1.60 (0.85)	.060	0.20	0.04	1.07
Variables not in the equation					
V(mb)	Removed in second step				
$t_{last\text{-}LC}$	Removed in third step				
V(lb)	Removed in fourth step				
V(rf$_3$)	Removed in fifth step				

The model was significant ($X^2(7) = 356.9$, $p < .001$, $R^2{}_N = .56$, $R^2{}_{CS} = .39$) and is defined by the following equation:

$$P(LC_{right}) = \frac{1}{1 + e^{-EP}} \tag{1}$$

$$\begin{aligned} EP &= 1.87 - 0.73V(mf) - 2.75V(rf) + 1.25V(rb) - 1.83V(rf_2) \\ &-0.19v_{targ.,ego} - 0.60v_{targ.=lim.} - 1.60Entry_w - 0.71Entry_{wo} \end{aligned} \tag{2}$$

Considering the number of situations for each scenario and the significant predictors of model 1, regression models for a LCs to the right were built for two scenarios. First, a scenario in which vehicles (*V(rf)*) and (*V(rb)*) were present (Figure 6, S 1a). Secondly, a scenario in which, in addition to these two vehicles, vehicle (*V(mf)*) existed (Figure 6, S 1b). The existence of a highway entry was not considered for these models due to too few cases for the respective values ($N < 25$; [2]), as well as existence of an approaching vehicle on the left lane, and the time since the last LC, as these could not make a significant contribution in model 1. On the basis of the number of cases for the respective values and the qualitative statements of participants, the type of vehicle was exclusively considered for *V(rf)*. Table 3 presents an overview of the number of cases for the respective models.

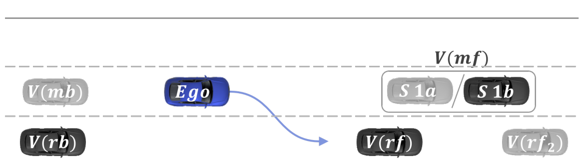


Figure 6: Scenario for model 1a (S 1a) and model 1b (S 1b)

Model 1a was significant ($X^2(6) = 356.1$, $p < .001$, $R^2{}_N = .79$, $R^2{}_{CS} = .48$) and included distances to *V(rf)* and *V(rb)*, relative velocity to *V(rf)* and *V(rb)*, existence of *V(mf)* and vehicle type of *V(rf)* (cf. Table 5). Next to the predictors of model 1a, the resulting regression model 1b contained the distance to *V(mf)* and the existence of *V(mb)*. The model 1b was significant ($X^2(7) = 267.0$, $p < .001$, $R^2{}_N = .81$, $R^2{}_{CS} = .45$; Table 6).

Table 5: Results of the logistic regression model 1a (LC right)

	B (*SE*)	*p*	*Exp(B)*	95 % *CI Exp(B)* Lower	Upper
Variables in the equation					
Constant	-1.01 (0.81)	.213	0.36		
$d_{V(rf),ego}$	0.03 (0.01)	< .001	1.03	1.02	1.04
$v_{V(rf),ego}$	0.46 (0.07)	< .001	1.58	1.37	1.82
$Type_{V(rf)}$	-2.05 (0.47)	< .001	0.13	0.05	0.33
$d_{V(rb),ego}$	0.03 (0.01)	< .01	1.03	1.01	1.05
$v_{V(rb),ego}$	-0.20 (0.06)	< .01	0.82	0.72	0.92
V(mf)	-1.11 (0.54)	< .05	0.33	0.11	0.95
Variables not in the equation					
$v_{targ.,=lim.}$	Removed in second step				
V(mb)	Removed in third step				
$v_{targ.,ego}$	Removed in fourth step				
V(rf$_2$)	Removed in fifth step				

Table 6: Results of the logistic regression model 1b (LC right)

	B (*SE*)	*p*	*Exp(B)*	95 % *CI Exp(B)* Lower	Upper
Variables in the equation					
Constant	-5.95 (1.41)	< .001	0.003		
$d_{V(mf),ego}$	0.03 (0.01)	< .001	1.03	1.02	1.05
$d_{V(rf),ego}$	0.03 (0.01)	< .001	1.04	1.02	1.05
$d_{V(rb),ego}$	0.05 (0.02)	< .001	1.05	1.02	1.09
$v_{V(rf),ego}$	0.59 (0.11)	< .001	1.81	1.45	2.26
$v_{V(rb),ego}$	-0.18 (0.09)	< .05	0.83	0.70	1.00
$Type_{V(rf)}$	-2.28 (0.65)	< .001	0.10	0.03	0.37
V(mb)	1.56 (0.78)	< .05	4.75	1.03	21.93
Variables not in the equation					
$v_{targ.,=lim.}$	Removed in second step				
$v_{V(mf),ego}$	Removed in third step				
V(r$_2$)	Removed in fourth step				
$v_{targ.,ego}$	Removed in fifth step				

Lane Change to the Left. The following models assess the probability of a *LC* from the right (ego lane) to the middle lane (target lane). Identical to the LC to the right, an exploratory model was built first, which considered the influence of the existence of all relevant vehicles. The independent variable existence of a highway entry was not taken into account because there were too few cases for the individual values of the variables ($N < 25$; [2]). A total of 438 cases could be considered, 257 were positive (*LC*) and 181 negative (*no LC*) (Table 3). The regression analysis revealed that the existence of *V(rf)*, *V(mb))*, *V(lb)*, and *V(mf)* as well as the variable $v_{targ.=lim.}$ and $v_{targ.,ego}$ influenced the decision to initiate a LC to the left. $t_{last\text{-}LC}$, the existence of *V(rb)* as well as of *V(rf$_2$)* and *V(rf$_3$)* were removed and not included in the model (cf. Table 7). The resulting model 2 was significant ($X^2(6) = 127.74$, $p < .001$, $R^2{}_N = .34$, $R^2{}_{CS} = .25$).

Table 7: Results of the logistic regression model 2 (LC left)

	B (SE)	*p*	*Exp(B)*	95 % *CI Exp(B)*	
				Lower	Upper
Variables in the equation					
Constant	-1.81 (0.47)	< .001	0.16		
V(mf)	1.41 (0.35)	< .001	4.10	2.06	8.16
V(rf)	1.58 (0.38)	< .001	4.86	2.31	10.21
V(mb)	-1.33 (0.25)	< .001	0.26	0.16	0.43
V(lb)	0.59 (0.25)	< .05	1.80	1.11	2.93
$v_{targ.,ego}$	0.13 (0.04)	< .01	1.14	1.05	1.23
$v_{targ.=lim.}$	-1.19 (0.33)	< .001	0.31	0.16	0.58
Variables not in the equation					
$V(rf_3)$	Removed in second step				
$V(rf_2)$	Removed in third step				
$t_{last\text{-}LC}$	Removed in fourth step				
V(rb)	Removed in fifth step				

As for *LC* to the right, the influence of the specifications of relevant vehicles were considered in a second step for *LC* left. Based on the results of model 2 and with respect to the number of available cases, two scenarios were chosen. First, a scenario in which vehicles *V(mb)* and *V(rf)* were present (Figure 7, S 2a). Secondly, a scenario in which vehicle *V(mf)* also existed (Figure 7, S 2b).

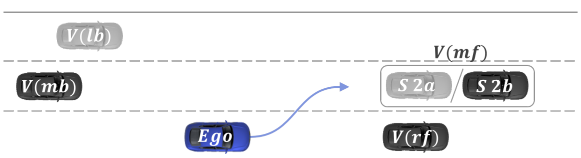


Figure 7: Scenario for model 2a (S 2a) and model 2b (S 2b)

The resulting regression model 2a indicated that of the additionally considered variables the distance to *V(mb)* and the vehicle type of *V(rf)* have significant influence on the LC decision. The variable $v_{targ.,ego}$ and relative velocity to *V(mb)* and *V(rf)* as well as the distance to *V(rf)* were removed during the stepwise selection (Table 8). The model was significant ($X^2(5) = 131.5$, $p < .001$, $R^2{}_N = .59$, $R^2{}_{CS} = .44$). Furthermore, regression model 2b was significant ($X^2(6) = 112.7$, $p < .001$, $R^2{}_N = .57$, $R^2{}_{CS} = .42$) and included distances to *V(mf)* and to *V(mb)*, vehicle type of *V(rf)*, relative velocity to *V(mf)*, existence of *V(lb)*, and the variable $v_{targ.=lim.}$. Except for $d_{V(mf),ego}$, all predictors were significant (cf. Table 9).

Table 8: Results of the logistic regression model 2a (LC left)

	B (SE)	*p*	*Exp(B)*	95 % *CI Exp(B)*	
				Lower	Upper
Variables in the equation					
Constant	-5.15(0.93)	< .001	0.01		
$d_{V(mb),ego}$	-0.05 (0.07)	< .001	0.96	0.94	0.97
$Type_{V(rf)}$	1.40 (0.41)	< .001	4.05	1.81	9.05
V(mf)	1.85 (0.77)	< .05	6.36	1.41	28.75
V(lb)	1.01 (0.41)	< .05	2.75	1.23	6.14
$v_{targ.=lim.}$	-1.36 (0.51)	< .01	0.26	0.10	0.70
Variables not in the equation					
$v_{targ.,ego}$	Removed in second step				
$v_{V(mb),ego}$	Removed in third step				
$d_{V(rf),ego}$	Removed in fourth step				
$v_{V(rf),ego}$	Removed in fifth step				

Table 9: Results of the logistic regression model 2b (LC left)

	B (SE)	*p*	*Exp(B)*	95 % *CI Exp(B)*	
				Lower	Upper
Variables in the equation					
Constant	-2.18(0.71)	< .01	0.11		
$d_{V(mb),ego}$	-0.05 (0.01)	< .001	0.96	0.94	0.97
$d_{V(mf),ego}$	-0.01 (0.01)	.064	0.99	0.98	1.00
$v_{V(mf),ego}$	-0.12 (0.06)	< .05	0.89	0.80	1.00
$Type_{V(rf)}$	1.35 (0.43)	< .01	3.85	1.65	9.00
V(lb)	0.93 (0.43)	< .05	2.53	1.09	5.86
$v_{targ.=lim.}$	-1.53 (0.53)	< .01	0.22	0.08	0.61
Variables not in the equation					
$v_{V(mb),ego}$	Removed in second step				
$d_{V(rf),ego}$	Removed in third step				
$v_{V(rf),ego}$	Removed in fourth step				
$v_{targ.,ego}$	Removed in fifth step				

3.3.3 Accuracy of Regression Models. The assumption of multicollinearity for a logistic regression analysis is fulfilled with tolerance values greater than 0.1 ([32] as cited in [15]) and VIF values below 10 ([34] as cited in [15]) for all presented models. The linearity of the logit of the metric scaled variables could be achieved for model 1, model 2, and model 2b. The predictor $d_{V(rf),ego}$ in model 1a, the predictors $d_{V(rf),\ ego}$, $v_{V(rb),ego}$ and $d_{V(rb),ego}$ in model 1b and the predictor $d_{V(mb),ego}$ in Model 2a do not fulfill the linearity of the logit. A consideration of the standardized residuals, Cook distances, standardized DF-beta values, and lever values reveal a good mapping of the data by the respective models (cf. Table 10). In some models outliers are detected (> 1 % of the values outside ± 2.58). However, since the associated Cook distances are below 1, no great influence of these cases on the overall model can be assumed ([42] as cited in [15]). Due to the experimental design with repeated measurements, in which several cases were from the same participant, the assumption of independent error terms is violated here. However, since the multicollinearity of all models is very low (VIF values all < 2), it can be assumed that the different measurement are sufficiently independent of each other.

4 DISCUSSION

The aim of the study was to gain first insights about drivers’ expected LC behavior for conditionally automated highway driving. The evaluation of the subjective data revealed that participants felt well, awake, and calm during the whole driving study, had high trust in the automation system, and perceived the dynamics of LC maneuvers as suitable and rather low. Thus, it can be concluded that none of these aspects had a strong impact on LC decisions made by the participants.

The results of regression analysis point out that the preceding vehicle on the ego and target lane as well as the vehicle approaching on the target lane have a decisive impact on the LC decision. Moreover, the desire to perform a LC to the right is influenced by vehicles entering the highway and the existence of a second vehicle in front on the target lane. Those finding go along with the motivation mentioned in LC models of [11] and [18]. Tactical motivation can be represented via the significant influence of the preceding vehicle for LC decision to the left and of the relative velocity to the target velocity. Cooperative motivation is supported

Table 10: Accuracy of the different logistic regression models (* [7] as cited in [15]; † [42] as cited in [15], k: number of predictors)

Criteria	Basis of decision-making for positive assessment	Model 1	Model 1a	Model 1b	Model 2	Model 2a	Model 2b
Standardized residual	≤ 5 % of the values > ± 1.96	✓4.59 %	✓2.59 %	✓1.58 %	✓4.11 %	✓4.82 %	✓3.41 %
	≤ 1 % of the values > ± 2.58	× 3.51 %	× 1.29 %	✓0.68 %	✓0.68 %	× 2.63 %	× 2.93 %
Cook's Distance	< 1 *	✓	✓	✓	✓	✓	✓
Standardized DFBeta	< 1	✓	✓	✓	✓	✓	✓
Leverage	≤ $(3(k+1)/N)$ †	✓	✓	✓	✓	✓	✓

by the impact of vehicles entering the highway. Due to few cases this variable could not be considered for LCs to the left. However, in all 18 situations the event was positive (triggering LC). Hence, also in respect to qualitative data, highway entering vehicles can be considered as a cooperative motivation for LCs seen during automated driving. The significant effect of the type of preceding vehicle on the right lane for both LCs to the right and left, can also be found in the model by Gipps [18], which defined heavy vehicles as one influencing factor. Furthermore, results of the models for LC to the left, indicate that the expected velocity (significant influence on vehicle type) is more important than the actual velocity (missing influence on relative velocity to the preceding vehicle).

The scenario where a slower vehicle in front of the ego-vehicle on the middle lane overtakes a truck with low velocity difference could be a reason why the existence of a preceding vehicle reduces probability for LCs to the right as participants might want to overtake the truck as well. This is also supported by the negative impact of distance to the preceding vehicle in model 1b, as in this scenario distance to the slower preceding vehicle is only the safety distance to be maintained. This also clarifies the increase in probability for LCs at a greater distance to the preceding vehicle. Positive influence of the preceding vehicle on the target lane, can be explained by the fact that a LC was often initiated after an approaching vehicle has overtaken. This can also outline why in model 2b a lower distance to this vehicle increases the relative probability of a LC to the left.

The identification of cooperative and speed-driven driving strategy via evaluation of thinking aloud gives impulse to take a closer look at the impact of approaching traffic on LC decisions to the right. In the final survey, approaching traffic was also mentioned several times as an important influencing factor, but could not be shown qualitative via regression models. One possible explanation could be that the identified driving strategies may have affected LC decisions in opposing directions. However, considering qualitative data, approaching vehicles can be determined as one factor affecting LC decision to the right, which was not considered in previous LC decision making models for automated driving (e.g. [29, 44]).

Since the study was conducted in real traffic, some environmental variables could not be controlled, such as behavior of surrounding vehicles or weather. However, in scope of the exploratory context such a field study offered the most representative results in comparison to a driving simulator or test track study. The release of LCs by the safety driver may have caused short delays between initiation of LCs and actual start time. This was crucial due to safety-critical aspects. However, every initiated LC was retrospectively rated by the participant and excluded from the data set afterwards if it was rated unsuitable due to a delayed start time. Moreover, participants might have acted differently for initiating LCs as they focused on them. However, another data evaluation comparing this data to manually driven data indicates that participants did not behave differently due to their knowledge about the study topic [36]. A further limitation of the study is the limited perception of surrounding vehicles at 200 m. Vehicles that were not within the range of sensor vision are still clearly perceptible by humans and may have influenced LC decisions, but are not represented by the data. A later realization of an automation system would also be limited to this range. Peduzzi et al. [38] recommends ten events per variable for a logistic regression. The regression model 1b with seven predictors falls with $N = 64$ positive events (LC) below the minimum number of 70 events. Thus, validation of the model with a higher number of events is recommended. Due to the violation of linearity of logit of models 1a, 1b, and 2a, a generalization of these models must also be questioned. Furthermore, step-wise methods carry the risk of both overfitting and underfitting [15]. Cross-validation of the models is therefore recommended. Although a complete generalization of the models must be viewed critically, the logistic regression analysis in this exploratory study has provided meaningful and important results. While other methods of predicting binary criteria, such as neural networks or support vector machines, offer greater flexibility and would also have allowed to consider the influence of all variables simultaneously, van der Ploeg et al. [45] was able to show that logistic regression analysis deliver the most stable results, especially for small data sets. In addition, regression analysis can help to better understand the strength and direction of the impacts of the individual parameters.

The study provides first important insights on expected LC behavior during automated driving. We could define important influencing factors on LC during highway driving considering the passenger's view that can serve as a foundation for developers implementing tactical behavior for automated driving. So far, the choice for parameters included in LC decision making models was mainly based on safety aspects. We could reveal influencing factors that should be considered when designing an automated driving style that also meets the driver's expectations. For example as parameters in a fuzzy logic or as input on higher level decision making. Furthermore, the results give directions for future necessary studies and research. Identified variables in this study with an important influence can be observed in a more holistic view of scenarios, longer time spans, and temporal sequences. Additionally, factors, such as motivation of the car ride, dynamics of LCs, traffic density, or non-driving related tasks, could have influence on LC decisions.

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