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Analysis of Time-to-Lane-Change-Initiation Using Realistic Driving Data

Sarang Jokhio, *Student Member, IEEE*, Pierluigi Olleja, Jonas Bärgman, Fei Yan, and Martin Baumann

***Abstract*— Lane changing is a complex, yet extremely common driving manoeuvre. Studying lane changes can provide insight into how long drivers wait after activating their turn signal before changing lanes - a time that we call time-to-lane-change-initiation (TTLCI). TTLCI can offer valuable insights into driver behaviour prior to changing lanes. However, a better understanding of TTLCI, particularly in real-world settings, is lacking. To address this knowledge gap, we investigated TTLCI using driving data collected on public roads in Gothenburg, Sweden. We used the Kaplan-Meier (K-M) method and the mixed-effect Cox Proportional Hazard (CPH) model (statistical techniques from survival analysis) to comprehensively analyze TTLCI and identify factors that significantly influence it. The results of the K-M method indicate that most lane changes were initiated within two seconds of activating the turn signal. The mixed-effect CPH model showed that the speed of the lane-changing vehicle, the type and direction of the lane change, the presence of lead and lag vehicles, and the lag gap were all significant factors. These findings provide new insights into pre-lane-change behaviour and pave the way for future studies, in part by improving current lane change models. Moreover, the findings have implications for future regulations concerning turn-signal usage by human drivers. Additionally, our results can contribute to the development of algorithms for autonomous vehicles by improving their ability to detect imminent lane changes by surrounding vehicles.**

***Index Terms*— Lane change, time-to-lane-change-initiation, realistic driving data, mixed effect Cox model, autonomous vehicles.**

I. INTRODUCTION

LANE changing is a complex manoeuvre commonly performed in everyday driving. For example, a driver might change lanes for a discretionary reason, such as for the speed advantage, or a mandatory reason, such as exiting a highway or avoiding a lane closure. In all cases, the driver must make various decisions before executing the lane change. Decisions highlighted in various studies include selecting a target lane [1], communicating the intention to the surrounding traffic [2], finding an appropriate gap [1], and selecting the proper speed [3]. In addition, these studies have demonstrated that lane change behaviour is influenced by a range of factors, including the direction and type of lane change, the presence of other vehicles in the target lane, and individual driver characteristics.

Over the past few decades, lane-change research has mainly focused on investigating the duration of an entire lane change manoeuvre, gap acceptance (finding an appropriate gap in the target lane; see fig 1), and the impact of lane changes on surrounding traffic [1], [4], [5]. However, communicating the intention to change lanes, a crucial aspect of safe driving has not been given as much attention. Typically, drivers alert other drivers (particularly in the target lane) of their intention to change lanes using a turn signal. This action is mandatory in many countries worldwide, including Germany and Sweden. However, studies (mainly conducted in the United States (US) and China) have shown that many drivers do not always use their turn signal while changing lanes [6], [7], [8].

Recent studies have shown that using a turn signal before initiating a lane change increases cooperative behaviour by drivers in the target lane, such as opening up a gap for the vehicle to move into [2], [9]. Thus signalling can improve traffic safety and promote drivers' cooperative behaviour. In addition, Ponziani [10] pointed out that proper turn signal usage could avoid many crashes that occur during lane changing. Although the literature does not provide an exact definition for "proper turn signal use" it generally means activating the signal before initiating a lane change.

In the US, a few states (such as California and Idaho) require drivers to use a turn signal five seconds before changing lanes [11], [12]. However, many countries do not have clear rules about how long a driver should turn on the indicator before the lane change. For example, according to section 7, rule 5 of German Road Traffic Regulations, a driver should signal the lane change intention in good time [13]. However, individual drivers might interpret "good time" differently, which makes the communication of the intentions between drivers unclear and may further lead to misunderstandings and even crashes. On the other hand, the German Federal Ministry of Transport and Digital Infrastructure (BMDV) has recently implemented a regulation mandating that autonomous vehicles (AVs) activate their turn signals at least three to five seconds before initiating a lane change [14].

The current literature on the communication of intention during a lane change is mainly focused on the frequency of

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This work involved human subjects or animals in its research. The authors confirm that all human/animal subject research procedures and protocols are exempt from review board approval.

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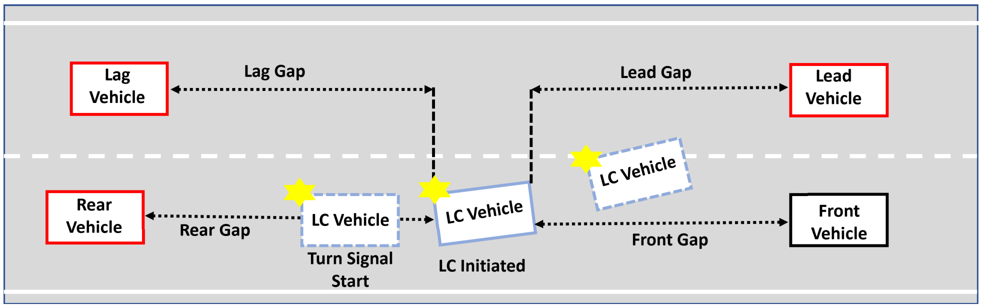

Fig. 1. A typical discretionary lane change scenario. The red vehicles are the ones whose impact is evaluated on LC vehicles. Relevant gaps are measured when LC is initiated. The terms in the figure will be used throughout this paper.

turn signal usage [6], [8], [10]. However, recordings of real traffic situations in which drivers use the turn signal before starting to change lanes can be used to provide additional helpful information about driver behaviour. The details could help answer the important question, "How long after signalling do drivers typically wait before starting a lane change?" We refer to this time as time-to-lane-change-initiation (TTLCI). TTLCI information could help researchers determine whether drivers use turn signals in time to warn other road users. Some drivers might use the turn signal to follow the law yet entirely ignore its fundamental purpose of warning other drivers in adequate time and starting their lane change quickly after signalling. In this situation, a lag vehicle driver (see figure 1) reacting to the lane change might decelerate abruptly, disrupting traffic and creating the potential for a collision.

Kaufmann et al. [2] found that the lag vehicle driver prefers an early warning (at least 20 meters before) from the lane-changing vehicle driver. Furthermore, in their study, a longer TTLCI was perceived as more cooperative when the turn signal was used later. The appropriate use of turn signals will also be crucial in future mixed traffic scenarios when autonomous vehicles operate alongside conventional human-driven vehicles on shared roads. AVs rely on other vehicles' direct communication (such as turn signals) to predict an upcoming manoeuvre [15]. Therefore, it is necessary that drivers consistently use turn signals when changing lanes in mixed traffic scenarios to facilitate the safe and efficient movement of both human-driven and AVs. In the early stages of deployment, AVs will likely be introduced on high-speed roads such as motorways and highways. Lane-changing maneuvers are a common phenomenon on high-speed roads. As such it is necessary to investigate different characteristics of lane changing (e.g. TTLCI) on these roads. An improved understanding of lane changing characteristics will not only contribute to improved lane-changing models but also to the development of AV algorithms designed to understand human driver behavior.

The importance of an adequate TTLCI and its potential impact (both in current and future mixed traffic) is obvious. Based on the evidence provided in the current literature, it is also clear that a substantial proportion of drivers are not using their turn signals, or at least not properly, before initiating a lane change. The duration of the typical TTLCI and what factors affect it are currently unknown. Furthermore, most existing traffic regulations lack clear guidelines for the proper use of turn signals by human drivers. For these reasons, it is highly relevant to investigate drivers' turn signal usage, ideally in real traffic on real roads. Therefore, this paper aims to investigate drivers' TTLCI during a lane change situation. Furthermore, the paper aims to investigate which factors impact the TTCLI.

We used survival analysis (see section III) to analyze the existing data on TTLCI because it is well-suited for time-to-event data. Survival analysis, widely used in the medical sciences, has recently gained popularity in transportation and traffic engineering [16] since it provides better explainability for the data than other methods [16], [17], [18]. For example, many researchers have used hazard-based duration models (a survival analysis technique) to study incident duration [19], [20], [21]. In the last decade, survival analysis has also attracted the attention of researchers studying lane change and overtaking behaviour. For example, Vlahogianni [22] used survival analysis to model an overtaking manoeuvre using driving simulator data in order to investigate the factors influencing the manoeuvre's duration on two-lane highways. More recently, survival analysis has also been used to study lane change duration. For example, Wu et al. [23] used Cox regression analysis (a semi-parametric method of survival analysis) to analyze mandatory lane change duration data collected by an uncrewed aerial vehicle in a freeway construction area. Li et al. [24], used survival analysis to study the LC duration and factors influencing it. Survival analysis was also used in a study by Ali et al. [25] to quantify the impact of a connected driving environment on safety during mandatory lane-changing. It can be seen in the studies mentioned above that survival analysis is a potent tool for extracting meaningful information from time-to-event (or duration) data. Therefore, we chose this method to analyze the TTLCI.

The remainder of this paper is structured as follows. Section II-B describes the data (including descriptive statistics in subsection II-B) and the detailed methodology used to identify the LC trajectories. Next, a detailed overview of the survival analysis techniques and their mathematical formulation is presented in Section III. Third, the survival analysis results are provided in Section IV. Finally, the discussion and conclusion are provided in Section V.

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TABLE I
VARIABLES AND THEIR DESCRIPTIONS

Variable	Short Description	Unit
Time-to-lane-change-initation (TTLCI)	Waiting time before the start of lane change	Seconds (s)
Speed	Speed of LC vehicle	Kilometer per hour (kph)
LC Direction	Lane changes to the right lane of left lane	Right or Left
LC Type	Lane change to the single or multiple lane	SLC or MLC
Rear Vehicle	Presence of rear vehicle at the start of lane change	Binary: Yes or No
Rear Gap	Time gap between LC and rear vehicle at the start of lane change	Seconds (s)
Lag Vehicle	Presence of lag vehicle at the start of the lane change	Binary: Yes or No
Lag Gap	Time gap between LC and lag vehicle at the start of the lane change	Seconds (s)
Lead Vehicle	Presence of lead vehicle at the start of the lane change	Binary: Yes or No
Traffic Density	Number of vehicles per unit length of road	veh / km / lane
Driver Type	Whether the driver was accredited or regular	Binary: accredited or regular

II. Data Description

The purpose of our study was to analyze TTLCI in real-world scenarios under clear conditions, such as during clear weather and daytime. AVs are also likely to be deployed under these conditions. Therefore, the data used in this study was obtained from a large driving dataset collected as part of the L3Pilot Project. [26]. The European Commission funded the L3Pilot project from September 2017 to October 2021 to test the viability of automated driving on public roads. The dataset used in this study was a subset of data collected by Volvo Car Corporation on the urban motorway known as the ring road in Gothenburg, Sweden. The vehicles (Volvo XC90s) were fitted with cameras facing out toward traffic (front and rear) and in towards the driver, as well as radars, accelerometers, angular rate sensors, and GPS. The data from the vehicle's Control Area Network (CAN) bus, which included details such as turn indicator usage and vehicle speed, were also obtained. Additionally, information about the longitudinal and lateral position and speed of surrounding vehicles, as well as traffic density, was collected using radars.

The data used in this study are different from data commonly referred to as "naturalistic driving data." Naturalistic driving studies (e.g., SHRP2 [27] in the United States and UDRIVE [28] in Europe), typically involve the unobtrusive and uncontrolled collection of data over extended periods of time during everyday driving – the driving being performed as part of the drivers' everyday lives. The data we used were collected during one to a few journeys, each lasting approximately 60 minutes each. However, the data collection process was uncontrolled and relatively unobtrusive during those drives, aiming to collect reasonably naturalistic driving behaviors. Therefore, we refer to this dataset as "realistic driving data" since the data were also collected on actual roads but not during everyday driving, distinguishing it from commonly known "naturalistic driving data" and "test track data".

The L3Pilot data were divided into two groups: (1) baseline (manual driving, performed solely by the driver) and (2) treatment (autonomous driving functions were in use). In the treatment group, only "accredited drivers" were involved. In this context, the term "accredited" refers to drivers who hold certification for operating prototype vehicles for testing specific features [26]. The accredited drivers were compensated for their driving time. In the baseline group, both accredited and regular drivers participated. The regular drivers were recruited within the company [26]. Accredited drivers typically have extensive driving experience compared to regular drivers. Our research aimed to examine the TTLCI in the absence of any impact from autonomous driving features; therefore, we only considered the baseline trips in this study.

Table I shows the different variables and their notation used in this study. We had considered incorporating the type of surrounding vehicle in our analysis. Initially, our strategy was to determine the type of the vehicle based on its dimensions, specifically its length and width. However, we found a lot of missing data regarding the vehicle's length and width in the original database. To prevent potential bias resulting from data imputation, we ultimately chose to exclude this variable. The road type was not manipulated in the L3Pilot, and all were vehicles operated only on a single type of road in Gothenburg, i.e., an urban motorway. Therefore, variables like road type and lane width were also excluded from the analysis. The initiation and end of a lane change were identified from the lane-changing vehicle data, described in detail below.

A. Identification of Lane Change Initiation and End

During a lane change, a driver moves laterally from one lane to another while driving straight. Over the past few decades, different data collection methods have been used to study lane change behaviour, including cameras mounted on high-rise buildings, drones, driving simulators, and instrumented vehicles. Therefore, it is very challenging to identify the start of the lateral movement from the time-series vehicle trajectory data, so there are several definitions for it. The choice of a particular definition is determined by the availability of the input variables in the data set [29]. The most commonly used variables to define the start and end points of lane change are lateral distance, lateral velocity, and lateral acceleration [4], [7], [8], [24], [30], [31], [32]. For example, Wang et al. [31], used heuristic rules to identify lane change trajectories from the Next-Generation Simulation (NGSIM) data set, collected by Federal Highway Administration [33], using synchronized digital video cameras along the highway. They used a lateral velocity threshold of -0.2 m/s was used to identify the initiation and completion of a lane change. Similarly, Mullakkal-Babu et al. [32] used a 0.33 m/s lateral velocity threshold to determine the initiation and completion of a lane change from NGSIM dataset. On the other hand, Dang et al. [7], used data collected in Beijing, China using an instrumented vehicle. Their definition of lane change was based on changes in lateral position (between 0 and 3.75 m); the vehicle was said to have crossed the lane if the value of the lateral position was greater than 2.5 m. A review paper by Xi and Crisler [29] provides an overview of the studies defining lane change start and end from 1970 to 2012.

In this particular study, we chose to define the initiation and end of a lane change based on thresholds of the LC vehicle's lateral velocity and lateral distance with respect to the lane markings. We selected lateral velocity and lateral distance as our key variables because they show distinct patterns for identifying lane change initiation and completion, compared to other variables like lateral acceleration or steering angle. In our study, a 'distinct pattern' in either lateral velocity or lateral distance is characterized by well-defined lows, highs, and flat segments in the time-series data. Specifically, a substantial increase or decrease in the slope indicates the onset of a lane change, whereas flattening of the curve after that, indicates that the lane change has been completed. To set the thresholds, an essential part of the extraction process, we initially analyzed the lateral velocity and lateral position of the LC vehicle during free driving. Free driving in L3Pilot is defined as "the subject vehicle following its path without being influenced by other vehicles in its path". This step was performed to account for noise as the vehicle fluctuated within its lane, even when it was not changing lanes or being influenced by surrounding vehicles. As expected, we found that drivers' lateral velocity (and, correspondingly, the lateral position) varied somewhat during free driving. Our analysis found that during 90% of the free driving time the lateral speed was below 0.17 m/s, both to the left and to the right. Additionally, the lateral position within the lane was within 0.36 m to the left and 0.42 m to the right of the centre of the lane 90% of the time.

In this study, the lane change scenarios were first filtered using the scenario definition provided in L3Pilot, which considered the distance to lane markings and compared it with some threshold [26]. The next step was to determine a suitable threshold for the initiation and end of a lane change. Previous studies have assumed that the lateral velocities of a vehicle at the beginning and end of a lane change are zero [4], [24]. However, this assumption, or the use of too low a threshold, can lead to the inclusion of noise in lane change trajectories, which could result in the algorithm misidentifying the start or end of a lane change. We tested different lateral velocity thresholds from 0.10 m/s to 0.30 m/s in increments of 0.05 m/s. We also verified random cases by watching the videos to see if a lane change actually occurred. With the higher thresholds (0.20 m/s to 0.30 m/s), the vehicle had typically already crossed the lane boundary before the lateral velocity criteria were fulfilled. Thus for our analyses, we used a lower lateral velocity threshold of 0.15 m/s–ensuring that the vehicle was still in the current lane at the start of the lane change while largely avoiding false positive identifications of lane changes.

However, a lateral velocity threshold is not sufficient to define the initiation of a lane change because drivers might change lanes slowly without ever reaching the lateral velocity criterion. Thus an additional criterion is needed. A lateral

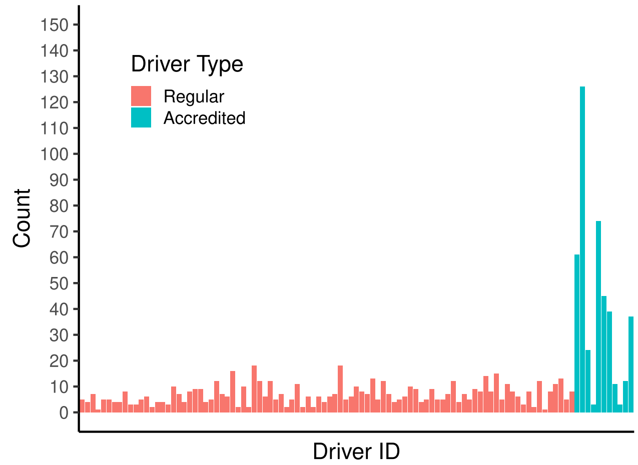

Fig. 2. The number of lane changes per driver ID. The x-axis represents driver IDs, which range from 1-92 for regular drivers and 101-111 for accredited drivers. Individual ID labels have been omitted for clarity due to the high number of individual IDs. The lane changes are sorted in the order they were extracted (i.e., from one and onwards).

distance threshold of 6 cm from the lane marking was selected, calculated by subtracting half of the vehicle width from the distance between the centre of the vehicle and lane markings. Note that most of the lane change starts were determined based on the lateral velocity threshold; the lateral distance criterion determined only a small portion of the overall lane changes. Two additional criteria determined the end of the lane change: when the vehicle's lateral velocity remained below 0.15 m/s for at least one second or when the lateral distance to the lane marking exceeded 6 cm after the vehicle had moved to the target lane. The algorithm evaluated all four criteria to identify lane change initiation and endpoints. It should be emphasized that the primary focus of this investigation is on the initiation phase of the lane change maneuver rather than the entire process.

B. Descriptive Statistics

In total, 1791 lane change cases were extracted. However, only the 1073 cases in which the driver used the turn indicator before starting a lane change were considered in this study. Since survival analysis does not model a negative time duration–in cases in which the driver used an indicator after starting a lane change–those cases were omitted. In the dataset, the average age of drivers was 40.2 years, with a range of 23 to 64 years. Out of the 103 drivers, 71 were male and 32 were female. Approximately 70% of the drivers had over ten years of driving experience, while the rest either had less or an unstated number of years. The distribution of the number of lane changes per driver was imbalanced, as seen in Figure 2. Although only 11 of the 103 drivers were accredited, they accounted for nearly 40% of the lane changes. This disparity was due to the fact that the accredited drivers drove more (multiple times per day) and thus generated more driving data than the regular drivers. On average, single journeys by regular drivers lasted approximately 60 minutes. In comparison, in baseline driving, accredited drivers completed multiple journeys per day, collectively contributing to several hours of data per driver. Given the substantial number

TABLE II
DESCRIPTIVE STATISTICS OF LANE CHANGE WAITING TIMES

Type	Category	Freq	Time-to-lane-change-Initiation			
			Min	Max	Mean	Std. Dev
Total	Total	1073	0	6.70	0.97	0.92
LC Direction	Right	719	0	6.70	1.009	0.96
	Left*	354	0	4.50	0.91	0.83
LC Type	SLC	1007	0	6.70	0.94	0.89
	MLC*	66	0	4.90	1.4	1.23
Lag Vehicle	Yes	749	0	5.60	1.009	0.94
	No*	324	0	6.70	0.90	0.88
Lead Vehicle	Yes	549	0	6.7	1.04	0.98
	No*	524	0	4.90	0.91	0.86
Rear Vehicle	Yes	627	0	6.70	0.99	0.95
	No*	446	0	4.90	0.95	0.88

* The baseline or the reference level against which all other levels are compared (see section IV).

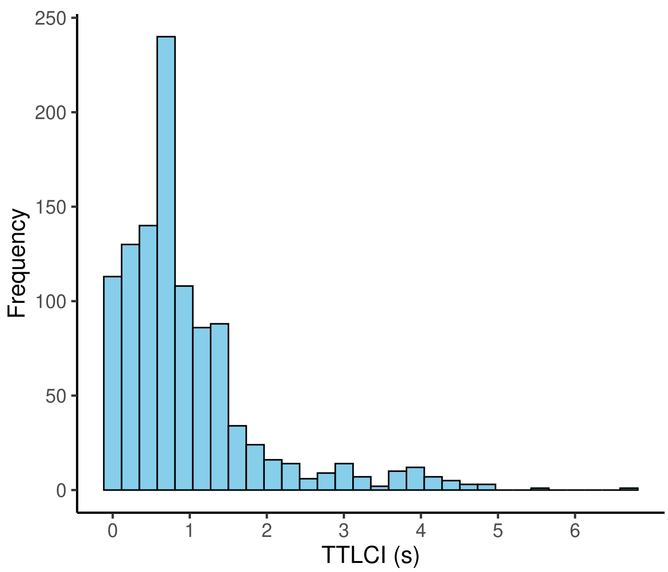

Fig. 3. Distribution of Time-to-lane-change-initiation, defined as the time from the start of turn signal until the initiation of a lane change.

of lane changes from the accredited drivers, we opted to include their data to avoid the loss of potentially valuable insights. However, we conducted supplementary analysis with individual datasets (accredited vs regular drivers) to ensure that the inclusion of both groups did not introduce any biases or obscure behavioural patterns unique to each group (see the Appendix).

Table II shows the categorization of the lane change cases and the respective descriptive statistics; Figure 3 shows the overall distribution of TTLCI.

Table II shows that most lane changes occurred toward the right lane. Lane changes to the right occur mainly for two reasons: (a) the driver is taking an exit from a highway, or (b) the driver is moving back to the right (slower) lane after making a lane change to the left to avoid a slow-moving vehicle. The lane changes to the right also took longer to initiate than those to the left. In everyday driving, most of the drivers perform a lane change to an adjacent lane. However, in some cases (e.g., when taking an exit), a driver may perform a lane change across multiple lanes. The table shows that MLC's mean value is greater than SLC's. This indicates that drivers wait longer before initiating a lane change when crossing multiple lanes. The delay might be caused by the presence of lag vehicles in both the adjacent and target lanes, which the driver must consider. Drivers also wait longer if there is a lag vehicle in the target before initiating a lane change for all cases.

III. SURVIVAL ANALYSIS

Survival analysis, also known as time-to-event or time-to-failure analysis, is a collection of statistical methods in which the dependent variable is the time until an event occurs. Survival analysis is popular in medical studies, where the outcome of interest is often the time to death–for example, after a patient has been diagnosed with cancer [17]. Survival analysis can demonstrate how the probability of survival (also known as the survival function) changes over time. Survival analysis can also be applied to other fields when time-to-event data are relevant, so it is well suited to the study of lane change initiation data as in our case. To be consistent with the method terminology, we use the term survival function to refer to the probability of initiating a lane change. The survival analysis can handle highly skewed and censored data. Here missing data are considered 'censored'; for example, when the start of the turn signalling is known, but the lane change initiation time is missing. For details on censored data, see the work by Gijbels [34].

While the survival function provides information about how long an individual has survived after exposure, the hazard function provides the opposite information and focuses on the failure, i.e., on the occurrence of a particular event [35]. In our study, the survival function focuses on the likelihood of a lane change not occurring within a given time frame. The starting point for this time frame is when the driver activates the turn signal. The survival function $S(t)$ estimates the probability that a lane change has not yet happened by the specified time t [17]. This can help understand how long drivers typically wait before initiating a lane change after using their turn signal. For our purposes, the survival function $S(t)$ is the probability that the initiation of a lane change survives from the time origin (here, after using the turn signal) to some specified time t in the future. The hazard function $h(t)$, on the other hand, examines the instantaneous rate of lane change initiation at a specific time t, given that a lane change has not occurred up to that point. It represents the probability that a driver will initiate a lane change exactly at time t, assuming they haven't changed lanes before that time [17].

There are many different parametric and non-parametric methods for estimating the survival function. However, the nonparametric methods that make no assumptions about the underlying data distribution are the most popular. Among those, the Kaplan-Meier (K-M) method is widely used to estimate and visualize the survival function [36]. The K-M method is a powerful method for estimating the probabilities of a particular event over a period of time. It allows the visualization of the overall trend as well as comparisons between different groups. The survival function in K-M method is computed by Equation (1).

$$S_t = S_{t-1} * \frac{N_t - E_t}{N_t} \tag{1}$$

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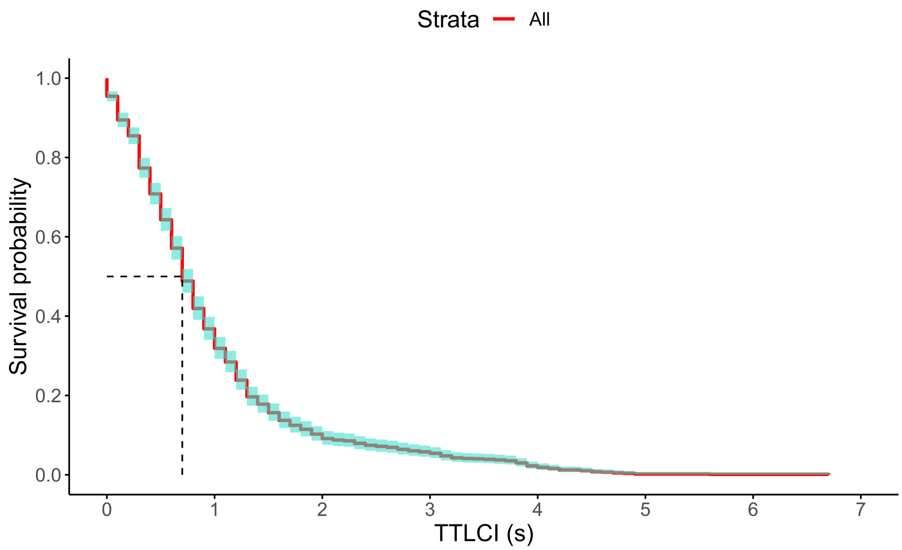


Fig. 4. K-M estimate of survival probability for all variables. The shaded area represents the confidence interval. The dotted line represents mean survival time (MST). "Strata" refers to the grouping of individuals based on a categorical variable (in this case entire group is considered).

Here, N_t represents the total count of lane changes that are subject to the event at a given time t. Conversely, E_t is the count of occurrences (in this context, instances of lane change initiations) at the same time t.

Like linear regression, the survival analysis method can also assess the impact of several predictors on the dependent variable. Cox proportional hazards (CPH) regression is one of the more widely used regression techniques for survival analysis [37]. In contrast to linear regression, CPH regression models the relationship between a time-to-event response variable and one or more predictors. That is, CPH regression considers the effects of time on the response variable. The CPH regression is semi-parametric, so it does not make any assumptions about the data distribution. However, it does make a parametric assumption about the effect of the independent variables (here, TTLCI) on survival time. Using the observed time-to-event data, the CPH regression builds a mathematical relationship between independent variables and the hazard function. The hazard function provides insights into the probability of an event's occurrence (here, initiation of a lane change), given that the participant has survived (in this case waited) up to a specific time [38].

We discussed in the data description section regarding variability and imbalance in the dataset. To better account for driver level variablity we used mixed effect CPH model. Mixed effect model (also known as the Frailty model) is an extension of the standard CPH model [39]. The standard CPH model assumes that the hazard function is proportional to a baseline hazard function multiplied by an exponential term of covariates (predictor variables). This model assumes that the effects of these covariates are fixed across all individuals. Mixed Effects Cox Models, on the other hand, introduce random effects or frailties to account for unobserved heterogeneity or shared characteristics among clusters of individuals (e.g., lane changes from different drivers) [39]. The mixed effect CPH model is given by Equation 2.

$$h_i(t) = h_0(t) * exp(\Sigma(\beta_n X_n i) + u_i) \tag{2}$$

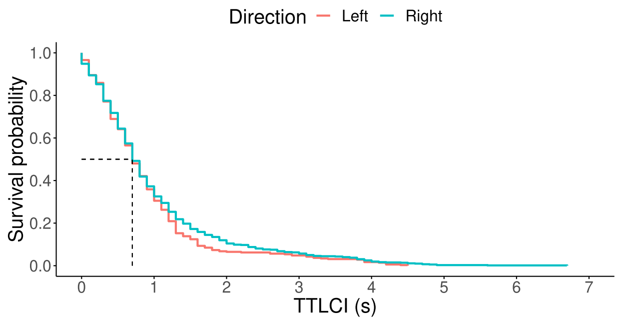
where $h_i(t)$ represents the hazard function for the i-th subject at time t, $h_0(t)$ is the baseline hazard function, β_n represents the coefficients of the fixed effects (covariates) $X_n i$, and u_i represents the random effects for the i-th subject. The fixed effects are weighted by their respective coefficients, and the random effect u_i accounts for the variability among subjects (Driver ID) that is not captured by the fixed effects. The baseline hazard represents the hazard rate when the values of all continuous variables are set to zero and all categorical variables set to their reference (baseline) level. The regression coefficients are estimated using maximum likelihood estimation [40].

IV. Results

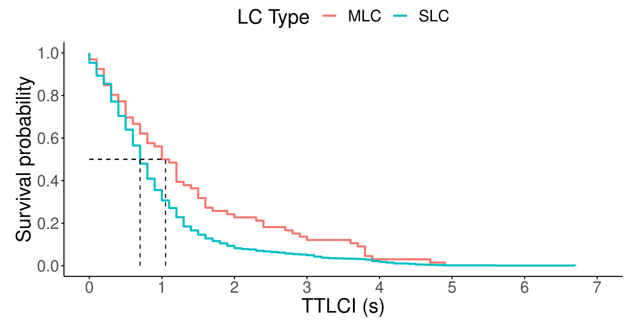
This section provides the detailed survival analysis of the TTLCI. Table II shows all the categorical variables and their frequencies. The "*" sign represents the baseline of the respective variable, to which all the other levels are compared [41]. Since we only used cases with a positive waiting time, no case was dropped from the analysis. The model was implemented using Surival [42] and coxme [43] packages in R programming language [44].

A. Kaplan-Meier Survival Estimation

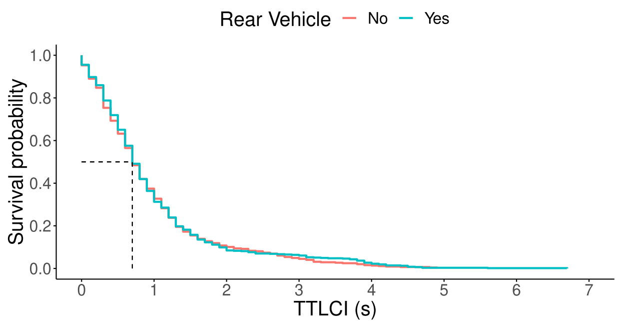
The estimation of the K-M survival function (represented by the step-like curve) of TTLCI is presented in Figure 4. The x-axis represents TTLCI in seconds and the y-axis represents the probability of TTLCI. The shaded areas in the graph represent the confidence intervals (CIs). The probability of survival in the beginning (at 0 seconds) is 1.0, indicating that no lane change initiation event has occurred yet. However, as the time increases, the probability of survival decreases, indicating an increase in event occurrences (initiations of a lane change). The graph shows that the survival function rapidly decreases over the first two seconds. The steep decline implies that most lane changes were initiated within this time period after the turn signal was activated. In fact, this



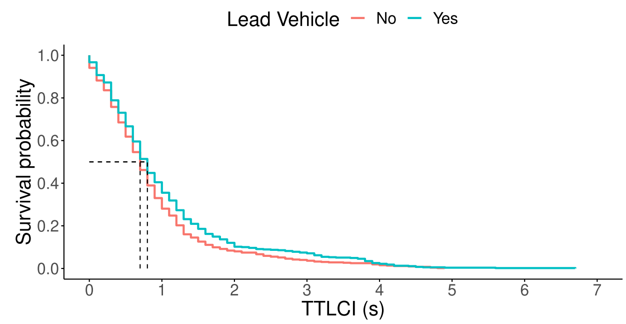
(a) K-M estimate of survival probability for lane change direction



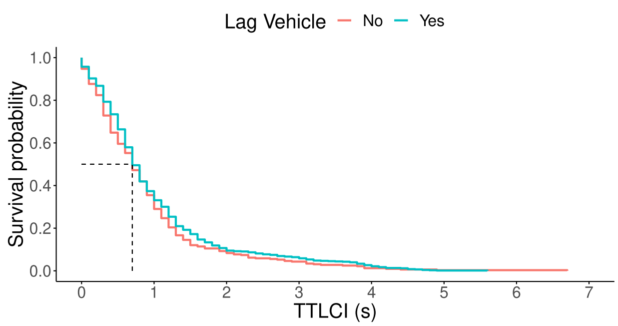
(b) K-M estimate of survival probability for lane change type



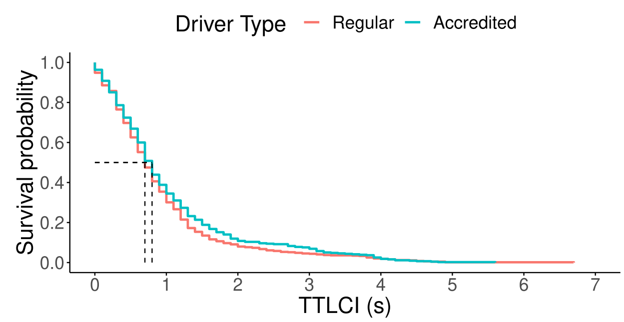
(c) K-M estimate of survival probability for rear vehicle presence



(d) K-M estimate of survival probability for lead vehicle presence



(e) K-M estimate of survival probability for lag vehicle presence



(f) K-M estimate of survival probability for driver type

Fig. 5. Kaplan-Meier estimate of survival probability for lane change Categories as per Table II.

time frame accounts for almost 90% of the total lane change cases. The median survival time, or in this case the TTLCI, is shown by the intersection of the dotted horizontal line (at 0.5) and vertical line (at 0.7 s). That is, 50% of lane changes were initiated within 0.7 seconds. After 2 seconds, the probability gradually decreases, indicating that fewer lane change are initiated as time goes on. Approximately 8% of lane changes were initiated between 2 and 4 seconds, and only 2% were initiated more than 4 seconds after the turn signal was activated.

As mentioned earlier, the K-M survival curve is also helpful for comparing different groups. Figure 5 displays the individual K-M survival curves for the variables in Table II.

The spaces between the curves indicate that the two groups have different survival experiences; one group has a higher probability of survival over time than the other. In the context of our study, this implies that one group has a longer TTLCI than the other group. To determine whether the difference between the two groups is statistically significant, the non-parametric log-rank test could be used [45]. Given the detailed assessment of the variables using Cox regression presented in Section IV-B, we decided not to use the log-rank test here. The decision to use Cox regression instead of the log-rank test was driven by several factors. Firstly, Cox regression allows for the simultaneous assessment of multiple variables and their impacts on survival times, offering a more comprehensive understanding of the factors influencing TTLCI. Secondly, Cox regression provides hazard ratios, which quantify the relative effect of each variable on the hazard function, giving us more insight into the relationships between the variables and the TTLCI. Lastly, Cox regression can handle time-varying covariates and adjust for confounding factors, enabling a more robust data analysis. Therefore, due to the advantages offered by Cox regression over the log-rank test, we decided to focus on this statistical method in our survival analysis to compare survival times between groups.

TABLE III
SCHOENFELD RESIDUAL TEST RESULTS

Predictor	Chisq	df	p-value
Speed	0.00354	1	0.953
LC Direction	3.41987	1	0.064
LC Type	0.00125	1	0.972
Rear Vehicle	0.06358	1	0.801
Rear Gap	0.17766	1	0.673
Lag Vehicle	0.79645	1	0.372
Lag Gap	3.26076	1	0.071
Traffic Density	2.92754	1	0.087
Lead Vehicle	0.01019	1	0.920
Driver Type	0.30427	1	0.581
Global	14.50546	10	0.151

As stated in section II-B, the 11 accredited drivers performed nearly 40% of the lane changes. This imbalance is also reflected in the K-M graph as shown in figure 5f. The graph suggests that the survival probability is higher (TTCLI is shorter) for accredited drivers, with a clear separation of the two curves. However, these results should be interpreted with caution, given the imbalance in sample size between the two groups. To better account for the differences between the two groups we included Driver Type (accredited vs. regular drivers) as a predictor (fixed effect) in the CPH regression model (see Section II-B).

B. Cox Proportional Hazard Regression

One major assumption in the CPH model is that the hazard ratio remains unchanged over time with different predictor variables or their respective levels [35]. To test this assumption, we used the Schoenfeld residual approach [46], which is one of the most widely used methods for assessing the PH assumption [47]. The proportional hazards assumption implies that the hazard ratio for any two individuals should remain constant over time. If this assumption holds, the scaled Schoenfeld residuals should not exhibit any systematic pattern or trend with respect to time. It calculates the chi-squared test statistic and associated p-value for each predictor variable to test the null hypothesis that there is no correlation between the residuals and time. The Schoenfeld residual test results are presented in Table III. The output shows the global p-value as well as for each predictor variable. In this case, none of the p-values are below 0.05, which means there is no strong evidence that the proportional hazards assumption is violated for any of the predictor variables.

Table IV provides information about the model fit, which can be helpful when assessing the performance and significance of the model. The "Null" model represents the baseline model, which does not include any predictors. The "Integrated" model only includes fixed effects (i.e., predictors). The "Fitted" model is the mixed-effect CPH model that includes both fixed effects and random effects. The log-likelihood is the natural logarithm of the likelihood function, which quantifies the probability of observing the data given a particular set of model parameters. The BIC (Bayesian Information Criterion) is used for model selection and comparison by considering both the goodness of fit and the complexity [48]. When comparing models, a higher log-likelihood and lower BIC values are preferred. Based on log-likelihood and BIC criteria, we can see that the mixed-effect Cox model (represented as Fitted) performed better compared to the "Null" and "Integrated" models.

TABLE IV
MODEL COMPARISON

Metric	NULL	Integrated	Fitted
Log-likelihood	-6419.031	-6363.253	-6301.784
Test Statistics			
Chisq		111.56	234.50
df		11.00	57.18
p-value		<0.001	<0.001
BIC		34.80	-164.52

TABLE V
RANDOM EFFECTS

Group	Variable	Stadard deviation
Driver ID	Intercept	0.374

Table V shows the results model results for random effects for the intercept Driver ID. Recall from section III that the random effects account for the variation in the data that is not explained by the fixed effects. Adding random effects allows each driver to have a different baseline hazard rate rather than assuming that all drivers share the same baseline hazard rate. The distribution of the random effects is assumed to be Gaussian (or normal), with a mean value of zero [43]. The standard deviation (one standard deviation above the mean) of the random intercept, in this case, is 0.374. A unique characteristic of the mixed-effects Cox model is that the standard deviation of the random effect can be directly interpreted [43]. The value of 0.374 corresponds to a relative increase in the probability of the event happening, given by exp(0.374) = 1.45. This suggests that for a driver who is one standard deviation above the mean, there is almost a 45% increased probability of the event (initiating a lane change) occurring compared to the average probability across all drivers.

Finally, the model results for the fixed effects are presented in Table VI. The column 'Coefficients' shows the regression coefficients and the column '*p*-value' shows the significance. The column 'Exp(Coeff)' shows the hazard ratio. The hazard ratio was computed using an exponent of the regression coefficient. In the context of a categorical variable, the hazard ratio evaluates the relative probability of an event happening for a specific category in comparison to another category. For a continuous predictor variable, the hazard ratio indicates the multiplicative change in the probability of the event occurring for every one-unit increment in that predictor. A hazard ratio exceeding one signifies an increased probability of the event occurring. In other words, the higher the hazard ratio, the more likely the lane change initiation will occur. Conversely, a hazard ratio of less than one indicates that a unit increase for a particular variable will decrease the hazard. A hazard ratio of one is associated with no effect on the event occurrence.

Results of the CPH model show that six out of ten variables significantly impacted the hazard: speed, lane change direction, lane change type, presence of the lead vehicle and the lag vehicle, and the lag gap. However, the remaining variables (i.e., presence of the rear vehicle, the rear gap,

TABLE VI
COX MIXED-EFFECTS MODEL RESULTS

Predictor	Coeff	Exp(Coeff)	Std. Error	p-value
Speed	0.025	1.025	0.004	<0.001
LC Direction (right)	-0.150	0.860	0.072	0.039
LC Type (SLC)	0.388	1.474	0.136	0.005
Rear Vehicle (yes)	0.148	1.160	0.117	0.210
Rear Gap	-0.063	0.939	0.0591	0.280
Lag Veh (yes)	-0.298	0.742	0.106	0.005
Lag Gap	0.139	1.150	0.045	0.002
Traffic Density	0.001	1.001	0.007	0.870
Lead Vehicle (Yes)	-0.199	0.819	0.067	0.003
Driver Type (Accredited)	-0.160	0.852	0.146	0.270

overall traffic density, and driver type) had no significant impact on the hazard. Recall from Section III that the hazard function estimates the probability that an event (in our case, the initiation of lane change) has occurred. The regression coefficients predict the hazard for the event as a function of the predictor variable in the model. They represent the changing hazard when the continuous predictor variable is changed by one unit (or compared to baseline in the case of a categorical variable), holding all the other predictor variables constant. A positive coefficient shows a positive relationship between the hazard for the event and the predictor variable: the higher the positive value of the predictor variable, the greater the hazard for the event. A higher hazard indicates a lower survival time (in our case, a shorter TTLCI). Conversely, a negative regression coefficient is associated with a negative relationship between the hazard and the predictor variable: the higher the value of the predictor variable, the lower the hazard for the event, which translates into a longer survival time, or TTLCI.

The lane-changing vehicle's speed has a positive coefficient, indicating an increased hazard for the event to occur with higher speeds; the drivers tend to wait less before initiating a lane change with the higher the speed. Specifically, a one-unit (km/h) increase in the vehicle's speed increases the hazard 1.024 times. In other words, the probability of a lane change initiation increases by 2.4% for each 1 km/h increase in the vehicle speed.

The negative coefficient for lane change direction (baseline level: left lane change) indicates a decrease in the hazard for lane changes to the right. The decrease in hazard for the event indicates a higher TTLCI. For a lane change to the right, the hazard was reduced by a factor of 0.86 (or by 14%), implying that drivers took longer to initiate a right lane change than a left lane change. The lane change type (reference level: MLC) positively correlated with the hazard. This indicates that the drivers tended to initiate an SLC earlier than an MLC. In the case of an SLC, the hazard increased 1.47 times (or by 47%) compared to an MLC.

The presence of a lag vehicle (reference level: no lag vehicle) was negatively associated with the hazard, implying that the presence of a lag vehicle decreases the hazard by 26%. However, when a lag vehicle was present, the hazard increased by almost 16% with every unit increase in the lag gap, indicating that the TTLCI value decreases as the lag gap increases. Last but not least, the presence of a lead vehicle in the target lane was also negatively associated with the hazard, suggesting that its presence decreased the hazard by 18.2%. This result implies that the TTLCI is longer when a lead vehicle is present in the target lane.

V. GENERAL DISCUSSION

The overall goal of this paper was to conduct a detailed analysis of time-to-lane-change-initiation (TTLCI) using survival analysis techniques. The TTLCI is the amount of time a driver waits after activating the turn signal and before initiating a lane change. In this study, we used the realistic lane change data of Swedish drivers that was collected on public roads in Gothenburg, Sweden. We used the Kaplan-Meier method (graphical univariate analysis) and a mixed-effect Cox proportional hazard model (a regression technique).

Our results show that, in most cases, a lane change was initiated within two seconds after a driver indicated the intention to change lanes by using the turn signal. Although no prior studies have specifically investigated TTCLI, a driving simulator study by [2] manipulated the wait time (1, 2, and 3 sec). They defined wait time as the "Period from turn signal start until the vehicle begins to change the lane." It is essentially the same as the TTLCI. Their results showed that other drivers perceived a wait time of three seconds as more cooperative. However, our results show that only a small portion of lane changes were initiated after three seconds. Furthermore, our results show that half of the total lane changes were initiated within 0.7 seconds after the signaling started. This timing indicates that the lane-changing drivers typically were not using their turn signals properly. The drivers may not be taking enough time to check their surroundings before changing lanes. However, further research is needed to understand why drivers initiate lane changes with improper turn signal usage. While no precise definition of proper turn signal use is commonly accepted in the literature, it is understood to mean turning on the signal before initiating a lane change. An example of proper turn signal usage is described in California, USA's traffic law, which requires drivers to activate their turn signal at least five seconds before changing lanes.

This paper also investigated which factors have a statistically significant impact on the TTLCI and what effect they have by applying a mixed-effect CPH model. The chosen factors were determined by their potential influence on lane change behavior in general, as reported in existing literature. The mixed effect CPH model is an extension of the standard CPH model, a popular survival analysis technique used to model the relationship between the hazard function (hazard rate) and explanatory predictor variables. The random effects result showed a variation in the hazard rates across different drivers. The variability in the baseline hazard rate across different drivers suggests that some drivers have a higher risk of the event occurring than others. In other words, some drivers tend to initiate the lane change quicker than others. This variability could be attributed to unmeasured factors specific to the individual drivers. Future studies should investigate how driver-specific characteristics affect the TTLCI.

The results for the fixed effects indicated that speed, lane change direction, lane change type, presence of the lead vehicle and the lag vehicle, and the lag gap significantly impacted the hazard function. The speed of the vehicle is a primary motivation behind discretionary lane changes, as drivers may change lanes to achieve a higher speed or to avoid slower vehicles [49]. We show that higher lane-changing vehicle speed was associated with a shorter TTLCI. While the effect of speed on TTLCI has not been previously reported in the literature, existing studies on lane change duration suggest that an increase in speed leads to a shorter duration of lane change [24]. Moreover, the speed of the lane-changing vehicle has been shown to influence the surrounding vehicles [50]. Exploring a potential relationship between speed, TTLCI, and lane change duration could be an interesting avenue for further research.

The direction of the lane change is another important factor that affects the overall lane change process. Previous research pointed out that the direction does impact characteristics like lane change duration [4], [6]. Our model results also showed a significant difference in the TTLCI while making lane changes to the right (higher TTLCI) compared to the left. One possible explanation is that lane changes to the right often happen after a driver overtakes (lane change to the left) the slow-moving vehicle. Hence, the driver waits a bit longer before returning to the original lane (i.e., the right lane). No prior literature has been found on the difference in TTLCI for different lane change directions.

In everyday traffic, the majority of lane changes involve switching to an adjacent lane, commonly referred to as single-lane changes (SLCs). However, drivers may also execute multiple-lane changes (MLCs) for various reasons, such as taking an exit on a highway. Prior research has shown differences in driver behaviour when performing MLCs as opposed to SLCs [51]. Our findings similarly show a significant difference in the TTLCI between SLC and MLC. The TTLCI was longer for MLC than SLC, possibly due to the increased complexity of the manoeuvre. When making an MLC, the driver must account for vehicles in all the target lanes before initiating the lane change, which may require additional time. Therefore, we suggest considering the type of lane change when examining driver behaviour in lane-changing scenarios in future studies.

The presence of a lag vehicle, presence of a lead vehicle, and the gap to the lag vehicle also significantly affected the TTLCI. It took longer to initiate a lane change if a lag vehicle was present in the target lane. However, if a lag vehicle was present and the gap between the lag vehicle and the lane-changing vehicle was increasing, the TTLCI was found to be reduced. We could not find any previous studies that provide insights on the correlation between accepting lag gaps and TTLCI. However, research on gap acceptance at unsignalized intersections has shown that drivers who wait longer are more likely to accept smaller gaps [52], [53], [54]. Although gap acceptance at intersections and lane-changing situations have their own distinct characteristics, there may be similarities as well. In lane-changing situations, it is possible that a driver may reject available gaps before accepting the next one, similar to intersection gap acceptance. On German autobahns, especially during moderate to high traffic, there tends to be a substantial speed difference between lanes [55], [56]. If a driver gets stuck behind a slower truck (the speed limit for trucks is 80 km/hr) in the right lane, it can be difficult to find a gap due to the high speeds in the left lane. This gap acceptance behaviour may vary based on individual driver comfort zones [57] and can be influenced by various factors such as waiting times and time constraints (e.g., that a driver is in a rush), but that is out of scope of this study.

Similar to the presence of a lag vehicle, the presence of a lead vehicle was also found to increase the TTLCI. Overall, these findings align with prior research [58, e.g.,], indicating that the presence of neighbouring vehicles influences lane-changing behaviour.

Within the L3Pilot project, both accredited and regular drivers participated in the data collection process. The overall data collection process was divided into baseline trips (both types of drivers participated) and trips when the automated driving functions were active. In this study, we only considered the baseline trips but for both types of drivers. Due to the considerable amount of lane changes by accredited drivers, we chose to incorporate their data to preserve potentially valuable insights. Nevertheless, we conducted a supplementary analysis to check if merging both groups introduced any bias. The comparison of the two groups showed consistent directions of the effect for eight of the nine variables and for six of the variables which had a significant impact on the TTLCI in the combined dataset, with varying effect sizes across the variables and groups. These results suggest that despite their inherent differences, there seem to be substantial similarities in TTLCI behaviour between the two groups. A detailed comparison of the results for both groups is provided in the Appendix.

A. Implications

Our study provides detailed insights into driver behaviour before initiating a lane change. The results could help improve the current microscopic models of lane change decision-making, which do not consider the waiting time (or TTLCI) as an input parameter [59]. These models generally assume that a lane change is initiated as soon as the decision by the driver is made. However, as our results show, drivers also tend to wait before initiating a lane change. The TTLCI information can be incorporated in virtual simulation models (e.g. traffic simulations [60] and counterfactual simulations [61]). Lane change decision-making models considering TTLCI could provide a more realistic simulation of lane change behaviour.

As mentioned in the introduction section, lane changes also impact the traffic in the target lane [5, see,]. For example, Wang et al. [8] found that 44% of drivers decelerated while responding to a cut-in (a lane change where a vehicle abruptly moves to the target lane in front of them). The lane change behavior of human drivers (mainly how they use their turn signals) could also have a severe impact on AVs in mixed traffic, where AVs share the same road space as human-driven vehicles. Previous studies have shown that conventional vehicles will influence the performance of AVs [62] such as when cutting in [63]. If a human driver initiates a lane change without proper signalling, an AV might brake abruptly, causing discomfort for its occupants and disrupting traffic [63], [64].

For safe interaction with AVs in future mixed traffic, it is important to improve our understanding of human drivers' behaviour during lane changes and similar situations. An AV should be able to interpret the intention of human drivers and communicate its intentions when required. The TTLCI information from this study can be used to develop new AV algorithms (or improve existing ones) to detect and predict the timing of upcoming lane changes.

As described in the introduction section, many countries (including EU countries) currently lack detailed guidelines on how to use turn signals, especially in lane change situations. Although turn signals are mandatory in many countries, there are no specific rules regarding the timing of the signal when changing lanes. The goal of using turn signals before changing lanes is to warn surrounding drivers and give them ample time to react. Our results suggest that the majority of drivers initiate their lane changes within two seconds after signalling their intention. This duration is actually shorter than three to five seconds, which is required by recent German regulations for turn signal usage by AVs [14]. While our findings may not be generalizable to the wider population, the methodology can be used to investigate TTLCI in different countries.

B. Limitations and Future Work

While the data we used were collected on real roads, they were limited to passenger cars. The characteristics of heavy vehicles are different; hence we expect different lane change initiation times. Based on the findings of previous studies, it is anticipated that heavy vehicles will require a longer time to initiate a lane change than passenger cars, as this pattern has been observed in lane change duration [4], [65]. Given the greater impact of heavy vehicles on traffic, future studies should consider studying their lane change initiation behavior and comparing it to passenger cars. Our results also show the influence of surrounding vehicles on the lane change initiation behaviour of car drivers. However, we did not examine the impact of different types of vehicles on that behaviour. We expect, however, that car drivers' lane change initiation behaviour is different in the presence of heavy vehicles.

Our dataset did not categorize motivation, which refers to the difference between discretionary and mandatory lane changes [66]. Future studies should consider motivation while studying lane change initiation behaviour. We expect to see a difference, with mandatory lane changes exhibiting quicker initiation. This result is suggested by current studies, which show that lane change behaviour (such as gap acceptance and lane change duration) differs in discretionary and mandatory lane changes.

The external environment also plays a crucial role in lane-changing behaviour. The external factors can include but are not limited to road environment (e.g., type of road), traffic environment, and time of the day. In this paper, we only considered the impact of the traffic environment, i.e., surrounding vehicles. Given that the data was gathered exclusively during daytime on a single urban motorway–(the Gothenburg ring road), neither light condition nor road type was manipulated in the studies. However, it is worth noting that the first AVs (e.g. SAE level 3) are being, or will be, deployed under daytime and divided highway conditions. As this study aimed to support the development of AVs, the limitation of excluding their manipulation may not be that problematic. However, future studies should include various types of roadways, such as motorways and local roads, and different times of day to understand the factors influencing TTLCI more comprehensively- but that would be relevant mostly for the development of AVs further in the future.

The interactions during a lane change are highly dynamic, with the behaviours of the lane-changing vehicle and surrounding vehicles being interdependent (i.e., exhibiting game behaviour) [67], [68]. Within these complex interactions, there may be cases where a driver is unable to initiate and complete a lane change. For example, a driver might initiate a lane change, but lag vehicle's behaviour might change (such as speed up), forcing the driver to abandon the lane change. However, identifying such cases from datasets, like the one we used, presents a significant challenge and was beyond the scope of our study. Future research should consider these specific scenarios and analyze their potential impact on lane change initiation behaviour.

It is important to note that the data for this study were collected exclusively in Gothenburg, Sweden. The country of Sweden has its own unique set of road conditions, traffic laws, and driving behaviours. Therefore, the results are most directly applicable to similar settings (around other cities in Sweden) and perhaps in neighbouring Scandinavian countries. However, certain conclusions drawn from the study–such as the influence of speed and direction of lane change on TTLCI, could have broader applicability. In studies from various countries, the speed of the lane-changing vehicle and direction have been shown to influence the duration of the lane change similarly [4], [24], [31]. Even though TTLCI and lane change duration are not same thing, they are components of the overall lane change process, and therefore, their results should be comparable. While the data used in this study is country-specific, the overall methodology and some of the key findings could serve as a foundation for similar studies in other countries.

Finally, the demographics of drivers could provide valuable insights into their impact on TTLCI. However, our data set was unbalanced in terms of participant numbers and lane change cases, and age and driving experience data were only available for regular drivers. That is, for accredited drivers, we only had data on gender. Due to these data limitations, we did not perform an analysis of these demographic factors in our study. Future studies should consider including driver demographics (such as age, driving experience, and driving style) with a more balanced dataset.

Appendix

The supplementary models were run with two independent datasets. The Table VII presents the standard deviations of the random intercepts for regular and accredited drivers.

The random intercept represents the baseline hazard rate for each driver, accounting for the individual differences not explained by the fixed effects in the model. The results suggest

TABLE VII
RANDOM EFFECTS FOR REGULAR AND ACCREDITED DRIVERS

Group	Variable	Std Dev	
		Regular drivers	Accredited drivers
Driver ID	Intercept	0.389	0.289

TABLE VIII
COX MIXED-EFFECTS MODEL RESULTS FOR REGULAR DRIVERS

Predictor	Coeff	Exp(Coeff)	Std. Error	p-value
Speed	0.016	1.016	0.005	<0.001
LC Direction (right)	-0.142	0.868	0.099	0.150
LC Type (SLC)	0.429	1.536	0.171	0.012
Rear Vehicle (yes)	0.006	1.006	0.154	0.970
Rear Gap	-0.037	0.964	0.078	0.630
Lag Veh (yes)	-0.264	0.768	0.141	0.062
Lag Gap	0.099	1.104	0.058	0.086
Lead Vehicle (Yes)	-0.188	0.828	0.087	0.030
Traffic Density	0.011	1.011	0.010	0.270

TABLE IX
COX MIXED-EFFECTS MODEL RESULTS FOR ACCREDITED DRIVERS

Predictor	Coeff	Exp(Coeff)	Std. Error	p-value
Speed	0.035	1.036	0.006	<0.001
LC Direction (right)	-0.121	0.886	0.111	0.280
LC Type (SLC)	0.362	1.436	0.236	0.130
Rear Vehicle (yes)	0.297	1.346	0.189	0.120
Rear Gap	-0.087	0.916	0.095	0.360
Lag Veh (yes)	-0.334	0.716	0.165	0.043
Lag Gap	0.173	1.188	0.074	0.020
Lead Vehicle (Yes)	-0.218	0.804	0.108	0.043
Traffic Density	-0.007	0.993	0.010	0.480

slightly more variability in the baseline hazard rates across Non-Pro drivers than across Pro drivers. This could potentially indicate that accredited drivers exhibit more consistent behavior compared to regular drivers. Nonetheless, considering that our dataset consists of only 11 accredited drivers compared to 92 regular drivers, additional research is needed to examine the differences between the two groups thoroughly.

For the sake of comparison of fixed effects, we can use the direction of the coefficient and its significance as represented by the p-value in Tables VIII and IX.

Overall, it can be observed that for both cases, eight out of nine variables have the same coefficient direction or sign, except for the traffic density. However, the different coefficients between the two groups suggest varying intensities or strengths of these patterns. The overall model, which combines two datasets, also shows the same trend. It can be observed that pro-driver table has more significant variables compared to the non-pro. These differences can be attributed to several factors, such as data imbalance, variance between subjects, and effect size. In conclusion, both groups exhibit a similar trend in TTLCI behavior with varying effect sizes. Therefore, we include both groups in the overall model. Nonetheless, further research is needed with a more balanced dataset regarding the number of drivers and lane change observations.

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DATA AVAILABILITY

The datasets generated and/or analyzed during the current study are not publicly available due to privacy concerns and restrictions imposed by the data collection source

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