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Investigating autonomous vehicle discretionary lane-changing execution behaviour: Similarities, differences, and insights from Waymo dataset

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ABSTRACT

Recently released autonomous vehicle datasets like Waymo can provide rich information (and unprecedented opportunities) to investigate lane-changing behaviour of autonomous vehicles, requiring data from multiple drivers and lanes with different objectives. As such, the study investigates the discretionary lane-changing execution behaviour of autonomous vehicles and compares its behaviour with human-driven vehicles from Waymo and Next Generation Simulation (NGSIM) datasets. Several behavioural factors are statistically analysed and compared, whereas the discretionary lane-changing execution time (or duration) is modelled by a random parameters hazard-based duration modelling approach, which accounts for unobserved heterogeneity. Descriptive analyses suggest that autonomous vehicles maintain larger lead and lag gaps, longer discretionary lane-changing execution time, and lower acceleration variation than human-driven vehicles. The random parameters duration model reveals heterogeneity in discretionary lane-changing execution behaviour, which is higher in human-driven vehicles but decreases significantly for autonomous vehicles. Whilst contradictory to a general hypothesis in the literature that autonomous vehicles will eliminate heterogeneity, our finding indicates that heterogeneous behaviour also exists in autonomous vehicles (although to a lesser extent than in human-driven vehicles), which can be contextual to prevailing traffic conditions. Overall, autonomous vehicles show safer discretionary lane-changing behaviour compared to human-driven vehicles.

1. Introduction

Lane-changing is a complex driving manoeuvre, often resulting in disturbing traffic flow conditions and deteriorating traffic safety. For instance, lane-changing has been linked to capacity drops (Cassidy and Rudjanakanoknad, 2005), stop-and-go oscillations, and triggering congestion (Zheng et al., 2011, Ahn and Cassidy, 2007). Similarly, lane-changing is often associated with different crash types, such as rear end and sideswipes. For instance, in the year 2019, 830 lane change crashes were reported in New South Wales, Australia (TfNSW, 2020), whereas in the same year, lane change crashes contributed 3 % to the total crashes in Queensland, Australia

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(DTMR, 2020). In the United States, sideswipes accounted for 13 % of the total crashes in 2019 (NHTSA, 2020). These statistics demonstrate the risky nature of lane-changing manoeuvres and the need to understand the lane-changing decision-making process better.

In general, lane-changing manoeuvres can be classified into two types: mandatory lane-changing (performed to reach a specific destination or follow a designated route) and discretionary lane-changing (performed to gain speed advantage or achieve better driving conditions) (Zheng, 2014). As the name suggests, mandatory lane-changing refers to urgent lane-changing manoeuvres whereby drivers must change lanes to follow the desired route. During mandatory lane-changing, drivers must administer the remaining distance in the acceleration lane and assess surrounding vehicle speeds to complete the manoeuvre safely (Ali et al., 2018). Besides evaluating surrounding vehicle speeds, drivers during discretionary lane-changing require assessing the efficacy of available lanes. As such, discretionary lane-changing manoeuvres become more complex and exert a significant workload, creating stress during driving and making these manoeuvres risky, dangerous, and error-prone (Ali, 2020). Hence, this study focusses on investigating discretionary lane-changing behaviour.

Discretionary lane-changing behaviour can be assessed at three levels: decision-making, execution, and impact. The decision-making level reflects a driver's gap selection behaviour, the execution level indicates the driver's physical movement from one lane to another, and the impact level suggests how discretionary lane-changing impacts the traffic stream in the current and target lanes. The literature review suggests the decision-making level has been extensively studied (Marczak et al., 2013, Bham, 2009, Goswami and Bham, 2007, Toledo et al., 2005, Toledo et al., 2003), whereas lane-changing execution and impact levels have received less attention in the literature. This study focusses on discretionary lane-changing execution level as it is linked with both decision-making and impact levels.

Discretionary lane-changing execution has been studied for conventional vehicles (e.g., Moridpour et al. (2010), Hetrick (1997), Toledo and Zohar (2007) — these studies have either descriptively studied lane-changing execution or modelled using statistical models) and to some extent for connected vehicles or vehicles operating in a connected environment (Ali et al., 2021c, Ali et al., 2020c), but not for autonomous vehicles. One possible reason for this limited attention to autonomous vehicles' lane-changing execution behaviour is perhaps because of substantial focus on the longitudinal movement since it is safer and easier to achieve or two-dimensional trajectory planning, so lane-changing is not considered separately. This shortcoming reaffirms the fact that autonomous vehicle's research and development is still in the development phase. As such, understanding how autonomous vehicles make lane-changing decisions becomes paramount for properly designing their algorithms and lane-changing decision models. Without well-tailored models for autonomous vehicles or using existing models, we are likely to trap in the ecological inference fallacy problem and our estimates for autonomous vehicles are likely to be misleading and biased. As such, this study focusses on assessing lane-changing execution characteristics of autonomous vehicles.

One of the challenges for operational research related to autonomous vehicles is the lack of real data. To overcome this issue, studies in the past have conducted numerical simulations to demonstrate several benefits of these vehicles (Guériau et al., 2016, Reina and Ahn, 2015). These studies, however, did not consider human factors, which is important when assessing microscopic driving behaviour like lane-changing (Sharma et al., 2018). As an alternative, several field autonomous vehicle experiments have been conducted, through which not only autonomous vehicle data have been collected, but these vehicles are used as probes to collect data related to other road users, such as human-driven vehicles, pedestrians, and bicyclists. As a result of these experiments, several open-access autonomous vehicle databases are increasingly becoming popular and providing unprecedented opportunities to study microscopic driving behaviour, which was not possible before. Some open access databases for these vehicles are: Argo dataset (Chang et al., 2019), Lyft Level 5 autonomous dataset (Kesten et al., 2019), BDD100K (Yu et al., 2020), nuScenes dataset (Caesar et al., 2020), and Waymo open dataset (Sun et al., 2020). Although each respective data collection agency has made these datasets public, they require significant pre-processing to make them suitable for microscopic driving behaviour research like NGSIM (FHWA, 2007). Very recently, however, Hu et al. (2022) processed the Waymo open dataset, made it public, and demonstrated its feasibility for car-following research. As a follow-up study building on a similar methodology and more nuanced data processing (described later in the paper), this study utilises the rich information from the autonomous vehicle Waymo open dataset for understanding discretionary lane-changing execution behaviour.

More specifically, this study aims to investigate and model lane-changing execution characteristics of autonomous vehicles using the publicly available Waymo open dataset. This study rigorously evaluates differences and similarities in lane-changing execution characteristics of autonomous vehicles with respect to conventional (or human-driven) vehicles and connected vehicles (human-driven vehicles with driving assistance). In achieving the study objective, this study makes twofold contributions. First, as one of the first studies focussing on discretionary lane-changing execution behaviour of autonomous vehicles, this study provides detailed insights into how these vehicles perform lane-changing executions and whether they are safer — as they are deemed to be — than human-driven vehicles. Second, using an advanced econometric framework (i.e., a random parameter hazard-based duration modelling approach), this study probabilistically models lane-changing execution behaviour, further providing a deeper understanding of how lane-changing completion varies over time for different vehicle classes.

The rest of the paper is structured as follows. Section 2 briefly summarises relevant studies, forming the background of the current study. Section 3 explains the datasets and analysis methods, including Waymo data processing and duration model development. Whilst results are presented in Section 4, these results are discussed in Section 5, with Section 6 summarising study findings and providing an outlook for future research.

2. Background

Since this study focusses on lane-changing execution behaviour, this section briefly summarises some representative studies on lane-changing execution behaviour. However, providing a comprehensive review of this topic is beyond the scope of the study.

Table 1 summarises representative lane-changing execution studies, and some key observations from this table are as follows. First, most studies have obtained their trajectory data after video processing, such as NGSIM, whereas some studies have also used driving simulators to collect trajectory data. Second, past studies have predominantly focussed on analysing the lane-changing execution of non-connected vehicles conventional vehicles (called as conventional vehicles), with a few exceptions for connected vehicles and automated vehicles. Such a high emphasis on conventional vehicles is understandable primarily because of data availability, whereas the latest vehicle technologies (e.g., connected vehicles and automated vehicles) have gained attention in the last decade or so mainly using numerical simulations with a few exceptions of driving simulators and field studies. As such, the novelty of these vehicles and the consequent data scarcity could be reasons for fewer studies on these vehicles. Third, lane-changing execution behaviour is evaluated for both lane-changing types (mandatory and discretionary), whilst a few studies did not clearly mention whether they investigated lane-changing execution behaviour for mandatory lane-changing or discretionary lane-changing. Fourth, lane-changing duration[3] has been determined using different methods, e.g., noted by an observer accompanying a driver in their vehicle, manually recording from videos, and using automated algorithms. The data recorded by an observer may induce bias in driving behaviour, and similarly, manually recording starting points from videos is likely subject to human errors and bias. To overcome these issues, a few studies have developed automated algorithms to determine the lane-changing starting point. For instance, Ali et al. (2018) applied a tracing algorithm to lane lateral shift profiles to determine the lane-changing starting point. The developed algorithm showed excellent performance, verified from ground truth in the driving simulator data log. In another study, Wavelet Transform was used due to its excellent performance in detecting singularities in traffic data (see Zheng and Washington (2012) for more details) and compared with the tracing algorithm (Ali et al., 2020c). Results showed similar results of wavelet transform as the tracing algorithm. Finally, lane-changing durations vary across studies, with the minimum and maximum lane-changing durations as 0.7 s and 21.6 s, respectively.

The literature related to understanding driving behaviour in the autonomous vehicle context is rather limited, with a few studies analysing car-following behaviour (Hu et al., 2023, Hu et al., 2022, Wen et al., 2022), whilst only one study is found in lane-changing context. Nilsson et al. (2017) analysed lane-changing durations of automated trucks in a driving simulator study and found that lane-changing durations for automated trucks may be lower than conventional trucks, reflecting sudden manoeuvring from the current lane to the target lane, which could be risky. This finding contrasts most of the literature where autonomous vehicles are found to be safer (Hu et al., 2023). However, this contrasting finding could be attributed to different driving tasks being analysed in these studies (e.g., the study of Hu et al. (2023) is in the context of car-following). Such an inconsistency needs to be investigated and motivates this study.

Further, as noted in Table 1, lane-changing durations vary within a given range, even for human-driven and autonomous vehicles. As such, this heterogeneity should be captured through an advanced modelling framework designed for capturing heterogeneity. To this end, Ali et al. (2021b) applied a random parameters modelling framework, which showed that lane-changing durations for connected vehicles might increase or decrease relative to conventional vehicles. However, evidence of applying such a modelling framework to autonomous vehicles lane-changing durations is relatively scant. Using this modelling framework will also reveal the determinants affecting the lane-changing durations of autonomous vehicles.

To summarise, our understanding of the lane-changing execution behaviour of autonomous vehicles remains elusive because of the following research questions. (1) Can methods used in literature for detecting the lane-changing starting point be applied to autonomous vehicles?, (2) What factors affect lane-changing durations of autonomous vehicles?, (3) Is influencing factors' relationship with lane-changing durations homogeneous or heterogeneous?, (4) How the lane-changing execution behaviour of autonomous vehicles varies compared to conventional vehicles?. These questions are answered in this study.

3. Dataset and analysis

3.1. Dataset

3.1.1. Waymo open dataset

For autonomous vehicles defined as Society of Automotive Engineer Level 4, the Waymo open dataset is utilised, which can be found on the Waymo website (Waymo, 2023). The Waymo data were collected in 2019, but the actual date and time has been anonymised to maintain privacy of road users. This dataset contains a perception dataset for three-dimensional object detection and tracking, and motion datasets for motion/interaction prediction. This study used the motion dataset of approximately 103,354 segments (Sun et al., 2020). Note that one segment (also referred to as a scenario) corresponds to one episode of driving. This study used 70 % of the dataset containing features already tracked by Waymo (it was used for the Waymo Challenge training purpose). A typical Waymo data segment includes 200 frames with a data resolution of 0.1 s. For each frame, environment context, timestamp, autonomous vehicle's pose, camera images, camera labels, Lidar points, etc., are obtained from camera images, which were used for lane-changing execution investigation. This dataset contains information about Waymo's autonomous vehicles and other vehicles detected by the Waymo vehicles through its sensors, which are assumed to be all human-driven vehicles, as no specific information is provided.

[3] The lane-changing duration is defined as the time difference between the start of the lateral movement from the current driving lane to reaching the target lane.

Table 1
A summary of lane-changing execution studies.

Study	Data collection	Vehicle type	LC type	LC duration measurement	LC duration (s)
Worrall and Bullen (1970)	Aerial images	Conventional	—	—	2.3–4.8
Finnegan and Green (1990)	Literature review survey	Conventional	NA	NA	4.9–7.6
Wiedemann and Reiter (1992)	NA	Conventional	—	—	2.18–2.69 for passenger cars 2.08–4.51 for heavy vehicles
Chovan et al. (1994)	Instrumented vehicle	Conventional	—	—	2–16
Tijerina et al. (1997)	Field study	Conventional	—	Noted by an observer	3.5–6.5 for urban streets3.5–8.5 for highways
Hetrick (1997)	Field study	Conventional	Mandatory	Noted by an observer	3.4–13.6
Hanowski (2000)	Field study	Conventional	—	—	1.1–16.5
Salvucci and Liu (2002)	Simulator study	Conventional	—	Identified by verbal protocols	5.14
Lee et al. (2004)	Instrumented vehicle	Conventional	—	Manual extracted from videos	6.3
Toledo and Zohar (2007)	Field study	Conventional	Discretionary	Manually extracted from lateral profiles	1–13.3
Moridpour et al. (2010)	Field study	Conventional	Discretionary	—	1.1–8.9 for passenger cars
Cao et al. (2016)	Field study	Conventional	Mandatory	—	1–6.8
Nilsson et al. (2017)	Simulator study	Conventional and automated	Discretionary	Obtained from the start of a turn indicator	7.7 for conventional 3.9–8.2 for automated
Zhao et al. (2017)	Field study	Conventional	Mandatory and discretionary	Obtained from lane markers in trajectory data	1.1–7.8 for mandatory 1.3–7.9 for discretionary
Ali et al. (2018)	Simulator study	Connected	Mandatory	Obtained from tracing algorithm	7.1–7.3
Yang et al. (2019)	Field study	Conventional	Mandatory and discretionary	Obtained from automatic extraction algorithm	0.7–16.1
Yuan et al. (2019)	Simulator study	Conventional	Mandatory	Manually extracted from lateral profiles	3.5–4.5
Ali et al. (2020c)	Simulator study	Connected	Discretionary	Obtained from Wavelet Transform	5.11–8.43
Ataelmanan et al. (2021)	Field study	Conventional	Discretionary	Manually extracted from vehicle's lane cross shift	1–6.5
Li et al. (2022)	Field study	Conventional	Discretionary	Manually extracted from lateral profiles	3.5–21.6 for passenger cars 4.16–15.12 for heavy vehicles

NA: not applicable; "—" missing or not mentioned; LC: lane-changing.

As such, this study uses the Waymo open dataset to obtain autonomous and human-driven vehicle lane-changing trajectories.

Waymo autonomous vehicles are fitted with high-resolution sensors that collect large-scale data in three U.S. cities, i.e., San Francisco, Phoenix, and Mountain View. Fig. 1(a) shows a Waymo car that is fitted with five calibrated and synchronised Lidars (1 mid-range and 4 short-range) and five cameras (front and sides). For object tracking, three-dimensional bounding boxes for Lidar data were manually annotated by Waymo in line with ground truth. This dataset contains rich information about road types (urban streets and freeways), weather (sunny and rainy), and time of day (dawn, day, dusk, and night). This study focusses on urban streets that contain 96.5 % of the dataset. It is worth noting that the open dataset contains a large number of observations, and data quality is superior and better than NGSIM (Hu et al., 2022).

In preliminary data processing, the original Waymo open dataset is restructured to an accessible tabular format of trajectory data like NGSIM. The restructured dataset contains 25 attributes, including the segment environment information (time of day, weather, etc.), object features (object type, length, etc.), and object tracking trajectory (position, speed, heading, etc.). Qualitative verification is performed using camera videos and trajectory view animations generated from them. Then, lane changes performed by Waymo autonomous vehicles are extracted by recording their IDs, their leaders in the current lane and the target lane, and followers in the current lane and the target lane. A typical example of the Waymo autonomous vehicle's trajectory can be seen in Fig. 1(c). Similarly, lane changes performed by human-driven vehicles were also extracted for comparison and recorded in a similar format. Note that for vehicles detected by Waymo in their periphery, we assumed that they are all human-driven vehicles as no specific information is provided (similar to two previous studies on the Waymo open dataset, see Hu et al. (2023) and Hu et al. (2022)). Great efforts have been dedicated to ensuring only discretionary lane-changing manoeuvres were extracted. These efforts include considering lane-changers only in inner lanes for discretionary lane-changing. Further, lane-changers who start from the inner lanes and move toward the intended turning lane were excluded. Similarly, lane-changes to exclusive turning lanes were not considered. We also acknowledge that to be 100 % sure, trajectories beyond 20 s are required to decipher that lane-changing at mid-blocks ultimately leads to an intended turn at intersections. Finally, lane changes performed by autonomous and human-driven vehicles close to intersections were excluded. Note that following the guidelines for influence areas near an intersection (Yuan and Abdel-Aty, 2018), all lane-

(a)

(b)

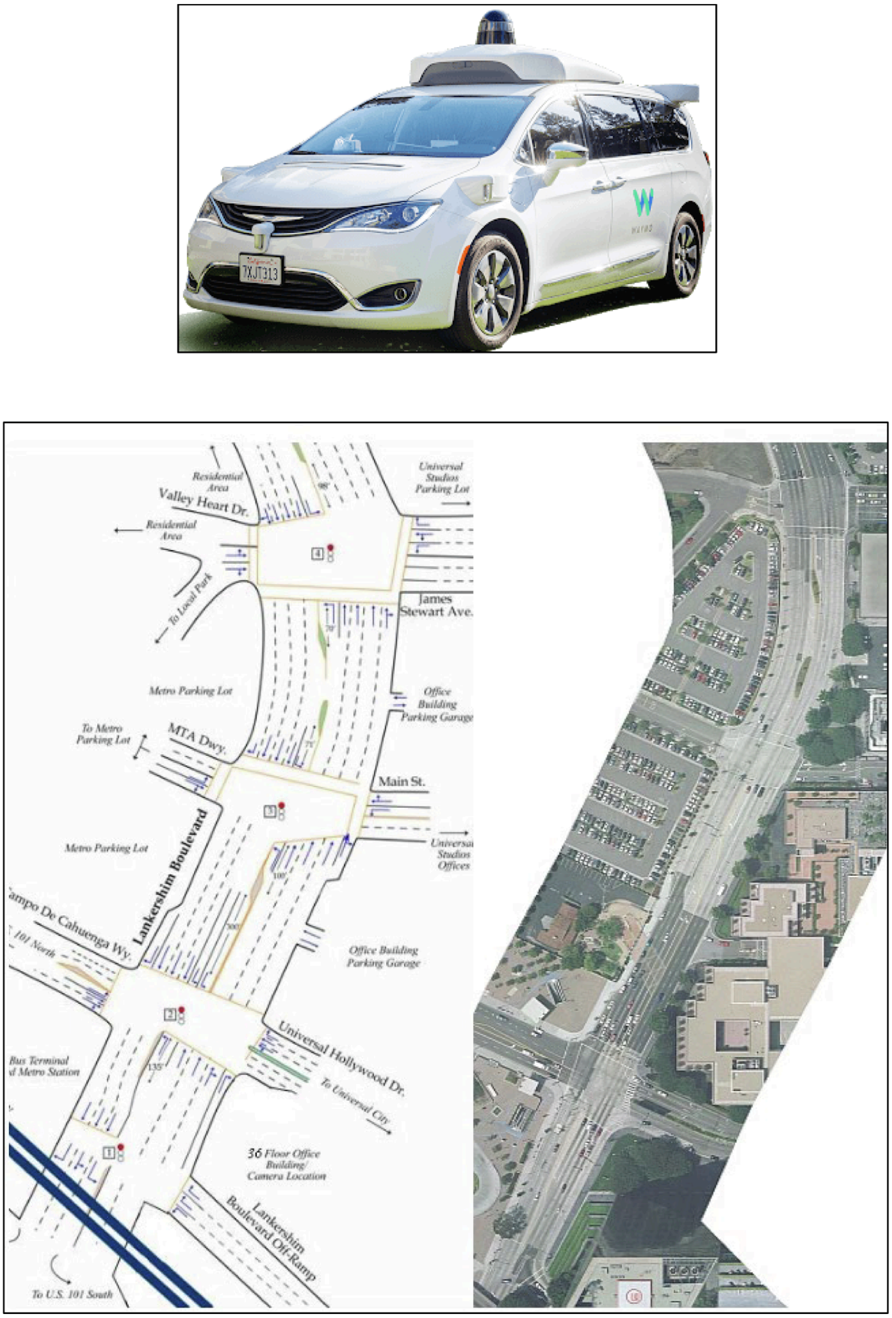

Fig. 1. Schematics: (a) Waymo vehicle (Waymo, 2023), (b) Lankershim Boulevard study site (FHWA, 2007), and (c) a typical layout of an urban road segment and lane-changing trajectory.

changings located within 80 m of an intersection were excluded, which also aligns with the Federal Highway Administration guidelines (Rice, 2010). Given the limited sample size, factors such as time of day, road types, and weather affecting lane-changing are not considered. However, future studies should consider these factors when analysing the lane-changing execution behaviour of autonomous vehicles.

Since this study is a follow-up study of an earlier study (Hu et al., 2022), the same optimisation-based outlier removal method and a wavelet denoising method are applied to the trajectory data. These two methods resulted in outlier-free trajectories and filtered out noise from trajectories. Using these methods, the quality of resulting trajectories is sufficiently improved, which is suitable for investigating lane-changing execution behaviour.

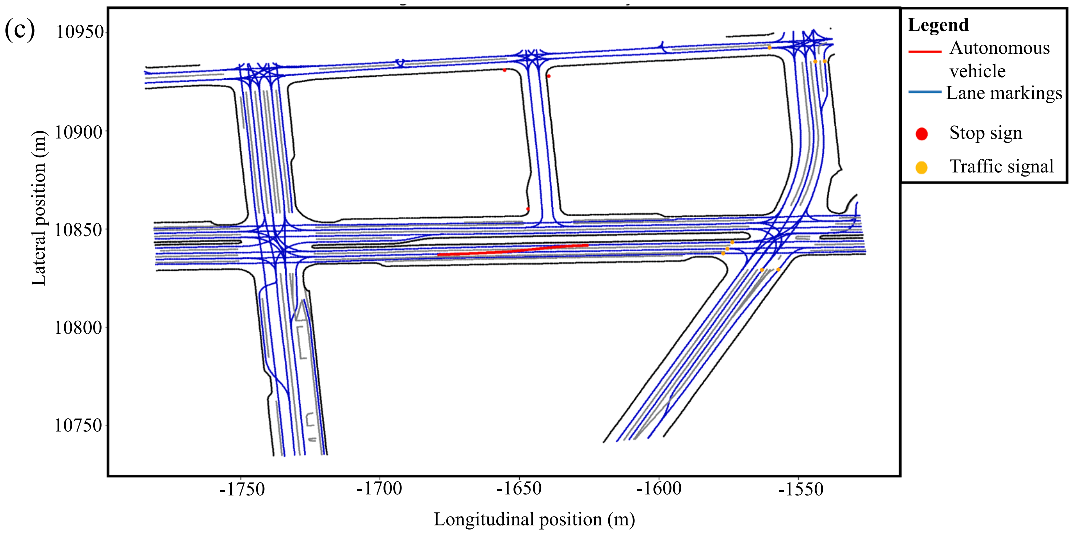

Fig. 1. (*continued*).

3.1.2. NGSIM dataset

Since the Waymo open dataset provides discretionary lane-changing manoeuvres of autonomous vehicles and human-driven vehicles on urban roads, similar discretionary lane-changing manoeuvres are obtained from NGSIM data for comparison, which contains a relatively large sample size. To this end, the Lankershim Boulevard dataset (FHWA, 2007) has been used, which was collected in the Universal City neighbourhood of Los Angeles, California, on June 16, 2005. The study site (Fig. 1(b)) contains three to four-lane arterials with an approximate length of 500 m, and five cameras were placed in a nearby high-rise building. Trajectories were processed from videos at a resolution of 0.1 s, with detailed lane positions and speeds. A total of 30 mins data (8:30 a.m. to 8:45 a.m. and 8:45 a.m. to 9:00 a.m.) are used in this study. Note that discretionary lane-changing manoeuvres are extracted following the same procedure applied to the Waymo dataset for a fair comparison.

From the Waymo open dataset, 147 and 151 discretionary lane-changing manoeuvres on urban arterials performed by autonomous and human-driven vehicles are extracted. From the Lankershim Boulevard dataset (NGSIM thereafter), 1263 discretionary lane-changing manoeuvres performed by human-driven are extracted and used in this study.

Note that although Waymo also collected human-driven vehicle data, the sample size is comparatively small. To this end, the NGSIM dataset is utilised, offering a dataset from a greater number of human-driven vehicles. However, it must be noted that there is a significant gap between Waymo and NGSIM data collection, which would have significantly affected car performance, region — the same state but different cities (and thus driving population), advanced driving assistance systems, traffic regulations, safety culture, and change in driving behaviour over time. Whilst these factors are uncontrollable and lead to unobserved heterogeneity, this study

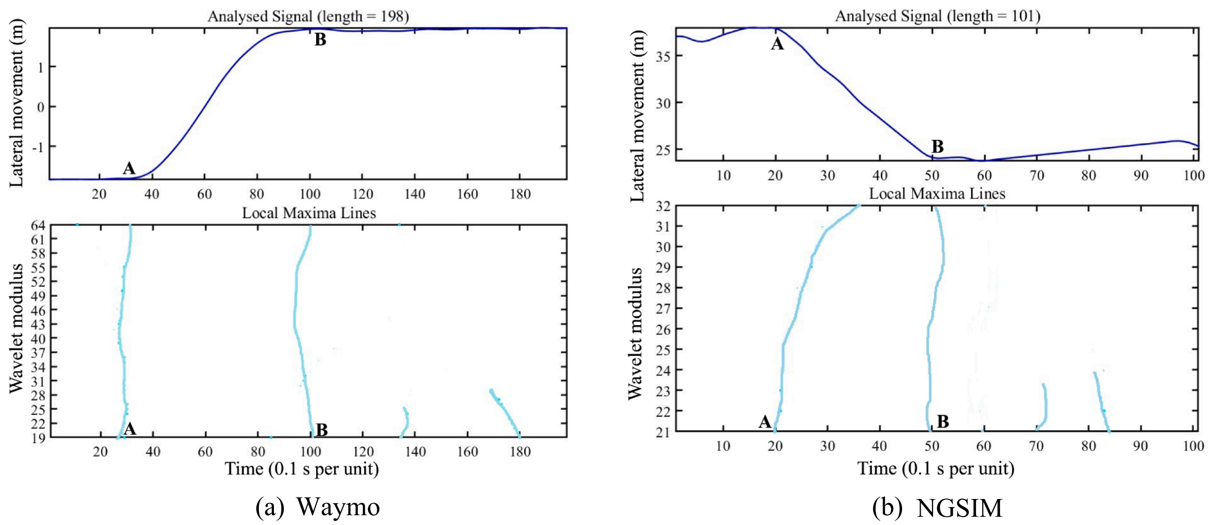

Fig. 2. A typical example of discretionary lane-changing duration using lateral movement profiles.

only compares autonomous vehicles and human-driven vehicles from Waymo data. Further, to verify the relationship between human-driven vehicle discretionary lane-changing execution and its determinants, NGSIM data were used, providing rich information with a greater sample size. As such, caution must be exercised when interpreting and comparing the modelling results.

3.2. Data processing

Existing trajectory databases do not provide sufficient information about the discretionary lane-changing start point, hindering determining lane-changing durations. From past studies (Ali et al., 2018, Toledo and Zohar, 2007), using lateral movement profiles can assist in determining lane-changing durations, and several methods are used for determining the discretionary lane-changing start point, such as manual extraction, tracing algorithm, and Wavelet Transform. This study applies Wavelet Transform, which has shown promising results in detecting singularities in traffic data (Zheng and Washington, 2012, Zheng et al., 2011) and extracting the discretionary lane-changing starting point (Ali et al., 2020c) and failed lane-changing attempts (Ali et al., 2020b).

Fig. 2 displays a typical example of the wavelet transform's application to detect the discretionary lane-changing starting point (Point A in Fig. 2(a)), which has been used to determine discretionary lane-changing duration. Mallat and Hwang (1992) and Zheng and Washington (2012) concluded that wavelet modulus could assist in detecting subtle changes in a signal (i.e., a lateral movement profile in this study). From maxima lines, drawn through wavelet modulus, the discretionary lane-changing starting point (i.e., Point A) and ending point (i.e., Point B) can be located, and its corresponding times are used to determine the discretionary lane-changing duration. Using these points, the time difference between the lane-changing starting and ending points is called *discretionary lane-changing duration*.

Several influencing factors are extracted at or before Point A that can explain discretionary lane-changing execution behaviour, which are summarised in Table 2. Note that not all these explanatory variables were used in the model development due to reasons described in Section 4.

Table 2
Descriptive analyses of driving behaviour indicators considered in this study.

Indicator	Waymo (AV)		Waymo (HV)		NGSIM (HV)		Significance of the linear mixed model
	Mean (SD)	Min (Max)	Mean (SD)	Min (Max)	Mean (SD)	Min (Max)	
Lane duration (s)	7.573(2.374)	4.500(17.200)	5.895(2.102)	2.200(12.000)	7.129(4.013)	0.500(19.900)	AV-HV (W) < 0.001 AV-HV (N) = 0.01
Spacing (m)	2.461(6.901)	7.765(8.038)	10.010(1.785)	7.028(12.977)	7.850(9.772)	0.258(35.283)	AV-HV (W) < 0.001AV-HV (N) < 0.001
Speed of SV (m/s)	13.021(6.827)	2.025(16.436)	4.476(2.258)	0.056(13.640)	10.703(3.917)	0.012(16.141)	AV-HV (W) < 0.001AV-HV (N) < 0.001
Speed of leader in CL (m/s)	7.021(2.127)	1.001(14.281)	13.021(6.827)	2.008(36.436)	9.856(4.337)	1.020(16.285)	AV-HV (W) < 0.001AV-HV (N) < 0.001
Relative speed in CL (LV - AV) m/s	0.715(2.602)	−11.749(9.083)	1.208(0.708)	0.003(2.498)	−0.163(5.153)	−0.718(15.855)	AV-HV (W) = 0.029 AV-HV (N) = 0.06
Lag gap (m)	15.154(81.042)	6.533(179.143)	8.791(65.617)	2.731(196.777)	12.575(18.870)	2.070(195.585)	AV-HV (W) = 0.473AV-HV (N) = 0.326
Speed of FV in TL (m/s)	11.671(6.218)	0.021(29.355)	13.361(7.055)	0.271(38.989)	8.438(5.330)	1.781(16.266)	AV-HV (W) = 0.014AV-HV (N) < 0.001
Relative speed in TL (AV - FV) m/s	0.756(4.448)	−9.354(11.823)	1.325(5.667)	−18.732(15.912)	−4.673(5.382)	−0.739(13.758)	AV-HV (W) = 0.318AV-HV (N) = 0.039
Lead gap (m)	15.285(75.624)	4.008(66.299)	16.905(72.579)	0.021(294.858)	11.933(23.451)	3.780(37.952)	AV-HV (W) < 0.001AV-HV (N) < 0.001
Speed of LV in TL (m/s)	13.023(7.430)	0.002(14.881)	11.223(9.247)	1.251(14.032)	8.620(5.171)	2.750(16.361)	AV-HV (W) = 0.119AV-HV (N) < 0.001
Relative speed in TL (LV - AV) m/s	0.683 (5.307)	−14.029 (10.858)	−3.463 (8.918)	−27.439 (14.714)	−0.163 (5.153)	−0.718 (15.855)	AV-HV (W) < 0.001AV-HV (N) < 0.001

SV: subject vehicle; AV: autonomous vehicle; HV: human-driven vehicle; CL: current lane; LV: lead vehicle; FV: following vehicle; TL: target lane; SD: standard deviation; Min: minimum; Max: maximum; W: Waymo dataset; N: NGSIM dataset.

3.3. Hazard-based duration model

This study applies hazard-based duration models for modelling discretionary lane-changing durations, defined as the time a driver takes to complete their discretionary lane-changing manoeuvres. Hazard-based duration models are frequently applied for various transport applications where the time until an event occurs is under consideration. These models provide time-varying probabilities that could inform how quickly discretionary lane-changing manoeuvres have been completed, reflecting the riskiness of lane-changing execution. Ensuing subsections describe the formulation of the hazard-based duration modelling approaches considered in this study.

3.3.1. A Weibull model with gamma heterogeneity

Assume $F(t)$ denotes the cumulative distribution function providing the probability of not completing a discretionary lane-changing manoeuvre before the time t, leading to

$$F(T) = P(T < t), \tag{1}$$

where, $P(\bullet)$ corresponds to the probability and T is a random time variable. The probability density function ($f(t)$) can be obtained as the first derivative of $F(T)$ as

$$f(t) = \frac{dF(T)}{dt}. \tag{2}$$

From the probability density function, the corresponding hazard function ($h(t)$) can be obtained, giving the conditional probability of not completing a discretionary lane-changing manoeuvre between t and $t + dt$, given that the manoeuvre has not been completed up to time t. mathematically, it can be written as

$$h(t) = \frac{f(T)}{1 - F(t)}. \tag{3}$$

The corresponding survival function ($S(t)$) provides the probability of an incomplete discretionary lane-changing manoeuvre duration being greater than or equal to some specified time t, which can be obtained as

$$S(t) = P(T \geq t) = \frac{f(T)}{h(t)}. \tag{4}$$

Two approaches have been used for developing hazard-based duration models to incorporate the effect of covariates on the hazard function: proportional hazards and accelerated failure time. The former approach considers hazard ratios to be constant over time, whereas the latter approach allows covariates to rescale the baseline survival function (where all covariates are zero) (Washington et al., 2020). This study applies an accelerated failure time approach, whereby an intrinsically linear function is used to express the relationship of discretionary lane-changing execution duration with its explanatory variables as

$$ln(T) = \boldsymbol{\beta X} + \varepsilon, \tag{5}$$

where, $\boldsymbol{\beta}$ denotes a vector of estimable parameters, $\boldsymbol{X}$ indicates the vector of covariates, and ε is an error term. The conditional survival and hazard functions for the accelerated failure model can be obtained (Washington et al., 2020) as

$$S(t|\boldsymbol{X}) = S_0[t \times EXP(\boldsymbol{\beta X})], \tag{6}$$

$$h(t|\boldsymbol{X}) = h_0[t \times EXP(\beta\mathbf{X})] \times EXP(\beta\mathbf{X}), \tag{7}$$

where, S_0 and h_0 are baseline survival function and hazard function, respectively.

Estimating survival and hazard functions in a fully parametric setting requires specifying a distribution. Some commonly used distributions in the literature are Weibull, lognormal, gamma, Gompertz, log-logistic, and exponential (Washington et al., 2020). Discretionary lane-changing durations have been found to follow a Weibull distribution (Ali et al., 2021b, Ali et al., 2020b, Ali et al., 2020c). Further, the selection of Weibull distribution follows theoretical and statistical evaluation. From theoretical perspective, discretionary lane-changing execution duration (or time to complete a discretionary lane-changing manoeuvre) often depends upon on relatively rare events, such as unanticipated behaviour of other road users, personal characteristics, and so on. As such, discretionary lane-changing execution time can be defined as a function of rare events, ensuring the appropriateness of extreme value-based Weibull distribution for modelling duration data, which is aligned with duration modelling literature (Ali et al., 2023, Balusu et al., 2020, Nam and Mannering, 2000). From statistical evaluation, a wide range of distributions were tested and empirically compared, and Weibull distribution was found statistically superior to other distributions, as confirmed by an Anderson-Darling test. The null hypothesis for this test was that the duration variable followed a Weibull distribution, and the test statistic confirmed a failure to reject the null hypothesis at a 95 % confidence level (*test statistic* = 0.39; p-value = 0.47). Beside this evidence, models with other distributions were developed, but these models did not provide superior fit than the model with Weibull distribution. Note that distribution fitting was performed individually for autonomous and human-driven vehicles and combined as well, and the Weibull distribution provided a superior fit for combined lane-changing durations for autonomous and human-driven vehicles. Further, the same Weibull distribution was found superior for the lane-changing durations of autonomous vehicles. As such, the Weibull distribution is selected in this study, and its probability density function can be written as

$$f(t) = \lambda P(\lambda t)^{P-1} EXP[-(\lambda t)^P], \tag{8}$$

leading to the hazard function

$$h(t) = \lambda P(\lambda P)^{P-1}, \tag{9}$$

where λ and P denote the location and shape parameters of the Weibull distribution, respectively.

Equation (5) represents a fixed parameters model, assuming the influence of explanatory variables on discretionary lane-changing duration is the same for each observation. As such, parameters are fixed and remain constant across observations. This strong assumption may become problematic when unobserved factors associated with the determinants of discretionary lane-changing executions are not accounted for. As such, capturing unobserved heterogeneity becomes paramount (Mannering et al., 2016) and is considered in this study because substantial unobserved heterogeneity may exist in discretionary lane-changing execution because of a lack of full information, such as automation level, surrounding traffic dynamics, and so on. To this end, unobserved heterogeneity can be captured by introducing a heterogeneity term in the condition survival function (Nam and Mannering, 2000). Assume that the heterogeneity term is denoted as w, which is distributed over the population as $g(w)$ with a conditional survival function $S(t|w)$, leading to an unconditional survival function as

$$S(t) = S(t|w)g(w)dw. \tag{10}$$

In the context of Weibull distribution, w is assumed to follow a gamma distribution (Washington et al., 2020, Nam and Mannering, 2000, Hui, 1990) with mean $= 1$ and variance $(\theta) = 1/k$, such that

$$g(w) = \frac{k^k}{\Gamma(k)} EXP[-kv]w^{k-1}. \tag{11}$$

The survival function for Weibull distribution can now be obtained as

$$S(t|w) = EXP[-(w\lambda t)^P]. \tag{12}$$

The unconditional survival function can now be expressed as

$$S(t) = \int_0^\infty S(t|w)g(w)dw = \left[1 + \theta(\lambda t)^P\right]^{\frac{-1}{\theta}}, \tag{13}$$

leading to the hazard function

$$h(t) = P(t)^{P-1}[S(t)]^{\theta}. \tag{14}$$

Note that when $\theta = 0$, such a case reflects that heterogeneity is not present and the hazard reduces to Eq. (9), and the variance of the heterogeneity term (w) becomes zero.

3.3.2. A Weibull model with random parameters

Contrasting to gamma heterogeneity, another common approach to capture unobserved heterogeneity is using random parameters models (Mannering et al., 2016) that allow random parameters to vary across the observations. The gamma heterogeneity model presented in the previous section can be viewed as a restrictive form of a random parameters model whereby a single gamma distributed heterogeneity term captures variation across observations. The random parameters can be specified as (Washington et al., 2020)

$$\boldsymbol{\beta}_i = \boldsymbol{\beta} + \Gamma\gamma_i, \tag{15}$$

where, $\boldsymbol{\beta}$ indicates the vector of mean values of the random parameter, γ is the user-specified term (e.g., gamma distributed, a normally distributed term, etc.), and Γ represents the Cholesky matrix. The unrestricted form of this matrix allows for capturing the correlation between random parameters.

The random parameters model is estimated using a simulated maximum likelihood with 1,000 Halton draws (Bhat, 2003), ensuring the stability of model parameter estimates. A likelihood ratio test is performed to determine whether a correlated random parameters model is statistically different from an uncorrelated random parameters model (where off-diagonal elements of the variance–covariance matrix are zero).

4. Results

4.1. Descriptive analysis of discretionary lane-changing execution behaviour

Fig. 3 depicts probability and cumulative distributions for discretionary lane-changing execution behaviour, characterised by discretionary lane-changing durations, related to autonomous and human-driven vehicles obtained from Waymo and NGSIM datasets. Some key observations from Fig. 3 are as follows. First, the mean duration for autonomous vehicles in the Waymo dataset is 7.6 s, whereas the corresponding mean durations for human-driven vehicles in the Waymo and NGSIM datasets are 5.9 s and 7.1 s,

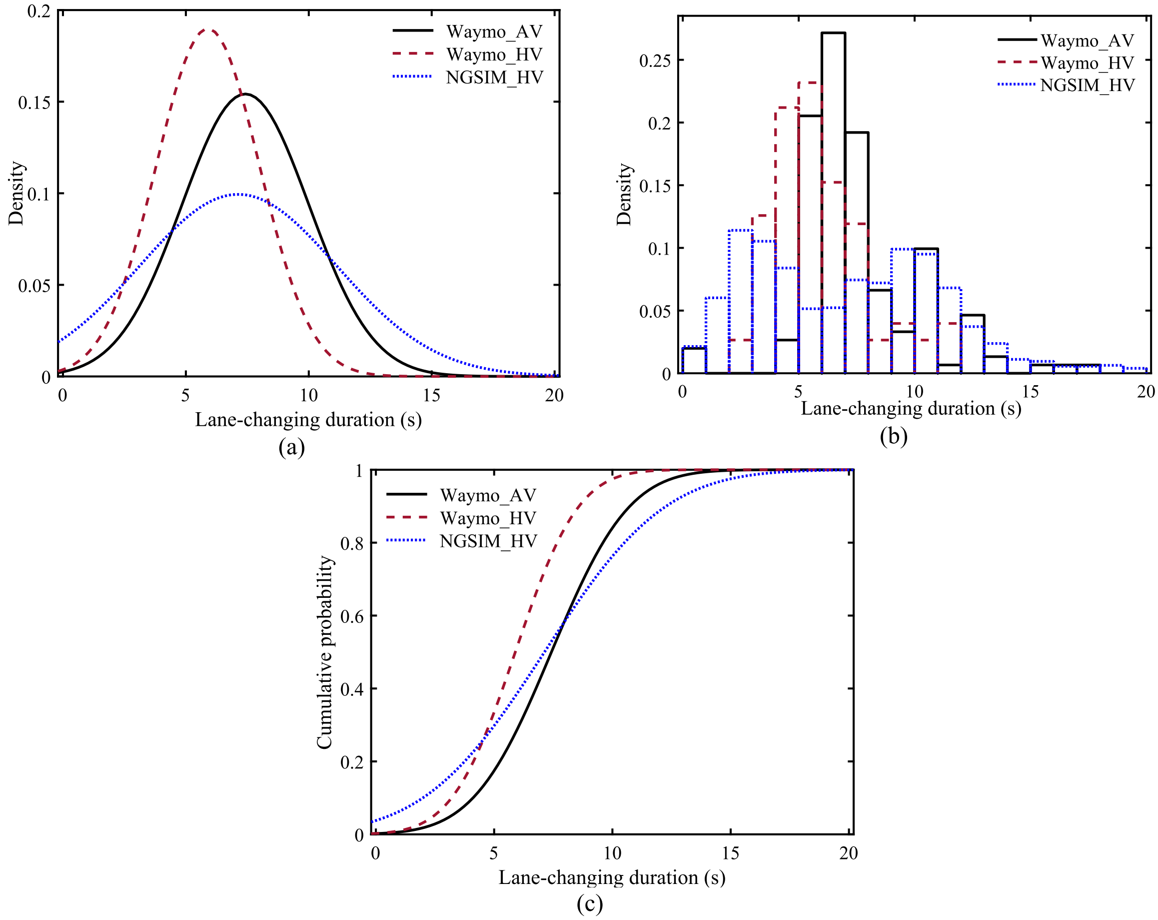

Fig. 3. Comparison of lane-changing durations across different vehicle classes. **Legend**: AV: autonomous vehicles; HV: human-driven vehicles.

respectively. It can be observed that the durations of autonomous vehicles are about 1.35 and 1.02 times longer than human-driven vehicles in Waymo and NGSIM datasets, respectively. A comparison of means through paired *t*-tests suggests a statistically significant difference between the lane-changing durations of human-driven vehicles in the Waymo and NGSIM datasets. These results suggest that autonomous vehicles take relatively longer to complete their discretionary lane-changing manoeuvres than human-driven

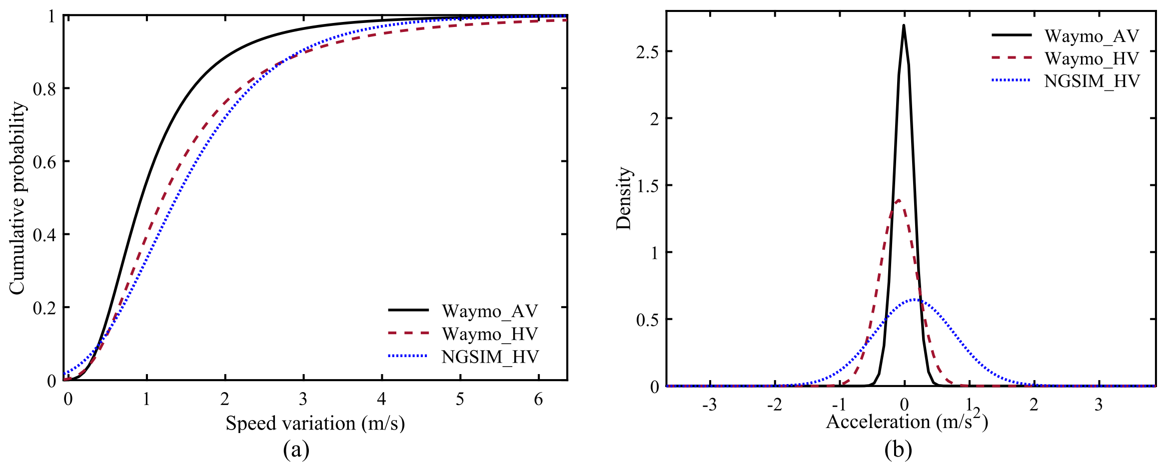

Fig. 4. Comparison of (a) speed variations and (b) accelerations across different vehicle classes. **Legend**: AV: autonomous vehicles; HV: human-driven vehicles.

vehicles.

Second, the 10th percentiles of lane-changing durations are calculated to understand shorter and risky lane-changing durations (see Fig. 3(b)). The 10th percentile for autonomous vehicles is 5.42 s, whereas the corresponding values for human-driven vehicles in the Waymo and NGSIM datasets are 3.7 s and 2.3 s, respectively. This finding sheds light on the presence of relatively riskier lane-changing execution of human-driven vehicles — we further discuss this finding in more detail in the next section.

Third, speed variations — calculated as the standard deviation of speed — are computed during the lane-changing execution period and are shown in Fig. 4(a). Speed variations are reported as a measure of risky driving conditions and have been linked to crash frequency in the literature (Zheng, 2012). In the context of this study, speed variations inform about whether lane-changing executions are risky or safe for different vehicle types. To this end, Fig. 4(a) indicates that speed variations in human-driven vehicles (Waymo and NGSIM) are relatively larger than in autonomous vehicles, reflecting the risky lane-changing execution of human-driven vehicles. This finding is further confirmed using two-sample Kolmogorov-Smirnov tests, suggesting that the distribution of speed variations of autonomous vehicles and human-driven vehicles (Waymo and NGSIM) are not the same (p-value < 0.05).

Fourth, accelerations (or decelerations) during the discretionary lane-changing execution period are measured, and results are presented in Fig. 4(b). It is evident from this figure that human-driven vehicles exhibit sparse accelerations compared to autonomous vehicles, reflecting their heterogeneous acceleration behaviour, which can be attributed to human accelerating behaviour. Contrastingly, accelerations of autonomous vehicles are relatively more homogeneous, implying more stable and safer discretionary lane-changing execution behaviour. These distributions are also tested using two-sample Kolmogorov-Smirnov tests, which indicate significant differences in acceleration patterns of different vehicle types (p-value < 0.05).

Finally, acceleration variation — computed as the standard deviation of acceleration —is calculated during the discretionary lane-changing execution period. Acceleration variation has been reported as a measure of reckless driving, which is reflected by higher acceleration variation values indicating faster driving and applying sudden brakes (Jones and Potts, 1962). The mean acceleration variation for autonomous vehicles is 0.203 m/s^2, whereas the corresponding acceleration variation for human-driven vehicles in the Waymo and NGSIM datasets are 1.134 m/s^2 and 2.051 m/s^2, respectively. These results suggest that acceleration variation is about fivefold higher in human-driven vehicles, reflecting risky discretionary lane-changing execution behaviour. Paired t-tests are performed to compare means of acceleration variation for different vehicles, and results confirm statistically different acceleration variations across different vehicles (p-value < 0.05).

4.2. *Discretionary lane-changing execution modelling*

4.2.1. *Model comparison and selection*

In this study, two main modelling approaches are tested and compared for capturing heterogeneity in discretionary lane-changing execution behaviour: gamma heterogeneity and random parameters. Separate and joint models for each vehicle class (autonomous and human-driven in Waymo and NGSIM) are developed and compared. A likelihood ratio test is performed to justify whether a combined model for all vehicle classes should be preferred over separate models. The test statistics for all the vehicle classes model versus three

Table 3
Summary of estimation results of the random parameters duration models.

Parameter	AV		HV (Waymo)		HV (NGSIM)	
	Estimate (z-statistics)	exp(β)	Estimate (z-statistics)	exp(β)	Estimate (z-statistics)	exp(β)
Non-random parameters						
Constant	2.419(60.05)	—	2.055(33.84)	—	2.362(47.57)	—
Acceleration variation	−0.049 (−3.04)	0.95	−0.108 (−2.09)	0.90	−0.145 (−4.95)	0.87
Relative speed (LV – SV) in the current lane	0.0154(2.03)	1.02	−0.039(2.66)	0.96	−0.0145 (−5.39)	0.99
Relative speed (LV – SV) in the target lane	—	—	0.045(2.46)	1.05	0.069(3.09)	1.07
Gap size	—	—	—	—	0.446(3.13)	1.56
Random parameters						
Speed of SV (mean)	−0.0245 (−8.34)	0.98	−0.0163 (−5.57)	1.01	−0.105 (−2.16)	0.90
Speed of SV (SD)	0.005(4.48)	—	0.015(5.96)	—	0.227(3.34)	—
Relative speed (SV – FV) in target lane (mean)	0.0163(3.42)	1.02	−0.0146(3.15)	0.99	−0.012 (−3.87)	0.99
Relative speed (SV – FV) in target lane (SD)	0.0252(6.22)	—	0.0187(4.68)	—	0.571(2.33)	—
Scale parameter (P)	1.197(11.11)	—	2.263(14.17)	—	2.527(41.07)	—
Model statistics						
Number of observations	147		151		1263	
Log-likelihood at convergence	−291.11		−308.61		−1145.16	

SV: subject vehicle; HV: human-driven vehicle; CL: current lane; LV: lead vehicle; FV: following vehicle; TL: target lane; SD: standard deviation.

separate sub-models corresponding to each vehicle class (autonomous, human-driven in Waymo, and human-driven in NGSIM) is $\chi^2 = -2[-1761.52 - (-291.11 - 308.61 - 1145.16)] = 33.28$. With four degrees of freedom, the test statistic suggests that the null hypothesis that individual models for different vehicle classes have the same parameters can be rejected at a 95 % confidence level. Based on this finding, separate models for each vehicle class are estimated. Note that the above test statistic relates to random parameters models, and similar results were obtained for gamma heterogeneity models.

Building on this finding, to compare a Weibull gamma heterogeneity model with a random parameters model, Vuong statistics (Vuong, 1989) is applied since these models are not nested, and as such, a likelihood ratio cannot be applied. An absolute value of Vuong statistic less than the critical value (1.96) at a 95 % confidence level implies that the test does not support preferring one model over another. However, a positive value of Vuong statistic greater than 1.96 favours model 1 over model 2 and similarly, a negative value of Vuong statistic less than −1.96 favours model 2 over model 1. As an illustration, this study considers model 1 as the random parameters model for autonomous vehicles, whereas model 2 is the gamma heterogeneity model for autonomous vehicles. The comparison yields a positive value of Vuong statistic (3.19), which is greater than 1.96 (the 95 % confidence level); therefore, model 1 (the random parameters model) is preferred over model 2. Similar results were obtained for models for other vehicle classes.

For the random parameters model, the models developed in this study find two significant random parameters, for which the recent literature suggests capturing correlation that provides insights into interactive effects on lane-changing execution behaviour (Ali et al., 2021a). To this end, correlation among random parameters can be captured using the unrestrictive form of the Cholesky matrix. As such, a comparison of an uncorrelated random parameters model and a correlated random parameters model is performed herein. The log-likelihood values (degrees of freedom) of the uncorrelated random parameters and correlated random parameters models are −291.11 (8) and −299.78 (9), respectively. A likelihood ratio test statistic for comparing the uncorrelated and correlated random parameters models is $\chi^2 = -2[-299.78 - (-291.11)] = 17.34$. With one degree of freedom, the null hypothesis that both models are the same can be rejected at a 95 % confidence level (p-value < 0.05). Further, the correlation between the random parameters is found to be statistically insignificant (p-value > 0.05), as tested by the post-hoc estimation procedure mentioned in Fountas et al. (2018). As such, this study adopts an uncorrelated random parameters model.

4.2.2. Model interpretation

Table 3 provides the model estimation results of the random parameters duration models fitted to discretionary lane-changing durations for different classes of vehicles (autonomous vehicles, human-driven vehicles in the Waymo open dataset, and human-driven vehicles in the NGSIM dataset). Several models were developed, and the parsimonious models for each vehicle class are presented in Table 3 where all parameters are statistically significant at a 95 % confidence level.

The model's scale (or Weibull) parameters (P) for autonomous vehicles, human-driven vehicles in Waymo, and NGSIM are 1.197, 2.263, and 2.527, respectively. A t-test on the scale parameter suggests that it is significantly greater than one, indicating an increasing hazard function implying that the discretionary lane-changing completion probability increased over time. Further, all three models comprise both random and non-random parameters, whereby the latter represents a different set of non-random parameters across three models, and the former contains consistent random parameters across three models, allowing a comparison of the heterogeneous impact of explanatory variables on discretionary lane-changing execution behaviour. Several distributions are tested for the random parameters, such as normal, lognormal, Weibull, uniform, and triangular, but the normal distribution provides a relatively superior model fit compared to its counterparts, which is consistent with past literature (Ali et al., 2021b, Mannering et al., 2016). The common non-random parameters in the three models are acceleration variation and relative speed in the current lane, whereas the models for human-driven vehicles in the Waymo and NGSIM datasets contain additional parameters, which are the relative speed of the leader in the current lane to the subject vehicle and available gap size in the target lane.

To develop insights into the effects of the explanatory variables on the survival time of discretionary lane-changing completion, the exponent of each coefficient $[(1 - \exp(\beta)) \times 100]$ is computed, indicating a *per cent* change in survival time corresponding to a unit increase in the continuous variable and a change from zero to one for categorical variables (Washington et al., 2020). Ensuing paragraphs first discuss the effect of variables with non-random parameters followed by those with random parameters.

Acceleration variation — measured as the standard deviation of acceleration/deceleration before lane-changing execution — is found to be significant and negatively associated with lane-changing execution durations across three models. A negative relationship between acceleration variation with lane-changing execution duration suggests that an increase in acceleration variation is likely to lead to shorter lane-changing execution durations. Whilst this relationship is found to be consistent across all models, its effect (in terms of magnitude) on lane-changing execution durations appears to vary across different models. For instance, with every one m/s^2 increase in the acceleration variation, lane-changing execution durations tend to decrease by 5 %, 10 %, and 13 % for autonomous vehicles, human-driven vehicles in Waymo, and in NGSIM, respectively. This finding indicates a relatively risky lane-changing execution behaviour of human-driven vehicles compared to autonomous vehicles, which could be partly attributed to erratic and heterogeneous human behaviour. However, this finding does not discount the fact that risky lane-changing execution exists in autonomous vehicles as well, but to a lesser extent than in human-driven vehicles.

The relative speed parameter — measured as the speed difference between the leader in the current lane and the subject vehicle's speed — is significant in all the models but shows a different relationship for autonomous and human-driven vehicles. For autonomous vehicles, the model reveals a positive relationship, implying that with an increase in relative speed (meaning that the leader is moving faster than the autonomous vehicle), discretionary lane-changing durations are likely to increase (more specifically, a 2 % increase with every one m/s increase in relative speed). Contrastingly, a negative relationship for human-driven vehicles is found, implying that discretionary lane-changing durations are shorter despite the leader moving faster than the subject driver. Since a higher relative speed can be a proxy of more space between the leader and subject driver in the current lane, there is no urgency of lane-changing and lower rear-end collision risk in the current lane that could force drivers to complete discretionary lane-changing manoeuvres quickly. As such, this finding may reflect aggressive discretionary lane-changing execution of human drivers, particularly in forced lane-change situations where the followers do not cooperate during the lane-changing decision-making process.

Two variables (relative speed of the leader in the current lane to the subject driver and available gap size in the target lane) are found to be significant in the human-driven vehicles models, whereas no statistically significant relationship is found in the autonomous vehicle's model, perhaps because of small sample size. A direct relationship of gap size indicates that discretionary lane-changing execution durations increase with an increase in gap size in the target lane, which is intuitive because of no urgency of completing lane-changing. The relative speed (subject vehicle to the following vehicle in the target lane) parameter can be interpreted in the same way.

For random parameters, it has been found the speed of lane-changing (or subject) vehicles (autonomous and human-driven vehicles) and the relative speed of the subject vehicle with the following vehicle in the target lane are significant in all the models. Both the mean and standard deviation of the random parameter for the speed of the subject vehicle are significant in the model. It is worth noting here that the subject vehicle's speed is instantaneous, measured at the onset of discretionary lane-changing execution rather than the speed during lane-changing execution, which will lead to an endogeneity issue. Whilst the mean value of the random parameter for speed is negative in all the models, significant heterogeneity is observed across the models, and two noteworthy observations are as follows. First, with the increased speed of autonomous vehicles, discretionary lane-changing completion times decrease; however, the magnitude of the decrease is heterogeneous, as evidenced by the distribution of this parameter, see Fig. 5(a). Second, akin to autonomous vehicles, the relationship between human-driven vehicles' speed is negative. However, significant heterogeneity is observed in these parameters, i.e., about 14 % (Fig. 5(b)) and 32 % (Fig. 5(c)) of coefficients are actually positive. This finding indicates that the discretionary lane-changing completion time may not always decrease with an increase in speed. This heterogeneity can be explained by the fact that during the discretionary lane-changing execution process, drivers continuously adjust their speed with respect to other drivers in the target lane (leader and follower) and may exhibit speed fluctuations, leading to longer lane-changing durations.

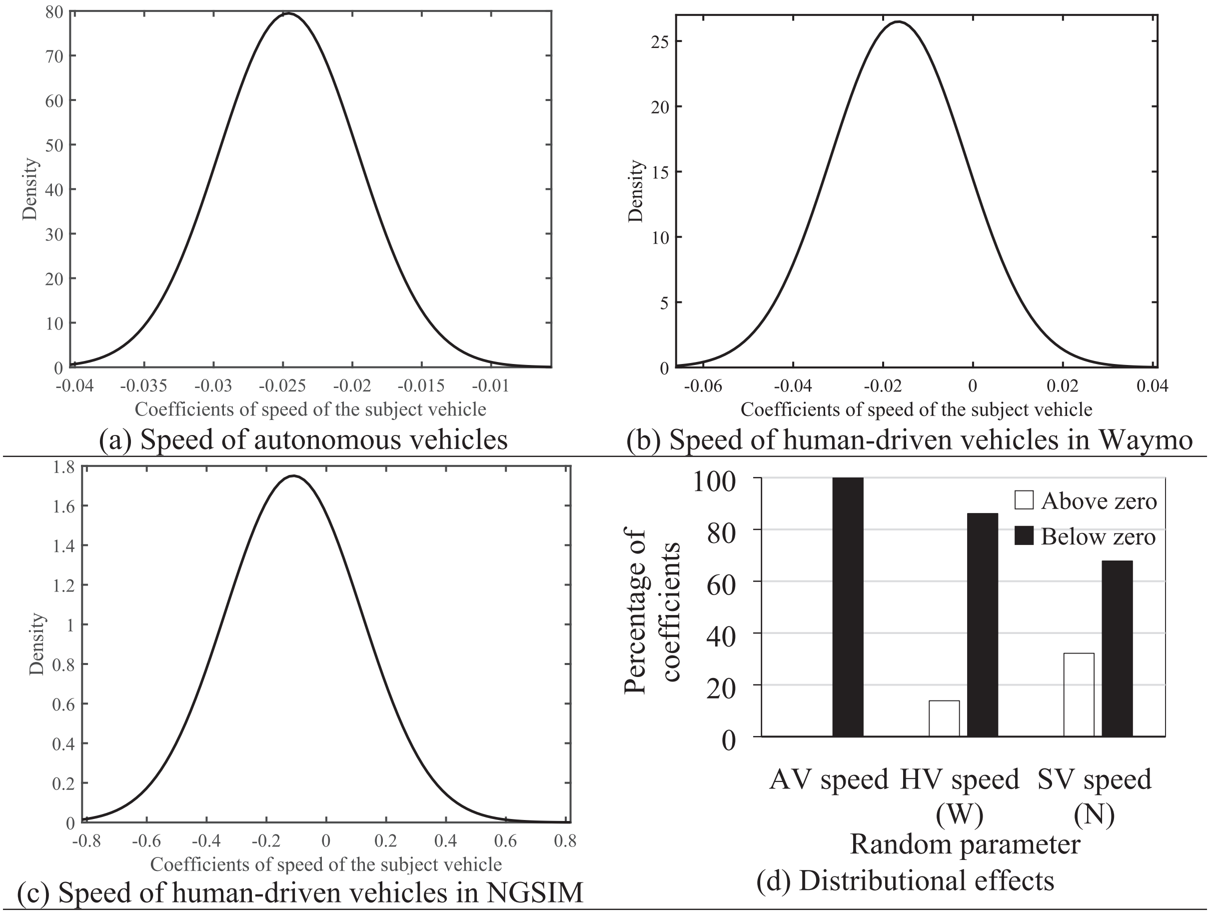

Fig. 5. Schematics of distributions of random parameters and distributional effects. **Abbreviations:** AV: autonomous vehicle; HV: human driven vehicle; W: Waymo; N: NGSIM.

Another significant random parameter in all the models is the relative speed of the subject vehicle to its following vehicle in the target lane. Interestingly, the sign conventions for the mean of the random parameter changes for autonomous and human-driven vehicles are positive and negative, respectively. A negative (positive) relationship indicates that with an increase in the relative speed (meaning that the subject vehicle is moving faster than the following vehicle), the discretionary lane-changing completion time increases (decreases) for autonomous vehicles (human-driven vehicles). When the subject vehicle moves faster than the following vehicle, the risk/urgency of completing the lane-changing manoeuvre is low, leading to a longer discretionary lane-changing completion time of autonomous vehicles. Contrastingly, although the following vehicle is moving slower than the subject vehicle, human drivers often complete their lane-changing manoeuvres quickly to avoid any safety–critical event that may arise due to prevailing traffic conditions. Significant heterogeneity can be observed from the distributional effects of the relative speed random parameter, suggesting that the discretionary lane-changing completion time may increase or decrease. For instance, it increases with an increase in the relative speed for most autonomous vehicles (74.11 %), but necessarily for all, whereas it decreases with an increase in the relative speed for most human-driven vehicles (78.25 % in Waymo and 51.84 % in NGSIM), but not for all.

As mentioned in Section 3.3, one of the advantages of hazard-based duration models is obtaining time-varying probabilities, which can provide deeper insights into the discretionary lane-changing completion probability for different vehicle classes. Using the developed models, the survival probabilities of not completing discretionary lane-changing manoeuvres can be calculated using the survival function (Eq. (6)) and mean parameter estimates (Table 3). For instance, the survival probability at time t for autonomous vehicles (AVs) can be re-written as

$$S^{\mathrm{AVs}}(t) = exp\left(- exp(- 1.197(-2.419 - 0.049 \times 1.345 + 0.0154 \times 0.715 - 0.0245 \times 13.02 + 0.0163 \times 0.755))) \cdot t^{1.197} \right). \tag{16}$$

The resulting survival curves are displayed in Fig. 6. In general, it is evident from the figure that the probability of not completing discretionary lane-changing manoeuvres decreases as time elapses. Fig. 6 shows that autonomous vehicles take longer to complete their discretionary lane-changing manoeuvres than human-driven vehicles. For instance, the survival probability of not completing discretionary lane-changing manoeuvres for autonomous vehicles at 0.5 s is 71 %, whereas, the corresponding probabilities for human-driven vehicles in the Waymo and NGSIM datasets are respectively 81 % and 84 %. Interestingly, at 1 s, these vehicle classes reveal similar probabilities of not completing discretionary lane-changing manoeuvres, reflecting some similarities in discretionary lane-changing execution behaviour of autonomous and human-driven vehicles.

From Fig. 6, it can be deduced that the discretionary lane-changing completion time for autonomous vehicles is about 3 s, whereas the corresponding times for human-driven vehicles in the Waymo and NGSIM datasets are 2.1 s and 2 s, respectively. Results indicate that the probability of not completing discretionary lane-changing manoeuvres increases for human-driven vehicles compared to autonomous vehicles. As noted in the literature (Ali et al., 2021b), increased time for completing discretionary a lane-changing manoeuvre of autonomous vehicles reflects smooth and safe manoeuvring, whereas shorter lane-changing completion time of human-driven vehicles indicates sudden/abrupt movements, which could be risky and lead to safety–critical events.

5. Discussion

5.1. Comparison of discretionary lane-changing execution behaviour of different vehicle classes

This study focusses on understanding the discretionary lane-changing execution behaviour of autonomous vehicles (Level 4) and compares its behaviour with other vehicle classes, that are, human-driven vehicles with no information supply (or conventional vehicles) and human-driven vehicles with information assistance (or connected vehicles). Autonomous vehicle trajectories are extracted using the freely available Waymo dataset, whereas human-driven vehicle trajectories are extracted from the same Waymo dataset and NGSIM dataset. For connected vehicles, trajectories from a driving simulator experiment are obtained (Ali et al., 2020a).

The comparative analysis[4] of discretionary lane-changing execution behaviour of different classes reveals different mean discretionary lane-changing durations for autonomous vehicles (7.5 s), connected vehicles (8.4 s), and human-driven vehicles in Waymo (5.8 s). The discretionary lane-changing completion time appears to be shorter for human-driven whereas longer for connected vehicles, implying the impact of information supply on the discretionary lane-changing competition time. We conjecture that the shorter discretionary lane-changing completion time of human-driven vehicles with no information supply can be attributed to their risky driving and consequent aggressive behaviour, as drivers of these vehicles have little to no information on whether the following driver will cooperate for lane-changing and whether such cooperation will remain for the entire lane-changing execution period. As such, drivers tend to quickly complete their manoeuvre, which often comes at the cost of exhibiting higher acceleration or jerky behaviour, leading to creating traffic disturbance and deteriorating safety. Contrastingly, when drivers are assisted with information about their surrounding traffic, their lane-changing completion time increases as drivers are aware of available gap size and actions of the following vehicles, leading to smoother and safer lane-changing manoeuvring. A notable aspect of these two vehicle classes is the presence of human drivers who make decisions either in the presence of information or not, leading to uncertainty and impreciseness, which may result in safety–critical events.

[4] It is worth mentioning here that we realise that several differences exist in comparing discretionary lane-changing execution behaviour, e.g., difference in driving in real life (where Waymo data were collected) and driving simulator experiment, which is a controlled environment. However, despite these differences and considering heterogeneity exist in these datasets, a comparison of discretionary lane-changing durations is performed to provide insights into safer/risky lane-changing execution.

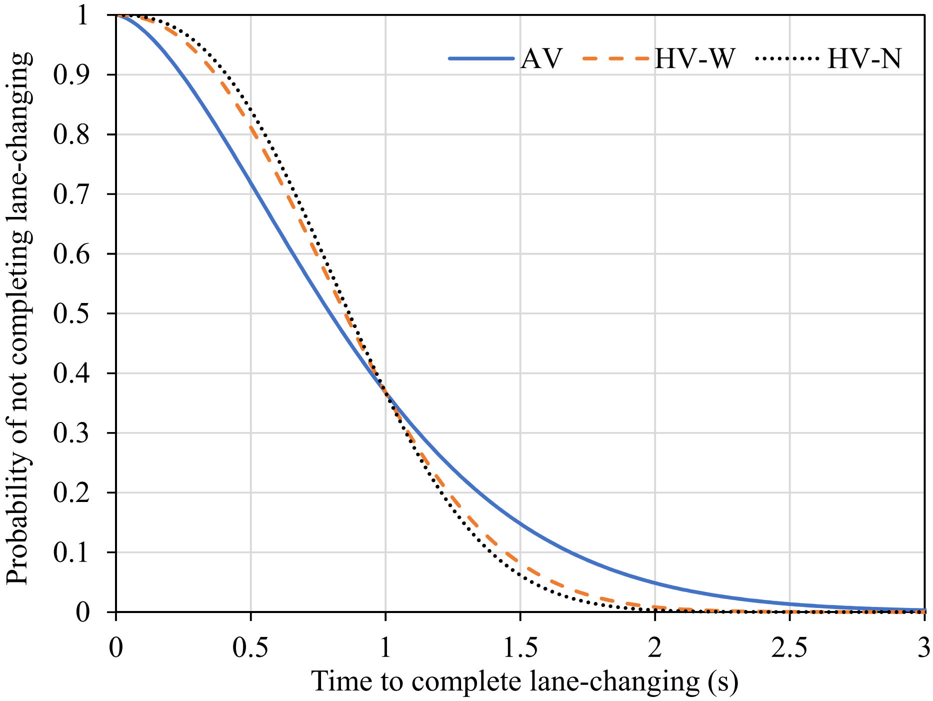

Fig. 6. Survival probability of discretionary lane-changing completion across different vehicle classes. **Abbreviations:** AV: autonomous vehicle; HV-W: human-driven vehicle in the Waymo open dataset; HV-N: human-driven vehicle in the NGSIM dataset.

Interestingly, the discretionary lane-changing completion time of autonomous vehicles is longer than human-driven vehicles but shorter than connected vehicles, suggesting relatively safer lane-changing execution compared to human-driven vehicles with no information supply. The minimum discretionary lane-changing completion time of autonomous vehicles (i.e., 4.5 s) suggests that these vehicles only perform lane-changing when sufficient time is available with significantly lower collision risk. It is expected that autonomous vehicles (Level 4) behave more conservatively than human-driven vehicles without connectivity, out of the liability concern. It is surprising, however, that the lane-changing execution time for connected vehicles is even longer than autonomous vehicles (Level 4), which might be because autonomous vehicles (Level 4) tend to avoid being too sluggish. Some differences might be attributed to the different environment setups (naturalistic for autonomous vehicles and simulator experiments for connected vehicles). Future research is needed to further confirm the difference and investigate the causes.

Note that, the lane-changing episodes in the Waymo dataset represent no congestion or light-to-moderate congestion and very rare heavy congestion. It is, however, unknown whether the difference in lane-changing execution behaviours between different vehicle classes will still hold in heavy congestion. Previous research found smaller gaps exist during heavy traffic conditions and some past studies reveal a direct relation of lane-changing durations to available gap sizes in the target lane (Ali et al., 2021b), implying that with smaller gap sizes, lane-changing durations become shorter. Therefore, future research is needed to study autonomous vehicle's lane-changing behaviours in heavy traffic. For example, to see whether autonomous vehicles will select smaller gap sizes in the target lane. If so, will autonomous vehicles perform risky/abrupt lane-changing manoeuvring?.

Further, this study found that autonomous vehicles take longer than human-driven vehicles. Clearly, a longer duration significantly impacts traffic flow efficiency as physical lane change manoeuvring creates disturbances in the current and target lanes (Ali et al., 2020b). From our findings, it can be deduced that higher safety margins during discretionary lane-changing execution may come at the cost of decelerating the following vehicles in both lanes for a relatively long time, which may create stop-and-go oscillations (Zheng et al., 2011). Since this study only evaluated the discretionary lane-changing execution behaviour of autonomous vehicles, its consequent impact on surrounding traffic (e.g., capacity drops) has not been explored and left for future research. Meanwhile, some preliminary evidence on autonomous vehicles' impact during car-following has recently been presented; for example, the proportion of string unstable behaviour of autonomous vehicles is less than that of human-driven vehicles (Hu et al., 2023). Similar analyses can be performed to ascertain the effects of discretionary lane-changing execution on surrounding traffic and compare such effects across different vehicle classes.

5.2. *Impact of autonomous vehicle's different lane-changing execution behaviours*

In the literature, the importance of lane-changing execution has not been fully recognised despite several studies reporting its significant impact on surrounding traffic in congested traffic conditions (Moridpour et al., 2010). In microsimulation tools, lane-changing execution is rather over-simplified and considered an instantaneous event, which contrasts several findings of several studies that lane-changing execution duration varies between 0.7 s and 21.6 s (see Table 1 for more information). The results on autonomous vehicle lane-changing execution suggest that the execution process should not be neglected, especially with the presence of autonomous vehicles because of its noteworthy impacts on several aspects. For instance, one of the impacts is on traffic flow throughput. Per capacity drop theory (Jin et al., 2015, Laval et al., 2007), in the process of a vehicle changing from one lane to another, the vehicle “virtually” occupies double lanes, which leads to a capacity drop. This phenomenon suggests that autonomous vehicle’s lane-changing will produce a larger capacity drop. Another impact is on traffic flow stability. As shown by the literature, a lane-changing manoeuvre consists of deceleration/acceleration patterns, which impose disturbance that can propagate to upstream vehicles and get exacerbated. Autonomous vehicle’s longer lane-changing execution could imply a larger disturbance. Of course, the disturbance magnitude also depends on the magnitude of deceleration and acceleration. As such, future research is needed to further quantify such magnitude of disturbance and compare with human-driven vehicles.

Another impact pertains to safety. Presumably, a vehicle is exposed to higher collision risk during the lane-changing execution process, and the risk accumulated is larger if the process is longer. Thus, on the one hand, autonomous vehicles tend to select a larger gap, which implies a smaller risk. On the other hand, its longer execution is associated with higher risk. It is yet to be seen the net safety level compared to human-driven vehicles. An investigation to comprehensively assess the safety risk in autonomous vehicle’s lane-changing is ongoing.

It is also interesting to note that the autonomous vehicle’s different lane-changing execution behaviours from their human counterparts may trigger unexpected behaviour in human drivers nearby. For example, the longer execution might trigger a sense of frustration in some human drivers leading to erratic behaviour and imposing safety hazards. Future research is needed to study the impacts of autonomous vehicle-human driver interaction.

5.3. Policy implications

The modelling results can have profound implications on policies and autonomous vehicle manufacturers. For instance, as longer lane-changing durations negatively impact traffic efficiency and emissions, vehicle manufacturers can modify autonomous vehicle path planning algorithms to make lane-changing manoeuvres smoother and more efficient, making autonomous vehicles less likely to disrupt the traffic flow during lane-changing. Similarly, although an insignificant relationship has been found between lane-changing durations and available gaps for autonomous vehicles, there is abundant literature suggesting that larger gaps are likely to lead to safer executions. To this end, new algorithms can be designed such that autonomous vehicles wait for a safe and suitable opening before changing lanes rather than perform a quick/abrupt lane change that requires them to accelerate and decelerate, which potentially disrupts traffic flow. As noted in this study, acceleration variation and similar other measures significantly impact lane-changing durations, promoting cooperation with autonomous vehicles can reduce the amount of acceleration and deceleration that is required when changing lanes, consequently leading to smaller vehicular emissions and safer execution.

As autonomous vehicles continue to be developed and deployed, it is critical to consider how they will co-exist and share space with human-driven vehicles. This is a complex issue, as autonomous vehicles and human-driven vehicles have different capabilities and limitations. For example, Hu et al. (2023) autonomous vehicles can perceive their surroundings more accurately in various types of stimuli than human drivers, but they may not be able to understand the intentions of human drivers as well. Also, human drivers’ decisions are driven by various human factors, such as aggressiveness, anger, and impatience. To suppress such consequences, policymakers could start initiatives like public awareness campaigns and driver education programs to help human drivers understand the capabilities and limitations of autonomous vehicles and to inform them about the infrastructural changes made to cater to the need for autonomous vehicles, such as dedicated lane change lanes. Similarly, although not tested in the study due to data limitation, some widely suggested policies based on recent literature include wider lanes, better lane markings, and dedicated lanes for lane changes. Wider lanes would give autonomous vehicles more space to change lanes safely, and better lane markings would make it easier for autonomous vehicles to detect where they are allowed to change lanes (Formosa et al., 2024). Dedicated lane-changing lanes would also enable autonomous vehicles to change lanes without disrupting traffic flow in the other lanes (Sha et al., 2024).

6. Conclusions and future research directions

This study investigated the lane-changing execution behaviour of Level 4 autonomous vehicles using the publicly available Waymo open dataset. Using the lateral movement profile, discretionary lane-changing execution behaviour was investigated. The lane-changing start point and thereby lane-changing durations were computed using a wavelet-based local maxima lines method. Data from Waymo and NGSIM were also obtained and similarly processed to compare autonomous vehicles’ behaviour with human-driven vehicles. Descriptive analyses were performed for different driving behavioural factors and a hazard-based duration model was developed to relate the discretionary lane-changing completion time with its determinants. Whilst the existence of heterogeneity is well-known in human-driven vehicles, we conjectured the existence of heterogeneity in autonomous vehicles as well. As such, two methodologies for incorporating heterogeneity were applied, namely, gamma heterogeneity and random parameters approaches, to capture unobserved heterogeneity.

Descriptive analyses revealed that discretionary lane-changing execution durations are longer for autonomous vehicles compared to human-driven vehicles, indicating gradual manoeuvring of autonomous vehicles, thereby exhibiting safer lane-changing execution behaviour. Similarly, the lead and lag gaps when lane-changing execution is performed were also larger for autonomous vehicles compared to human-driven vehicles, suggesting lower rear-end crash risk for autonomous vehicles. Larger gaps could also be a plausible reason for longer lane-changing execution durations for autonomous vehicles. Corroborating these findings, speed variations and acceleration variations revealed a relatively stable or less fluctuating behaviour of autonomous vehicles, whereas large speed variations (and acceleration variation) were associated with human-driven vehicles, reflecting their risky lane-changing execution behaviour.

To understand the factors affecting discretionary lane-changing execution across different vehicle classes, separate random parameters models were developed for autonomous vehicles and human-driven vehicles using the Waymo open dataset and the NGSIM dataset. Note that the random parameters models were found to be superior to gamma heterogeneity models. Whilst two random parameters were found to be significant and consistent across all the models, non-random parameters varied for different vehicle classes along with varying sign conventions. The random parameters uncovered heterogeneity associated with discretionary lane-changing execution behaviour whereby more heterogeneous behaviour is observed in human-driven vehicles than autonomous vehicles. However, our findings indicated that even when human drivers are not performing discretionary lane-changing execution in autonomous vehicles, heterogeneity still exists, which is contextual to traffic conditions, reflecting real-time decision adjustment of autonomous vehicles. However, in the case of human-driven vehicles, this heterogeneity is further exacerbated by human drivers making decisions, thereby creating more uncertainty.

Finally, we have discussed the potential implications of autonomous vehicle's lane-changing execution on traffic flow throughput, stability, safety, and autonomous vehicle-human interactions. Specifically, autonomous vehicle's longer execution can lead to a larger capacity drop and can impose a stronger disturbance to traffic flow, which should be rigorously assessed.

This study can be extended in several facets. Firstly, although this study loosely classified lane changes as discretionary lane-changing due to short scenarios (20 s long), tracking an autonomous vehicle for mandatory lane-changing becomes difficult, and as such, mandatory lane-changing is not analysed. Secondly, we have pointed out the potential implications of autonomous vehicles on a set of issues pertaining to traffic flow throughput, stability and safety, whereas further research is needed to further investigate and quantify these issues. Thirdly, the lane-changing episodes have very rare heavy condition cases, and as such, more research is required to investigate whether the observations found herein still hold in heavy congestion. Last but not least, the results pertain to only one autonomous vehicle manufacturer, whereas it will be interesting to see whether autonomous vehicles from other manufacturers display similar behaviour features/behaviours.

CRediT authorship contribution statement

Yasir Ali: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Anshuman Sharma:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Danjue Chen:** Writing – review & editing, Methodology, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The Waymo open dataset is utilised, which can be found on the Waymo website (https://waymo.com/open/)

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References

Ahn, S., Cassidy, M., 2007. Freeway traffic oscillations and vehicle lane-change maneuvers. In: Proceedings of the 17th International Symposium on Transportation and Traffic Theory, pp. 691–710.

Ali, Y., 2020. Investigation of Lane-Changing Behaviour in a Connected Environment Ph.D. The University of Queensland.

Ali, Y., Zheng, Z., Haque, M., 2018. Connectivity's impact on mandatory lane-changing behaviour: Evidences from a driving simulator study. Transportation Research Part C 93, 292–309.

Ali, Y., Sharma, A., Haque, M., Zheng, Z., Saifuzzaman, M., 2020a. The impact of the connected environment on driving behavior and safety: A driving simulator study. Accident Analysis and Prevention 144, 105643.

Ali, Y., Zheng, Z., Haque, M., Yildirimoglu, M., Washington, S., 2020b. Detecting, analysing, and modelling failed lane-changing attempts in traditional and connected environments. Analytic Methods in Accident Research 28, 100138.

Ali, Y., Zheng, Z., Haque, M., Yildirimoglu, M., Washington, S., 2020c. Understanding the discretionary lane-changing behaviour in the connected environment. Accident Analysis and Prevention 137, 105463.

Ali, Y., Haque, M., Zheng, Z., Bliemer, M., 2021a. Stop or go decisions at the onset of yellow light in a connected environment: A hybrid approach of decision tree and panel mixed logit model. Analytic Methods in Accident Research 31, 100165.

Ali, Y., Zheng, Z., Haque, M., 2021b. Modelling lane-changing execution behaviour in a connected environment: A grouped random parameters with heterogeneity-in-means approach. Communications in Transportation Research 1, 100009.

Ali, Y., Zheng, Z., Haque, M., Yildirimoglu, M., Washington, S., 2021c. CLACD: A complete LAne-Changing decision modeling framework for the connected and traditional environments. Transportation Research Part C 128, 103162.

Ali, Y., Raadsen, M., Bliemer, M., 2023. Modelling speed reduction behaviour on variable speed limit-controlled highways considering surrounding traffic pressure: A random parameters duration modelling approach. Analytic Methods in Accident Research 40, 100290.
Ataelmanan, H., Puan, O., Hassan, S. Examination of lane changing duration time on expressway. IOP Conference Series: Materials Science and Engineering, 2021. IOP Publishing, 012078.
Balusu, S., Mannering, F., Pinjari, A., 2020. Hazard-based duration analysis of the time between motorcyclists' initial training and their first crash. Analytic Methods in Accident Research 28, 100143.
Bham, G., 2009. Estimating driver mandatory lane change behavior on a multi lane freeway. In: 88th Annual Meeting of the Transportation Research Board, Washington, DC, pp. 1–22.
Bhat, C., 2003. Simulation estimation of mixed discrete choice models using randomized and scrambled Halton sequences. Transportation Research Part B 37 (9), 837–855.
Caesar, H., Bankiti, V., Lang, A., Vora, S., Liong, V., Xu, Q., Krishnan, A., Pan, Y., Baldan, G., Beijbom, O.N., 2020. A multimodal dataset for autonomous driving. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 11621–11631.
Cao, X., Young, W., Sarvi, M., Kim, I., 2016. Study of mandatory lane change execution behavior model for heavy vehicles and passenger cars. Transportation Research Record 2561, 73–80.
Cassidy, M., Rudjanakanoknad, J., 2005. Increasing the capacity of an isolated merge by metering its on-ramp. Transportation Research Part B 39 (10), 896–913.
Chang, M.-F., Lambert, J., Sangkloy, P., Singh, J., Bak, S., Hartnett, A., Wang, D., Carr, P., Lucey, S., Ramanan, D.A., 2019. 3d tracking and forecasting with rich maps. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 8748–8757.
Chovan, J., Tijerina, L., Alexander, G. and Hendricks, D. 1994. Examination of lane change crashes and potential IVHS countermeasures. Final Report.
DTMR. 2020. *Summary Road Crash Report, Queensland Road Fatalities* [Online]. Customer Services, Safety & Regulation Division, Department of Transport and Main Roads, Brisbane, Australia: Queensland Transport. Available: https://cars.tmr.qld.gov.au/Static/documents/RoadCrashReport/Weekly/WeeklyReport_Latest.pdf [Accessed 7 August 2022].
FHWA. 2007. *Research Data Exchange, Lankershim Boulevard Dataset* [Online]. Available: https://www.fhwa.dot.gov/publications/research/operations/07029/index.cfm [Accessed 12-02-2023].
Finnegan, P., Green, P., 1990. Time to Change Lanes: A Literature Review. IVHS Technical Report-90-13. The University of Michigan, Transportation Research Institute, Ann Arbor, Michigan.
Formosa, N., Quddus, M., Man, C., Singh, M., Morton, C., Masera, C., 2024. Evaluating the impact of lane marking quality on the operation of autonomous vehicles. Journal of Transportation Engineering, Part A 150 (1), 04023126.
Fountas, G., Anastasopoulos, P., Abdel-Aty, M., 2018. Analysis of accident injury-severities using a correlated random parameters ordered probit approach with time variant covariates. Analytic Methods in Accident Research 18, 57–68.
Goswami, V., Bham, G., 2007. Gap acceptance behavior in mandatory lane changes under congested and uncongested traffic on a multilane freeway. 86th Annual Meeting of the Transportation Research Board, Washington, DC.
Guériau, M., Billot, R., El Faouzi, N.-E., Monteil, J., Armetta, F., Hassas, S., 2016. How to assess the benefits of connected vehicles? A simulation framework for the design of cooperative traffic management strategies. Transportation Research Part C 67, 266–279.
Hanowski, R., 2000. The Impact of Local/Short Haul Operations on Driver Fatigue. PhD Dissertation. Virginia Polytechnic Institute and State University.
Hetrick, S., 1997. Examination of Driver Lane Change Behavior and The Potential Effectiveness of Warning Onset Rules for Lane Change or" Side" Crash Avoidance Systems. Master of Science. Virginia Polytechnic Institute and State University.
Hu, X., Zheng, Z., Chen, D., Zhang, X., Sun, J., 2022. Processing, assessing, and enhancing the Waymo autonomous vehicle open dataset for driving behavior research. Transportation Research Part C 134, 103490.
Hu, X., Zheng, Z., Chen, D., Sun, J., 2023. Autonomous vehicle's impact on traffic: empirical evidence from Waymo open dataset and implications from modelling. IEEE Transactions on Intelligent Transportation Systems 24 (6), 6711–6724.
Hui, W., 1990. Proportional Hazard Weibull Mixtures. Working Paper. Department of Economics, Australian National University, Canberra.
Jin, W.-L., Gan, Q.-J., Lebacque, J.-P., 2015. A kinematic wave theory of capacity drop. Transportation Research Part B 81, 316–329.
Jones, T., Potts, R., 1962. The measurement of acceleration noise—A traffic parameter. Operations Research 10 (6), 745–763.
Kesten, R., Usman, M., Houston, J., Pandya, T., Nadhamuni, K., Ferreira, A., Yuan, M., Low, B., Jain, A., Ondruska, P. 2019. *Lyft level 5 AV dataset* [Online]. Available: https://apera.io/a/tech/561428/lyft-level-5-dataset [Accessed 15 September 2023].
Laval, J., Cassidy, M., Daganzo, C., 2007. Impacts of lane changes at merge bottlenecks: a theory and strategies to maximize capacity. In: Traffic and Granular Flow'05, 2007. Springer, pp. 577–586.
Lee, S., Olsen, E., Wierwille, W., 2004. A Comprehensive Examination of Naturalistic Lane-Changes. National Highway Traffic Safety Administration, United States.
Li, G., Yang, Z., Pan, Y., Ma, J., 2022. Analysing and modelling of discretionary lane change duration considering driver heterogeneity. Transportmetrica B 1–18.
Mallat, S., Hwang, W.L., 1992. Singularity detection and processing with wavelets. IEEE Transactions on Information Theory 38 (2), 617–643.
Mannering, F., Shankar, V., Bhat, C., 2016. Unobserved heterogeneity and the statistical analysis of highway accident data. Analytic Methods in Accident Research 11, 1–16.
Marczak, F., Daamen, W., Buisson, C., 2013. Merging behaviour: Empirical comparison between two sites and new theory development. Transportation Research Part C 36, 530–546.
Moridpour, S., Sarvi, M., Rose, G., 2010. Modeling the lane-changing execution of multiclass vehicles under heavy traffic conditions. Transportation Research Record 2161, 11–19.
Nam, D., Mannering, F., 2000. An exploratory hazard-based analysis of highway incident duration. Transportation Research Part A 34 (2), 85–102.
NHTSA. 2020. *Crashes, by First Harmful Event, Manner of Collision, and Crash Severity* [Online]. Washington, D.C. Available: https://cdan.nhtsa.gov/SASStoredProcess/guest [Accessed 12 December 2022].
Nilsson, P., Laine, L., Jacobson, B., 2017. A simulator study comparing characteristics of manual and automated driving during lane changes of long combination vehicles. IEEE Transactions on Intelligent Transportation Systems 18 (9), 2514–2524.
Reina, P., Ahn, S., 2015. On macroscopic freeway merge behavior: Estimation of merge ratios using asymmetric lane flow distribution. Transportation Research Part C 60, 24–35.
Rice, E., 2010. Access Management in the Vicinity of Intersections. Federal Highway Administration, Report No. FHWA-SA-10-002.
Salvucci, D., Liu, A., 2002. The time course of a lane change: Driver control and eye-movement behavior. Transportation Research Part F 5 (2), 123–132.
Sha, H., Singh, M., Haouari, R., Papazikou, E., Quddus, M., Quigley, C., Chaudhry, A., Thomas, P., Weijermars, W., Morris, A., 2024. Network-wide safety impacts of dedicated lanes for connected and autonomous vehicles. Accident Analysis and Prevention 195, 107424.
Sharma, A., Ali, Y., Saifuzzaman, M., Zheng, Z., Haque, M., 2018. Human factors in modelling mixed traffic of traditional, connected, and automated vehicles. In: Advances in Human Factors in Simulation and Modeling: Proceedings of the AHFE 2017 International Conference on Human Factors in Simulation and Modeling, July 17–21, 2017, The Westin Bonaventure Hotel, Los Angeles, California, USA. Springer, pp. 262–273.
Sun, P., Kretzschmar, H., Dotiwalla, X., Chouard, A., Patnaik, V., Tsui, P., Guo, J., Zhou, Y., Chai, Y., Caine, B., 2020. Scalability in perception for autonomous driving: Waymo open dataset. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 2446–2454.
TfNSW. 2020. *Centre for road safety* [Online]. Available: https://roadsafety.transport.nsw.gov.au/statistics/interactivecrashstats/nsw.html?tabnsw=2 [Accessed 7 August 2022].
Tijerina, L., Garrott, W., Glecker, M., Stoltzfus, D., Parmer, E., 1997. Van and Passenger Car Driver Eye Glance Behavior During Lane Change Decision Phase. Interim Report. Transportation Research Center Report, National Highway Transportation Safety Administration, Washington DC.
Toledo, T., Koutsopoulos, H., Ben-Akiva, M., 2003. Modeling integrated lane-changing behavior. Transportation Research Record 1857, 30–38.
Toledo, T., Choudhury, C., Ben-Akiva, M., 2005. Lane-changing model with explicit target lane choice. Transportation Research Record 1934, 157–165.
Toledo, T., Zohar, D., 2007. Modeling duration of lane changes. Transportation Research Record 1999, 71–78.

Vuong, Q., 1989. Likelihood ratio tests for model selection and non-nested hypotheses. Econometrica 307–333.
Washington, S., Karlaftis, M., Mannering, F., Anastasopoulos, P., 2020. Statistical and econometric methods for transportation data analysis. Chapman and Hall/CRC.
Waymo. 2023. *Waymo Open Dataset* [Online]. Available: https://waymo.com/open/ [Accessed 20 September 2023].
Wen, X., Cui, Z., Jian, S., 2022. Characterizing car-following behaviors of human drivers when following automated vehicles using the real-world dataset. Accident Analysis and Prevention 172, 106689.
Wiedemann, R., Reiter, U., 1992. Microscopic Traffic Simulation: The Simulation System MISSION, Background and Actual State. CEC Project ICARUS (V1052), Final Report.
Worrall, R., Bullen, A., 1970. An empirical analysis of lane changing on multilane highways. Highway Research Record 303.
Yang, M., Wang, X., Quddus, M., 2019. Examining lane change gap acceptance, duration and impact using naturalistic driving data. Transportation Research Part C 104, 317–331.
Yu, F., Chen, H., Wang, X., Xian, W., Chen, Y., Liu, F., Madhavan, V., Darrell, T., 2020. Bdd100k: A diverse driving dataset for heterogeneous multitask learning. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 2636–2645.
Yuan, J., Abdel-Aty, M., 2018. Approach-level real-time crash risk analysis for signalized intersections. Accident Analysis and Prevention 119, 274–289.
Yuan, J., Abdel-Aty, M., Cai, Q., Lee, J., 2019. Investigating drivers' mandatory lane change behavior on the weaving section of freeway with managed lanes: A driving simulator study. Transportation Research Part F 62, 11–32.
Zhao, D., Peng, H., Nobukawa, K., Bao, S., Leblanc, D., Pan, C. 2017. Analysis of mandatory and discretionary lane change behaviors for heavy trucks. *arXiv preprint arXiv:1707.09411*.
Zheng, Z., 2012. Empirical analysis on relationship between traffic conditions and crash occurrences. Procedia-Social and Behavioral Sciences 43, 302–312.
Zheng, Z., 2014. Recent developments and research needs in modeling lane changing. Transportation Research Part B 60, 16–32.
Zheng, Z., Ahn, S., Chen, D., Laval, J., 2011. Freeway traffic oscillations: microscopic analysis of formations and propagations using wavelet transform. Procedia-Social and Behavioral Sciences 17, 702–716.
Zheng, Z., Washington, S., 2012. On selecting an optimal wavelet for detecting singularities in traffic and vehicular data. Transportation Research Part C 25, 18–33.