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Empirical research on car-following and lane-changing: Recent developments, emerging vehicle technologies' impact, and future research needs

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ABSTRACT

A sound understanding of driving behaviour is indispensable for properly modelling and predicting traffic dynamics, and accurately evaluating its impact on efficiency, safety, energy consumption, and the environment. This understanding becomes more critical in the era of emerging vehicle technologies, which are expected to significantly influence driving behaviour. Thus, this paper reviews empirical research efforts dedicated to understanding driving behaviour. Particularly, longitudinal (car-following) and lateral (lane-changing) driving tasks for conventional, connected, and automated vehicles are reviewed. Car-following behaviour is reviewed using different characteristics, like response time, time headway, etc., whereas lane-changing behaviour is reviewed from three aspects: decision-making, execution, and impact. This paper envisions several future research directions by identifying the limitations of existing research efforts and linking them to microscopic modelling. Also, realising emerging vehicle technologies are on horizon, the current empirical research on driving behaviour related to these vehicles is thoroughly reviewed, and research needs are emphasised.

1. Introduction

Understanding driving behaviour is essential to decipher how individual drivers influence traffic flow efficiency, safety, energy consumption, and the environment. Such understanding underpins microscopic driving behaviour modelling, characterised by car-following and lane-changing, which respectively represent longitudinal and lateral interactions of vehicles in the traffic stream. This study focusses on reviewing these two primary driving tasks.

Despite progress in modelling car-following and lane-changing behaviours, many driving behaviour aspects remain ambiguous. For instance, desired speed's definition (an integral parameter in many car-following models, such as Intelligent Driver Model and Optimum Velocity models) is uncertain — is it the posted speed limit, or is it limited by the leader's speed (if available), or if other than these two, and can we quantify it using empirical data? Similarly, waiting time before merging for lane-changing significantly impacts freeway traffic but rarely receives due attention. Thus, simulation packages often ignore waiting time and remove waiting vehicles after a threshold (TSS, 2002). As such, understanding empirical research evidence on these and other driving behaviour aspects is crucial for developing better and more realistic driving behaviour models.

Recognising the importance of these fundamental driving tasks (car-following and lane changing), several reviews have been published in the literature, with the majority of them related to car-following models (e.g., Chandler et al. (1958), Hoogendoorn and Bovy (2001), Saifuzzaman and Zheng (2014), Aghabayk et al. (2015), and so on). Conversely, lane-changing has received less attention as evidenced by a relatively small number of review papers (Toledo, 2007, Moridpour et al., 2010b, Rahman et al., 2013, Zheng, 2014). Whilst all these reviews contribute to a better understanding of driving behaviour models, they share some common shortcomings. First, all these reviews, except Toledo (2007), singularly focus on car-following or lane-changing due to the depth and breadth of each topic. Second, these reviews mainly summarise microscopic models and points out relevant research challenges (e.g., see Saifuzzaman and Zheng (2014) and Zheng (2014) for car-following and lane-changing, respectively). However, these reviews lack focus on empirical research, which is essential for proper understanding of

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driving behaviour — a fundamental step for developing sound and robust models. Third, these studies consider traditional vehicles, neglecting emerging vehicle technologies' impact on driving behaviour mainly because these reviews were published prior to the recent breakthrough of such technologies (e.g., connected and automated vehicles). Yet, the absence of technology's effect review hampers the understanding of traffic flow considering connected and automated vehicles, thereby risking the applicability of traditional models.

Building on the shortcomings of the review studies cited above, the contribution of this paper is threefold. First, unlike previous reviews that focus on microscopic modelling of car following or lane-changing, this study focusses on improving our understanding on car-following and lane-changing characteristics through empirical findings, which will directly or indirectly assist in developing new or improving existing car-following and lane-changing models. It is worth reiterating that this study does not solely focus on all empirical studies, rather the focus is on car-following and lane-changing studies with empirical data/evidence. To the best of authors' knowledge, this is the first study that comprehensively reviews empirical research on two driving tasks together, which provides a complete and sound understanding of driving behaviour. Our study provides in-depth summary of these areas (e.g., driver heterogeneity) and their importance, forming a foundation for realistic microscopic driving behaviour modelling. Thus, this review with a focus on the empirical studies of driving behaviour is an important complement to the existing reviews with a focus on modelling of driving behaviour. Second, the impact of emerging vehicle technologies like connected, automated, and connected and automated vehicles on driving behaviour (empirical studies only) is thoroughly reviewed and summarised, which is largely missing in the literature. Finally, general and specific future research needs are elicited and linked to microscopic models, which will assist in developing more realistic and accurate microscopic models.

The rest of the paper is organised as follows. Section 2 provides the overall review framework, whereas Section 3 reviews major empirical research efforts. Sections 4 and 5 present future research in general and in the era of emerging vehicle technologies. Finally, Section 6 concludes this study.

2. Review framework

2.1. Literature selection

The paper presents a two-stage approach to review empirical research on driving behaviour, as shown in Fig. 1. Stage 1 involves an in-depth review of existing studies focussing on various aspects of driving behaviour, encompassing longitudinal (car-following) and lateral (lane-changing) driving interactions in different driving environments. Stage 2 builds upon the findings of Stage 1 to identify research needs in these two behaviours. The paper undertakes a thorough literature search across multiple databases using relevant keywords and Boolean operators. Fig. 2 displays the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Liberati et al., 2009) flow diagram, illustrating the number of studies obtained and included at each stage. A total of 735 studies were initially obtained, which were subsequently refined to 323 relevant studies after eliminating duplicates and unrelated papers. Note that the review is selective, focussing on representative studies rather than an exhaustive compilation. Studies purely centred on modelling, numerical simulations, or lacking consideration of human factors (more information to follow in the next section) are excluded. Ultimately, 184 studies meeting the inclusion criteria are included in the study.

2.2. Scope

The study scope is limited to reviewing the studies on car-following and lane-changing behaviours on motorways (or freeways) and arterials (sub-urban and rural roads), whereas driving behaviour at signalised intersections (e.g., responding to yellow light), mid-block sections (e.g., responding to pedestrian crossing), unsignalised intersections, and roundabouts is not considered. Moreover, this study covers representative studies on driving behaviour in the literature rather than attempting to include all the available studies exhaustively. In our review framework, "representative" refers to two aspects. First, if there were studies providing a similar outcome, e.g., similar range for reaction/response time, we have selected one study as a representative study. Second, studies from the same author(s) on the same topic (e.g., effect of heavy vehicle on lane-changing durations) using the same dataset, and

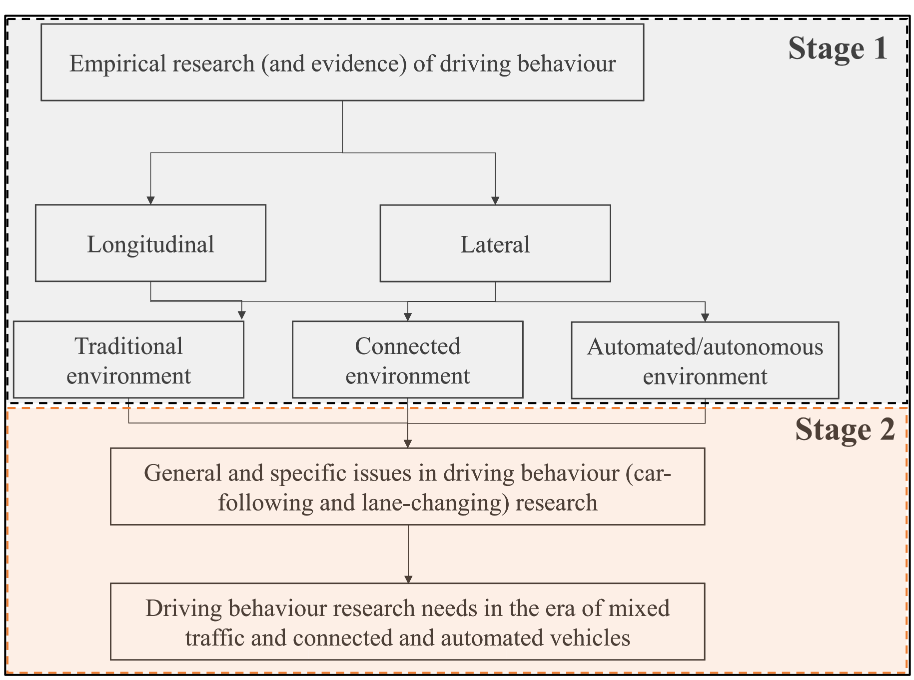


Fig. 1. The overall review framework.

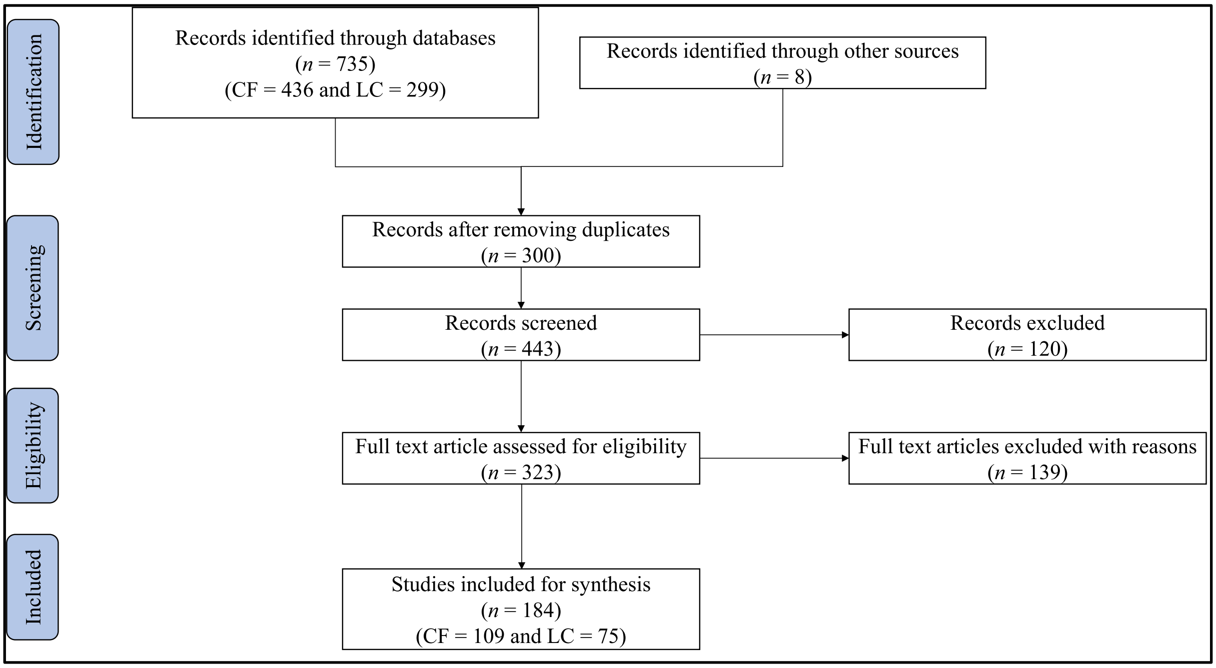


Fig. 2. PRISMA flow diagram for the systematic review. Abbreviations: CF: car-following; LC: lane-changing; *n*: number of studies.

providing similar outcomes, we have selected one study as a representative study. Finally, "representative" also implies herein that not all studies are discussed, but only a few are summarised, which are selected based on the narrative and information that they provide. Similarly, studies that purely focus on modelling car-following and lane-changing behaviours rather than understanding individual driving behaviour using empirical data are excluded. Further, studies that solely rely on numerical simulations to investigate issues related to driving behaviour — most commonly attributed to vehicle technological advancements, such as connected vehicles and automated vehicles — are not considered, primarily because of the lack of consideration of human factors, which is considered crucial in explaining and understanding driving behaviour.

Given the vastness of the topic ('empirical research on driving behaviour'), the scope of this study is further limited to research studies providing direct or indirect empirical evidence of car-following and lane-changing behaviours through real-data sources, such as naturalistic driving, test field driving, and driving simulators. For instance, studies focussing on response time estimation and modelling using different methodologies are reviewed. Similarly, studies providing insights into the relationship of car-following and lane-changing behaviours are considered, which could be descriptive in nature and/or may use mathematical modelling like duration models. Lastly, studies focussing on driving state, e.g., distracted or drivers with health conditions like attention-deficit/hyperactivity disorder are not considered as several reviews are already available for them (e.g., Papantoniou et al. (2017) and Tamm et al. (2012)). Similarly, given our study focusses on human driving behaviour, studies in connected and automated vehicles (CAVs) domain are not considered because the driver is not performing car-following and lane-changing tasks and engage only during takeover requests. Therefore, such studies provide little information about human driving behaviour useful for developing more realistic and robust microscopic models.

2.3. Bibliometric analysis

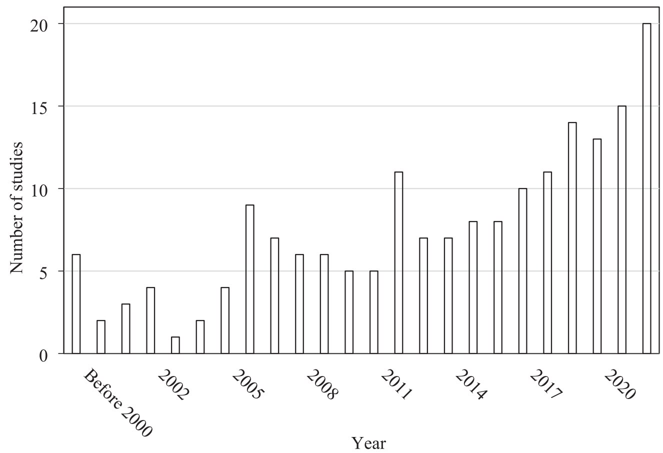
Fig. 3 presents bibliometric analysis of the selected literature, representing the publication period (Fig. 3(a)), classification of studies based on vehicle technologies (Fig. 3(b)), and sources of publications. A few observations from this analysis are as follows. Firstly, empirical studies on driving behaviour have gained prominence after 2000 s, whereby data collection and processing techniques emerged significantly. Similarly, the past decade has seen a spike in driving behaviour studies (Fig. 3(a)), which could be attributed to alternative data collection techniques, such as drones, LiDARs, and autonomous vehicles as probes. Secondly, studies predominantly focus on understanding driving behaviour for conventional (or traditional) vehicles (Fig. 3(b)) whilst some recent studies have focussed on evaluating the impact of connected vehicles (or vehicles operating in a connected environment) on driving behaviour. Finally, a close inspection of sources where studies have been published (Fig. 3(c)) suggests diversity in the journals, with a majority of studies published in traditional driving behaviour journals like 'Accident Analysis and Prevention', 'Transportation Research Parts C and F' and others.

3. A review of driving behaviour studies

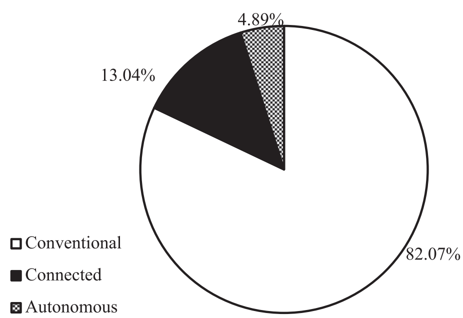
3.1. Car-following characteristics

3.1.1. Response (and reaction) time

Response time significantly impacts traffic flow characteristics and safety (Sun et al., 2020b). Different terminologies, such as response time and reaction time, are used in the literature. Scott and Gray (2008) defined response time — in the human factors literature — as the temporal difference between the instant/point when the stimulus is presented and when the driver responds. However, the same definition is called reaction time in traffic flow theory literature (Ranjitkar et al., 2003), and similarly, known with different names, such as perception response time, brake-response time, and so on in other areas. As Sharma et al. (2019) pointed out, these definitions reflect inconsistency and semantic incoherencies in the research community regarding response time and reaction time when defining the same measure, leading to developing of inadequate models. Sharma et al. (2019) clearly defined response time and reaction time as follows. The response time is defined as the time difference between the stimulus and the response by the driver with or without deliberately delaying the response. Conversely, the reaction time is defined as the time difference between the stimulus and the response without any deliberate delay by the driver. The



(a) Yearly publications trend



(b) Proportion of publications for different vehicle technologies

Journal	No. of studies	Proportion (%)
Accident Analysis and Prevention	29	15.76
Transportation Research Part C: Emerging Technologies	22	11.96
Transportation Research Part F: Traffic Psychology and Behaviour	19	10.33
Transportation Research Record	15	8.15
Journal of Transportation Engineering, Part A: Systems	8	4.35
IEEE Transactions on Intelligent Transportation Systems	5	2.72
Journal of Advanced Transportation	5	2.72
Analytic Methods in Accident Research	4	2.17
Plos one	3	1.63
Human factors	3	1.63
Transportation letters	2	1.09
IEEE Access	2	1.09
IET Intelligent Transport Systems	2	1.09
International Journal of Transportation Science and Technology	2	1.09
Journal of the Institution of Engineers	2	1.09
Operations research	1	0.54
Physica A: Statistical Mechanics and its Applications	2	1.09
Safety Science	2	1.09
Transportation in Developing Economies	2	1.09
Transportmetrica A	2	1.09
Other journals (e.g., Journal of Intelligent Transportation System, Journal of Transportation and Traffic Engineering (English Edition), and Journal of Transportation Safety & Security, Applied ergonomic, Canadian Journal of Civil Engineering, Computer-Aided Civil and Infrastructure Engineering, Ergonomics, Journal of Safety Research, and others)	34	18.48
Conferences (TRB, IEEE, and others)	18	9.78

(c) Sources of publications

Fig. 3. Synthesis of bibliometric analysis.

reaction time can be considered as latent that can be approximated as the minimum response time. This paper reviews whether and how response and reaction times are measured in a car-following scenario, with which dataset, and the range reported for response and reaction times.

Table 1 summarises notable efforts related to response and reaction times, and some key observations are as follows. First, most studies examined hard braking as a stimulus, except Fu et al. (2019) who studied cut-in responses. However, several stimuli, such as acceleration from the standstill position, gradual deceleration, and others, remain largely unexplored (more details in Section 4). Second, many studies attempted to understand response (or reaction) time using a driving simulator and naturalistic setting, whereby the former data collection type provides a controlled driving environment, and the latter type reveals true (and volatile) driving behaviour, which may be difficult to observe in a driving simulator. Third, response time estimation in an urban road setting has received comparatively less attention. Fourth, driving simulator-based studies measured response time via brake and accelerator pedal pressure, whilst real-world studies used manual measurements with a few exceptions, which are prone to human bias. Along this line, Sharma et al. (2019) proposed a wavelet transform-based method to estimate response time using trajectory data. Makridis et al. (2019) determined response time as the instantaneous time-gap value that deviates from the desired one, and consequently, a response from the adaptive cruise control controller of the following vehicle is determined as the response time. Although these methods showed promising results, a rigorous testing and comparison with other methods is required.

Fifth, many studies measured average response (or reaction) time for the population, which restricts our understanding of how response (or reaction) time varies across different age groups and gender. Sixth, the average response time varied across studies, ranging from 0.2 s to 14 s, linked to differing study goals. Finally, most studies viewed response time as monotonous and tied to the leader's stimulus; however, Zhang et al. (2019b) revealed heterogeneity in responses, which can be linked to driver traits and traffic flow, indicating driver-level differences.

Recent years have seen a surge in research focussing on the impact of vehicle technologies on driving behaviour. An emerging technology is a connected environment, involving vehicle-to-vehicle, vehicle-to-infrastructure, and vehicle-to-everything communications. Research on emerging technologies' impact often relies on simulations due to limited data availability, with exceptions like Zhang et al. (2023) who noted that a connected environment decreased response time during tunnel entrance, which could be attributed to enhanced situational awareness allowing drivers to respond earlier. Investigating diverse stimuli's effects on response times remains a growing research field, necessitating further exploration to comprehend response time changes.

Automated vehicles (at Level 5) relieve drivers from car-following, invoking engaging in secondary tasks, thereby compromising situational awareness. Recent years witnessed significant research on automated vehicles, delving into driver activities when not driving, loss of situational awareness, and responses to automated systems. Few studies address driver response in emergencies due to the automated system's driving role. Rauffet et al. (2020) found longer response times due to situational awareness loss in takeover requests. Another study combating driver fatigue in partial and full vehicle automation found longer response time when steering and braking (Neubauer et al., 2014).

Finally, response (or reaction) time has been analysed/modelled by various techniques including but not limited to analysis of variance, Bayesian neural networks, hierarchical regularised regression, survival (or hazard-based duration) regression, random effects, random intercept, among others.

3.1.2. *Time headway*

Time headway is a frequently used car-following characteristic, especially for assessing safety. It can be defined as the temporal difference between two successive vehicles passing a common reference point. A shorter time headway indicates a safety–critical event, reflecting smaller safety margins and requiring evasive manoeuvres to avoid a collision. Table 2 summarises representative studies on time headways, and some notable observations are as follows. First, the driving simulator and field collected data have been used to estimate time headway distributions for both motorways and urban roads, and time headway varies between 0.1 s to 14.8 s. Second, differences in time headways are found when following passenger cars and heavy vehicles (Aghabayk et al., 2012). Third, it has also been used to measure the effects of driving assistance systems, such as adaptive cruise control, forward collision warnings, and so on. For instance, Ariansyah et al. (2023) reported that drivers maintained longer time headways when they are supported by information supply through in-vehicle information systems compared to driving without it. Fourth, different methods are applied to analyse/model time headways like analysis of variance (ANOVA), linear regression, principal component analysis, and seemingly unrelated regression. Finally, all studies mentioned in Table 2 considered the monotonous impact of driving assistance on time headways, implying that time headways will only increase or decrease corresponding to a particular leader's stimulus, whereas driver-level heterogeneity has been largely ignored in the existing literature.

3.1.3. *Space gap*

Space gap is a commonly used characteristic for understanding car-following behaviour. In traffic safety studies, it complements time headway and can be defined as the spatial difference between the rear bumper of the leading vehicle and the front bumper of the following vehicle. Wilde (1982) described space gap choice using the Homeostasis theory and reported that drivers often increase their space gap to the leader whilst travelling at a higher speed to decrease rear-end collision risk. To this end, Table 3 summarises notable efforts in examining space gap majorly conducted through driving simulator studies, with a few exceptions where field experiments were performed. These studies examined space gaps in different types of roadways, including motorways, rural roads, and urban arterials and found them to vary between 7 m to 100 m. Space gaps are found to be affected by the type of lead vehicles. For instance, Aghabayk et al. (2014a) compared the effects of lead vehicle type (passenger car vs heavy vehicle) on space gaps and found that space gaps in front of heavy vehicles are larger than the corresponding values in front of passenger cars, which paved the way for developing lead vehicle type-aware car-following models (e.g., Aghabayk et al. (2013)). Further, our review suggests some notable techniques used in space gap studies are linear regression, multivariate analysis of variance (MANOVA), binary logistic regression, among others. Notably, space gaps have rarely been applied to quantify the effects of driving assistance systems, with no study focussing on driver-level heterogeneity. In one of those limited attempts, Wang et al. (2024) noted large space gaps in a connected environment compared to a traditional environment.

3.1.4. *Speed-based measures*

Speed is frequently used to understand car-following behaviour, reflecting traffic flow conditions and safety. In a car-following situation, the driver's speed is often governed by its leader conditioned on traffic flow conditions. In free-flow conditions, drivers mostly drive at the speed limit. Reflecting how speed varies for a given driver over time in the entire journey, a speed profile provides several insights into car-following behaviour and assists in identifying risky instances. Speed profiles can be directly obtained from trajectory data, and in case it is unavailable (e.g., loop detector data), it can be estimated using secondary methods, e.g., via licence plate recognition (Mo et al., 2017). In another study, Andrieu et al. (2013) used Functional Data Analysis (specifically the monotone smoothing spline method) for estimating speed profiles. Different speed-based measures are used to examine car-following behaviour and its safety, and some representative measures

Table 1
Summary of representative studies on response and reaction times.

Study	Stimulus	Dataset	Roadway	Method	Driver assistance	Driver group/ gender	Response or reaction time	RT range (s)	Heterogeneity observed/ measured (Yes/ No)	Vehicle type
Summala et al. (1998)	Braking	Field experiment	–	Brake pedal release	No	20 females and 8 males/ no age group	Reaction time	0.7 – 6	No	Conventional
Warshawsky-Livne and Shinar (2002)	Braking	Driving simulator	–	Accelerator pedal release	No	36 males and 36 females/ three age groups	Perception-reaction time	0.3 – 0.44	No	Conventional
Zhang and Bham (2007)	–	NGSIM	Freeway	Analytical (graphical)	–	–	Reaction time	0.2 – 3.8	No	Conventional
Makishita and Matsunaga (2008)	Buzzer sound	Field experiment	City road	Pressing switch	No	10 males/ three age groups	Reaction time	0.2 – 4	No	Conventional
Aghabayk et al. (2012)	–	NGSIM	Freeway	–	No	–	Reaction time	1.8 – 2	No	Conventional
Xu et al. (2012b)	Acceleration and deceleration	Driving simulator	Highway and urban road	Accelerator/ gas pedal release	No	24 males and 24 females/ no age group	Reaction time	0.5 – 3.5	No	Conventional
Dozza (2013)	Braking	Field experiment	–	Graphical	No	38 female and 56 male drivers/no age group	Response time	0.5 – 5	No	Conventional
Xue et al. (2015)	Acceleration and deceleration	Driving simulator	Urban road	–	No	24 males and 23 females/ no age group	Reaction time	1.72 – 8.21	No	Conventional
Ashok et al. (2016)	Braking	Real car	Rural road	Brake pedal release	No	65 male/ young and older groups	Reaction time	0.53 – 0.73	No	Conventional
Jurecki et al. (2017)	Hard braking	Driving simulator	Motorway	Accelerator Pedal release	No	Young (all male)	Response time	0.6 – 1.1	No	Conventional
Liu and Ho (2018)	Sudden braking	Driving simulator	Urban road	–	In-vehicle information	48 participants/ no age groups	Response time	1.6 – 1.8	No	Connected
Wu et al. (2018b)	Braking	Driving simulator	Highway	Brake pedal release	In-vehicle information	54 participants/ three age groups	Response time	6 – 14	No	Connected
Arbabzadeh et al. (2019)	Braking	SHRP2	–	Manual (from video)	No	–	Reaction time	0.5 – 7.8	No	Conventional
Fu et al. (2019)	Cut-in position	Field experiment	Freeway	Manual video processing	No	26 males and 20 females/ no age group	Reaction time	0.7 – 1.95	No	Conventional
Makridis et al. (2019)	Urban conditions (acceleration, deceleration)	Field experiment	Urban road	Analytical (based on trajectory)	ACC	23 lap-tests/ no information of participants	Response time	0.8 – 1.2	No	Automated
Guo et al. (2020)	Braking	Driving simulator	Expressway	Accelerator pedal release	No	64 males and 37 females/ no age group	Reaction time	0.3 – 4.2	No	Conventional
Sharma et al. (2019)	Hard braking	Driving simulator	Highway	Wavelet transform	Connected environment	50 males (28 females)/no age groups	Response time	1.56 – 2.43	No	Connected
Zhang et al. (2020)	Braking	Driving simulator	Rural road	Brake pedal release	No	35 males/no age group	Reaction time	1.45 – 1.55	No	Conventional
Zhu et al. (2020a)	Braking	Driving simulator	Rural road	Brake pedal	Vibrotactile warnings	17 males (7 females)/no age group	Response time	0.9 – 1.08	No	Connected
Zhu et al. (2020b)	Acceleration	Field experiment	Freeway	Manual (graphical)	In-vehicle information	60 drivers	Reaction time	1.33 – 1.43	No	Connected
Chen et al. (2021)	Braking	Driving simulator	Urban road	Brake pedal release	No	50 males/ Middle-aged and older groups	Reaction time	1.18 – 1.46	No	Conventional
Durrani et al. (2021)	Braking	Driving simulator	Highway	Accelerator pedal release	No	33 males (17 females)/five age groups	Reaction time	0.4 – 4	No	Conventional

(continued on next page)

Table 1 (*continued*)

Study	Stimulus	Dataset	Roadway	Method	Driver assistance	Driver group/ gender	Response or reaction time	RT range (s)	Heterogeneity observed/ measured (Yes/ No)	Vehicle type
Li et al. (2021)	Deceleration	Field experiment	Highway and rural road	Analytical (based on trajectory)	ACC	96 driving cycles of a three-vehicle platoon	Response time	0.7 – 2.2		Automated
Raju et al. (2022)	Braking	Field experiment	Provincial road	Analytical (defined by the switch points)	ACC	–	Response time	1.24 – 3.17	No	Automated
Čulík et al. (2022)	Hard braking	Driving simulator	Highway	–	No	15 males (15 females)/no age group	Response time	0.44 – 1.01	No	Conventional

ACC: Adaptive cruise control; "–": not mentioned; RT: response (or reaction) time.

Table 2
Summary of time headway studies.

Study	Dataset	Roadway	Driving assistance	Time headway range (s)	Heterogeneity observed/measured (Yes/No)	Vehicle type
Winsum and Heino (1996)	Driving simulator	—	No	0.67 ~ 1.52	No	Conventional
Dingus et al. (1997)	Field experiment	Urban road	Yes	1.5 ~ 2.7	No	Connected
Bao et al. (2012)	Field experiment	Urban road	Yes	0.7 ~ 3.1	No	Connected
Saffarian et al. (2012)	Driving simulator	Highway	Yes	0.1 ~ 5	No	Connected
Duan et al. (2013)	Driving simulator	Urban road	No	0.78 ~ 14.8	No	Conventional
Leblanc et al. (2013)	Field experiment	Urban road	Yes	1.5 ~ 2.4	No	Connected
Moridpour (2014)	NGSIM	Freeway	No	0.5 ~ 3.5	No	Conventional
Zhang et al. (2016)	Field experiment	—	No	1.63 ~ 2.34	No	Conventional
Itkonen et al. (2017)	Driving simulator	Highway	No	2 ~ 7.9	No	Conventional
Siebert et al. (2017)	Driving simulator	City, rural, and highway roads	No	1.5 ~ 2.4	No	Conventional
Ding et al. (2019)	Field experiment	Freeway	No	4.15 ~ 4.38	No	Conventional
Das et al. (2019)	Field (trajectories)	Expressway	No	0.75 ~ 1.19	No	Conventional
Loulizi et al. (2019)	Field experiment	—	No	0.81 ~ 2.6	No	Conventional
Bao et al. (2020)	Field experiment	—	Yes	1.55 ~ 1.75	No	Connected
Khansari et al. (2020)	Field (trajectories)	Freeway	No	0.4 ~ 1.5	No	Conventional
Ramezani-Khansari et al. (2021)	Driving simulator	Highway	No	0.76 ~ 1.5	No	Conventional

Table 3
Summary of space gap studies.

Study	Dataset	Roadway	Driving assistance	Space gap range (m)	Heterogeneity observed/measured (Yes/ No)	Vehicle type
Brackstone et al. (2002)	Field experiment	Motorway	No	14 ~ 27	No	Conventional
Puan (2004)	Field (trajectories)	Rural road	No	10 ~ 35	No	Conventional
Broughton et al. (2007)	Driving simulator	Highway	No	27.12 ~ 58.55	No	Conventional
Mitsopoulos-Rubens et al. (2007)	Driving simulator	Rural road	No	27.5 ~ 44.9	No	Conventional
Kang et al. (2008)	Driving simulator	Urban road	No	16.5 ~ 20.3	No	Conventional
Duan et al. (2013)	Driving simulator	Urban road	No	8.7 ~ 37.1	No	Conventional
Ding et al. (2019)	Field experiment	Freeway	No	80 ~ 90	No	Conventional
Zhang et al. (2019a)	Field (NGSIM)	Arterial	No	7 ~ 100	No	Conventional

are described herein.

Relative speed is the difference between the leader's speed and the following vehicle's speed, providing insights into normal and risky traffic conditions. For instance, a negative relative speed implies that the follower travels faster than its leader and is at risk of a rear-end collision. Further, relative speed has also been considered a stimulus affecting the driver's response (or reaction) time and safety. For example, Sheu and Wu (2015) found a relationship between drivers' relative speed and their reaction time. Similarly, another study investigated relative speed and space headway relationship and reported that the spread of relative speed with respect to space gaps is narrower for heavy-heavy vehicle pair, which is less than half of the corresponding values for the other combinations (heavy-passenger car, passenger car-heavy, and passenger car-passenger car) (Aghabayk et al., 2014b).

Speed variation (or fluctuation) can be defined as the standard deviation of speed, with large speed variations being a precursor of traffic crashes (Zheng et al., 2010). Whilst analysing rear-end crash precursors, Lee et al. (2011) developed Bayesian logistic regression models and found that speed variation increases the propensity of rear-end crashes. Further, speed variation has also been found to affect traffic flow conditions, e.g., heavy vehicles exhibited smaller variations when following cars, leading to dampened traffic oscillations (Chen et al., 2016). Moreover, driving in a connected vehicle environment has been reported to smaller speed variations compared to a traditional environment (Wang et al., 2024).

Desired speed has been used as one of the car-following model parameters in well-known models, such as the Intelligent Driver Model (Treiber et al., 2000). The desired speed can be defined as the speed that a driver wants to attain constrained by roadway, traffic, and driver characteristics. It remains unclear what a driver's actual desired speed is since the driver's desired speed is a latent characteristic. To this end, Ramezani-Khansari et al. (2021) developed a relationship between time headway and desired speed, and it was found that time headways decreased with an increase in desired speed. Despite being a popularly used model parameter, no empirical evidence can be found regarding the extent to which desired speed can vary.

3.1.5. Acceleration-based measures

Acceleration indicates drivers' tendency to increase and/or decrease their speed during driving, which can significantly affect traffic flow characteristics and safety. For example, abrupt deceleration indicates risky situations, elevating the propensity of rear-end collisions. A direct relation between deceleration and braking has been reported, whereby both excess and inadequate braking are directly associated with rear-end collision risk as evaluated through a Cox Proportional hazard model (Zhang et al., 2023). To this end, different acceleration-based measures can also be used to characterise normal or riskier car-following behaviour, and some representative measures are summarised herein.

Acceleration noise (or variation) is the standard deviation of acceleration/deceleration of a driver. Herman et al. (1959) proposed and used acceleration noise to describe driver-vehicle–road interaction in different conditions, whereby its higher values reflect risky behaviour. Acceleration noise can characterise whether risky behaviour has been increased or decreased because of any external stimulus. For instance, Sharma et al. (2020) developed a random parameters duration models for acceleration noise to determine whether advance information on hard braking reduces the driver's acceleration noise in a connected vehicle environment. Results revealed that acceleration noise decreased in a connected vehicle environment; however, the magnitude of the decrease is not constant and conditioned on other factors, such as driver demographics.

Jerks represent fluctuations in acceleration/deceleration and can be obtained as the derivative of acceleration/deceleration. A jerk can distinguish normal braking from braking in riskier situations. Bagdadi and Várhelyi (2011) developed log–log regression models and found that the expected number of accidents are directly related to the number of critical jerks exhibited by a driver.

3.2. Lane-changing behaviour

This section reviews studies on the three stages of lane-changing behaviour, i.e., decision-making, execution, and impact.

3.2.1. Lane-changing decision-making

A critical component of the lane-changing decision-making process is gap acceptance behaviour, which generally follows the gap acceptance theory (Marczak et al., 2013). According to this theory, critical gaps are compared with available gaps and a lane-change decision is made if the available gap is greater than the critical gap. An issue using the gap acceptance theory is that if drivers do not receive gaps larger than critical gaps whilst traversing the entire acceleration lane, theoretically, they will get stuck at the end of the acceleration lane and will not be able to change lanes to the mainline traffic — a common issue observed in microsimulation packages (Marczak et al., 2013, Zheng, 2014).

Table 4 illustrates the factors considered for understanding and analysing gap acceptance behaviour, which can be broadly classified into four categories (Toledo et al., 2003): (a) *neighbourhood variables* describe surrounding traffic dynamics, (b) *path plan variables* explain drivers' decisions to follow a certain path, (c) *network knowledge and experience variables* reflect drivers' considerations and preferences based on their transportation network knowledge and experience, and (d) *driving style and capabilities variables* capture driver's personality.

Several studies (see Table 4) related to gap acceptance behaviour during mandatory lane-changing can be found in the literature (Bham, 2009, Marczak et al., 2013, Vechione et al., 2018, Daamen et al., 2010). For instance, Bham (2009) fitted distributions to accepted and rejected gaps extracted from NGSIM data and reported that rejected gaps should be considered. Similarly, Daamen et al. (2010) empirically analysed merge location, accepted and offered gaps, and relaxation phenomenon, and found that during free flow and congested conditions, most lane changes occur in the first half and at the end of the acceleration lane, respectively. Several modelling methodologies are used for gap acceptance in the literature and some of the prominent methods are log-linear regression, probit logit model, and machine learning methods like Bayes classifier and decision trees — a detailed review of these methods can be found in a recent review (Wen et al., 2021).

Meanwhile, gap acceptance behaviour during discretionary lane-changing has also been analysed. Moridpour et al. (2010a) determined the effects of a heavy vehicle on gap acceptance behaviour using NGSIM data and reported that drivers tend to avoid following heavy vehicles. Note that this study did not develop any model, rather graphically and descriptively analyse gap acceptance behaviour. Similarly, Vechione et al. (2018) compared mandatory and discretionary lane-changing manoeuvres whereby cumulative distributions of different decision variables were statistically compared (Kolmogorov–Smirnov and paired t-tests), and found that the gap between the subject vehicle and the leader vehicle in the current lane differs in these two lane-changing types.

Earlier studies provide insights into different factors affecting gap acceptance behaviour; however, the evidence of how human factors (e.g., driving experience and demographics) impact gap acceptance behaviour is scant. Developing sound and comprehensive models require complete information of factors affecting gap acceptance behaviour. Whilst some prior research (Bham, 2009) reported that driver's personality traits (e.g., aggressiveness, sensation seeking, etc.) affect gap acceptance behaviour during mandatory lane-changing, how these personality traits can be obtained from trajectory data is not defined. In addition, our understanding of how human factors affect gap acceptance behaviour during discretionary lane-changing remains elusive.

Several modelling methodologies are used for gap acceptance behaviour (see a thorough list in Table 1), which include but are not limited to linear regression, logistic regression, artificial intelligence, and mixed effects methods.

Whilst studying gap acceptance behaviour in a connected environment, considering human factors becomes more important because the anticipated benefits of a connected environment are a function of the driver's characteristics (Sharma et al., 2017). More specifically, the information (or driving aids) presented by a connected environment can assist in lane-changing driving tasks and ignoring these driving aids would nullify the impact of a connected environment. Despite the data paucity of a connected environment, a few studies have conducted driving simulator experiments to understand gap acceptance behaviour (Zhang et al., 2023, Zhao et al., 2023). For instance, a study found that the information supply from a connected environment enabled drivers to comprehend the merging operation more effectively, resulting in smaller initial merging gaps and shorter post-merging adjustment times (Wang et al., 2024).

Table 4
Summary of gap acceptance studies.

Study	Variables considered in gap acceptance behaviour	Data source	Modelling method	Vehicle type
Ahmed et al. (1996)	Gap length, relative speed, remaining distance, delay in completing merging manoeuvre	Field data collected at I-95	Intrinsically linear	Conventional
Hwang and Park (2005)	Lead and lag gaps, front gap (spacing), remaining distance, and type of vehicle (heavy vehicle or passenger car)	Field data collected in China	Probit logit model	Conventional
Bham and Goswami (2007)	Personality traits (e.g., aggressiveness, sensation seeking, etc.), and urgency of the LC	NGSIM I-80 dataset	Deterministic and stochastic methods	Conventional
Wu et al. (2007)	Speed and position of SV, speed, and relative distance to leader and follower	Instrumented vehicle	Empirical analysis	Conventional
Kim et al. (2008)	Critical lead and lag gaps, and relative speed	Field data collected in Seoul	Comparison of available gap with critical gap	Conventional
Bham (2009)	Critical gaps based on accepted and rejected gaps	NGSIM I-80 dataset	No model was developed	
Daamen et al. (2010)	Merge location, accepted and offered gaps, and relaxation phenomenon	Field data collected in Netherlands	Descriptive analyses	Conventional
Kondyli and Elefteriadou (2011), Kondyli and Elefteriadou (2012)	Speed and position of SV and lead and lag gaps	Field data collected at I-95	Log-linear	Conventional
Gurupackiam and Jones Jr (2012)	Traffic density (e.g., congestion)	Field data collected in Alabama	Descriptive analysis	Conventional
Hou et al. (2012)	Speed of SV, relative speed of lead and lag vehicles, distance to lead and lag vehicles in the target lane, and remaining distance	NGSIM US 101 dataset	Genetic fuzzy logic approach	Conventional
Marczak et al. (2013)	Offered gap, headway, position on acceleration lane, speed difference between potential leader and follower, and speed difference between SV and follower	Field data collected in Netherlands	Descriptive analyses	Conventional
Hou et al. (2013)	Relative speed of lead and lag vehicles, distance to lead and lag vehicles in the target lane and remaining distance	NGSIM US 101 dataset	Bayes classifier and decision trees	
Qi et al. (2015)	Lag and lead time gap in the target lane, lead time gap in the current lane	Field data collected in US	Descriptive analyses	Conventional
Cao et al. (2016)	Speed and acceleration, relative speed of lead and lag vehicles	Field data collected in Australia	Probabilistic model	Conventional
Zhu et al. (2017)	Time headway to lead and lag vehicles in the target lane and relative velocity	NGSIM US 101 and I 80 datasets	Descriptive analyses	Conventional
Vechione et al. (2018)	Front gap before LC, rear and front gaps after LC	NGSIM I-80 dataset	Descriptive analyses	Conventional
Yang et al. (2019)	Traffic density, weather condition, light condition, vehicle type, acceleartion, and speed	Shanghai naturalistic driving data	Three-level mixed-effects linear regression	Conventional
Wang et al. (2024)	—	Driving simulator data	Descriptive analyses	Connected

Note that SV refers to Subject Vehicle; LC refers to lane-changer.

For automated vehicles, given longitudinal and lateral control operations are performed by an automated vehicle per se, drivers only need to supervise their vehicles (partial automation). Madigan et al. (2018) reported that when resuming driving from a partially automated vehicle, drivers showed higher lane positioning, speed deviations, and lateral accelerations during lane changes compared to conventional driving. Moreover, given that lateral control is performed by algorithms explicitly designed for automated vehicles, this study does not review those algorithms related to automated vehicles because it is the automated vehicle system instead of drivers who make gap acceptance decisions. A recent study utilising Waymo dataset analysed gap acceptance behaviour of autonomous vehicles and human-driven vehicles during discretionary lane-changing and reported statistically significant differences in gap acceptance behaviour (Wen et al., 2023).

3.2.2. *Lane-changing execution*

Another component of lane-changing behaviour is lane-changing execution, commonly characterised by lane-changing durations (Moridpour et al., 2010a). It can be defined as the difference between the start of a lane-changing manoeuvre from the current lane and the completion of a lane-changing manoeuvre in the target (or adjacent) lane.

One of the critical aspects of computing lane-changing durations is how accurately the start of a lane-changing manoeuvre is identified because most trajectory databases do not provide sufficient information about the start of a lane-changing manoeuvre. Whilst some of the previous studies do not describe how the information related to the start of a lane-changing manoeuvre can be extracted from different data sources (Moridpour et al., 2010a), some studies used various approaches to pinpoint the start of a lane-changing manoeuvre (see Table 5), e.g., aerial photographs (Worrall and Bullen, 1970), an observer accompanying the driver (Hetrick, 1997), self-reported information (Salvucci and Liu, 2002), slope-based method (Zhu et al., 2017), rule-based method (Nie et al., 2016), visual inspection of lateral profiles (Toledo and Zohar, 2007), automatic lateral movement algorithm (Yang et al., 2015), and Wavelet Transform (Zheng and Washington, 2012). Although some of these methods can detect the start of a lane-changing manoeuvre from trajectory databases where the ground truth is unknown, these methods have their shortcomings, as described in Section 4. Further, Table 5 also indicates that lane-changing duration varies across studies, highlighting driver-level heterogeneity.

Another aspect of lane-changing execution is the factors affecting lane-changing durations, which can be classified into traffic operational factors and demographics. Traffic operational variables included dynamic traffic variables, such as speed and acceleration of vehicles (Toledo and Zohar, 2007) along with type of lead vehicle. Demographics included driving experience, age, and gender (Li et al., 2015). These factors are incorporated in lane-changing duration models that can predict/estimate lane-changing durations in a traditional environment.

Some representative studies on lane-changing execution are summarised as follows. Aghabayk et al. (2011) reported that lane-changing duration increases when the size of vehicles increases. Another study found that lane-changing duration is longer if the lead vehicle speed is lower and lane-changing vehicle is a heavy vehicle (Durrani et al., 2016). A study comparing lane-changing execution of passenger cars and heavy vehicles reported twofold findings (Moridpour et al., 2010c). First, heavy vehicles revealed an almost constant speed during lane-changing execution, implying that no significant speed adjustment was required corresponding to the speed of surrounding traffic in the target lane. Second, passenger cars accelerated to adjust their speeds

Table 5
A summary of lane-changing execution studies.

Study	Data	Methodology	Lane-changing duration (s)	Vehicle type
Worrall and Bullen (1970)	Aerial images	Manual	1.25 to 1.95	Conventional
Chovan et al. (1994)	Field data	Lateral profile	2 to 16	Conventional
Hetrick (1997)	Field study	Observer	3.4 to 13.6	Conventional
Tijerina et al. (1997)	Field study	Observer	3.5 to 8.5	Conventional
Hanowski (2000)	Field study	Manual	1.1 to 16.5	Conventional
Salvucci and Liu (2002)	Simulator study	Self-reporting	5.14	Conventional
Lee et al. (2004)	Instrumented vehicle	Steering angle	6.3	Conventional
Toledo and Zohar (2007)	Field study	Lateral profile	1 to 13.3	Conventional
Moridpour et al. (2010c)	NGSIM dataset	Lateral profile	1.1 to 8.9	Conventional
Cao et al. (2016)	Field study	Lateral profile	1 to 6.8	Conventional
Nie et al. (2016)	NGSIM	Rule-based method	1.1 to 8.9	Conventional
Zhu et al. (2017)	NGSIM	Slope-based method	1.1 to 8.9	Conventional
Ali et al. (2018)	Simulator study	Automated algorithm	4 to 7.8	Connected
Yang et al. (2019)	Shanghai naturalistic data	Automatic algorithm	0.7 to 16.1	Conventional
Ali et al. (2020c)	Simulator study	Automated algorithm	5.6 to 8.43	Connected

according to the speeds of the lead and lag vehicles in the target lane (Moridpour et al., 2010c). These two findings clearly indicate differential lane-changing execution behaviour, with comparatively lower effect of heavy vehicles on traffic in the target lane. Along this line, Cao et al. (2016) found that drivers would adjust their lane-changing execution if a traffic conflict was detected, which would impact surrounding traffic. A study investigating characteristics of heavy vehicle lane-changing execution reported that navigation speed significantly influences lane-changing duration of heavy vehicles and lane-changing duration decreases with the increase in speed, indicating the substantial impact of traffic conditions on lane-changing durations (Li et al., 2022b). A subsequent study analysing passenger car/heavy vehicle difference found greater heterogeneity in heavy vehicles due to poor manoeuvrability and reinforced that heavy vehicles require more time to complete the lane-changing manoeuvre (Li et al., 2023a). Finally, a study developed survival models and found that the median survival time of heavy vehicles is 0.57 s longer than passenger cars (Li et al., 2022a). Further, heavy vehicles maintained a longer time headway and distance headway with the preceding vehicle when changing lanes, and their lane-changing durations were less susceptible to interactions with the preceding vehicle and more susceptible to their own speed.

Third, assessing the impact by considering type of vehicle and their role (lane-changer or leader or follower) is critical for traffic flow and safety analysis. As well-acknowledged in literature (Durrani et al., 2016), due to size differences, consequent vehicle dynamics, and driving behaviour (safe distance, acceptable headways in congested/uncongested traffic conditions, and cooperation from other drivers), future studies should quantify their effects on traffic flow characteristics and safety, which could be used for developing an integrated lane-changing model capable of describing lane-changing decision-making, lane-changing execution, and its impact.

Whilst the above discussion relates to a traditional environment, a few studies have also investigated lane-changing durations in a connected environment, and they were found to increase compared to a traditional environment. Such increase in duration was attributed to the available information about surrounding traffic, which drivers can utilise and take more time to more cautiously change lanes when the distance between the subject vehicle and the following vehicle is larger (Ali et al., 2018). Similarly, another study used a fuzzy logic model and found that a smart advisory information system for lane-changing decreased lane-changing durations (Li et al., 2015). It was argued that the system provided instructions about preparing and changing lanes earlier, resulting in shorter lane change durations. Instructing drivers when and how to change lanes will likely induce bias in lane-changing execution behaviour. Using connected vehicle data, Bakhit et al. (2017) detected lane-changing initiation with artificial neural network and multiple logistic regression models. Whilst the former model showed better performance accuracy, both models identified the vehicle speed, acceleration, and speed relative to the lead vehicle as the most significant attributes for lane-changing initiation.

Finally, several modelling methods are used for lane-changing durations like hazard based-duration, linear regression, support vector machine, mixed effects methods, and others.

3.2.3. *Lane-changing impact*

Lane-changing has been frequently reported to negatively affect traffic flow efficiency (Ahn and Cassidy, 2007) and deteriorate traffic safety (Pande and Abdel-Aty, 2006). Lane-changing manoeuvres trigger congestion, can cause a capacity drop of about 8–18 %, and form and dissipate shock and rarefaction waves on roadways (Jin, 2010). Moreover, improper lane-changing decisions are reported to increase crash risk and can cause rear-end and sideswipe collisions (Liu et al., 2022).

Several relevant studies describe the impact of lane-changing on aggregated (or macroscopic) traffic. However, few studies explain the impact of lane-changing on an individual driver and the vehicles surrounding a lane-changer in the current and target lanes that are directly (or indirectly) affected. In particular, the immediate follower of a lane-changer may be affected the most because the following driver needs to maintain a higher safety margin without disrupting its current state of motion. However, a lane-changing manoeuvre has been reported to modify the driving behaviour of the immediate follower, e.g., Zheng et al. (2013) noted that a follower experienced anticipation, relaxation, and change in its characteristics. Similarly, the follower in the current lane is also affected by lane-changing, and it has been reported that the lane-changing impact on the following vehicle in the current lane usually lasted longer than that in the target lane, leading to aggravating traffic congestion at the upstream (Wang and Coifman, 2008).

The lane-changing impact is likely to vary across vehicle classes; however, only limited evidence can be found in the literature for such an impact. Li et al. (2020) used support vector regression and reported that motorcycles' lane changes posed the highest crash risk to the traffic stream compared to other vehicle classes, whereas, contrastingly, another study using fixed, random, and linear mixed models reported heavy vehicles exerted more impact on the following vehicles than other vehicle classes (Shin et al., 2022). These findings are preliminary and need rigorous evaluation by considering a diverse fleet.

The studies mentioned above did not clearly mention the type of lane-changing, resulting in ambiguity as to whether both lane-changing types (mandatory and discretionary) will have similar or different effects. Along this line, Ali et al. (2020b) measured and statistically compared the impact of mandatory and discretionary lane-changing on the immediate follower in the target lane. They reported that the average speed reduction of followers responding to lane changes was almost twice in mandatory lane-changing compared to that of discretionary lane-changing. Except for this study, no solid evidence related to lane-changing impact corresponding to its type can be found.

Determining the appropriate time when lane-changing impact should be measured is also critical and expected to provide key insights into how driving behaviour deteriorates in the target lane. To this end, Mullakkal-Babu et al. (2020) developed a double sinusoidal lateral acceleration model and compared the relative kinematic state of neighbouring vehicles at the onset and the end of a lane change. Results suggested a lower speed differential between the lane changer and its follower when measured at the end of the lane change compared to when measured at the start. Except for this study, the literature lacks evidence of how lane-changing impact varies throughout the lane-changing execution period.

The review described herein mainly reflects the impact of lane-changing in a traditional environment, whereas it is envisaged that such negative impacts of lane-changing are likely to be suppressed (if not completely eliminated) with the advent of emerging vehicle technologies. Yun et al. (2017) using analysis of variance found that in-vehicle information was effective and had a positive impact on lane-changing safety under medium to high-density conditions, whereas such effectiveness tends to diminish in light-density conditions. Similarly, other studies reported a higher safety margin in a connected environment (Monteiro and Ioannou, 2021). In the case of automated vehicles, a comparative study of conventional manual driving, partially automated driving (operating at Society of Automotive Engineers (SAE) Level 2), and conditionally automated driving (operating at SAE Level 3) used analysis of variance and found that during conditionally automated driving, drivers have higher deviations in lane positioning and speed, along with higher lateral accelerations during lane changes compared to partially automated driving (Madigan et al., 2018). This finding indicates that conditional automated driving creates more traffic disturbances than other driving conditions.

Finally, like car-following behaviour, space-based, speed-based, and acceleration-based measures are important characteristics of lane-changing behaviour, as they can influence the safety, efficiency (thus, the lane-changing duration), and smoothness (thus, comfort level) of a lane-changing manoeuvre. However, few studies have focussed on these empirical aspects during lane-changing.

3.3. Data collection methods used for driving behaviour research

This section describes representative data collection methods commonly used for driving behaviour research. It is worth noting that the aim of this section is not to provide an exhaustive review of all studies available in the literature, rather highlight which methods are used — interested readers are referred to recent review papers for more information (Guo et al., 2018, Wang et al., 2021, Zaidan et al., 2022, Boylan et al., 2024). Also, for this section, we did not use the PRIMSA review framework as many of the studies will not qualify to our selection criteria.

Table 6 presents an overview of different data collection methods, type of vehicles (traditional or connected), and a list of representative studies. Following are some noteworthy observations from Table 6. First, the most frequently used data collection methods are driving simulators, naturalistic, field experiments, and others, with recent studies focussing on using smartphones, wearable devices, and multi-modal physiological datasets (Tao et al., 2024). Second, naturalistic datasets are frequently used for conventional vehicles, but such datasets are very few for connected vehicles (e.g., Connected Vehicle Safety Pilot Model Deployment) and automated vehicles (e.g., Waymo, Lyft, Argoverse). Third, advanced sensing technologies for fixed infrastructures, i.e., LiDARs mounted at intersections, are used for traffic safety evaluation, but driving behaviour assessment especially for advanced vehicles remains unexplored. Since no single data collection method provides all the required information necessary for comprehensively evaluating driving behaviour (e.g., video recordings do not contain driver demographics; naturalistic driving has no control over testing conditions), studies have combined several data sources to understand driving behaviour, e.g., Risto and Martens (2014), Helman and Reed (2015), Hussain et al. (2019), and others. It is worth noting that not all the data collection methods listed in Table 6 are used for car-following and lane-changing assessments.

Table 6
Data collection methods for empirical research.

Data collection method	Vehicle type	List of representative studies
Driving simulators	(i) Conventional (ii) Connected (iii) Automated	(i) Yang et al. (2013); Haque & Washington (2014); Boda et al. (2018) (ii) Cornu (2012); Yang et al. (2017); Huang et al. (2022) (iii) So et al. (2021); Weigl et al. (2021); Sultana and Hassan (2024)
Test tracks/field operational test	(i) Conventional (ii) Connected (iii) Automated	(i) Daniels et al. (2010); Boda et al. (2018); Günther et al. (2019) (ii) Adell et al. (2011); Hayat et al. (2014); Song et al. (2016) (iii) Papakostopoulos et al. (2021); He et al. (2024)
Instrumented vehicles	(i) Conventional (ii) Connected (iii) Automated	(i) Charlton et al. (2013); Itkonen and Lehtonen (2020); Ventsislavova et al. (2021) (ii) Bifulco et al. (2014); Ameen (2021) (iii) Wang et al. (2015); Varotto et al. (2020)
Naturalistic	(i) Conventional (SHRP 2) (ii) Connected (SPMD) (iii) Automated (Waymo, Lyft, Argoverse)	(i) Papazikou et al. (2019); Chen and Chen (2022); Das and Ahmed (2023) (ii) Liu and Khattak (2016); Mohammed (2019); Liu and Khattak (2020) (iii) Singh et al. (2024); Hu et al. (2023); Lanzaro et al. (2023)
Video recording	Traditional	Vechione et al. (2018); Fries et al. (2022); Gu et al. (2023)
LiDARs	Conventional	Wu et al. (2018a); Tarko et al. (2021); Zheng et al. (2024)
Smartphones	Conventional	Papadimitriou et al. (2019); Lißner et al. (2020); Fattahi et al. (2023)
Wearable devices	Conventional	Steinberger et al. (2017); Lu et al. (2021); Scherz et al. (2023)
Telematics	Conventional	Winlaw et al. (2019); Chan et al. (2023); Meuleners et al. (2023)
Surveys/questionnaires	(i) Conventional (ii) Connected (iii) Automated	(i) Jamson et al. (2008); Cordazzo et al. (2014); Bakhshi et al. (2022) (ii) Young et al. (2012); Cristea and Delhomme (2014); Payre and Diels (2020) (iii) Eriksson (2014); Lee et al. (2023); Weigl et al. (2023)

SHRP 2: Second Strategic Highway Research Program; SPMP: Safety Pilot Model Deployment.

4. Future research directions

This section imparts insights from prior research on driving behaviour and suggests future directions for developing sound and robust car-following and lane-changing models. It highlights (a) specific research needs, and (b) general research requirements for a deeper understanding of driving behaviour.

4.1. Specific research needs

4.1.1. Car-following behaviour

Response (or reaction) time is a commonly used parameter in car-following modelling and related traffic safety studies, and the reviewed empirical evidence supports its significance. To this end, the first issue is assumptions related to reaction time whilst modelling car-following behaviour. For instance, some psychological models assumed that the drivers start their reaction only when the relative speed and space gap exceed certain perception thresholds in different car-following states, which may not be entirely true (Durrani and Lee, 2024). The second issue is that several studies use the terms "reaction time" and "response time" interchangeably as echoed in (Sharma et al., 2019). Such a semantic incoherency in science can lead to improper model building. Sharma et al. (2019) clearly distinguish the difference between reaction time and response time as follows. Reaction time is a combination of latent response time and observable response time, whereas response time consists of two main components: latent response time and observable response time. Latent response time is the duration between the presentation of a stimulus and the initiation of detectable muscle activity, encompassing sensation, perception, decision-making, initiation, and delay. Sensation refers to the time required to detect the stimulus, whilst perception involves interpreting it. Decision-making is the period during which the driver determines the appropriate response to the stimulus. Initiation marks the beginning of muscle activity, although no movement is yet observed, and delay refers to the intentional postponement of the response. Observable response time, or movement time, is the interval between the start and completion of the foot movement. Reaction time is derived by subtracting the delay time from the latent response time.

Another exigent issue is determining response (or reaction) time from trajectory data where ground truth is unavailable. Several analytical and well-tested methods for this purpose are worth investigating. For instance, Sharma et al. (2019) used a wavelet-transform based method to estimate response time and tested it on noise-free data, noisy data, and real (physical) response data obtained from a driving simulator experiment. Although the proposed method showed a good performance, a comparison of how other techniques (e.g., segmentation-based approach, see Keogh and Pazzani (1998) for more details) perform is needed to judiciously select a method for obtaining response (or reaction) time from trajectory data. Table 1 demonstrates that response and/or reaction time is predominantly measured as the consequence of the braking stimulus of the leader, whereas other stimuli (e.g., responding to lane-changing, braking of different vehicle classes, variable speed limit, etc.) should also be considered to diversify the range of response (or reaction) time as in Hu et al. (2023). For instance, stimulus generated by different lane-changing requests will lead to different response (or reaction) time, as aggressive lane change requests may result in shorter response time, which can have significant implications on traffic safety. Along this direction, response (or reaction) time has been measured to demonstrate the effects (positive or negative) of advanced information assistance systems, such as forward collision warnings (Bakowski et al., 2015), adaptive cruise control (Makridis et al., 2019), and so on; however, almost all previous studies reported monotonous effects of such systems on the response (or reaction) time. The use of simple statistical analyses, such as analysis of variance and pairwise comparison, is the root cause of this issue, which can be overcome by using advanced techniques, such as random parameters and latent class modelling approaches that can provide insights into driver-level heterogeneity.

Speed and its measures are key factors in car-following behaviour, although few empirical studies delve into it. Relative speed, preferable over instantaneous speed, can reveal lane satisfaction and risk. For instance, negative relative speed, when the subject driver outpaces the leader, indicates potential rear-end collision risk. Moreover, speed variation measures unveil risky traffic states, with large variations reflecting traffic disruptions and increased crash likelihood but its impacts on crash severity (e.g., severe and non-severe injuries) remain unexplored. Finally, speed profiles can be used in detecting different driving regimes for understanding exogenous factors triggering a change in speed.

A few studies (e.g., Ramezani-Khansari et al. (2021)) have established a relationship between car-following characteristics, such as time headway and desired speed. Such relationships must be developed and rigorously tested to better understand car-following behaviour. For instance, how are critical jerks associated with response time? Can relative speed be used instead of deceleration? Such empirical relations will be useful in advancing our understanding of car-following dynamics and developing more accurate car-following models. These relationships can also be useful when a specific characteristic cannot be estimated/obtained directly from the data.

Interestingly, not all car-following model parameters can be obtained/observed from the data. For example, some well-known models like the Intelligent Driver Model (IDM) have desired model parameters (desired speed, desired time gap, amongst others) that are difficult to observe/measure from the real data for two reasons. First, desired parameters are latent, and as such, they can only be inferred. Second, there is inherent ambiguity in their definitions. For example, the desired speed is defined as the speed a driver desires to achieve during their drive (Summala, 2007). If so, is it the maximum speed a driver can attain conditioned on vehicle capabilities, roadway conditions, and road infrastructure (speed limit)? Or is it traffic condition specific? Also, is it fixed for a driver, or does it change depending on the driving regime?. Similar questions can be raised for other desired parameters in IDM and other car-following models. Answering these questions will significantly improve our understanding and modelling of car-following behaviour, and especially assist in calibrating these parameters reliably by fixing a realistic range of these parameters in the calibration process (Punzo et al., 2021).

4.1.2. Lane-changing behaviour

(1) Lane-changing decision-making.

Most existing studies employed gap acceptance theory for modelling gap acceptance behaviour, and these studies suffer two issues. First, some important factors associated with gap acceptance are not adequately studied in the literature. For instance, rejected gaps, that lead to driver impatience, are critical in explaining and modelling gap acceptance behaviour but are not frequently used in the literature (Marczak et al., 2013). Similarly, driver's personality traits, such as aggressiveness, sensation seeking, the urgency of a lane-change, and so on, as well as demographic information (Bham and Goswami, 2007), are rarely linked to gap acceptance, and their omission may have significant ramifications on gap acceptance behaviour. For example, young, aggressive drivers opt for small gaps, endangering safety and efficiency. Second, these studies neither evaluated the overall prediction capability of lane-changing decision models nor reported individual performance of gap acceptance theory-based models in predicting gap acceptance. The latter aspect could be attributed to the entangled nature of utility theory models (Ahmed et al., 1996), where the individual performance of gap acceptance theory-based models is challenging to obtain from the entire lane-changing modelling framework. Assessing the performance of gap acceptance theory-based models becomes important as Marczak et al. (2013) reported the inadequacy of gap acceptance theory in modelling gap acceptance behaviour. Aligned with this observation, as most gap acceptance theory-based models are statistical models and their prediction accuracy is often reported to be low (Karlaftis and Vlahogianni, 2011), the use of machine learning algorithms can be promising. Machine learning models (especially neural networks) are often called black-box models, and they provide high prediction performance at the cost of interpretability (Karlaftis and Vlahogianni, 2011). With gap acceptance behaviour being well studied using statistical models and the relationship of gap acceptance with its determinant being well-known, researchers can use machine learning models for better predictive performance. Moreover, recent developments in the area of explainable artificial intelligence can be utilised to interpret model output, e.g., SHapley Additive exPlanation (SHAP) has the ability to provide a graphical output (Li et al., 2023b) that can be used in lieu of statistical models to interpret the relationship of gap acceptance with its explanatory variables. However, the application of SHAP in investigating lane-changing behaviour (in particular, gap acceptance) is limited and further research is needed. More specifically, future research studies can compare the performance of machine learning models with gap acceptance theory-based models, which will assist in developing benchmarking guidelines based on objective justification of selecting a particular approach for modelling gap acceptance behaviour. Given that gap acceptance is an integral part of lane-changing decision models, the use of a better modelling approach is also expected to improve the overall prediction accuracy of microscopic lane-changing decision models.

Next, lane-changing manoeuvres can either be successful or failed. Despite failed lane-changing attempts being more detrimental to traffic flow and safety compared to successful ones (Zheng, 2014), its importance in lane-changing decision modelling has not been fully recognised mainly due to the difficulty of detecting failed lane-changing attempts from trajectory data. To this end, although the wavelet transform-based method has been used and performed well in detecting subtle changes in lateral movements and failed lane-changing attempts (Zheng and Washington, 2012), its comparison with other advanced techniques merits investigation. A direct consequence of the difficulty of detecting failed lane-changing attempts is small evidence of why failed lane-changing occurs and in what situations they are more prevalent. Such information will reveal drivers-at-risk who can be educated and properly trained to minimise such failed lane-changing attempts. Meanwhile, to assist during failed lane-changing attempts, a connected environment has been shown to reduce their occurrences (Ali et al., 2020b). However, recent research indicates that not all failed lane-changing attempts can be eliminated in a connected environment. It is, therefore, necessary to evaluate the cases where a connected environment is less effective, learnings of which can be used to improve the design of a connected environment tailored to the needs of specific users. Addressing these aspects will overcome the structural incompleteness of lane-changing decision models (Zheng, 2014), where failed lane-changing attempts are not considered, rendering poor performance and unrealistic estimates of lane-changing decision models.

In the literature, lane-changing decision-making is often modelled as a one-way decision-making process, focussing on the lane-changer only whilst ignoring the immediate follower in the target lane. However, lane-changing is an interactive decision-making process where the decisions of the lane-changer significantly impact the immediate follower in the target lane and vice versa. For instance, in heavy traffic conditions on a freeway, a driver either waits or accelerates to attain an acceptable gap in the mainstream traffic, whereas the immediate follower would respond to such a situation by showing courtesy or discouraging the lane-changing action (Kang and Rakha, 2018). To this end, lane changers and followers' roles should be analysed in the decision-making process so that lane-changing decisions can be better captured. To this end, a few interesting avenues to explore are as follows. First, a follower's response to different lane-changing types (e.g., free, cooperative, and forced) should be analysed. As reported by Ji and Levinson (2020), a follower often accelerates, decelerates, or remains unaffected by a lane-changing attempt, and it would be interesting to determine how a follower's decision varies with the types of lane-changing. In addition, whether different lane-changing types increase or decrease response time, and how they are associated with human factors are worth investigating. By doing so, a lane-changing decision time window that describes how frequently a driver makes a lane-changing decision could be obtained, as there is no consensus in the literature about the length of a decision time window. Such information will assist in calibrating a lane-changing model whereby discretising is performed based on decision time window. Second, it is important to determine dependency in decisions made by drivers during the lane-changing decision-making process so that the effects of risky decisions can be avoided/minimised. For instance, if a follower at a given time instance decides not to cooperate and discourages the lane-changing action of a lane-changer, will the same follower at the next time instance cooperate or act in the same way requires further investigation. Such understanding is necessary to improve driver education during licencing to promote cooperation during lane-changing interactions. Third, a follower's response may change when they are assisted in a connected environment; understanding their interactions in a connected environment with different responses, lane-changing types, and driver demographics would reveal the true picture of a connected environment's impact and assist in capturing such impact in lane-changing decision modelling. Finally, the research needs mentioned above could be associated with both aspects of lane-changing decisions: successful and failed.

Given that there are two types of lane-changing manoeuvres (mandatory and discretionary), some previous studies (Toledo et al., 2003) tend to merge them despite their distinct nature. Studying differential lane-changing behaviour would provide more insights into developing separate or combined models. Meanwhile, lane-changing models in the literature are predominately discrete in time, and there is a clear need to develop continuous lane-changing models where decisions would be continuously evaluated at each time instant. Such models can be easily integrated with continuous car-following models, and also bypass the need (and ramifications) to select a decision time window for discrete models.

(2) Lane-changing execution

Most lane-changing execution studies focussed on explaining the relationship of lane-changing durations with its determinants in an aggregated manner, which leads to a large range of reported lane-changing durations. However, lane-changing duration should be analysed separately for various lane-changing types (e.g., free, cooperative, and forced) and corresponding to the action of a follower (e.g., accelerating, decelerating, and remaining unaffected). Such information will assist in capturing subtlety associated with different lane-changing types and develop realistic microscopic lane-changing models. There exist at least three research gaps along this line.

First, a critical component of studying lane-changing duration is pinpointing the start and end of lane-changing execution. Although previous studies have employed different techniques (e.g., wavelet transform, manual recording, self-reported, slope-based approach, etc.) based on different data sources, and a satisfactory performance of wavelet transform is consistently reported. However, wavelet transform-based methods still suffer an important issue: hard to automate the process. Further research is needed in automating the procedure of using wavelet transform to detect the critical points of lane-changing execution, without sacrificing its accuracy.

Second, lane-changing execution is more than just about lane-changing duration. How the lane-changing vehicle actually move from the current lane to the target lane whilst negotiating and interacting with the immediate surrounding vehicles in both lanes is the most crucial part of the lane-changing execution — this aspect is largely ignored in the literature. There are a few studies (Xu et al., 2012a, Papadimitriou and Tomizuka, 2003) focussing on planning a trajectory for the lane-changing vehicle, but these studies are mainly from the mathematical perspective, and empirical studies that aim to shed light on driving behaviour of all the vehicles involved during the lane-changing execution process are rare.

Meanwhile, lane-changing durations should be analysed separately for various lane-changing types (e.g., free, cooperative, and forced) and corresponding to the action of a follower (e.g., accelerating, decelerating, and remaining unaffected). A critical component of studying lane-changing durations is pinpointing the start and end of lane-changing execution. Although previous studies have employed different techniques (e.g., wavelet transform, manual recording, self-reported, slope-based approach, etc.) based on different data sources, there is no consensus on selecting an appropriate technique. Future research must compare techniques for extracting lane-changing durations and validate their choice by comparing results with ground truth. Further, past studies used linear regression for modelling lane-changing durations, ignoring its dynamic execution. A hazard-based approach is more suitable for modelling event durations as it accounts for dynamic nature and estimates manoeuvre completion odds based on elapsed time, highlighting end-of-duration occurrences after a set time. Employing this approach reveals insights into diverse lane-change types and follower responses in both traditional and connected environments (Zhang et al., 2023).

Finally, connecting lane-change execution to lane-change decisions merits investigation. A comprehensive microscopic lane-changing model encompassing both aspects is important for building realistic simulation tools. Moreover, lane-changing impact should be analysed considering lane-changing execution, given the impact is likely to last during the entire duration episode in the current and target lanes. More empirical work on lane-changing execution will contribute to all these potential research avenues.

(3) Lane-changing impact

Lane-changing impact has remained a less studied topic than the other two aspects of lane-changing behaviour. Combining spatial and temporal variation, lane-changing impact has nine different combinations, and this number tends to grow exponentially if different lane-changing types (free, cooperative, and forced), attempts (successful or failed), driving environment (traditional and connected), vehicle types (heavy vehicle and normal car), more followers, and driver characteristics are considered. Recognising that lane-changing negatively affects traffic flow and safety (Laval and Leclercq, 2008), it is important to assess the extent of the impact. He et al. (2022) suggested that 4 to 5 followers are affected by lane-changing, but a more rigorous evaluation is required to ascertain the number of followers affected. Also, gauging and comparing the impact on traffic stream during and after lane-changing is crucial, which will aid in building realistic lane-changing impact models.

Differential impacts of lane-changing (mandatory vs. discretionary) require an in-depth study. Specifically, understanding how delay before mandatory lane-changing and speed reduction before discretionary lane-changing can harm upstream traffic is crucial. Such information will be useful in developing realistic microscopic lane-changing models where these parameters appear to be rarely used. Moreover, analysing impacts on driver groups by age and gender aids comprehensive impact model development, capturing driver-level heterogeneity.

4.2. General research needs

4.2.1. Data collection methods and sources

The underpinning of analysing driving behaviour primarily depends on the data used. Several data collection methods and sources have been used, which can be classified as naturalistic and simulated. The former group includes video recording, instrumented cars, drones, lidars, autonomous vehicles as probes used on real roads or experimental testbeds, whereas the latter group mainly uses driving simulators, providing simulated environment. For traditional vehicles, a few naturalistic trajectory datasets are freely available, including NGSIM (FHWA, 2007), HighD (Krajewski et al., 2018), pNEUMA (Barmpounakis and Geroliminis, 2020), and Zen (ZTD, 2023). These datasets provide unprecedented opportunities to study different aspects of driving behaviour. Some disadvantages of collecting naturalistic vehicle trajectories include significant cost, labour intensive and error prone in processing such data, limited temporal and spatial coverage (e.g., limited road section(s) or intersection(s)), and uncontrolled environment. However, safety critical events (e.g., sudden braking of lead vehicle and lane cutting) in naturalistic settings may be rare (or will require extensive data collection period). Further, information in trajectory data is still too limited to enable us to fully understand driving behaviour. For instance, driver demographic information is generally unavailable in naturalistic trajectories, limiting researchers from analysing driver heterogeneity's impact on driving behaviour. To this end, the driving simulator is an effective tool for collecting high-quality trajectory data coupled with human factor information. Using driving simulators, data related to car-following and lane-changing behaviours can be collected in a controlled environment designed for various scenarios of interest, some of which can be difficult and unsafe to perform in field experiments. Meanwhile, using driving simulators ground truth (e.g., response time) can be directly or indirectly obtained to validate different aspects of driving behaviour. A frequent criticism on driving simulator studies is the small sample size, which is understandable because recruiting a large and representative sample of drivers can be challenging. Although there is no upper limit on sample size — the more the merrier; an adequate sample size can be determined through analytical approaches (see Kadam and Bhalerao (2010) for more details). Another related issue is the realism in driving simulator environment. In most driving simulators, only one driver is performing driving tasks whilst the rest of traffic is scripted, mimicking robotic behaviour. Whilst studies have programmed surrounding traffic in the simulated environment following real-world behaviours, replicating subtle and nuanced human driving behaviour remained a challenge.

Along the same lines, a research need is merging diverse datasets for enriched driving behaviour comprehension. Whilst prior studies used surveys and focus group data for understanding lane-changing (Sun and Elefteriadou, 2011), parallel efforts for car-following are missing. Moreover, to understand the psychological aspects of driving behaviour, linking survey responses with trajectory data is required, e.g., Li et al. (2023c) conducted a survey on understanding conventional drivers' responses to fully automated vehicle's lane-changing intentions. Also, a method for integrating the realism of naturalistic trajectories with the controllability of driving simulator data is highly desirable, but currently non-existent in the literature.

4.2.2. Experimental design and setup

In general, experimental design and setup are integral parts of driving simulator experiments. Most of previous experiments focussed on understanding different aspects of driving behaviour and a few facets remained unexplored. For instance, ideally the design for studying car-following behaviour should encompass different regimes (free acceleration, cruising at the desired speed, accelerating behind the leader, deceleration behind the leader, following the leader at a constant speed, and standing behind the leader) as identified by Sharma et al. (2018). Earlier studies have shown a significant influence of these regimes on car-following model calibration and validation (Hu et al., 2023). Still, there is a significant lack of understanding of how driving behaviour might vary among these regimes. Barring a few studies (Hu et al., 2023), almost all studies ignored driving regimes in trajectory data whilst understanding and modelling driving behaviour. We envisage that driving behaviour in these regimes is likely to be different, as shown in a recent study (Hu et al., 2023) but needs thorough examination. Such efforts will provide insights into which portion of the trajectory is more suitable for understanding specific behaviour and should be catered for in future data collection endeavours. Finally, novel applications of connected vehicles like green light optimum speed advisory and naked roads (i.e., taking off all physical road signs and present them through in-vehicle information systems) should be tested.

Similarly, the experimental setup should consider both lane-changing types: mandatory and discretionary, allowing a comparison of change in driving behaviour from mandatory to discretionary and vice versa, which could assist in joint modelling of two lane-changing types. Further, for a proper understanding of failed lane-changing attempts and its modelling, they should be carefully designed with many possible triggers, e.g., hard braking of the lead vehicle in the target lane and sudden speeding behaviour of the following vehicle in the target lane. Finally, designing lane-changing scenarios in different road types (rural/urban/motorways) will allow comparing differences in lane-changing behaviours, which can assist in developing more realistic microscopic lane-changing models for each specific road type.

4.2.3. Modelling methodologies

Several modelling methodologies have been used for understanding driving behaviour in the literature, with multiple methodologies available for modelling the same driving behaviour characteristic. In principle, the choice of modelling methodology should be governed by the need and the type of response (or dependant variable). For the need, statistical and machine learning models can be developed, whereby statistical models are better suited for explaining causal relationship and determinants and machine learning models often provide better predictive capabilities. Similarly, for the type of response variable, when modelling events with durations or any behaviour reflecting time to completion of an event (e.g., response time or lane-changing durations), hazard-based duration or survival models can be developed. These models are probabilistic and well-suited for analysing time related data where a need arises to study the elapsed time until the end (or occurrence) of an event or the duration of an event (Washington et al., 2020). Similarly, for driving simulator data with panel data, Generalised Estimation Equation models could be used, allowing to capture correlated data where the correlation is a result of repeated observations of the same driver. Another peculiarity of these models is no requirement of the distribution of the response observations, and the response observations do not necessarily have to be independent. For complex phenomena, multi-level or hierarchical modelling can be performed, allowing the dependent variable to have different characteristics for different factors. Finally, when modelling decisions or categorising driving behaviour, discrete choice models can be applied (Train, 2009), e.g., lane-changing decisions (yes/no) and aggressive, timid, and safe driving.

As mentioned in Section 3, driver-level heterogeneity is currently not fully understood. Intra-driver heterogeneity requires studying the same decisions over time, whereas inter-driver heterogeneity involves understanding driving behaviour in different situations. Obviously, the latter involves multiple factors and needs detailed data. Next, connecting diverse heterogeneities, such as heterogeneity in the driving behaviour in different driving regimes, the effects of driving aids in a connected environment, and inter- and intra-driver heterogeneity, advances this unexplored field. More realistic driving behaviour models are anticipated from such endeavours. To this end, many of the modelling methodologies mentioned above can be extended to include random parameters, allowing the estimated parameters to vary across observations/individual drivers to capture variation in driving behaviours. Other alternatives to classic random parameters models include latent class (finite mixture) models, latent class models with random parameters within classes, and Markov switching models (a detailed description of these models can be found in Washington et al. (2020)). Finally, multivariate modelling approaches (with two or more dependant variables) can simultaneously capture two processes, e.g., lane-changing decisions and execution. This type of methodology can also be applicable in joint modelling of car-following and lane-changing behaviours, allowing to capture similarities and differences in a unified manner. Such modelling efforts can make existing microsimulation tools more realistic, whereby these two models are embedded together to perform simulations.

The aforementioned modelling methodologies are well-suited for explaining driving behaviour, but their predictive performance is generally lower compared to machine learning models. With post-hoc explainable artificial intelligence methods gaining prominence, machine learning models can now provide both explanation and predictive power, and a detailed review of several machine learning algorithms can be found in Wen et al. (2021). Using advanced machine learning methods like autoencoder, attention mechanism, and transformers can be useful for computational efficiency and precise estimation (see Guo et al. (2022)) for using connected vehicle data for lane-changing detection.

Our review suggests relatively smaller applications of machine learning methods for different car-following and lane-changing behaviours, which could be primarily because of inability of these models to provide causal inferences. As the field of machine learning is growing rapidly, the use of causal inference models is likely to benefit to better understand car-following and lane-changing behaviours.

5. Driving behaviour in the era of emerging vehicle technologies

With the rapid advancement of communication and automation technologies, several vehicle technologies have paved their way into the traffic stream. These include connected vehicles, automated vehicles, and connected and automated vehicles. Whilst these vehicles have shown promise in helping solve major transport issues, integration of these vehicles with current traditional vehicles, forming mixed traffic, will bring new challenges. Along this line, Lee et al. (2022) summarised challenges and future directions for connected vehicles, forming the base of some urgent research needs in this direction for connected vehicles and other vehicle technologies. This section summarises some urgent research needs in this direction.

Most early studies on vehicle technologies' impact on traffic are based on numerical simulations. Whilst numerical simulation is a reasonable compromise to the scarcity of data, findings from past research are oversimplified because a critical component — human factors that play a central role in driving behaviour — is often ignored (or not accounted for) (Saifuzzaman and Zheng, 2014). To this end, the first and most crucial task is data collection. Recently, several new datasets for automated vehicles have been released, such as the nuScenes dataset (Caesar et al., 2020) and the Waymo Open dataset (Sun et al., 2020a), which contains both information on the movement of automated vehicles itself and information on the surrounding environment. However, such datasets can be difficult for traffic flow researchers to understand and use, as pointed out by Hu et al. (2022), due to the following reason: different types of sensors are used, and some of them are new to researchers in traffic flow community; information collected by these sensors is diverse and complex; and the structure and format of these datasets are not user friendly. Despite these challenges, these datasets are very useful for driving behaviour research. Overall, traffic scenarios included in these datasets are still quite limited, and there is a great need of having data that cover all road types, traffic conditions, driver groups, weather conditions, geometries, and interactions between automated vehicles and other road users (e.g., cyclist, e-scooters, pedestrian, etc.). Data that contain crashes and safety–critical events are particularly valuable.

Recognising the challenges associated with field data collection, some studies have designed a driving simulator experiment to collect trajectory data in a controlled environment (Wang et al., 2024). A connected environment can provide dynamic and personalised information to individual drivers. However, almost all previous studies only used a single driving simulator to analyse the impact of a connected environment on the subject driver. Since driving behaviour is an interactive decision-making process, analysing the full effects of emerging vehicle technologies like a connected environment on driving behaviour is hard to analyse using a single driving simulator. To this end, connected driving simulators can be used where the impact of emerging vehicle technologies could be analysed on multiple drivers simultaneously.

Understanding the effects of these emerging vehicle technologies solely through trajectory data may not be sufficient. Therefore, data from other sources to further augment trajectory data becomes necessary. With these emerging vehicle technologies, a major issue is analysing user acceptance and trust in the system, particularly in a connected environment. Although some studies collected survey data related to user acceptance and trust in the system of a connected environment (Ali et al., 2020a), these surveys are yet to be fused with trajectory data to gain more insights into driving behaviour. Along the same lines, evidence of incorporating such latent measures (e.g., trust and acceptability) into microscopic car-following and lane-changing models is scant. Further, studies based on driving simulator experiments can only reveal relative changes in driving behaviour caused by vehicle technologies (e.g., connected environment), which is observed across different scenarios. There is a clear need to translate and replicate the relative change in the field because driving behaviour observed in a driving simulator will likely differ from naturalistic behaviour.

Although data collected via driving simulators can assist in understanding traffic safety, crash records for these vehicles with emerging technologies will not accrue soon until these vehicles are fully operational at a large scale. Thus, understanding the safety benefits of these vehicle technologies is challenging because most safety modelling is based on crash data. To this end, non-crash-based methods, like the extreme value theory approach, are recommended (a detailed review of this modelling approach and how it can be used for different vehicle technologies can be found in Zheng et al. (2021)). This approach has the inherent capability of extrapolating crash risk from frequently observed extreme events (e.g., braking/conflicts) to rare events (crash) using Hydén's pyramid (Hydén, 1987), and its good performance has been reported in many studies (e.g., Songchitruksa and Tarko (2006) and Hussain et al. (2022)). The extreme value theory approach has recently been applied to quantify the crash risk associated with connected vehicles (Nazir et al., 2023) and autonomous vehicles (Ranjitkar et al., 2003).

Providing additional information in a connected environment could be beneficial in lowering the riskiness of (young) drivers, as some studies found that drivers tend to select relatively bigger gap sizes when they are driving in a connected environment compared to a traditional environment (Wang et al., 2024). However, this increased safety margin may come at the cost of a reduction in traffic flow efficiency. Thus, there is a clear need to determine the optimal use of a connected environment where traffic safety could be enhanced along with maximising traffic flow efficiency. Further, it is expected that a connected environment's impact is likely to be different for different lane-changing types (mandatory and discretionary) and driver demographic (age groups and gender). Along this line, different drivers are believed to have different levels of acceptance and trust in a connected environment, which are important factors to be considered in evaluating the success of a connected environment (Sharma et al., 2017). Also, such understanding can provide insights into whether it can suppress (if not completely eliminate) lane-changing impacts during different lane-changing types. Such impact needs to be captured and translated into microscopic lane-changing models, whereby capturing how a connected environment influences lane-changing behaviour compounded by human factors is still at its infancy.

Lastly, there is an urgent need to empirically investigate driving behaviour in mixed traffic where traditional vehicles are sharing space with connected and automated vehicles because it is likely to take a long period of time (certainly longer than what many pundits once predicted) before we can witness the dominance of connected and automated vehicles on roads. We envisage that whilst individually, these vehicles may provide benefits, without a sound understanding of their interactions, such effects may diminish (or reduce) when different vehicle technologies are mixed. Thus, examining the impact of mixed traffic on driving behaviour and measuring traffic safety measures in such a mixed traffic situation becomes crucial. To this end, several factors should be considered, including (a) penetration rate of connected vehicles, automated vehicles, and traditional vehicles, (b) spatial distribution of these vehicles in the platoon, (c) automation level of automated vehicles and takeover effect, and (d) cooperative behaviour between connected vehicles and impairments of a connected vehicular environment, such as delayed information supply and intermittent loss of information. The findings from such analysis will pave the way for developing more realistic models for connected and automated vehicles and capturing connected and automated vehicles' effects on local and network-level dynamics.

6. Conclusions

This paper stands apart from previous reviews by focussing on empirical evidence related to driving behaviour. The review pinpoints research gaps and limitations for car-following and lane-changing tasks. Whilst car-following research is one of the oldest topics in traffic engineering, challenges persist, notably the need to reliably derive car-following parameters like response time from trajectory data. Recommending deceleration-based metrics for risky behaviour assessment, this study urges greater attention to the execution and impact of lane-changing decisions. Incorporating human factors into lane-changing models is also emphasised. Finally, a better understanding of the effects of emerging vehicle technologies like connected and automated vehicles in mixed traffic is crucial to determine whether these technologies can suppress the major externalities of road transport related to traffic efficiency, safety, and energy consumption/vehicle emissions. Understanding and quantifying such effects will also enable developing models tailored to these emerging technologies, which will lay the foundation for developing safe, efficient, and sustainable strategies for managing traffic mixed with these futuristic vehicles.

CRediT authorship contribution statement

Yasir Ali: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Anshuman Sharma:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Zuduo Zheng:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Funding acquisition, 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.

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Data availability

Data will be made available on request.

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