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REVIEW

Modelling and simulation of (connected) autonomous vehicles longitudinal driving behavior: A state-of-the-art

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Abstract
Microscopic traffic models (MTMs) are widely used for assessing the impacts of (connected) autonomous vehicles ((C)AVs). These models utilize car-following (CF) and lane-changing models to replicate the (C)AVs driving behaviors. Numerous studies are being lately published regarding the approximation of the driving behaviors of (C)AVs (especially CF behavior) with many state-of-the-art modelling methods. Still, there is no established CF model to mimic the accurate behavior of (C)AVs. Researchers often utilize existing mathematical CF models as well as limited data-driven models for (C)AVs modelling. Meanwhile, several studies conduct simulation-based impact assessments with various key performance indicators (KPIs). Identification of these KPIs is a crucial step for future studies. Hence, this paper presents a comprehensive outlook on different CF models with their adopted parameters for (C)AVs modelling and investigates how and in which aspects might the CF behaviors of (C)AVs are different from human-driven vehicles. In addition, the recent publications in data-driven CF models including their methodologies are explicitly discussed. This work also reviews simulation-based studies with the reported impacts and used KPIs. Finally, in light of the findings of this paper, several future research needs are highlighted.

1 | INTRODUCTION

With the development of advanced driving assistance systems (ADAS), such as adaptive cruise control, cooperative adaptive driving control, lane keeping assistance, or emergency brake assistance, our future transportation system is not far away from the revolution of autonomous vehicles [1]. We will soon witness a different traffic situation, where vehicles with a high degree of automation interact with low-level automated vehicles [2]. According to the Society of Automotive Engineers (SAE), vehicles are classified based on the degree of automation from non-automated (level 0) to full automation (level 5) [3]. Full automation level is commonly known as full self-driving, autonomous or driverless vehicles, where the vehicle itself is responsible for all safety functions and navigation of the road [1, 4].

The recent advanced sensing technologies (e.g. radar, lidar) and pattern recognition together with processing capabilities of artificial intelligence enable autonomous vehicles (AVs) to detect the precise image of the surrounding environment and react accordingly with the help of complex machine learning algorithms. Meanwhile, pervasive communication technologies allow AVs to exchange their driving status (i.e. speed, acceleration, position, and more) with other connected vehicles (V2V), as well as infrastructure (V2I), which is labeled as connected autonomous vehicles (CAVs) [5, 6]. In the remainder of this article, where applicable, we use the term (Connected) autonomous vehicles-(C)AVs to summarily describe AVs+CAVs.

(C)AVs have the potential to largely change traffic safety, mobility pattern, and transport network. It is expected that (C)AVs could improve traffic safety as a large number of accidents are associated with the drivers' errors and unfitness to drive (e.g. fatigue, alcohol, or drugs) [7–9]. (C)AVs open more mobility freedom by removing driving barriers, such as disability, driving license and old age [10, 11]. Meanwhile, (C)AVs could potentially change travel behavior, reduce traffic congestion [12], fuel consumption [13–15], and vehicle emissions [14], however, their certain effects are quantitatively not confirmed yet [4, 16]. Several corridor-wide trials of AVs have been conducted to estimate the impacts, however, due to large costs of AV fleets, as well as legal restrictions, large-scale tests are currently impractical. Researchers conduct simulation-based assessments to extrapolate the potential impacts of (C)AVs on a large-scale using traffic models. Especially several studies utilized microscopic traffic models (MTMs) to analyze and predict the impacts of (C)AVs on safety and traffic efficiency [6, 17–19].

The driving behavior of (C)AVs might significantly differ from human-driven vehicles. In MTMs, these behaviors are modelled with their longitudinal and lateral configurations. Longitudinal and lateral dynamics of a vehicle are also called car-following (CF) and lane-changing behaviors, respectively. A CF model is comprised of a set of actions that a driver decides on to follow the leading vehicle efficiently and safely. Several mathematical CF models have been developed to estimate driving behavior under various traffic conditions. However, many studies criticized the limitations of these models in capturing the diversity of driving behavior, as these models are simplified and only contain a small number of parameters [5, 20, 21]. Hence, data-driven models have attracted attention to replicate the complex driving behavior more accurately.

While most of the mathematical, as well as data-driven models, are used for modeling human-driven vehicles, there is no established CF model of the behavior of (C)AVs. Most of the researchers adopt and modify the parameters of the existing CF models to study the driving maneuvers of (C)AVs. Meanwhile, machine learning-based models are also developed based on human-driven vehicles' trajectories [due to limited (C)AVs traffic data], and thus can not guarantee to fully approximate the behavior of (C)AVs. However, the proposed methodologies in these studies could be potentially used for (C)AVs modelling, when field data of (C)AVs are available.

Numerous review articles have been published relevant to (C)AVs modelling in MTMs (e.g. [5, 20, 22]). For instance, [5] reviewed the summary of studies relevant to (C)AVs CF models and their impact assessments, where [20] recently reviewed the traditional CF models utilized for modelling (C)AVs including simulation tools. However, in both studies, they do not discuss how largely the CF behavior of (C)AVs differs from the human-driven vehicles. Mathematical CF models are comprised of relations and parameters to capture the driving behavior of vehicles. It is expected that the CF behavior through acceleration distributions, safety gaps, reaction time, and other CF model-related parameters of the (C)AV under specific traffic situation are different from human-driven vehicles. Researchers assume that (C)AVs could drive very close to the leading vehicle, and react very fast. However, the magnitude of these differences is subjective among researchers and have not addressed in the above-mentioned review articles . In addition, existing review papers cover the general impacts of (C)AVs on safety, mobility and the environment in various scenarios. However, key performance indicators (KPIs) used in simulation-based studies involving (C)AVs are not specifically reported. Hence, to fill these research gaps, a review reporting specific values of the mathematical CF model parameters for capturing the behavior of (C)AVs, as well as the identification of the KPIs for (C)AVs related studies under different situations is a necessity. It fosters a wide understanding of the potential driving behavior of (C)AVs from a scientific perspective and also helps future simulation-based impact assessments to select proper KPIs and CF model parameters. In addition, the output of this review will reveal interesting research gaps on (C)AVs modelling and impact assessment.

On the other hand, [22] studied research works related to the microscopic modelling of CAVs including traditional and newly developed models. However, there have been many recent studies utilizing machine learning techniques to model CF behavior. Several studies have proposed new methods to develop data-driven CF models. Since in existing review papers these data-driven models are not reported, a more recent review to cover the studies which have been recently published is required. Therefore, considering the above limitations, research gaps and the importance of the (C)AVs modelling and simulation-based impact assessment, this paper aims to provide a comprehensive review of relevant studies in the field of (C)AVs modelling, and impact assessments.

The collection of these articles follows a semi-structured approach. The reviewed articles in this paper include journal papers, conference papers, and technical reports. First, we gathered studies from the Scopus search engine using 8 keywords (*autonomous vehicles, connected autonomous vehicles, self(-)driving cars, car following models, simulation of autonomous vehicles, autonomous vehicles modelling, data-driven car following models, autonomous vehicles impact assessments*) for the publication year range 1990 - June 2022. The obtained papers were further screened according to their relevance and topics. Additionally, we collected related articles from the references of the screened papers. To have a general idea about different CF models, some studies related to CF models have been included.

The main contributions of this research work are as follows: (i) Overview of different CF models with their adopted parameters for (C)AVs modelling. This leads to understand how potentially the CF behavior of (CAVs) is different from human-driven vehicles and which CF model parameters are more crucial and sensitive in differentiating (C)AVs from human-driven vehicles. (ii) Summary of the lately published data-driven models for (C)AVs CF behavior, and (iii) Identification of set of KPIs used for impact assessments and the revealed impacts. This section reports the importance of KPIs in impact assessment studies, and reveals an outlook for future studies on usage of a certain KPI for a specific study area and under different conditions.

The remainder of this paper is structured as follows: In the following section, we review the recent literature on mathematical CF models for (C)AVs and adopted parameters. In Section 3, we introduce a summary of data-driven models mimicking (C)AVs CF behavior. Identification of KPIs utilized in impact assessments and the revealed reports are presented in Section 4. Finally, a conclusion in Section 5 explains the overall contribution of this article alongside further research directions.

2 | MATHEMATICAL CAR FOLLOWING MODELS

Driving behavior is the key element in microscopic traffic modelling and simulation. (C)AVs have significantly different driving behaviors in comparison to human-driven vehicles. These differences are due to sensing and communication technologies integrated in (C)AVs. AVs for instance have the ability to sense necessary information from the leading vehicles, whereas for CAVs, a stream of data (such as position, speed, acceleration etc.) are exchanged among CAVs as well as between CAVs and infrastructure (thanks to V2V and V2I communications). In case of human-driven vehicles, it is the driver who is responsible to capture the environment and act accordingly. Therefore, the driving behavior parameters, especially parameters for CF behavior such as acceleration, deceleration, desired speed, minimum gap etc. for human-driven vehicles, AVs and CAVs are different.

For human-driven vehicles, there are many established mathematical models to mimic their CF behavior. Most of these models focus on a driver's physical actions such as desired speed, acceleration, deceleration (i.e. Gazis-Herman-Rothery (GHR) model [23], Gipps model [24], intelligent driver model (IDM) [25], optimal velocity model (OVM) [26]), however, some also consider the psychological inputs of the drivers (i.e. Wiedemann model [27]). For (C)AVs simulation, however, there are no established models. A recent review of literature shows that a considerable amount of studies utilizing conventional mathematical models (i.e. IDM [25] and modified versions, MIXIC [28], Wiedemann [27], Krauss [29] etc.) to approximate the CF behavior of (C)AVs in a microsimulation framework [18, 30–33]. In many studies, the modelling of Adaptive Cruise Control (ACC) and Cooperative Adaptive Cruise Control (CACC) are refereed to AVs and CAVs modelling, respectively [18, 34–36].

2.1 | Intelligent driving model (IDM)

IDM and its modified versions are broadly used CF models for (C)AVs microsimulation studies [19, 37–44]. IDM first developed by [25] is one of the simplest and accident-free model which uses both the desired speed and space headway to generate realistic acceleration profile. The model ignores the reaction time, therefore, it and its modified versions can replicate the characteristics of AVs and CAVs, respectively. The basic form of IDM acceleration function is expressed as:

$$a_n(t) = a_{\max}^{(n)}\left[1 - \left(\frac{V_n(t)}{V_0^{(n)}(t)}\right)^{\delta} - \left(\frac{S_n^{*}(t)}{S_n}\right)^{2}\right], \tag{1}$$

where $a_{\max}$ is the maximum acceleration/deceleration of the vehicle n, V_n is the speed of the following vehicle, $V_0^{(n)}$ is the desired speed of the following vehicle, S_n is the gap distance between two vehicles, S_n^* is the desired spacing between two vehicles (see Figure 1), and δ is the model parameter.

The model is comprised of three terms. When the distance between the leading and following vehicles is relatively high, the third term becomes negligible, and thus the model acts as a free-flow model, where the desired speed of the driver controls the acceleration of the vehicle. On the other hand, for closer space headway between vehicles, the following vehicle will apply the CF strategy and reduce the free-flow acceleration by the magnitude of third term in Equation (1). Thus, one single equation can mimic both free-flow and CF regimes depending on different situations. Meanwhile, the desired space headway between two vehicles S_n^* is a function of the following vehicle speed V_n, and the speed difference between the leading and following vehicles ΔV_n, which can be calculated using Equation (2):

$$S_n^{*}(t) = S_0^{(n)} + V_n(t)T_n(t) + \frac{V_n(t)\Delta V_n(t)}{2\sqrt{a_{\max}^{(n)} b^{(n)}}}, \tag{2}$$

where $S_0^{(n)}$ is the minimum spacing at standstill situation, T_n is the desired (safe) time headway, and $b^{(n)}$ is the desired (comfortable) deceleration. The maximum acceleration and a comfortable deceleration rate ensure that the model does not produce unrealistic high acceleration/deceleration.

IDM was later extended by [45] to replicate the driving style adaptation effect to the surrounding traffic using a memory function. The IDM with memory (called IDMM) assumes that after experiencing congested traffic for while, most drivers adapt their driving behavior, for instance by increasing their desired time gap to the leading vehicle. According to [45], a single internal dynamic impacts the desired time gap decision. Thus, the new desired time gap $T_n(t)$ in Equation (2) is replaced by $T_n(\lambda)$, which is approximated as follows:

$$T_n(\lambda) = T_n\left[\beta_T + \lambda_n(1-\beta_T)\right], \tag{3}$$

where $\beta_T = T_{jam}/T_n$ is an adaptation factor, λ_n is the subjective level of service which takes values between 0 (standstill traffic) and 1 (free-flow traffic).

There exist many revised versions of IDM, each with different objectives [17, 19, 37, 38, 46–48]. For instance, [46] introduced some multiplication factors to ensure smooth driving behavior in different traffic situations (i.e. free-flow, upstream front, congested traffic, bottleneck, downstream front). It is assumed that the maximum acceleration of a vehicle is increased when leaving congestion, and the comfortable deceleration is decreased when an upstream-front is detected. Depending on

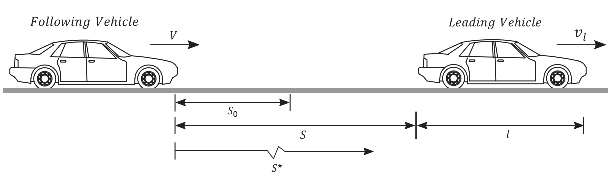

FIGURE 1 Illustration of IDM CF model parameters.

TABLE 1 Multiplication factors of IDM Model [46].

Traffic situation	λ_a	λ_b	λ_c	Driving style
Free flow	1	1	1	Comfort driving
Upstream front	1	1	0.7	Safe driving
Congestion	1	1	1	Comfort driving
Bottleneck	0.7	1.5	1	Breakdown prevention
Downstream front	0.5	2	1	High dynamic capacity

the which state is noticeable in next time step, the following factors are multiplied by the main IDM model parameters:

$$a^{(s)} = {\lambda_a}^{(s)} \cdot a, \quad b^{(s)} = {\lambda_b}^{(s)} \cdot b, \quad T^{(s)} = {\lambda_T}^{(s)} \cdot T,$$

where the superscript (s) indicates the traffic situation, a, b and T are maximum acceleration, comfort deceleration, and time gap, respectively. The values of the multipliers are listed in Table 1.

IDM model generates unrealistic deceleration rates when the gap is significantly lower than the desired gap. To avoid this, [19] combined the IDM with the Constant Acceleration Heuristics (CAH). The CAH is developed based on three main assumptions: (i) the acceleration of the following and leading vehicles will not change in the near future (in a few seconds), (ii) safe time headway or minimum distance is not required at any moment, and (iii) reaction time is neglected (drivers react without delay). To calculate the maximum acceleration of a vehicle while keeping the situation crash-free, two possible conditions (zero or nonzero velocity of the leading vehicle) at the time where the minimum gap is reached are distinguished. Hence, the maximum acceleration a_{CAH} given actual values of the gap s, velocity of the following vehicle v_f, velocity and acceleration of the leading vehicle v_l, a_l is expressed as:

$$a_{CAH} = \begin{cases} \frac{{v_f}^2 \cdot \bar{a}_l}{{v_l}^2 - 2s \cdot \bar{a}_l} & \text{if } v_l\left(v_f - v_l\right) \leq -2s \cdot \bar{a}_l \\ \bar{a}_l - \frac{\left(v_f - v_l\right)^2 \Theta\left(v_f - v_l\right)}{2s} & \text{otherwise} \end{cases}, \tag{4}$$

where $\bar{a}_l = min(a_l, a_f)$ is the effective acceleration, which avoids the artifacts that may cause by a leading vehicle with higher acceleration capabilities. The Heaviside step function Θ is used to eliminate negative approaching rates. [19] proposed an ACC model by combining the acceleration from the IDM and CAH. Depending on the CF situation, the decisive acceleration of the ACC vehicle is controlled by a comparison of the IDM and CAH acceleration profiles as follows:

$$a_{ACC} = \begin{cases} a_{IDM} & \text{if } a_{IDM} \geq a_{CAH} \\ (1-c) \cdot a_{IDM} + c \cdot [a_{CAH} & \\ + b \cdot tanh(\frac{a_{IDM} - a_{CAH}}{b})] & \text{otherwise} \end{cases}, \tag{5}$$

where the coolness factor c is an additional parameter compared to the original IDM model, which is assumed 0.99 in [19].

TABLE 2 IDM parameters for AVs modelling [18, 19].

Model parameters	Values
Desired speed (V_0)	120 km/h
Model parameter (δ)	4
Maximum acceleration ($a_{\max}$)	1.4 m/s^2
Desired deceleration (b)	2 m/s^2
Minimum gap distance at standstill (S_0)	2 m
Desired headway (T)	0.6 s
Maximum deceleration	2.8 m/s^2

In addition, [47] attempted to improve the safety of IDM model by modifying the desired gap equation (Equation 2) by adding a new term ($c_n \frac{v_n^2}{b_n}$). The new term indicates that with higher velocities, the desired minimum gap increases, and consequently the driver safety is improved. In addition, [37] added a reaction time variable in the original IDM acceleration equation. This study assumes that the reaction time variable can reasonably distinguish AVs from human-driven vehicles. The model parameters are adopted from literature with few adjustments. For instance, the time headway and reaction time for AVs are assumed 1 s and 0 s respectively. On the other hand, [38] proposed an improved IDM model to consider multi-front and rear vehicles. The model generates the acceleration profile of the following vehicle by employing information of multiple front and rear vehicles. Weight factors are added to each vehicle's information depending on their locations. The model parameters are based on assumptions by the authors.

The basic IDM model has been widely used to approximate the driving behavior of AVs in several studies. However, the main difficulty of the model is the observation of desired measures such as desired spacing, desired time headway, and desired speed for AVs. Thus, several studies used the IDM parameters from the literature which are either based on assumptions or limited field experiments. The parameters of AVs behavior utilized in many simulation studies are presented in Table 2.

Recent studies such as [17, 33], and [41] utilized IDM and its modified versions to conduct (C)AVs impact assessments. [17] studied the safety and mobility effects of AVs, CAVs, and connected vehicles (CVs) in a major freeway in Orlando, Florida. This study utilized the basic IDM to model the driving behavior of AVs, and a modified IDM based on [48] for CAVs modelling. In this study, a set of parameters of the IDM is adopted from [18, 19] both for AVs and CAVs modelling (see Table 2).

Similarly, [33] investigated the impacts of commercially available ACC vehicles on traffic stability and throughput. In this study, IDM is used to capture the CF behavior of human-driven, theoretical ACC and commercially available ACC vehicles. The parameters for both human-driven and theoretical ACC vehicles are take from [44, 46], where for commercially available ACC, set of calibrated parameters from the field experiment are deployed in the simulation platform. [41] utilized a revised version of IDM to study the effect of CAVs on freeway capacity. The revised IDM is based on [18] and [47] to ensure realistic behavior, and to improve the driving safety of CAVs. This study also uses the values of IDM parameters from the previous studies as depicted in Table 2. Similarly, [42] used IDM to model the behavior of ACC vehicles. In this study, several parameter settings of the IDM model are implied. In the base scenario, the parameters of the model are taken from [18, 19, 44], where other parameter settings are considered based on the commercially available ACC vehicles behavior and are taken from [18, 36].

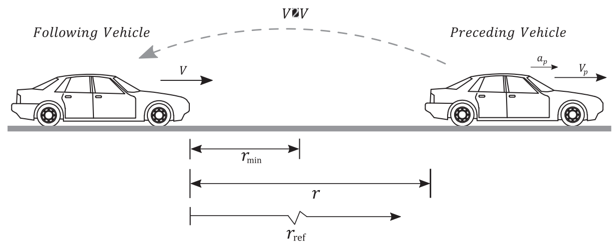

FIGURE 2 MIXIC CF model.

2.2 | MIXIC model

MICroscopic Model for Simulation of Intelligent Cruise Control (MIXIC) first developed by [28] to model ACC and later revised by the author in 2006 to incorporate CACC characteristics [49]. The model assumes that the following vehicle attempts to keep the relative speed to the leading vehicle at zero and the space gap at the desired speed. Thanks to the V2V communication, where certain driving information such as position, speed, acceleration etc. of both following and leading vehicles are exchanged. MIXIC model approximates the acceleration profile with two distinct components: (i) the controlling component, which delivers reference values, (ii) the vehicle model component, which converts the reference values into realized values. The reference acceleration can be calculated based on the speed difference of the following vehicle (intended speed and current speed) denoted as ($a_{ref,\Delta v}$) or the gap and speed differences between the following and leading vehicles symbolized as ($a_{ref,d}$). Minimum of both acceleration references ($a_{ref} = \min(a_{ref,\Delta v}, a_{ref,d})$) is the final acceleration reference value which is the input for the vehicle control. Meanwhile, the model considers the comfort driving behavior, and thus a_{ref} is limited to maximum acceleration of 2 m/s^2 and comfort deceleration of -3 m/s^2. The estimation of the reference acceleration based on speed difference is as follows:

$$a_{ref,\Delta v} = k \cdot (v_{\text{int}} - v), \tag{6}$$

where v_{int}, and v are intended and current speed, respectively, and k is the speed error factor constant.

The reference acceleration based on the speed and gap differences between the following and leading vehicles is calculated as:

$$a_{ref,d} = k_a \cdot a_p + k_v \cdot \left(v_p - v\right) + k_d \cdot \left(r - r_{ref}\right), \tag{7}$$

where a_p and v_p are the leading vehicle's acceleration and speed, respectively, r and r_{ref} are the current and reference gap to the leading vehicle as depicted in Figure 2, k_a, k_v, and k_d are the constant factors. The reference gap (r_{ref}) is defined as: $r_{ref} = \max(r_{safe}, r_{system}, r_{\min})$, where r_{safe}, r_{system}, r_{min} are the safe following distance, following distance based on the system time setting, and minimum following distance (set to 2 m), respectively. The safe following distance is a function of the deceleration capabilities of the following vehicle (d) and the leading vehicle (d_p) and is expressed as:

$$r_{safe} = \frac{v^2}{2} \cdot \left(\frac{1}{d_p} - \frac{1}{d}\right). \tag{8}$$

Similarly, the following distance according to the system time setting (time gap) is computed as: ($r_{system} = t_{system} \cdot v$). If the leading vehicle is equipped with CACC, t_{system} is set to 0.5 s, and 1.4 s otherwise.

[6] further developed a CAV model based on the MIXIC model. The proposed model also considers the sensor detection ranges of CAVs; however, the model parameters remain the same as the MIXIC model. According to [49], the model parameters are chosen as: $k = 1.0$, $k_a = 1.0$, $k_v = 0.58$, and $k_d = 0.1$.

Several studies utilized MIXIC and developed models based on MIXIC to conduct impact assessments of CAVs [6, 49–54]. For instance, [49] used MIXIC model to evaluate the influence of CACC on traffic flow characteristics. [39, 53] utilized the enhanced MIXIC model based on [6] to mimic the driving behavior of CAVs. This study approximates the driving behaviors of CAVs using CACC vehicles while cruising. Similarly, [51] recently used MIXIC model with default parameters values to replicate the driving behavior of (C)AVs and conduct impact assessments.

2.3 | ACC and CACC models

[54] developed a control algorithm similar to MIXIC to estimate the speed of an ACC-equipped vehicle in the next time steps. The proposed control method consists of two modes: (i) speed control mode, and (ii) gap control mode. The speed control mode aims to keep the speed of the following vehicle close to the speed limit, whereas in the gap control mode the goal is to maintain the desired gap between the two vehicles. According to this approach, the acceleration of a vehicle under the following conditions is controlled both by speed and gap and calculated as:

$$a = k_g(s - s_d) + k_s(v_d - v), \tag{9}$$

where k_g and k_s are the gap and speed control constants, s is the current space gap, ($s_d = t_d \cdot v$) is the desired distance between

TABLE 3 ACC-CACC model parameters.

Model parameters	Values
Desired time gap (t_d)	1.5 s (ACC), 0.7 s (CACC)*
Max. acceleration (a)	2 m/s^2
Max. deceleration (b)	−2 m/s^2
Constants (k_g, k_s)	−0.4, 0.25

*The average time gap of field test vehicles.

two vehicles, t_d is the desired time headway, and v_d is the desired speed. On the other hand, the acceleration of a vehicle under free-flow situations is only controlled by the speed and it is described as:

$$a_f = \max\left(\min\left(k_s(v_d - v), a\right), b\right), \tag{10}$$

where a and b are the maximum acceleration and deceleration, respectively. The minimum of the CF acceleration and free-flow acceleration is the decisive acceleration which is the input for estimation of the vehicle's speed in the next time step.

$$v_{t+\Delta t} = v_t + \min\{a, a_f\} \cdot \Delta t. \tag{11}$$

Utilizing the above model, [54] investigated the effects of CACC system on freeway traffic flow with different market penetration rates. In this study, certain parameters of the control algorithm are based on set of assumptions, where the desired time gap for ACC and CACC were extracted from the field test (see Table 3). The ACC-CACC model by [54] was used in [39, 53] to model the driving behavior of AVs and to study the impact of (C)AVs on traffic flow and CO_2 emissions. In [39], the parameters of the model are adjusted as follows: $t_d = 1.6$ s, $a = 2$ m/s^2, and $b = -3$ m/s^2.

[18] further improved the ACC model based on experimental results. In this study, the maximum acceleration and deceleration were limited to 1 and 2.8 m/s^2, respectively. On the other hand, [36] developed the ACC and CACC models utilizing experimental data from a field test of production vehicles. The model consists of a gap regulation and gap closing controllers. The simplified version of this model is applied in [18]. The gap error and its derivative are used to estimate the vehicle speed on each control cycle. The gap error of the n-th consecutive vehicle (e_n) is expressed as:

$$e_n = x_{n-1} - x_n - t_w \cdot v_n, \tag{12}$$

where x_{n-1} is the current position of the leading vehicle, x_n and v_n are the current position and speed of the following vehicle, respectively, and t_w is the time gap. The goal of the gap regulation controller is to minimize the gap error by a constant time-gap following policy. The speed of the following vehicle is therefore estimated as:

$$v_n = v_{nprev} + k_p \cdot e_n + k_d \cdot \dot{e}_n, \tag{13}$$

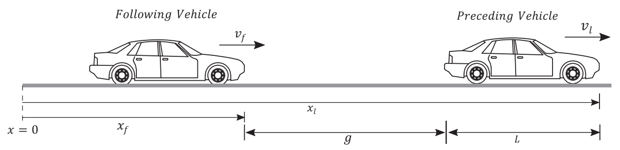

FIGURE 3 Description of the Krauss CF model parameters.

where v_{nprev} is the speed of the following vehicle in the previous iteration, k_p and k_d are the coefficients adjusting the time-gap error and its derivative ($k_p = 0.45$, and $k_d = 0.25$).

Several simulation-based impact assessment studies used the ACC and CACC models to approximate the behavior of (C)AVs. For instance, [55] used the ACC-CACC model of [54] to represent the ACC vehicle longitudinal behavior and to investigate the effects of AVs on traffic safety and efficiency . In this study, the maximum acceleration and deceleration were selected 2 and −3 m/s^2, respectively.

2.4 | Krauss model

The Krauss CF model developed by Stephan Krauss in 1997 is a space-continuous model [29]. Krauss model estimates the speed of the vehicle without deriving it from the acceleration profile of the vehicle. In Krauss model, the safe velocity of the following vehicle is calculated as follows:

$$v_{safe}(t) = v_l(t) + \frac{g(t) - v_l \cdot t_r}{\frac{v_l(t)+v_f(t)}{2b} + t_r}, \tag{14}$$

where v_l, v_f are the speed of leading and following vehicles at time t, respectively (see Figure 3), t_r is the reaction time of the driver, b is the maximum comfort deceleration of the vehicle, and $g(t)$ is the gap between the following and leading vehicles, which is computed as: $g(t) = x_l(t) - x_f(t) - L$, (x_l, x_f are the position of the leading and following vehicles, and L is average length of a vehicle). Meanwhile, to estimate the desired speed which is a decisive variable for determining the speed of the vehicle in next time step, the model takes the minimum of safe velocity, the road speed limit, and the vehicle's maximum capable speed to generate the desired speed of the vehicles, expressed as:

$$v_{des}(t) = \min[v_{\max}, v(t) + a \cdot \Delta t, v_{safe}(t)]. \tag{15}$$

Finally, the velocity and location of the vehicle at the next time step are computed as follows:

$$\begin{aligned} v(t + \Delta t) &= \max[0, v_{des}(t) - \eta], \\ x_f(t + \Delta t) &= x_f(t) + v(t + \Delta t) \cdot \Delta t, \end{aligned} \tag{16}$$

where η is the random perturbation (to capture the driving imperfection) and Δt is the simulation time step. According to [56], the η value is assumed to be 0.5 for human-driven vehicles and 0 for CAVs. In addition, several studies assumed

TABLE 4 Krauss model's parameters for different levels of automation [57].

Automation level	Mingap (m)	Accel (m/s^2)	Decel (m/s^2)	Sigma	Tau (s)
Level 0	2.5	2.6	4.5	0.5	1
Level 1	2	3.05	4.5	0.4	0.95
Level 2	1.5	3.5	4.5	0.3	0.9
Level 3	1.25	3.6	4.5	0.2	0.8
Level 4	0.75	3.7	4.5	0	0.7
Level 5	0.5	3.8	4.5	0	0.6

sigma = driving imperfection factor, Tau = reaction time.

Krauss model's parameters for (C)AVs [57]. These assumptions are often done based on the level of automation as presented in Table 4.

The findings of literature review depict that attempts have been made to study the impacts of (C)AVs using Krauss model [57–59]. [59] studied the effects of CAVs on traffic flow using the Krauss model. This research distinguishes the human-driven vehicles and CAVs by the reaction time and driving imperfection factor (sigma). The reaction time and sigma for human-driven vehicles are set to 1 s and 0.5, where for CAVs, 0.5 s and 0, respectively. Similarly, [58] investigated the impact of CAVs on signalized and unsignalized intersections safety. In this study, Krauss model is used to replicate the driving behavior of CAVs, assuming that CAVs have perfect driving behavior (sigma = 0) and can drive very close to the leading vehicle (mingap = 0.5 m), where sigma and mingap for human-driven vehicles are set to 0.5 and 1.5 m, respectively.

2.5 | Wiedemann model

The Wiedemann CF model originally formulated by Reiner Wiedemann in 1974 (also called Wiedemann 74 model) is one of the most widely used CF models. The model is the default CF model in PTV Vissim microsimulation tool. In this model, the term "perceptual threshold" is used to define threshold values for actions, that a driver perceives and responds to it. The perceptual threshold is a function of space headway and speed difference between the leading and following vehicles. The threshold values differentiate the driving regime into four parts: (i) free-flow, (ii) approaching slower vehicle, (iii) car following, and (iv) emergency braking regimes. The distribution of these thresholds is shown in Figure 4, and they are defined as:

- AX: The desired spacing between the front sides of two vehicles in standstill.
- BX: The desired minimum following distance, which is a function of AX, the safety distance, and the speed of the vehicle.
- SDV: It is the action point, where a driver consciously notices that he/she is approaching a slower leading vehicle; SDV increases with increasing speed difference between the leading and following vehicles.

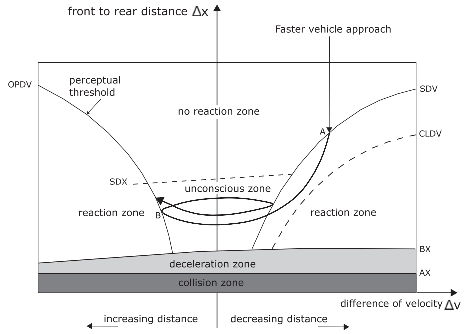

FIGURE 4 Wiedemann CF model [27].

- CLDV: It stands for closing delta velocity. Its an additional threshold that considers additional deceleration by applying the brakes.
- OPDV: The action point where a driver observes that the leading vehicle is driving fast, and thus he/she starts acceleration.
- SDX: The maximum distance when following a vehicle, which is approximately 1.5–2.5 times BX.

The model assumes that the driver acts differently in each regime, and therefore, the acceleration is estimated in each regime separately. According to the Figure 4, when a faster vehicle approaches relatively a slower vehicle, the relative distance between vehicles reduces until the deceleration perceptual threshold (SDV) is passed (point A in Figure 4). The driver will start deceleration to match the leading vehicle's speed. However, the driver also attempts to increase the space until the acceleration perceptual threshold (OPDV) is reached at point B. Then, the driver begins again the acceleration to reach the leading vehicle's speed. This process continuous in the unconscious reaction zone until it crosses the SDX line and reaches back to no reaction zone.

Besides Wiedemann 74 model, Rainer Wiedemann proposed the Wiedemann 99 CF model. Wiedemann 99 model was initially developed for replicating driving behavior on freeways, however, its application is not limited and several recent studies utilized it for urban traffic. Wiedemann 99 model is often used to represent the driving behavior of (C)AVs. In Wiedemann 99 model, besides the physical signs of driving, psychological reactions (such as observed width of the leading vehicle, visual angle change etc.) are also considered. The parameters of this model have been already extracted within the CoEXist project to capture the driving behavior of (C)AVs, however, the calibration of these parameters is based on a few AVs trajectories. The Wiedemann 99 model comprises 10 parameters, which are defined in Table 5.

[60] utilized trajectories of three test AVs (collected within CoEXist project), where two of them were driven autonomously on public roads and under normal traffic conditions to calibrate the parameters of the Wiedemann 99 model (see Table 6). Two longitudinal control communications such as CACC (which communicates with the leading vehicle) and degraded CACC referred as dCACC (without communication

TABLE 5 Wiedemann 99 CF model parameters.

Parameters	Description	Default value
CC0	Standstill distance: desired minimum distance between leading and following vehicles [m].	1.50
CC1	Time gap: desired headway time between leading and following vehicles [s].	0.90
CC2	Following distance variation: additional distance over the desired safety distance, where at this point following vehicle recognizes a slower leading vehicle [m]	4.00
CC3	Threshold for entering the deceleration zone: The time before a vehicle begins decelerating to the safety distance [s].	−8.00
CC4	Negative following threshold: negative speed variation between following and leading vehicles (the lower the value, the more sensitive the following vehicle's driver)	−0.35
CC5	Positive following threshold: a positive speed variation between the following and leading vehicles (the positive value of CC4).	0.35
CC6	Speed dependency of oscillation: influence of distance of speed variation (the larger the value, the higher the speed oscillation with increasing distance).	11.44
CC7	Oscillation acceleration: minimum variation of acceleration or deceleration while following.	0.25
CC8	Standstill acceleration: desired acceleration when starting from standstill [m/s^2].	3.50
CC9	Acceleration at 80 km/h [m/s^2]	1.50

TABLE 6 Wiedemann 99 CF model parameters for AVs modelling [60–62].

Model parameters	AV with CACC	AV with dCACC	AV cautious	AV normal	AV aggressive
CC0	4	6	1.5	1.5	1
CC1	0.3, 0.6, 1.0	1.0	1.5	0.9	0.6
CC2	0	0	0	0	0
CC3	−40	−40	−10	−8	−6
CC4	0	0	−0.1	−0.1	−0.1
CC5	0	0	0.1	0.1	0.1
CC6	0	0	0	0	0
CC7	0.25	0.25	0.1	0.1	0.1
CC8	3.5	3.5	3	3.5	4
CC9	1.5	1.5	1.2	1.5	2

with the leading vehicle) were installed on AVs in this pilot project. Meanwhile, the CoEXist project proposed modified parameters of AVs in the Wiedemann 99 model to capture different potential driving styles of AVs namely: AV cautious, AV normal, and AV aggressive as presented in Table 6.

Many articles utilized the Wiedemann 99 model with the proposed parameters by PTV Vissim to study the impacts of (C)AVs [1, 31, 32, 63–65]. Worth-mentioning that two extra driving behavior parameters are introduced within PTV Vissim simulation tool namely: the maximum look-ahead distance, and number of interaction vehicles. First, maximum look-ahead distance is the maximum area around the vehicle that can be detected by the radar and ultrasonic sensors of the AV. This parameter is usually assumed to be between 200 and 300 m. Second, the number of interaction vehicles refers to the number of preceding vehicles that the vehicle perceives downstream or adjacent to it on the same link to interact with them.

CF models for (C)AVs are not limited to established models such as IDM, MIXIC etc., several attempts have been made to propose new models, especially for ACC and CACC equipped vehicles. These proposed CF models are designed in such a way as to achieve certain objectives. Depending on various objectives, these models generate the velocity or acceleration profile of a vehicle to optimize specific policy targets including efficiency, safety, string stability, energy consumption, comfort and more [52, 66–75]. For instance, in a recent study, [66] developed a novel ACC algorithm based on model predictive control (MPC) and active disturbance rejection control (ADRC). This study considered driving safety, tracking capability, fuel economy, and comfort as the main policy targets for the optimization module. Similarly, [52] proposed a predictive cruise control approach to improve driving safety and comfort. In this study, the proposed model generates the acceleration profile of the following vehicle using the finite horizon constrained optimal control problem. In addition, [69] developed an ACC algorithm based on MPC and constraints softening. The aims is to optimize the CF requirements, safety, comfort, and economy. A detailed review of these microscopic models for CAVs is conducted by [22]. Since these methods are not integrated in microscopic simulation tools and require high computational resources, they are not widely used for impact assessment studies. Hence, a revisit is not the scope of this paper. In Table 7, the summary of reviewed simulation-based studies is presented, which describes specific information on the used CF model, vehicle type, and description of the model parameters. The table is sorted based on the publication date of the citations, which are displayed in reverse chronological order (newest to oldest).

To summarize, in most (C)AVs related studies, IDM, MIXIC and their modified versions are frequently used for modelling of (C)AVs. The Wiedemann 99 and Krauss models are also used for (C)AVs impact assessments. Depending on different CF model, researchers differentiate the driving behavior of (C)AVs from human-driven vehicles for time gap, reaction time, headway, and driving imperfection factor. Among these parameters, time gap is the most sensitive and crucial parameter which distinguishes (C)AVs from human-driven vehicles. When using IDM, it is assumed that (C)AVs could drive closer to the leading vehicle by around 50% less than the human-driven vehicles. The time headway is set 0.6 s in majority of studies for (C)AVs where this value is more than 1 s for human-driven vehicles. Considering other parameters of IDM model, researchers expected the same driving capabilities as in human-driven vehicles. Hence, maximum acceleration and comfort deceleration

TABLE 7 Summary of reviewed simulation-based studies: CF model, vehicle types, and description of the adapted parameters.

References	Year	CF model	Vehicle type	Description
[58]	2022	Krauss, IDM and CACC	CAV	Minimum headway, minimum gap, and acceleration values for all models are taken from [61], where deceleration value for CAVs is taken from [76].
[17]	2021	IDM	CAV	The parameters of the model are taken from literature as in Table 2.
[33]	2021	IDM	ACC vehicles	The parameters for both human-driven and theoretical ACC are take from [44, 46], where for commercially available ACC, set of calibrated parameters from the field experiment are deployed in the simulation platform.
[50]	2021	CACC	AV & CAV	The parameters of the model are adopted from [49].
[37]	2021	Modified IDM	AV	A reaction time variable is added in the original IDM model to distinguish AVs from human-driven vehicles. The parameters are adopted from literature where the time headway is assumed 1s for AVs.
[59, 77]	2021	Krauss	AV	Adjustments of the reaction time ($\tau = 0.5$) to mimic AVs.
[51]	2021	MIXIC	AV & CAV	The default model parameters based on [49] are used.
[78]	2021	Krauss, IDM and ACC	AV	Trajectories of human-driven vehicles were used to estimate the parameters of the models and use it for AVs.
[38]	2021	Improved IDM	CAV	The model considers multiple front and rear vehicles information to generate the following vehicle's acceleration. The model parameters are set based on assumptions.
[41]	2020	Modified IDM	AV	The parameters of the model are set as in Table 2, where the time headway between a CAV and human-driven vehicles is assumed 0.9s.
[30]	2020	IDM	CAV	The parameters' values of the model are selected from Table 2.
[76]	2020	Krauss	CAV	The emergency deceleration value was set based on a study by [79], where the values of minimum gap, maximum acceleration, and time headway are taken from [61].
[39, 53]	2020, 2018	ACC-CACC and enhanced MIXIC	AV & CAV	The parameters of ACC-CACC model are adopted from [54], where for enhanced MIXIC model the parameters are taken from [6].
[64]	2019	Wiedemann 99	CAV	The parameters of the Wiedemann 99 model are set as in Table 6, where the time headway is assumed 0.6s.
[60]	2019	Wiedemann 99	AV	The parameters of the Wiedemann 99 model are derived from empirical data (see Table 5, AV with CACC and AV with dCACC).
[32]	2018	Wiedemann 99	AV	The parameters are adopted from [1], where some modifications to the values of the parameters are set based on the assumptions.
[55]	2018	ACC-CACC and MIXIC	AV & CAV	ACC-CACC model based on [54] with default parameters, and enhanced MIXIC model of [6] are utilized.
[31]	2018	Wiedemann 99	AV	Modifications of the parameters of the model based on [61] to capture cautious and aggressive behaviors of AVs.
[57]	2018	Krauss	AV	The values of the model parameters are set based on assumptions.
[80]	2018	CACC	CACC	The parameters of CACC model are adopted from [18, 36].
[48]	2018	IDM	CAV	The default parameter values are modified from [19].
[42]	2017	IDM	ACC	The parameters the model are taken from [18, 19, 44, see Table 2].
[43]	2017	Modified IDM	AV	The enhanced IDM model includes multiplication factors for different traffic situations. The parameters are modified from [46, 81].
[6]	2016	IDM and enhanced MIXIC	AV & CAV	The model parameters are chosen based on recommendations of [49].
[1]	2016	Wiedemann 99	AV	The parameters of the model are adopted from [61], where the time headway ($cc1$) of the model is assumed (0.3s) for AVs.
[54]	2012	ACC-CACC	ACC & CACC	Parameters of the model are used from Table 3
[19]	2010	IDM with constant acceleration heuristic (CAH)	ACC	The coolness factor of the CAH is set to 0.99, where the parameters of IDM are taken from Table 2.
[46]	2007	Modified IDM	ACC	The modified IDM considers different driving situations using some multiplication factors (see Table 1), the other parameters remain as in Table 2.
[49]	2006	MIXIC	CACC	The model parameters are set as $k = 1.0$, $k_a = 1.0$, $k_v = 0.58$, and $k_d = 0.1$.

are identical for both (C)AVs and human-driven vehicles. Similarly, for MIXIC model, it is assumed that CAVs could drive with lower time gaps than human-driven vehicles. When a CAV follows another CAV, the time gap could be around three times lower than the condition when a CAV follows a human-driven vehicle. In ACC-CACC models, AVs are differentiated from CAVs by the time gap parameter. It is expected that due to the communication capabilities of CAVs and faster analysis of the surrounding environment, they could drive twice closer to the leading vehicle than the AVs.

Regarding the Krauss model, (C)AVs are differentiated from human-driven vehicles by two main parameters namely: reaction time and driving imperfection factor (sigma). Considering the reaction time, it is assumed that in comparison to human-driven vehicles where there is delay between the perception and reaction to a driving task, (C)AVs do not require extra time to react. The reaction time of (C)AVs is set to zero, where for human-driven vehicles it is more than 1 s. Meanwhile, it is expected that (C)AVs have perfect driving behavior (sigma = 0) and never make mistakes, whereas for human-driven vehicles this parameter is set to 0.5. Finally, Wiedemann model, the driving behavior of AVs is expected to be diverse, and three different driving styles are proposed (cautious, normal and aggressive). Different driving styles are categorized mainly based on the standstill distance and time gap. It is assumed that AV with aggressive driving style might have smaller distance to the leading vehicle and lower time gap. Although, many studies have the similar assumptions for potential driving behavior of (C)AVs, still there is not a concrete practical basis for the exact values of the assumed parameters. Thus, (C)AVs might behave differently than what are expected.

3 | DATA-DRIVEN MODELS

With the recent advancement in collecting high-fidelity traffic data, more accurate characteristics of driving could be achieved. Data-driven models provide the opportunity to approximate the CF behavior of human-driven vehicles as well as (C)AVs from field data. In contrast to mathematical models which are simplified and contain a small number of parameters, data-driven models have the flexibility to incorporate additional parameters that impact the driving behavior. Data-driven models require mass field data for verification and to ensure accuracy. Previous studies utilized human-driven vehicles' field data to verify data-driven models. Since the field data for (C)AVs are limited, there are explicitly few studies related to data-driven models for (C)AVs. Therefore, in this section, the aim is to review the proposed methodologies. Of course, these proposed methods could also be used for (C)AVs, when field data for (C)AVs are available. Studies relevant to the data-driven CF models can be divided into four main types: nonparametric models, artificial neural network, reinforcement learning, and deep reinforcement learning. However, many approaches have been proposed to combine mathematical models with data-driven models.

Nonparametric regression models are capable of fitting a large number of functional forms with no or weak assumptions. Attempts have been made to approximate the CF behavior using nonparametric methods [82, 83]. [82] developed a simple nonparametric CF model using the k-nearest neighbor approach. The k-nearest neighbor (kNN) is one of the simplest nonparametric method, which assumes the similarity between historical data/cases. In [82] the proposed model generates the average of the most similar driving cases. Similarly, [83] introduced a nonparametric CF model utilizing the locally weighted regression method, the Loess (locally estimated scatterplot smoothing) model. Similarly, [84] developed a nonparametric CF model to generate acceleration sequence in the next time step using a combination of the hidden Markov model (HMM) and Gaussian mixture regression (GMR). HMM is a stochastic model which is used to represent randomly changing systems. Since CF behavior has stochastic characteristics, [84] used the HMM to estimate the dependencies between the driving situation and the vehicle's acceleration. GMR on the other hand is utilized to classify different driving situation and vehicle's acceleration based on the probability distribution. Meanwhile, [85] proposed a CF model based on support vector regression to investigate the acceleration and deceleration asymmetry of driving behavior in traffic congestion environments. The model was used to obtain the equilibrium state of the vehicle during the CF process.

Several articles proposed CF models using artificial neural networks (ANNs) [86–92]. For instance, [88] introduced a CF model based on an ANN with one hidden layer. The proposed ANN takes speed, speed difference, and gap distance as inputs and generates the acceleration profile in the output layer. [89] further improved the model by considering the instantaneous reaction time delay as an extra input. In contrast to these conventional neural network-based models, recent studies proposed models considering several other influential inputs as well as the temporal variation of the data to accurately approximate driving behavior.

[93] and [94] proposed CF models using deep deterministic policy gradient (DDPG) algorithm. DDPG is a model-free method for learning continuous actions. In DDPG, two separate actor and critic networks are used. In [93] both networks are comprised of three layers: an input layer, one hidden layer, and an output layer. In the actor network, the input layer takes a state containing the speed of the following vehicle, the spacing between the following and leading vehicles, and the speed difference as inputs, where the following vehicle's acceleration is the output as a continuous action. In the critic network, the input layer includes both the state (same as the actor network) and the action (acceleration of the following vehicle), where the output layer is a generated scalar value. Different loss functions were considered in this study to maximize the output of the critic network by changing the action space of the actor network.

Similarly, [95] used real-world driving data gathered in the Next Generation Simulation (NGSIM) project to evaluate the performance of DDPG based CF model. [96] developed an encoder-decoder architecture-based CF model with transformer block to predict a long-sequence CF trajectories. The encoder uses multi-head self-attention to generate a mixed representation of past driving context utilizing historical speed and spacing data as inputs. The decoder takes the future leading vehicle speed as input and outputs the predicted future following vehicle speed profile in a generative way.

Since CF behavior of a vehicle follows a sequential pattern, several studies developed CF models based on Recurrent neural network (RNN) architecture [97–103]. [97] proposed a RNN model with the input layer containing the gap, speed difference, and the following vehicle's speed in different time steps (as a sequence), where the output is the predicted acceleration of the following vehicle in the next time step. [98] on the other hand, applied Gated Recurrent Unit (GRU) neutral networks. GRU is a temporal block that captures the temporal variation of data and predicts the output using inputs of several past time intervals. In the proposed model of [98], the input layer contains speed, the speed difference, and position differences in few last time intervals, where the output is the estimated speed in the next time interval. [99] proposed a CF model considering asymmetric driving behavior using Long Short-term Memory (LSTM) neural network. In comparison to GRU, LSTM considers longer sequential data and has more parameters than GRU, however, both methods are used to mimic the temporal variation of data. In [99], the input layer in different time intervals contains information such as the speed of the following vehicle, the speed difference to the leading vehicle, and the gap between vehicles in the current time step, whereas the output layer predicts the speed of the following vehicle in the next time step. On the other hand, [103] further enhanced the LSTM-based CF model by considering traffic oscillation in a platoon level. According to [103] the direct application of IDM/LSTM based models to predict the driving behavior in next time step in a platoon will induce an accuracy problem so-called error propagation. The prediction error propagates and accumulates both in temporal and spatial dimensions. Hence, in this study, an interconnected LSTM-based CF model is proposed.

[101] proposed a velocity control framework to address the phantom traffic jam using a DDPG equipped with a LSTM temporal block and attention mechanisms. In this framework, the spatial-temporal graph extracts information such as velocity and gap of multiple vehicles ahead in several time intervals, where the attention mechanism characterizes the interaction of the vehicle, and finally, the LSTM structure captures the driving behavior through time. This framework is specifically designed for CAVs, where a CAV can obtain driving information of multiple vehicles ahead through V2V communication. In addition, [102] further utilized LSTM architecture with a quantile-regression method. In this proposed framework, the output of the LSTM is not only a single output but a series of outputs as the different quantile of actions. For a given traffic state, the model predict set of actions, where kernal density estimation (KDE) is used to to estimate the continuous action distribution. The main advantage of this model is that it can obtain the driving behavior stochasticity.

[104] used generative adversarial imitation learning (GAIL) together with a temporal block-GRU to capture the CF behavior. The model consists of generator and discriminator parts. The generator scheme includes an actor critic structure (similar to DDPG) and extracts set of state-action pairs considering the temporal variation of the input states. The discriminator part compares the real state-action pairs with the generated one and updates the reward of the CF environment in an iterative way until the maximum reward is achieved. A similar method is used by [105] to develop a CF model which also considers the influence of driving time on driving behavior.

The findings of literature review show that several studies developed models by combining the mathematical models with the data-driven approaches. For instance, [106] proposed a novel CF model by combining a mathematical-based model (Gipps model) with a machine learning-based model (Backpropagation NN). This study assumes that the proposed model addresses both the lower accuracy of mathematical model and the shortcomings of machine learning-based models for the control of AVs. In the proposed method, the prediction values of machine learning-based and mathematical-based models are combined by weight values and the aim is to find the optimal combination weight value increasing the accuracy of the model. Moreover, [107] developed a family of CF models by integrating the parameters of mathematical CF models into a neural network. The aim is to take the advantage of mathematical models (data-efficient) and the data-driven model (generalizable). The loss function of the NN was designed in such a way to contain both the deviation from the data and the mathematical model [i.e. IDM, OVM (optimal velocity model)]. Similarly, [108] proposed a fusion modelling method, which combines the data-driven LSTM model with IDM. The adaptive Kalman filter algorithm is adopted to achieve an optimal estimation of the state of the system (CF behavior) based on both LSTM and IDM. The findings of this study proved that the combined LSTM-IDM model outperforms the accuracy of the IDM and LSTM models.

In summary, data-driven models could accurately replicate the CF behavior of (C)AVs. There are different methods proposed in the literature. However, we found that the recent deep-learning based models such as DDPG, RNN, GRU, LSTM, DDPG equipped with a LSTM, and GAIL with GRU outperform mathematical CF models, nonparametric models, and conventional neural network-based models and could be potentially used for modelling CF behavior of (C)AVs. However, most of these proposed models are not integrated into a simulation tool and hence they are not used in impact assessment studies. Table 8 presents the summary of reviewed data-driven models, which describes specific information on the developed CF model, model input and output, utilized dataset, and description of the model.

4 | SIMULATION-BASED IMPACT ASSESSMENT AND KPIs

A large spectrum of simulation-based studies focus on the identification of potential impacts of (C)AVs on the transportation system. Review of previous studies shows that an enormous amount of researches conduct impact assessments of AVs and CAVs for safety, mobility, and environmental effects (e.g. energy consumption and emissions). Key performance

TABLE 8 Summary of reviewed data-driven models: CF model, input, output, dataset, and description of the model*.

References	Year	Model	Input	Output	Dataset	Description
[82]	2015	kNN	$s, \triangle v, v$	v	NGSIM	In this study, k-nearest neighbor (KNN) generates the average of the most similar driving cases. The speed prediction in the next time step is based on the similar historical cases.
[83]	2015	Loess	s, v	v	Naples	The proposed method captures the releshionship between the speed of the following and leading vehicles, distance between them with the speed of the following vehicle in next time step (reaction time). Depending on the value of reaction time, the speed of the following vehicle is predicted.
[84]	2016	HMM + GMR	s, v	a	Driving trajectories	A combination of the hidden Markov model (HMM) and Gaussian mixture regression (GMR) to generate a sequence of acceleration in the next time step. HMM mimic the pattern between the driving situation and the vehicle's acceleration, where GMR generates the probability distribution of the acceleration to capture the stochasticity of driving behavior.
[85]	2013	SVR	$s, v, \triangle v$	v	NGSIM	The support vector regression (SVR) performs a linear regression by applying structural risk minimization (SRM) principle, to minimize the empirical risk and model complexity.
[86]	2003	ANN	$s, \triangle v, v_d, v$	a	Driving trajectories	This study utilized a simple ANN model with two hidden layers. The model inputs contains the following vehicle's desired and current speeds, the distance between leading and following vehicles, as well as their speed difference, where the output is the following vehicle's acceleration.
[87]	2007	ANN	s, v	v	Driving trajectories	The proposed one hidden-layer ANN model in this study predicts the speed of a vehicle and classifies the driving conditions into five categories namely: free driving, approaching, following I, following II, and danger. The results are compared with the Gipps CF model.
[88]	2011	ANN	$v, s, \triangle v$	a	NTDS	Similar to [87], this study proposed an ANN-based model to predict the acceleration of the vehicle in the next time step. The results are compared with the Gazis-Herman-Rothery (GHR) CF model.
[89]	2012	ANN	$v, \triangle v, s, \tau$	a	NGSIM	The proposed model considers the instantaneous reaction delay of the driver as an extra input to predict the acceleration of the following vehicle.
[90]	2013	ANN	$s, v, \triangle v$	v	NGSIM	The model is similar to [89], but predicts the speed of the following vehicle in next time step. The next time step depends on the reaction delay which is estimated by another neural network model.
[91]	2014	ANN	s, v	v	NGSIM	This study used a local neuro-fuzzy model to predict the speed of a following vehicle at time t based on the input information at time $(t - \tau)$, where τ indicates the reaction time of a vehicle. In this study, the CF behavior of heavy vehicles is considered.
[92]	2014	ANN	$s, \triangle v$	a	Trajectory data	This study utilized a feed-forward ANN similar to [89], with one hidden layer. However, the input information contains the speed difference, and distance to the leading vehicle for the last three time intervals. The output of the model is the acceleration of the following vehicle in the next time step.
[93]	2018	DDPG	$s, v, \triangle v$	Q	Trajectory data	In DDPG, two separate actor and critic networks are used. Both networks contain an input, one hidden, and an output layer. The actor-network generates the action (acceleration of the following vehicle), whereas the critic network exports a scalar reward value. The aim is to adjust the action in such a way as to maximize the reward.
[94]	2019	DDPG	v, P	v	Simulation data	In this study, DDPG same as in [93] is utilized to generate the time-optimal velocity of a vehicle.
[95]	2020	DDPG	$s, v, \triangle v$	Q	NGSIM	In this research, the reward function of the DDPG contains various features including safety, efficiency, and comfort. The model adjusts the output of the actor network (acceleration) aiming to maximize the reward function.
[96]	2022	Encoder-decoder	s, v	v	SH-NDS	In this framework, the encoder uses multi-head self-attention to generate a mixed representation of past driving context, where the decoder takes the future leading vehicle speed as input and predicts the future following vehicle's speed.
[97]	2017	RNN	$s, \triangle v, v$	a	NGSIM	The RNN model utilized in this study takes the sequence of the input information in different time steps and predicts the acceleration in the next time step.

(Continues)

TABLE 8 (Continued)

References	Year	Model	Input	Output	Dataset	Description
[98]	2018	GRU	$s, \triangle v, v$	v	NGSIM	The GRU temporal block is used to include the temporal variation of the input information in predicting the future speed profile.
[99]	2018	LSTM	$s, \triangle v, v$	v	NGSIM	This study utilized LSTM to capture the temporal variation of the input information. In comparison to GRU, LSTM considers longer sequential data.
[100]	2020	LSTM	$s, \triangle v, a$	a	Waymo	The model contains an encoder-decoder structure to learn the information hidden in the input features. This study uses the AV trajectories for training and validation of the model.
[101]	2021	LADDPG	$s, \triangle v$	a	NGSIM	In this study, a DDPG equiped with LSTM and attention mechanisms is proposed. In this framework, the spatial-temporal graph extracts information such as velocity and gap of multiple vehicles ahead in several time intervals, where the attention mechanism characterizes the interaction of the vehicle, and finally, the LSTM structure captures the driving behavior through time.
[102]	2021	QRLSTM	$s, \triangle v, v$	a	NDD	This study utilized LSTM architecture with a quantile-regression method. The output of the model is not only a single output but a series of values as the different quantiles.
[103]	2020	Int-LSTM	x, v, a	a	NGSIM	The interconnected-LSTM is used to solve the error propagation problem of a basic LSTM model.
[104]	2020	GAIL	$s, \triangle v, v$	a	NGSIM	The proposed model consists of generator and discriminator parts. The generator scheme includes an actor-critic structure (similar to DDPG) and extracts a set of state-action pairs considering the temporal variation of the input states. The discriminator part compares the real state-action pairs with the generated one and updates the reward of the CF environment in an iterative way until the maximum reward is achieved.
[105]	2020	GAN	$s, \triangle v, v, a$	x, v, a	Didi	The proposed model is similar to [104], however, it also includes the influence of driving time on driving behavior. The model contains the driver's reaction time model and the CF algorithm.
[106]	2019	Gipps + ANN	$s, \triangle v, v, a$	$x, , v, a$	NGSIM	In this research, a novel CF model by combining a mathematical-based model (Gipps model) with a machine learning-based model (Backpropagation ANN) is proposed. This study assumes that the proposed model addresses both the lower accuracy of mathematical model and the shortcomings of machine learning-based models for the control of AVs.
[107]	2021	IDM, OVM +ANN	$s, \triangle v, v$	a	NGSIM	This study developed a family of CF models by integrating the parameters of mathematical CF models into a neural network. The aim is to take the advantage of mathematical models (data-efficient) and the data-driven model (generalizable). The loss function of the NN was designed in such a way to contain both the deviation from the data and the mathematical model [i.e. IDM, OVM (Optimal velocity model)].
[108]	2019	IDM + LSTM	$s, \triangle v, v$	a	Trajectory data	This study proposed a fusion modelling method, which combines the data-driven LSTM model with IDM. The adaptive Kalman filter algorithm is adopted to achieve an optimal estimation of the state of the system (CF behavior) based on both LSTM and IDM.

x, s, v, a are the position, spacing, velocity, and acceleration of a vehicle, respectively. $\triangle v$ is the velocity difference between the following and leading vehicles, and τ is the reaction time.
*The studies are presented based on their categories from nonparametric models, artificial neural network, reinforcement learning, deep reinforcement learning and combined mathematical and deep learning models.

indicators (KPIs) used in these studies vary depending on the scope of the study. However, the identification of the most used KPIs and impact areas are very important for future studies in this field. Table 9 presents a brief description of all studies reviewed in this section, which explains specific information on the impact area, assessment criteria, KPIs, and findings. The table is sorted based on the publication date of the citations, which are displayed in reverse chronological order (newest to oldest). In the following paragraphs, we present a detailed explanation of selected articles, considering various impact areas together with the utilized KPIs in simulation-based studies.

4.1 | Mobility

Mobility impact assessments in the context of microsimulation-based studies refers to the traffic flow efficiency. The scope

TABLE 9 Summary of reviewed simulation-based studies including their assessment criteria, KPIs, network type and results.

References	Year	Assessment criteria	KPIs	Network	Results
[58]	2022	Traffic safety	Number of conflicts	Intersection	The higher the PRs of CAV, the safer the intersections. A 100% PR of CAV could totally ignore the number of crossing conflicts in both signalized and unsignalized intersections.
[50]	2021	Traffic efficiency	Capacity, queue length, total travel time	Urban road	A network with 100% PRs of CACC vehicle, increases the capacity, reduces the queue length in congested sections, and decreases the total travel time.
[37]	2021	Efficiency, throughput	Travel time, flow	Link	Higher PRs of AVs, reduce the travel time and increase the throughput. With 100% PR, the travel time reduces by 50%.
[17]	2021	Traffic safety and efficiency	TTC, number of conflicts, travel time	Freeway	AVs and CAVs improves travel time, however, CAVs outperform AVs, and at least 20% PR of CAVs and 40% PRs of AVs are required to reduce travel time. A system with both AVs and CAVs could also significantly improve safety. With high PRs of AVs and CAVs, number of conflicts reduced.
[33]	2021	Throughput and stability	Traffic flow, density	Freeway	The performance of commercially available ACC vehicles is different than theoretical ACC vehicles. Commercially ACC vehicles reduces the bottleneck capacity and string stability.
[78]	2021	Traffic efficiency	Mean speed, travel time	City center	With a 50% PR of AVs under different driving styles, mean speed of the network drops and travel time increases.
[51]	2021	Throughput	Speed, and traffic flow	Freeway	Under current traffic demand, a fully human-driven traffic shows better throughput, however, with a double demand, CAVs show the best performance.
[77]	2021	Flow analysis	Traffic flow, travel time	City	Traffic throughput improves by around 22% in a situation with automated vehicles in comparison to non-automated condition. Travel time reduces by 13.5% and 16.4% in partially and fully automated conditions, respectively.
[41]	2020	Capacity analysis	String stability, lane capacity	Freeway	Lower PRs of CAVs have negative impacts on the capacity, where 100% PR increases the capacity around 70–100% depending of the freeway speed limits.
[30]	2020	Traffic efficiency	Travel time	Freeway	With higher PRs of CAVs, average travel time decreases. This reduction is more obvious when PRs of CAVs increases under heavy traffic flows.
[76]	2020	Capacity analysis	Flow, density and speed	Urban road	Higher PRs of AVs increases the capacity. With a 100% PRs of AVs, the maximum capacity increases by 16–23%. Lower PRs of AVs does not show significant improvements, thus at least 40% PR is required.
[39]	2020	Traffic flow and emissions	Throughput and CO_2 per kilometer	Highway	A 100% PR of AVs reduce the average speed and flow, and generate the highest emission per kilometer. Whereas, CAVs improve the capacity of the network. However, in network wide, the total emission produced by AVs, and CAVs are not significantly different than human-driven vehicles.
[64]	2019	Safety analysis	Number of conflicts	Motorway	With a 100% PR of CAVs, more than 90% reduction in total number of conflicts is achieved.
[32]	2018	Safety	Number of conflicts	Roundabout	The higher the PRs of AVs results in increased number of conflicts. Negative safety impacts of AVs on roundabout does not change even with different design of roundabouts.
[80]	2018	Capacity analysis	Flow, string stability	Freeway	There is a quadratic relationship between the freeway capacity and PRs of CACC vehicles. At 100% PR, the freeway capacity is around 90% higher than a 0% PR.
[55]	2018	Throughput and emissions	Average harmonic speed, density, CO_2 and NO_x per kilometer	Ring road	With high PRs of AVs, the average speed of the network decreases and the density increases, where emissions also increases. In low PRs, CAVs have small negative impacts on average speed, density and emissions, where for high PRs, CAVs improves the situation. The best performance of CAVs is achieved with high demand scenarios.
[53]	2018	Throughput	Harmonic average speed	Ring road	In comparison to human-driven vehicles and with the constant demand, any PRs of AVs do not improve the traffic flow efficiency, however CAVs enhance the condition. In low traffic demands, human-driven vehicles always outperform CAVs.

(Continues)

TABLE 9 (Continued)

References	Year	Assessment criteria	KPIs	Network	Results
[31]	2018	Safety analysis	Number of conflicts	Signalized intersection and roundabout	Higher PRs of AVs with both driving styles (cautious and aggressive) could reduce the number of conflicts around 65% in signalized intersection and roundabout.
[42]	2017	Safety analysis	TET, TIT	Freeway	Driving behavior of ACC is a decisive factor for the safety impacts. Larger time headway and increased emergency deceleration capability results in improved safety.
[109]	2017	Traffic efficiency	Travel time, fuel consumption	On-ramp	With a 100% CAV PR, fuel consumption reduces by an average of 35% with different traffic flows. With high traffic flow, total travel time reduces drastically in comparison to 0% PR of CAVs. However, for low traffic volumes, no change in total travel time is achieved.
[43]	2017	Traffic efficiency, safety, string stability	Flow stability, travel time, speed dispersion	Freeway	With 0% AVs PR, irregular merging behavior of human-driven vehicles results in negative effect on string stability. However, only a 5% PR of AVs can improve string stability. Higher PRs of AVs leads to lower level of speed dispersion and results in enhanced safety. For average travel time, any PRs of AVs only slightly change is achieved. More reduction in travel time is achieved in congested sections of the freeway.
[6]	2016	Flow stability and throughput	Platoon size, flow and density	Ring road	AVs could prevent shockwave formation and propagation. Both AVs and CAVs can improve throughput and string stability, however AVs show better performance in terms of throughput than CAVs.
[1]	2016	Traffic efficiency	Average density, speed and travel time	Autobahn	A 100% PR of AVs improves the travel time by 9%, where average density enhances by around 8%.
[54]	2012	Capacity analysis	Lane capacity	Freeway	The higher the PRs of CACC vehicles, the better the freeway lane capacity could be achieved.
[49]	2006	Flow analysis, string stability	Traffic flow, number of shock waves, average speed	Freeway	Lower PRs of CACC ($<$ 40%) does not improve the throughput. Higher PRs of CACC results in improved string stability and throughput. Also, higher PRs of CACC lead to higher average speed and high reduction in number of shock waves.

of the studies in this area varies from intersections to links, highways, and networks. Most researchers exploited KPIs, such as traffic flow (e.g. traffic volume, density), average travel time, string stability, average velocity, and more in their studies. For instance, [50] studied the impact of CACC-equipped vehicles on traffic efficiency in urban roads with congested sections. This study selects traffic capacity, waiting time, queue length, and total travel time as the main KPIs. The findings of this study indicate that in comparison to conventional vehicles, CACC-equipped vehicles with a penetration rate (PR) of 100% can increase the traffic capacity by more than 2.6 times. The study claims that by increasing the PR of CACC-equipped vehicles, the waiting time on congested roads decreases. In addition, with a 100% PR, the queue length and total travel time significantly decrease on congested roads. In [37] a research is conducted to investigate the utilization of road capacity in mixed traffic (AVs and human-driven vehicles). The study showed that in an idealized environment with a 100% PR of AVs, capacity utilization in terms of travel time and throughput is improved. However, in a mixed traffic situation, capacity utilization degrades fastly with the higher PR of human-driven vehicles. On the other hand, [17] investigated the traffic efficiency and safety impacts of (C)AVs in a major freeway in Orlando, Florida. The results of their study depict that travel time is significantly reduced with the penetration of (C)AVs. The study also implies that CAVs substantially outperform AVs with the same PR both in terms of travel time reduction, and number of conflicts. The findings also suggest that at least 20% PR of CAVs and 40% PR of AVs are required to achieve reduced travel time in the network.

Furthermore, [33] investigated the impacts of commercially available ACC vehicles on traffic stability and throughput. The simulation results show that in comparison to theoretical ACC vehicles, the commercially available ACC equipped vehicles decreases the bottleneck capacity at higher PRs. The study also claims that traffic flow is string unstable when simulating the commercially available ACC vehicles. On the network level, [78] studied the impact of AVs with different driving styles in Munich city network. The findings depict that with 50% PR of AVs under different driving styles, mean speed of the network drops and travel time increases. [41] conducted a simulation-based study on the effect of CAVs on freeway capacity. The study claims that there is a negative impact on freeway capacity with small PRs of CAVs, where with higher PRs, the capacity increases. Meanwhile, speed limit is also indicated as an important variable in freeway capacity, where higher speed limits leads to improvement of capacity. Another interesting finding based on demand fluctuation is reported in [51]. This study evaluated the impacts of (C)AVs on throughput in a Freeway segment. It is claimed that under current traffic demand scenario, a 100% human-driven vehicles show better throughput, where with a double traffic demand, CAVs show the best performance. Since CAVs strictly obey the speed limits, their performance is not significantly noticeable with the current demand. However, with increased demand a smooth flow of traffic is achieved and consequently leads to a better throughput and speed.

AVs will likely have more cautious behavior than human-driven vehicles, and thus findings of a study by [53] indicate that AV alone will not probably improve the traffic flow. This article studied the effects of (C)AVs on traffic flow in a freeway, and showed that with the constant demand, CAVs with the V2V communication will significantly enhance network capacity and reduce traffic congestion. This study also claims that AVs with any PRs will show negative performance than human-driven vehicles. In case of CAVs, low PRs will worsen the traffic flow (as they act like AVs), where higher PRs increases the traffic flow efficiency. On the demand side, human-driven vehicles outperform CAVs on low traffic demands with any PRs of CAVs. Unlike [6, 53] claimed that AVs are more effective in preventing shockwave formation and propagation. The findings of this study revealed that under the utilized model's assumptions, both AVs and CAVs can improve throughput and string stability. It is also shown that AVs result in higher throughput than CAVs with same PRs. Meanwhile, utilizing different CF models with various parameters lead to distinct conclusions. [1] studied a situation where all vehicles in the system are AVs. This study assumes that AVs can drive very close to the leading vehicle. The outcome of this study showed that AVs have positive effect in traffic flow efficiency in higher traffic demands. The study claims that in a fully AV driving environment, average density improves by around 8%, where travel time reduces by 9%. [54] investigated the impacts of CACC-equipped vehicles on freeway traffic flow. The results revealed that there is a linear relationship among PRs of CACC vehicles and the freeway lane capacity. The study also mentioned that capacity improvement could be enhanced if the leading non-CACC vehicles share information with CACC vehicles.

4.2 | Safety

Simulation-based studies utilize surrogate safety measure (SSM) to evaluate the impact of (C)AVs on traffic safety. Time-to-collision (TTC), Post-encroachment time (PET), number of conflicts (using certain TTC and PET thresholds) are the most used KPIs for safety assessment in the literature [17, 31, 32, 42, 47, 58, 63, 64]. [58] investigated the effects of CAVs on the safety of signalized and unsignalized intersections. The results of this study revealed that CAVs can significantly reduce the number of conflicts on both intersections. In addition, it is claimed that a 100% PR of CAVs could ignore any crossing conflicts between vehicles. [17] used the number of conflicts, time-to-collision (TTC), and time exposed time-to-collision (TET) to quantify the safety impacts of (C)AVs under mixed traffic scenarios. The results implied that any mixture of AVs and CAV PRs into the existing transport system could improve safety. Meanwhile, higher PRs of (C)AVs result in reduced number of conflicts. Considering the demand fluctuation, [64] studied the impact of CAV PRs on safety with different demands (peak and off-peak traffic) in a motorway segment. The results show that PRs of CAVs substantially reduce the number of conflicts. This effect is more noticeable in higher traffic demands even at low PRs of CAVs.

Similarly, [31] studied the safety effects of AVs with different driving styles (cautious and aggressive) on a signalized intersection and a roundabout. This study used the number of conflicts as a KPI to quantify the safety impacts. The results suggested that high PRs of AVs with both cautious and aggressive behaviors could significantly reduce the number of conflicts. With a 100% PR of AVs, the number of conflicts reduces by around 65% in both intersections and roundabouts. Unlike [31, 32] highlighted the negative impacts of AVs on roundabout safety. The findings of this study showed that with increased PRs of AVs, the potential number of conflicts at roundabout also increased. It is also mentioned that even redesign of the roundabouts can not neglect this negative safety effect of AVs. This study suggested that utilization of SSM might be not a suitable tool to quantify the safety in roundabouts and thus new models are needed. In addition, [42] investigated the safety impact of ACC vehicles in congested conditions on a freeway. In this study, several potential behaviors of ACC vehicles such as time headway, maximum deceleration and more were tested. The findings of this study showed that the safety impacts of ACC are largely affected by their driving behavior. The study implied that with larger time headway, and increased emergency deceleration capability, the safety has improved. In this research, time exposed time-to-collision (TET) and time-integrated time-to-collision (TIT) were used as KPIs. Both TET and TIT are aggregated indexes from TTC.

4.3 | Environment

Accurate approximation of environmental impacts of (C)AVs requires consideration of many decisive variables including vehicle technology, travel demand, new modes of transport etc. However, researchers attempted to quantify the effect of (C)AVs assuming the same energy consumption and emission factors as for existing human-driven vehicles. For instance, [39] investigated the impact of (C)AVs on traffic flow and emissions on a highway network. The study estimated emissions using both the average-speed EMEP/EEA fuel consumption factors and the generic version of the European Commission's CO_2 MPAS model. The results revealed that a transport network with 100% AVs has the highest CO_2 emissions (g/km), where CAVs also generate more emissions in peak hour traffic (due to high utilization of network capacity). The study implied that the overall effect on the network is statistically not significant. The study claims that usage of the various CF models and their limitations lead to distinct driving profiles and thus generate different emissions. Moreover, a 20% increase in demand does not significantly change the emissions. Similarly, [55] conducted a simulation-based study to investigate the impact of (C)AVs on throughput and emissions in a ring road. In this study, various demand scenarios and PRs of (C)AVs, and different desired time gaps for the model settings are considered. CO_2 and NO_x emissions per kilometer are selected for environmental impacts. The findings of this study showed that in free-flow traffic, where vehicles are not bounded to speed limits, human-driven vehicles have the highest emissions. On the other hand, any PRs of CAVs could result in low emissions. According to the study, AVs drive with low speeds and thus force the engine to work less efficient. Hence, in comparison to CAVs, AVs increase emissions.

To conclude, used KPIs for impact assessment in MTMs differ depending on the assessment criteria and study area (i.e. intersection, link, freeway, city network). First, in mobility analysis, we noticed that most studies select flow, density, string stability, lane capacity and throughput when conducting capacity and flow analysis in freeways, highways and ring roads. Travel time and speed are frequently selected for traffic efficiency analysis both on link level and city-wide. Second, for safety analysis, the number of conflicts is the most used KPI in all type of study areas, where in freeway analysis, some studies also used TTC, TET and TIT. Finally, the studies related to emission analysis depict that CO_2 and NO_X per kilometer are used KPIs for impact assessment.

Although, this section clearly reveals the relation between the used KPIs and the study area in different studies, a standardized guideline to indicate which KPIs to be used for a specific study area, demand scale, and other influencing factors is missing. A KPI (e.g. travel time) might be useful for traffic efficiency analysis under different PRs of (C)AVs in a city-wide network but for moderate and low demands, where for high demands (congested network), this KPI might not represent the impact of (C)AVs.

5 | CONCLUSION AND RESEARCH GAPS

Simulation-based studies are widely conducted to analyze and predict the impacts of on traffic efficiency and safety. In MTMs, accurate quantification of the potential impacts depends on the true configuration of AVs and CAVs driving behaviors. These behaviors are modelled with CF and lane-changing models. In this paper, we review and summarize the recent AVs and CAVs simulation-based studies including their utilized CF model, adopted parameters, the reported impacts and the used KPIs for impact assessments. Moreover, a review of recent data-driven CF models with their methodologies is presented. The present review is crucial both in understanding the CF models parameters used for AVs and CAVs modelling in simulation tools, as well as identification of the set of KPIs for impacts analysis.

Regarding the mathematical CF models for (C)AVs modelling, we found that the most frequently adopted CF models are IDM and MIXIC and their modified versions. Wiedemann 99 and Krauss models are also utilized in MTMs for impact assessments. For IDM, many studies adopt the parameters of the model based on research done by [19, 44, 46]. Similarly for MIXIC model, the parameters' values are taken from [6, 49]. ACC and CACC models developed similar to MIXIC model have been also utilized for ACC and CACC vehicles modelling. Certain parameters of these models are based on assumptions and some are gathered from test vehicles [18, 54]. For Wiedemann 99 model, the parameters' values are extracted using trajectories of test AVs within the CoEXist project. On the other hand, in the Krauss model researchers often differentiate the driving behaviors of human-driven vehicles, AVs, and CAVs by headway gap, reaction time, and driving imperfection factor. For instance, it is assumed that CAVs could drive very close to the leading vehicle and could have perfect driving behavior.

Furthermore, there were attempts to develop data-driven models using human-driven vehicles trajectories and assume it for (C)AVs CF behavior, but they cannot guarantee the true behavior of future (C)AVs. However, the methods proposed in these studies could be potentially used for (C)AVs CF models, when field data are available. The findings of the literature review show that reinforcement learning and deep reinforcement learning algorithms, such as DDPG, RNN, GRU, LSTM, DDPG equipped with a LSTM, and GAIL with GRU are the most recent methods used for replicating CF behavior.

The findings of literature review reveal that large amount of studies conduct the impact assessment of (C)AVs for safety, mobility, and environmental effects. Most authors exploited KPIs, such as traffic flow (e.g. traffic volume, density, throughput etc.), average travel time, string stability, average velocity and more to assess the mobility impacts of (C)AVs. For safety analysis, time-to-collision (TTC), post-encroachment time (PET), and number of conflicts are the most used KPIs in the literature. Finally, the amount of CO_2, and NO_X emissions per kilometers (g/km) are used for emissions' evaluation. One important note is that most studies assume the same energy consumption and emissions factors used for existing human-driven vehicles and for (C)AVs. However, future vehicles will likely have different consumption technology and thus quantification of emissions is not accurate. On the other hand, several studies use various CF models with their own assumption for models' parameters. This may lead to inconsistent conclusions to (C)AVs impacts. Despite their results inconsistency, most studies revealed that AVs and CAVs with sensing and connectivity could considerably increase the road capacity. More optimistic views are for CAVs in comparison to AVs due to communication capabilities of earlier. A general finding of most studies depicts that higher PRs of AVs and/or CAVs could highly change the existing transport network both in terms of efficiency and safety. In addition, it is reported that demand is a sensitive factor in impact assessments. Increased demand scenarios leads to significant changes in the network especially for CAVs. Some studies assume that AVs will have more cautious behavior with larger headway gaps, where in some other researches, an aggressive behavior of AVs is assumed. This has resulted in opposing findings especially in terms of number of conflicts and consequently safety.

Although numerous attempts have been made to model the CF behavior of (C)AVs, a considerable number of research gaps still exist. First, the true driving behaviors of (C)AVs are still under investigation, which leads to strong assumptions in most studies. A model to capture the driving behavior of (C)AVs with calibrated parameters using real data is needed. This model could consider the sensing and communication technologies of AVs and CAVs, respectively, to accurately mimic their driving behaviors under various situations. The parameter calibration could also be done for established CF models, such as IDM, MIXIC, and Krauss. These models are integrated within simulation tools and hence could widely be used for impact assessments. Second, data-driven models could accurately capture the driving behavior of (C)AVs, however, they still need a mass field (C)AVs data for training, testing and validation. A data-driven model based on deep reinforcement learning which could capture the spatial and temporal variation of the driving behavior with field test data of (C)AVs is a worth pursuing research. In this research, different potential driving styles of (C)AVs (cautious, normal, aggressive) under various traffic situations could be considered. Meanwhile, it is very crucial to integrate data-driven models into the existing widely used simulation tools in a computationally efficient method. This will help to conduct large-scale impact assessments with more accurate outputs. Third, in most studies, KPIs are assigned by the authors for impact assessments studies, however, there should be a differentiation by which KPIs to be used for different study areas, demand scales and more. Hence, a study to analyze the sensitivity of each KPI in varying scenarios both in terms of supply and demand is needed. This study could create a standardized guideline for impact assessments studies and could thus guide future researchers to use most reasonable KPIs for their specific studies. Finally, in this review paper we discussed the CF behaviors of C(AVs), however, a comprehensive review of lane-changing models of (C)AVs and studies relevant to impact assessment of (C)AVs lane-changing polices is a highly significant research need.

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CONFLICT OF INTEREST STATEMENT

There is no conflict of interest to be disclosed.

DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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