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ORIGINAL PAPER

Understanding freight drivers' behavior and the impact on vehicles' fuel consumption and CO_2e emissions

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Abstract
Despite the significant impact of driver behavior on fuel consumption and carbon dioxide equivalent (CO_2e) emissions, this phenomenon is often overlooked in road freight transportation research. We review the relevant literature and seek to provide a deeper understanding of the relationship between freight drivers' behavior and fuel consumption. This study utilizes a real-life dataset of over 4000 driving records from the freight logistics sector to examine the effects of specific behaviors on fuel consumption. Analyzed behaviors include harsh acceleration/deceleration/cornering, over-revving, excessive revolutions per minute (RPM), and non-adherence to legal speed limits ranging from 20 to 70 miles per hour (mph). Our findings confirm existing literature by demonstrating the significant impact of certain driving characteristics, particularly harsh acceleration/cornering, on fuel consumption. Moreover, our research contributes new insights into the field, notably highlighting the substantial influence of non-adherence to the legal speed limits of 20 and 30 mph on fuel consumption, an aspect not extensively studied in previous research. We subsequently introduce an advanced fuel consumption model that takes into account these identified driver behaviors. This model not only advances academic understanding of fuel consumption determinants in road freight transportation, but also equips practitioners with practical insights to optimize fuel efficiency and reduce environmental impacts.

Keywords Green logistics · Driver behavior · Fuel consumption modeling · CO_2e emissions

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1 Introduction

In recent decades, there has been a widespread consensus that urgent action is needed to reduce greenhouse gases (GHGs) and mitigate the negative impacts of climate change (IPCC 2022). Since fossil fuel combustion is an important contributor to man-made carbon dioxide equivalent (CO_2e) emissions, fuel consumption plays a central role in the climate change debate (EIA 2021). The International Energy Agency has reported that the transportation sector relies the most on fossil fuels of any sector and accounted for 37% of total CO_2e emissions from end-use sectors in 2021. Since 1990, overall CO_2e emissions from the transportation sector have increased by 68%, driven primarily by road transportation (IEA 2019, 2022a). Although various efforts have been aimed at reducing emissions, the road freight transportation industry has seen a relative increase in CO_2e emissions by 8% globally in 2021 compared to 1990 levels, marking a larger increase than in any other sector (Schoettle et al. 2016; IEA 2022b). This is due to the growth of freight activities, economic development, urbanization, and the increasing average travel distance of each freight unit, just-in-time manufacturing, and fast delivery services (McKinnon 2008; EIA 2021).

Traditionally, the focus on planning road freight transport activities has been on decreasing operational costs and increasing profitability by only considering internal costs (i.e., fuel costs, drivers' wages, etc.). However, during the past decade, governments and non-governmental organizations have begun to realize the significance of environmental and social impacts on society related to transportation. "These impacts are termed as externalities, where other parties are entities that did not choose to incur the impact" (Demir 2018, p. 63). Green logistics aims to improve the production and delivery of freight in a more sustainable way, while considering environmental factors. The objectives of green logistics are not only based on economic factors, but also target reducing other severe effects on people and on the environment (including, but not limited to, the costs to the environment from accident and congestion). Green vehicle routing is a branch of green logistics that refers to vehicle routing problems where externalities of using vehicles, such as CO_2e emissions, are explicitly considered so that they are reduced through better planning (see, e.g., Asghari et al. 2020; Moghdani et al. 2020; Marrekchi et al. 2021).

Despite the ongoing search for and research into practicable alternative fuels and power units, traditional fuels (mainly diesel) will remain the dominant fuel in the road freight transport sector in the near future (ACEA 2020; Wetzel 2021). Apart from the road passenger transport sector, other forms of energy are difficult to adapt for use in heavy freight transport applications. As Zhou et al. (2016) demonstrated, potential efficiency improvements from new vehicle and engine technologies are limited (around 4–10% and 2–8%, respectively). Therefore, researchers, industry participants, and local governments have increased their focus on improving fuel efficiency. From this perspective, this research aims to investigate the impact of driver behavior on fuel consumption and CO_2e emissions.

This research offers unique insights into understanding fuel consumption in the road freight transportation industry, with a specific focus on the role of driver behavior. Our contributions are threefold. Firstly, we delve into the granular factors affecting fuel consumption and provide an exhaustive exploration of their individual impact, enriching the knowledge base in this field. Secondly, we offer a critical evaluation of several fuel consumption models and push the boundaries of current research by investigating their application in the context of driver behavior, a perspective often neglected in existing studies. Lastly, by presenting a real-world case study from the service logistics industry, we illuminate the practical implications of driver skills on fuel consumption. This contribution not only reinforces the theoretical discussions, but also provides actionable insights for industry practitioners. The remainder of this paper is organized as follows. Chapter 2 provides an overview of green road freight transport studies, coupled with an in-depth review of previous research on the influence of driver behavior on fuel consumption. In Chapter 3, we present and analyze various fuel consumption models, critically evaluating their ability to encapsulate the impact of driver behavior. Chapter 4 presents a comprehensive case study, utilizing the widely used macroscopic model, Computer Programme to Calculate Emissions from Road Transportation (COPERT), to translate theoretical discussions into tangible insights. This case study explores the real-world impact of driver behavior on fuel consumption, illustrating the practical applications of our research. Finally, Chapter 5 draws conclusions from the research and outlines potential directions for future investigations.

2 The importance of driver behavior study in road freight transport research

Although negative externalities from road freight transportation activities have attracted more attention recently, the emphasis on efficient fuel use in both communities of academia and logistics service providers has a comparatively long history, such as route planning and scheduling to avoid vehicles running for a long distance and being only partially loaded (e.g., Palmgren et al. 2003; Zhang et al. 2009; Braekers et al. 2013; Demir et al. 2022), vehicles running extra distances to reach their destinations (e.g., Dullaert et al. 2002; Chabrier 2006; Figliozzi 2009), and vehicles returning with an empty load to depots (e.g., McKinnon and Ge 2006; Aras et al. 2008; Peetijade and Bangviwat 2012). This is because fuel consumption is a primary budget for all road freight transport operations internally, accounting for approximately 33% of the operational costs (Lowe and Pidgeon 2014). Minimizing operational costs is arguably, therefore, the focus in designing road freight transportation activities (Demir et al. 2014). However, it is argued that managers or operators of road freight transportation have limited control over these aspects. This is because the structures of order demand from customer (e.g., cost, time, flexibility, and reliability) and the lack of freedom of choice of routes from drivers (freight drivers often operate outside of direct supervision traditionally and, therefore, have relatively high control of their daily activities) "are dictates which overrule efficient planning" (Belman and Monaco 2001; Lowe and Pidgeon 2014, p. 541).

Many variables affect vehicle energy use and emissions rates and have been well discussed by corresponding studies (e.g., Ahn et al. 2002; Sivak and Schoettle 2012; Carrese et al. 2013; Faria et al. 2017). In general, five main categories directly or indirectly influence fuel consumption and CO_2e emissions, including vehicle-, environment-, traffic-, operations-, and driver-related factors, as shown in Fig. 1 (with their respective impacts on fuel consumption shown by percentage). On the one hand, apart from road and ambient conditions, most factors can be influenced directly by drivers (Zacharof et al. 2016), indicating that driver-related factors should be considered a substantial contributing factor in emission rate control. Therefore, it is quite surprising that driver-related factors have drawn comparatively less attention compared to other factors. One possible explanation is that those other factors are much easier to quantify (Pandian et al. 2009).

Each of the main categories of factors is identified as being able to influence fuel consumption and, therefore, emission rates are discussed in turn below.

First, vehicle-related factors obviously can directly influence fuel consumption and CO_2e emissions. The characteristics of the engine, including size, type, shape, and power, affect engine efficiency and, thus, fuel performance (Sriwilai et al. 2016; Zhou et al. 2016). Vehicle mass significantly affects fuel consumption, especially at lower vehicle speeds (Bishop et al. 2014), although there are no common approaches to quantify the effects of additional mass on fuel consumption or CO_2e emissions (Fontaras et al. 2017). In addition to this, vehicle maintenance (e.g., a

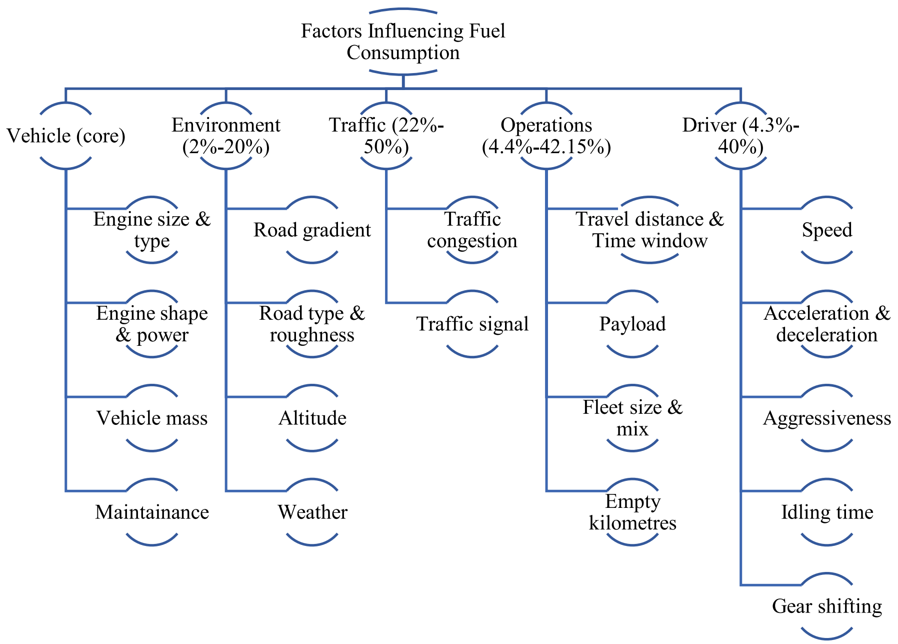

Fig. 1 Factors impact fuel consumption and emission rate (Zarkadoula et al. 2007; Barth and Boriboonsomsin 2009; Fontaras and Samaras 2010; Demir et al. 2011, 2014; Kamal et al. 2011; Carrese et al. 2013; Zhou et al. 2016; Fontaras et al. 2017; Yang et al. 2022)

properly tuned engine, fixing defective oxygen sensors, and adjusting tire pressure levels and tire alignment) can also impact fuel efficiency (Transportation Research Board 2006; Sivak and Schoettle 2012; Fontaras et al. 2017). It is worth mentioning that this paper mainly focuses on internal combustion engine vehicles. Although various electric vehicle models have been introduced in the freight market, electric heavy goods vehicles (HGVs) account for only 0.1% of total number of HGVs worldwide in 2021 (IEA 2022c). Due to the limited availability of data and research on their energy consumption and Scope 3 emissions characteristics, we intend to provide information on the current and dominant diesel-powered HGV fleet on the road today.

Next, factors related to the vehicles driving environment are considered. One of the main aspects of environmental-related factors that strongly impact fuel consumption and CO_2e emissions is the physical characteristic of the roads used, such as the gradient of the road, the type and roughness of the road, and the altitude (in different ways). For example, driving on an upslope requires far more power (more fuel consumption) to overcome gravity compared with a flat road, and a downslope conversely requires less power (less fuel consumption) (Demir et al. 2014; He et al. 2016). Furthermore, weather conditions (mainly wind, temperature, and ambient pressure) directly affect how vehicles are driven, as well as influencing the level of resistance experienced during the operation of the engine (Karlsson et al. 2012; He et al. 2016). Therefore, certain weather conditions, for example rain and snow, significantly adversely influence fuel consumption and, hence, CO_2e emissions because they alter the road surface characteristics, which eventually influence vehicle rolling resistance and grip that wheels must overcome (Fontaras et al. 2017).

In the traffic category, increased traffic congestion can again adversely influence fuel consumption and CO_2e emissions in several ways, including decreasing average and maximum speed of driving, increasing transient operation (i.e., acceleration and deceleration rates), and increasing engine idling time (the details about speed profile, acceleration and deceleration, and idling time will be discussed in the next section) (Greenwood and Bennett 1996; Greenwood et al. 2007; Merkisz et al. 2010; Abou-Senna and Radwan 2013). Like the adverse effects of traffic congestion, traffic signaling can directly influence the activities of acceleration and braking, which can negatively influence fuel consumption (Asadi and Vahidi 2010; Tielert et al. 2010; Shahariar et al. 2022).

Finally, operations related factors are possibly the most widely discussed area within the green road freight transport domain. The reason is that, compared to vehicle, environment, and traffic-related factors, road freight transportation operators have more control over this aspect through efficient planning. The most classic vehicle routing problem with time windows is widely used and extended with the objective of minimization of fuel consumption in many studies (e.g., Kara et al. 2007; Tavares et al. 2008; Bektaş and Laporte 2011; Suzuki 2011). These are known as green vehicle routing problems, a summary of which is shown in Table 1. As with vehicle mass, the additional payload also requires the engine to run with an increased need for more power via greater fuel consumption. Moreover, although smaller vehicles (less vehicle mass) consume less fuel than larger vehicles, one larger vehicle might consume less fuel than two

Table 1 Summary of main trend of research on general green routing problems

References	Studied problem (s)	Main contributions/outcomes
Sbihi and Eglese (2007, 2010)	Vehicle Routing and Scheduling Problem (VRPS) with environmental objectives	One of the first study links VRPS models with green logistics issues
Kara et al. (2007)	Energy Minimizing Vehicle Routing Problem (EMVR)	The first model minimizes a weighted distance function as an approach to reduce fuel consumption
Figliozzi (2010)	EMVR with time dependency constraint	The impact of traffic congestion on vehicle speed
Maden et al. (2010)	Vehicle Routing Problem (VRP) with time dependent	Emissions can be reduced by 7% comparing the time-varying speeds with constant speeds
Bektaş and Laporte (2011)	VRP with time window	To introduce Pollution-Routing Problem (PRP) which incorporates load, speed, and other parameters
Erdoğan and Miller-Hooks (2012)	Green VRP (GVRP)	It is the first time that GVRP is formulated with alternative fuel-powered vehicle
Lin et al. (2014)	Survey of related GVRP	To classify GVRP into three major problems: VRP concerning energy consumption, PRP, and VRP in reverse logistics
Demir et al. (2014)	PRP	To define a dual objective model to simultaneously minimize fuel consumption and driving time
El Bouzekri El Idrissi and Elhilali Alaoui (2014)	GVRP	To propose a dual objective model to minimize both total emissions and total transportation cost
Abdullahi et al. (2021)	GVRP	To integrate and trade-off three sustainability dimensions in the context of VRP
Sadati and Çatay (2021)	Multi-Depot GVRP	To introduce a variant of GVRP where customers are served from a set of depots

The following GVRP studies have been extended in more specific areas and different characteristics, factors, and constraints are considered smaller ones (Demir et al. 2014). Therefore, the selection of the appropriate size of vehicles and the mix of vehicles in the fleet has an important influence on fuel consumption. Lastly, empty running is one of the greatest challenges within the industry that causes wasted energy consumption. According to the American Transportation Research Institute (Premack 2017), trucks are driven almost 20% of miles without any load. The situation in the UK is worse, with approximately 30% of vehicles running with zero loads (GOV.UK 2021a).

Demir et al. (2014) pointed out that most research in the green road freight transportation area pays far more attention to certain factors, particularly the driving environment- and operations-related factors. Driver-related factors, on the other hand, are often overlooked, or at least are not studied in a very comprehensive way. One possible explanation is that these factors are much easier to quantify compared with driver related factors (Pandian et al. 2009). However, most of the factors can be directly influenced by drivers, in addition to road and ambient conditions (Zacharof et al. 2016). To contribute towards addressing this research gap in the green road freight transportation area, we aim to review the latest research on driver behavior in the context of freight transportation (some studies were based on the private driver aspect) in the following section.

To characterize individual driver behavior is a complicated process as parameters used to classify driver-related factors are varied, often depending on the objectives of the research (Ericsson 2001). Kuhler and Karstens (1978) were possibly the first of this kind to categorize driver behavior into 11 parameters, which include average speed and driving speed (not including stops), average acceleration and deceleration, mean length of the driving period, the average number of acceleration and deceleration changes, the proportion of acceleration and deceleration time, the proportion of time with constant speed, and proportion of stop time.

Andre (1996) reviewed previous studies and concluded that the most related parameters are duration, average speed, the average value of speed, acceleration, and deceleration, standard deviation of acceleration, relative and joint distribution of speed/acceleration/deceleration, the number of acceleration and deceleration shifts, idling time, positive kinetic energy, the number of stops per kilometer, running speed (not including stops), and average time of running period. However, Ericsson (2001) argued that if these variables of the driving pattern are used in fuel consumption and CO_2e emissions models, this could lead to some potential problems. First, presenting all factors in a comprehensive manner is difficult, making estimation quite challenging task. Second, the effects of one parameter might be obscured by another (or other) parameter(s) if they have opposing effects. Therefore, Ericsson (2000) divided driving pattern parameters into three measurement categories (i.e., level measures, oscillation measures, and distribution measures). The summary of the main parameters used in related research is shown in Table 2.

In the following subsections, we discuss the most important driver-related factors affecting fuel consumption.

Table 2 Summary of parameters used to quantify driving pattern within the selected studies

References	Considered parameters
Kuhler and Karstens (1978)	Average speed and driving speed (not include stops) Average acceleration and deceleration Mean length of the driving period Average number of acceleration and deceleration changes Proportion of acceleration and deceleration time Proportion of time with constant speed Proportion of stop time
Andre (1996)	Duration Average speed Average value of speed, acceleration, and deceleration Standard deviation of acceleration Relative and joint distribution of speed, acceleration, and deceleration The number of acceleration and deceleration shifts Engine idling time Positive kinetic energy The number of stops per kilometer Running speed (not include stops)
Ericsson (2000)	Level measures: average and standard deviation of the speed, acceleration, and deceleration Oscillation measures: frequencies of max and min values > 2 and 10 km/h, integral of the square of the acceleration, and relative positive acceleration Distribution measures: percentage of time in different speed intervals, time in different acceleration intervals, and time in different deceleration intervals
Sivak and Schoettle (2012)	Speed/revolutions per minute Cruise control using Air conditioner Engine idling time
Huertas et al. (2018)	Accelerations per kilometer Percentage idling/acceleration/deceleration/cruising Average speed, standard deviation speed, and maximum speed Average acceleration/deceleration Standard deviation acceleration/deceleration Maximum acceleration/deceleration
Giraldo and Huertas (2019)	Idling time Time spent accelerating/decelerating Percentage of idling time/ acceleration time/deceleration time/cruising time Average speed, standard deviation speed, and maximum speed Average acceleration/positive acceleration/negative acceleration Maximum acceleration Standard deviation of acceleration/positive acceleration Number of accelerations/accelerations per kilometer

2.1 Vehicle speed

Many studies claimed that vehicle speed profoundly influences fuel consumption and CO_2e emissions. Eglese and Black (2010) showed that vehicles with faster or slower speeds in optimal travel distance did indeed produce more CO_2e emissions than vehicles with the optimal speed taking an alternative route over a longer travel distance. Some research also confirmed that there is a U-shaped relationship between vehicle speed and fuel consumption, as well as CO_2e emissions (Berry 2010; Demir et al. 2012; Sivak and Schoettle 2012; Yao et al. 2020), as shown in Fig. 2.

In other words, fuel consumption (CO_2e emissions) decreases when the speed of the vehicle increases from the lower speed, and increases as the speed increases from the higher speed, and vice versa. It is commonly believed that CO_2e emissions would reach a relatively low level when the vehicle speed ranges between 30 and 50 miles per hour (Barth et al. 1999). However, the optimal speed and the sensitivity of increase or decrease in the speed have a little difference and depend on the characteristics of vehicle (Berry 2010), real-world traffic (Wang et al. 2014), and geographic areas (Khondaker and Kattan 2015). Compared with passenger vehicles, fuel consumption for freight vehicles is more sensitive to speed changes since vehicles will require higher engine power to overcome increased driving resistances (e.g., air drag) that are caused by increased vehicle weight (Zacharof et al. 2016). To be more specific, when a vehicle is loaded, the shape of the vehicle changes, affecting the flow of air around it. Added cargo creates more surface area, increasing the drag force on the vehicle. The weight of the cargo can compress the suspension, reducing ground clearance and increasing the frontal area presented to air. The heavier the load, the greater the aerodynamic drag, leading to higher fuel consumption and emissions (Genta and Morello 2013).

2.2 Acceleration and deceleration

On the other hand, Turkensteen (2017) argued that using average speed to estimate CO_2e emissions sometimes caused underestimated results, compared to actual

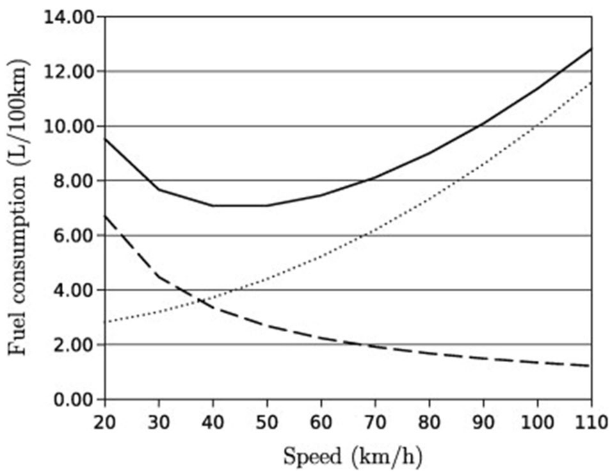

Fig. 2 Fuel consumption as a function of speed (the full line indicates total fuel consumption for a light-weight vehicle which has two components, the dashed line shows engine factors, and the dotted line represents total tractive power demand requirement (Source: Bektaş and Laporte 2011)

CO_2e emissions produced. This is because acceleration events cause significantly more fuel consumption than fuel saved from deceleration events (Ericsson 2001). The results from the study by LeBlanc et al. (2010) showed that acceleration events account for only 6% of total travel distance yet contribute 20% of total fuel consumption. Moreover, the changes of speed (increased acceleration and deceleration rates leading to vehicles not being driven at a steady speed) show far greater influence on CO_2e emissions than fuel consumption. This is because acceleration and deceleration events always produce a greater number of CO_2e emissions, which are being emitted to the atmosphere rather than consumed in the process of combustion. When vehicles are driven at steady speeds, most of the CO_2e emissions are consumed in the combustion process instead of being emitted into the atmosphere (Hillman and Plowden 1996; Miotti et al. 2021). Therefore, for vehicles with high acceleration and deceleration rates, the actual number of CO_2e emissions could be 40% higher than estimated CO_2e emissions based on average vehicle speed (Barth and Boriboomsin 2009).

Several studies indicated that the advantage of using acceleration/deceleration patterns as one of the main parameters to represent driver behavior difference among individuals is that they are very stable over time, compared with speed profiles (Robertson et al. 1992; af Wåhlberg 2000). Yet, compared with speed profiles, the pattern of acceleration and deceleration is not easily measured (to accurately quantify the effects on fuel consumption and CO_2e emissions) as there are more variables within the pattern (as Table 2 shows) (af Wåhlberg 2002). For example, a few studies argued that deploying harsh acceleration and deceleration too quickly to reach the target speed, then maintaining a stable speed, in fact caused less fuel consumption, compared with taking a longer time to reach the speed, under certain situations (Saerens and Van den Bulck 2013; Xia et al. 2013).

2.3 Aggressiveness

A common classification of driver behavior is to divide individual drivers into aggressive and non-aggressive drivers. This is because aggressiveness shows slightly different effects on different types or brands of vehicle (Berry 2010). Aggressive driving generally refers to a high maximum driving speed, harsh acceleration/deceleration/cornering, and high engine speed (Schipper 2011). As discussed in the previous sections, both vehicle speed (Sect. 2.1) and acceleration/deceleration (Sect. 2.2) are significant factors affecting fuel consumption and CO_2e emissions. Aggressiveness encompasses these factors, illustrating how they are interrelated when considering driver behavior.

Among the variables associated with aggressive driving, maximum speed is often reported as the most influential factor on fuel consumption. However, the degree of aggressive driving can vary, and the impacts on fuel consumption (CO_2e emissions) of aggressive driving consequences can also vary. For example, De Vlieger et al. (2000) classified drivers as the aggressive, the normal, and the calm based on average positive accelerations. Their results showed aggressive drivers produced between 20 and 40% more CO_2e emissions and calm drivers caused at least 5% fewer, both compared with normal drivers.

Based on both the acceleration rate and gear selection performance, another study from Fonseca et al. (2010) found that, compared to normal driving, aggressive driving led to 40% more CO_2e emissions (similar with De Vlieger et al. 2000), yet the calm drivers produced 15% less (much higher than De Vlieger et al. 2000). Meanwhile, aggressive driving behavior would lead to a remarkable increase in fuel consumption and CO_2e emissions in the city compared with the freeway. Under city driving conditions, fuel consumption increases due to longer engine idle times and more frequent acceleration/deceleration events. On the other hand, under freeway driving conditions, less fuel consumption is caused by shorter idle time, less frequent accelerations, and higher average speeds (Fontaras et al. 2017). In other words, fuel consumption (CO_2e emissions) under freeway driving conditions is largely determined by physical factors, such as vehicle-related factors or driving environment-related factors. Furthermore, compared with private drivers, professional drivers often face far more complex, and sometimes conflicting, objectives from different stakeholders (e.g., the constraints of delivery time/working hours/legal speed limits, increased workload due to increased delivery demand), which increase the possibility that they may perform more aggressively during their driving (Sümer et al. 2005). In summary, aggressiveness as a driver behavior category encompasses the interconnected factors of vehicle speed and acceleration/deceleration patterns, emphasizing the relationship between these factors in determining fuel consumption and CO_2e emissions.

2.4 Other factors

In addition to these aspects, gear selection is considered another important factor since manual transmission still plays a very important role within the road freight transport industry (safer and more cost-efficient) (Kilcarr 2018; Mall 2019). Gear selection is important for fuel economy since it changes the engine operation point and the powertrain inertia (Eckert et al. 2018; Alvarez et al. 2020). With appropriate gear change at an earlier time, fuel consumption and CO_2e emissions can be saved as follows. One study found that 19% of fuel consumption can be saved if drivers shift the third gear to fourth earlier, and 25% can be saved by an earlier change from the fourth to fifth gear (Dhaou 2011). Other studies also supported fuel consumption saving from appropriate gear change behavior of approximately 20% to 30% (Beckx et al. 2007; Blagojevic et al. 2017). Eckert et al. (2018) further pointed out that professional drivers who operate on a similar route have more potential to benefit from gear selection strategy compared with private drivers. Yet, it is difficult to distinguish gear change behavior between the aggressive and the normal, as optimal change varies depending on the specific dynamic driving scenarios encountered (e.g., traffic conditions and the environment) (Eckert et al. 2016).

Furthermore, engine idling time is normally the aspect most easily overlooked but does affect fuel consumption to a certain degree. One trial study from Edmunds (2005), cited in Sivak and Schoettle (2012 p. 7), assessed the effect of idling time on fuel consumption. The test compared two vehicles. One shuts down the engine every time and the other did not in a ten-mile route with stops of two minutes, ten times. The result showed that the first vehicle consumed 19% less fuel than the second (Table 3).

2.5 Research gaps

Although many studies have investigated the relationship between driver behavior and fuel consumption and CO_2e emissions, the road freight transportation sector has received relatively little attention until recently. Additionally, there has been a lack of comprehensive fuel consumption measurement for driver behavior. In other words, previous studies have tended to focus on the effects of driver behavior separately, such as the fuel consumption savings from gentle acceleration by 1.7% (af Wåhlberg 2007). Furthermore, previous studies suffer from a lack of extensive data (normally less than 200 individual driving records), as the small datasets used in these studies cannot ensure that their conclusions can be accurately applicable to a wide range of vehicle models and diverse conditions. In addition, little attention has been paid to the effects of cornering and compliance with a wide range of legal speed limits in terms of driver behavior in road freight transport research. Our research seeks to address these gaps by not only employing a large real-world traffic dataset but also by providing a comprehensive analysis of fuel consumption related to driver behavior. This analysis incorporates previously overlooked driving characteristics, such as cornering and adherence to varying legal speed limits, which enriches our understanding of fuel consumption patterns. Furthermore, our study contributes to the literature by developing a versatile driver behavior fuel consumption model that accounts for these additional driving features and is robust under diverse conditions. In doing so, we provide new insights and tools for researchers and practitioners alike to better manage fuel consumption and CO_2e emissions in the road freight transportation sector.

3 Fuel consumption and emission models

To quantify the effects of driver behavior on fuel consumption and CO_2e emissions, different energy consumption and emissions models, based on different approaches, structures, and requirements of data, are proposed in the literature (Rakha et al. 2003). Although vehicle manufacturers provide average fuel consumption values, it is not possible to offer related CO_2e emissions because the average fuel consumption is based on standard test cycles rather than real-life driving cycles (Demir et al. 2014). The difference in value between estimated CO_2e emissions offered by original equipment manufacturers and actual CO_2e emissions in real-world cases is around 10–12%. In some extreme cases, the difference can reach 30–40% (Fontaras et al. 2017). Demir et al. (2014) classified numerous fuel consumption and emissions models into three major groups: factor, macroscopic, and microscopic models.

Table 3 Summary of driver-related factors and its effects on fuel consumption and CO_2e emissions

Studied factor (s)	References	The effects on fuel consumption (F) and CO_2e emissions (E)
Vehicle (over) speed	Edmunds (2005), cited in Sivak and Schoettle (2012)	Increasing F by 30% with speeding in general
	Fonseca et al. (2010)	Increasing F by 40% with speeding in general
	Demir et al. (2012)	F increases 0.001 L for each km/hour as the speed increases from 55 km/h, and F decreases 0.02 L for each km/hour as the speed decreases from 100 km/hour
Acceleration/deceleration	Rakha and Ding (2003)	F and E are increased considerably with increased acceleration/deceleration events increase, especially at a high cruising speed
	af Wåhlberg (2007)	F increases 1.8 L/100 km with every increase of 0.1 m/s^2 in acceleration, and F decreases 2.8 L/100 km with each increase of 0.1 m/s^2 (to move toward 0 m/s^2) in deceleration
	Miotti et al. (2021)	F decreases by 6% in average if limit the intensity of acceleration and deceleration
General Aggressiveness	De Vlieger et al. (2000)	E increases up to 40%, comparing aggressive driving with normal driving
	El-Shawarby et al. (2005)	Aggressive driving increases F and E, yet it has more profound impacts on E than F
	Fonseca et al. (2010)	F and E increase by 14%, comparing aggressive driving with eco-driving
Gear selection	Beckx et al. (2007)	F increases by 30% through improper gear selection
	Dhaou (2011)	F decreases by 19% (earlier shift the third gear to fourth) and 25% (earlier change from the fourth to fifth)
	Blagojevic et al. (2017)	The difference of F is up to 19% under different gear shift patterns
Idling time	Edmunds (2005), cited in Sivak and Schoettle (2012)	F increases by 19% under longer idling time

However, factor models are the least complicated models (and therefore the least accurate) and are rarely used in recent academic research. The main macroscopic and microscopic models are briefly discussed below.

3.1 Macroscopic models

Macroscopic models are approaches usually used to estimate a wide-area emission that mainly rely on the average speed of vehicles and other average aggregate values. The main advantage of macroscopic models is their simplicity, as they only require aggregate data to be inputted (Demir et al. 2014). However, they are a less accurate approach since they lack information detail, such as acceleration and deceleration rates (Carrese et al. 2013). Common macroscopic models include COPERT, National atmospheric emissions inventory (NAEI), and Network for transport and environment (NTM).

Among these models, COPERT (European standard) is the most popular tool used in previous studies (e.g., Pérez-Martínez et al. 2014; Li et al. 2019; Ali et al. 2021). COPERT is an emission calculation model that estimates emissions of main air pollutants and CO_2e from various types of vehicles, such as light commercial vehicles, heavy-duty vehicles, urban buses, coaches, and passenger vehicles, across three driving modes: urban, rural, and freeway conditions (Kouridis et al. 2010). The main input includes the average speed, vehicle classes, and engine technologies. The estimated overall fuel consumption per gram can be generally expressed as:

$$F(v, D) = (e + (a \times \exp(-b \times v)) + (c \times \exp(-d \times v))) \times D$$

In detail, a to e represent coefficients based on different payload and gravidity, D is the overall travel distance, and v is the average vehicle speed. Other inputs are also applied in COPERT by several studies. For example, vehicle load and road angle were considered in COPERT in the study by Tavares et al. (2008).

The advantages of COPERT model are straightforward. First, it has demonstrated good accuracy, has been widely used in Europe, and has been tested against actual measurements (Franco et al. 2013). At the same time, it can be used to predict emissions from a variety of road vehicles, including passenger cars, buses, and heavy-duty vehicles (Ntziachristos et al. 2014), and considers the impact of various driving scenarios, such as urban, rural, and highway driving. The characteristics and strengths of the COPERT model, as well as its broad applications in previous studies, make it a valuable tool for our investigation. Given its ability to predict emissions from a variety of vehicles in various driving scenarios, we will employ the COPERT model in our case study to estimate and analyze fuel consumption. On the other hand, it requires input data on vehicle activity, such as distance traveled and speed, which may not always be available or accurate (Smit et al. 2012). Furthermore, since it is designed for regional or national-level assessments, the model may not be appropriate to estimate emissions from individual vehicles or small fleets (Ntziachristos et al. 2014).

NAEI is another emission modeling tool (the UK standard) that is widely applied in different sectors, such as agriculture and industrial processes, as well as transportation. In the road transportation sector, emissions are calculated in two ways. One is to combine the data of total fuel consumption with the fuel characteristics. Alternatively, it combines relevant driving emission factors with road traffic data (NAEI 2017). Based on different vehicle classes, the estimated fuel consumption (in liters per 100 km) with a fixed average speed can be calculated as follows:

$$F(v) = \frac{k\left(a + b \times v + c \times v^2 + d \times v^3 + e \times v^4 + f \times v^5 + g \times v^6\right)}{v}$$

Here, k and a to g represent coefficients, which are defined as specific characteristics of vehicles, and v represents average speed (Demir et al. 2014). The study by Maden et al. (2010) is one of the main studies in road freight transportation that employs the NAEI model for a vehicle routing and scheduling problem.

Compared to COPERT, NAEI uses more detailed input data, such as vehicle registration data, to estimate emissions from individual vehicles or small fleets. Furthermore, it considers a wider range of emission sources, including non-road mobile machinery, industrial processes, and agriculture, in addition to road transport (Lee et al. 2015). However, it may not be as widely used and tested as the COPERT model, particularly outside the UK. Furthermore, it may require more input data and resources to use effectively compared to the COPERT model, and it may not accurately reflect real-world driving conditions, as it relies on assumptions and default values that may not match actual driving patterns (Lee et al. 2015; Air Quality Expert Group 2021).

NTM is a general model to estimate environmental impacts for different modes of freight and passenger transport. It was developed primarily for transport activity providers to easily measure their carbon footprint (NTM 2015a). The NTM (road transport) takes into account distance, loading factors, type of roads (motorway, rural, and urban), and empty return trips. Fuel consumption with *F(lf)* (liter/kilometer) with different loads can be expressed as follows (NTM 2015b):

$$F(lf) = F(empty) + (F(full) - F(empty)) \times lf$$

Here, *F(empty)* represents the fuel consumption of empty vehicles (liters/kilometer), F (full) is the fuel consumption of fully loaded vehicles (liters/kilometer), and *lf* is the specific load factor. There are different default values of *F(empty)* and *F(full)* for 10 different vehicle types and characteristics (see NTM 2015c).

The NTM model can estimate the emissions from various modes of transport, including road, rail, air, and sea transport. Furthermore, it considers the effects of different vehicle technologies and fuel types on emissions. However, similar to NAEI, it may not accurately reflect real-world driving conditions or the effects of traffic congestion on emissions, and it requires input data on vehicle activity and characteristics, which may not always be available or accurate like COPERT (NTM 2015a; Alvizu et al. 2017).

3.2 Microscopic models

Microscopic models provide more accurate and detailed fuel consumption and emission rates, since they are based on instantaneous values such as speed variability. However, they are very complicated and require vast amounts of data (Carrese et al. 2013). A Comprehensive Modal Emission Model (CMEM) is the most popular microscopic model in related studies. CMEM is designed for heavy-duty vehicles and provides very precise estimations since it demands very detailed input parameters; for example, the speed of vehicle engine and friction coefficient of the engine (Scora and Barth 2006). CMEM consists of three modules: the engine power module, the engine speed module, and the fuel rate module; and the total fuel consumption (gram) can be simply shown as:

$$F_{cm}(T) = \int_{0}^{T} f_{cm}(t)dt$$

Here, fcm(t) is the fuel rate module by fuel rate (grams per second). Since it is simple to apply, compared with other microscopic models, CMEM is widely used in green road freight transportation, especially in pollution routing problems (Demir et al. 2014). For example, the study by Bektaş and Laporte (2011) used the engine power module, based on speed and load parameters, to determine vehicle speeds in different segments in each delivery route in order to achieve the optimal total cost, which consists of fuel consumption cost, labor cost (drivers), and emissions cost. In addition, the fuel rate model is used by Demir et al. (2012) to produce an overall fuel consumption value per second to present the arithmetic for speed optimization. Furthermore, CMEM was also used in the study by Franceschetti et al. (2013), who provided a trade-off between the emissions rate and the driver's cost under traffic congestion (Demir et al. 2014). Another widely used microscopic model for simulating fuel consumption is the Passenger Car and Heavy Duty Emission Model (PHEM), which is a combination of three different models and covers a wide range of engines and vehicles (Hausberger et al. 2010). Total emissions can be expressed simply as

$$E_{trans}(t) = E_{qs} + P_{rated} + F_{trans}$$

E_{trans} indicates that the emission value is under transient conditions, E_{qs} is the quasi-steady-state emission value interpolated from steady-state emission map, P_{rated} is the related engine power, and F_{trans} is the dynamic correction function (Demir et al. 2014).

Since the model can estimate emissions from a wide range of transportation modes and has been validated against real-world measurements (more accurate emission estimates), it is considered a comprehensive tool for policy-making and environmental assessments. However, it is a complex model that requires significant computational resources and expertise to operate, which may limit its use by some stakeholders. Additionally, its accuracy may be affected by uncertainties in input data, such as fuel quality and vehicle age (Barth et al. 2001; Scora and Barth 2006).

4 Case study

This research collected secondary data from a UK-based transport research organization (third-party) to measure how driver behavior affected fuel consumption and CO_2e emissions within road freight transport activities, and to determine which behaviors might affect fuel consumption and CO_2e emissions in more significant ways.

Secondary data recorded the actual fuel consumption value for 113 vehicles, including 83 HGVs and 30 light commercial vehicles (LCVs) from six different vehicle manufacturers. Each vehicle completed 63 trips, leading to an initial number of 7119 trips. However, invalid records such as unrecorded data and repeated records were present in the raw data from the company. After data processing and adjustments, a total of 4391 valid trips of 86 vehicles remained for analysis. In response to the potential overrepresentation of certain vehicles in the final dataset, we note that our data cleaning process was unbiased and invalid records were removed irrespective of the vehicle from which they originated. We performed additional analyses in which we standardized the number of trips per vehicle, ensuring that each vehicle contributed proportionally to the final results. This approach allowed us to limit potential bias and maintain a balanced representation of all vehicles in our study. Table 4 summarizes the data. We should note that our dataset did not include driver-specific information, such as whether the same or different drivers drove the same

Table 4 Summary of independent variables (one illustrated case)

Vehicle number	1
Manufacturer	DAF
Type	HGV
Engine model	LF FA 45.150 148 3920 2001
Age/years	11
Total fuel consumption/liters	31.9
Total travelled distance/miles	86.7
Total driving time/hours	02:45:14
Total journeys/times	14
a. Excessive speeding score	100%
b. Over rpm score	100%
c. Harsh acceleration score	42%
d. Harsh deceleration score	15%
e. Harsh cornering score	9%
f. Over 20 miles/h (mph) legal speed limit score	100%
g. Over 30 mph legal speed limit score	30%
h. Over 40 mph legal speed limit score	91%
i. Over 50 mph legal speed limit score	100%
j. Over 60 mph legal speed limit score	100%
k. Over 70 mph legal speed limit score	100%

vehicle. Although this absence of data might limit the precision of our results, we maintain that the general trends observed in this study still provide valuable insights, given the significant impact of driver behavior on fuel consumption and emissions.

There are 11 parameters (a–k in Table 4) that have been selected to quantify driver behavior. These 11 parameters were selected for two reasons. First, as discussed above, many previous studies have shown that these parameters are considered aspects of driver behavior that may have a significant impact on fuel consumption (CO_2e emissions). Second, due to limitations in the available data, these parameters are the aspects that can be recorded more effectively and efficiently in the company's standard practice. All these data are translated into percentile score form, which is based on Telematics Smart Box. The Telematics Smart Box is a device that enables the monitoring of driving behavior by collecting data in five main ways: through a black box, mobile application, on-board devices, plug & drive, and manufacturer-fitted on-board devices. Vehicle driving data was recorded and used to give scores, normally in the range of 0% to 100%, for driver behavior on each trip taken (General Accident n.d.; My policy n.d.).

Telematics scoring can provide a valid and accurate view of driver behavior, since a substantial number of variables on a number of trips are taken into account. In this case, six main elements are selected that largely visualize driver behavior, including excessive speed, over revolutions per minute (rpm), harsh acceleration and deceleration, harsh cornering, and compliance with different legal speed limits, ranging from 20 to 70 miles per hour. Essentially, the scores represent how well-behaved the driver was. In other words, the higher the score, the better, and vice versa. For example, as *a* column in Table 4, a 100% score means that an excessive speeding event never occurred with this driver on this trip. However, it does not represent that the driver obeyed all legal speed limits during the trip. As *g* and *h* columns show, the driver only obeyed the legal speed limit on 30% and 91% of the driving time when 30 and 40 mph were the current legal speed limits.

First, we focus on the relationship between average vehicle speed and (actual) fuel consumption with HGVs and LCVs. In this case, the average vehicle speed can be calculated based on the total traveled distance (D) and the total driving time (T), as follows:

$$v = \frac{D}{T} \tag{1}$$

Therefore, the v of vehicle 1 is 139.53 km (86.7 miles) / 2.75 h = 50.74 km/h. Meanwhile, fuel consumption (liter/100 km) can be calculated as follows.

$$F = \frac{Total\,Fuel\,Consumption\,(litres) \times 100}{Total\,Travelled\,Distance\,(km)} \tag{2}$$

Table 5. shows the example of HGVs with calculated vehicle average speed (km/h) and fuel consumption (liter/100 km).

Figure 3 illustrates the variation in fuel consumption in HGVs and LCVs as a function of the average vehicle speed. Fuel consumption per unit distance for HGVs and LCVs is expressed as a convex function. In detail, fuel consumption

Table 5 An example of the average speed and fuel consumption for HGVs

Vehicle number	Manufacturer	Type	Engine model	Average speed (km/h)	Fuel consumption (liter/100 km)
4	DAF	HGV	CF FTG 85.430 SLP 422 12580 E3	55.54	34.23
5	DAF	HGV	CF FTG 85.430 SLP 422 12580 E3	67.32	30.77
6	DAF	HGV	CF FTG 85.430 422 12580 E3	62.90	32.17
10	DAF	HGV	CF FTG 85.430 SLP 422 12580 2001	72.96	31.17
38	DAF	HGV	CF FTG 85.410 SLP E4 402 12900 2	66.85	29.85
39	DAF	HGV	CF FTG 85.410 SLP E4 402 12900 E	72.58	30.16
40	DAF	HGV	CF FTG 85.410 SLP E4 402 12900 2	69.99	29.63
41	DAF	HGV	CF FTG 85.410 SLP E4 402 12900 2	73.68	29.66
42	DAF	HGV	CF FTG 85.410 SLP E4 402 12900 E	78.35	29.46
43	DAF	HGV	CF FTG 85.410 SLP E4 402 12900 2	66.09	30.32
44	DAF	HGV	CF FTG 85.410 SLP E4 402 12900 E	71.96	29.54
45	DAF	HGV	CF FTG 85.410 SLP E4 402 12900 2	65.20	30.24
46	DAF	HGV	CF FTG 85.410 SLP E4 402 12900 2	65.76	30.28
47	DAF	HGV	CF FTG 85.410 SLP E4 402 12900 2	72.04	30.08
48	DAF	HGV	CF FTG 85.410 SLP E4 402 12900 E	72.21	30.34
49	DAF	HGV	CF FTG 85.410 SLP E4 402 12900 E	74.74	30.34
50	DAF	HGV	CF FTG 85.410 SLP E4 402 12900 2	71.25	29.67

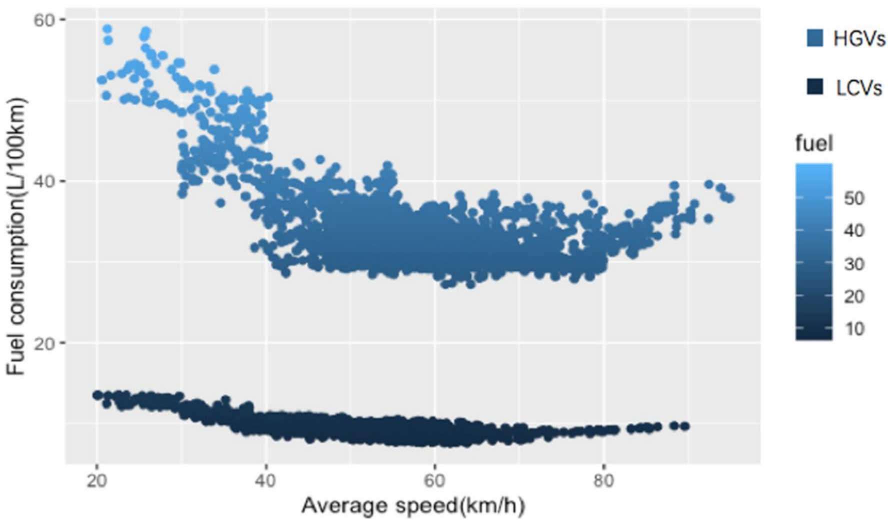

Fig. 3 The relationship between vehicle average speed and fuel consumption with HGVs and LCVs

for HGVs reaches the highest level when the average speed is less than 40 km/h (24.85 mph), and it decreases and reaches the relatively lower level as the average vehicle speed is approximately between 50 km/h (31.07 mph) and 80 km/h (49.71 mph) before it increases again when the speed is above 80 km/h (49.71 mph). At the same time, fuel consumption for LCVs shows a similar pattern (U-shaped) to HGVs. Fuel consumption reaches the highest level when the average speed of LCVs is less than 27 km/h (16.78 mph) and it remains at a relatively lower level when the speed is between 45 km/h (27.91 mph) and 65 km/h (40.39 mph), then increases again when the speed is above 70 km/h (43.5 mph). However, compared to HGVs, LCVs have less sensitivity to fuel consumption with variation in vehicle average speed. This result confirms the conclusion of Zacharof et al. (2016) that fuel consumption shows more dramatic changes over the speed changes on fuel consumption with heavier vehicles (which is discussed in Sect. 2.1). In addition to this, Fig. 3 indicates that fuel consumption can vary even with the same speed. For example, fuel consumption ranges from 29 to 40 (liter/100 km) when the speed is 50 km/h (31.07 mph). It is clear to say that other factors (environment-, traffic-, operations-, and other driver-related factors) profoundly affect fuel consumption.

To evaluate how driver behavior affects fuel consumption and CO_2e emissions, we then compare the difference between actual fuel consumption from the data and the estimated fuel consumption value. The estimated fuel consumption value is calculated by the macro fuel consumption model since the data do not contain instantaneous values such as speed variability. As mentioned in the last section, the main input for macro fuel consumption models is the average vehicle speed. For each individual trip, factors that aren't directly related to driver behavior, such as the vehicle's make and model, the length of the trip, and the road and weather conditions, are kept as consistent as possible. The difference between the actual fuel consumption and the estimated fuel consumption, calculated using the COPERT model (different coefficients were used based on vehicle and engine types), is then attributed to variations in driver behavior. This estimation assumes that non-driver factors are similar for both actual and estimated fuel consumption values of the same trip. We chose the COPERT model for several reasons. Firstly, it is widely accepted and trusted to estimate the emissions and fuel consumption of road transport. Secondly, it can calculate the fuel consumption for a variety of vehicle types and fuel types, an important feature, since our data included different vehicle types. Third, the user-friendly interface of the COPERT model made it an accessible tool, as we had limited time and resources to train on more complex models. Lastly, the use of the COPERT model in previous similar studies facilitated better comparability of our results with the existing literature.

The estimated fuel consumption is calculated by a basic speed function of fuel consumption (gram per km) during a known distance (Tavares et al. 2008), which can be expressed as

$$F(S) = a \times ve + b \times v + c \tag{3}$$

Here *abce* are coefficients that depend on vehicle categories and v is the average speed. Taking an example for the vehicle in Table 4, this vehicle is classified as diesel HGV with a weight class between 7.5 and 16 tons. Therefore, its fuel consumption (gram per kilometer) can be expressed as: $1068.4 \times v - 0.4905$ when the speed (v) ranges from 0 to 59.55 km/h (0 to 37 mph), and $0.0126 \times v$ $2 - 0.6589 \times v + 141.18$ when v is ranging from 59.55 km/h to 99.78 km/h (37 to 62 mph) (Kouridis et al. 2000). Since the actual fuel consumption value in the data used liter as the unit, the total fuel consumption (kilogram) related to a single speed function of the vehicle can be calculated as:

$$Total\,F(s) = ((a \times ve + b \times v + c) \times D) \times 1000 \tag{4}$$

Therefore, the fuel consumption related to driver behavior (D) per km (kilogram) can be calculated as Eq. (5):

$$F(D) = \frac{Actual\,Fuel\,Consumption - Total\,F(s)}{D} \tag{5}$$

Based on the multiple regression model, F(D) can be expressed as:

$$\begin{aligned} F(D) = & A_0 + A_1 \times Harsh\,deceleration\,score + A_2 \times Harsh\,acceleration\,score \\ & + A_3 \times Over\,20mph\,speed\,limit\,score + A_4 \times Over\,30mph\,speed\,limit\,score \\ & + A_5 \times Over\,40mph\,speed\,limit\,score + A_6 \times Over\,50mph\,speed\,limit\,score \\ & + A_7 \times Over\,60mph\,speed\,limit\,score + A_8 \times Over\,70mph\,speed\,limit\,score \\ & + A_9 \times \text{Harsh cornering score} + A_{10} \times \text{Over rpm score} + A_{11} \\ & \times \text{Excessive speeding score} \end{aligned}$$

Here, A_0 to A_{11} are constants which were calculated by multiple regression analysis (EViews 10). We chose a linear regression analysis for our study due to its simplicity, effectiveness, and interpretability. Linear regression allows us to quantify the relationship between fuel consumption and various driver behaviors and vehicle characteristics. Although this method assumes a linear relationship, we found it to be a robust and effective tool for our purposes. With respect to interaction effects, we did not initially include them in our analysis. We considered the individual impacts of various factors on fuel consumption, keeping our model more straightforward for interpretability. However, we acknowledge that interaction effects between variables could provide additional insights into the complexities of fuel consumption. Future research could further explore these potential interactions. The result of the data process is shown in Table 6.

The regression results illustrate that driver behavior has a strong relationship with fuel consumption but is limited in certain aspects. First, harsh acceleration is strongly correlated with fuel consumption, which confirms the general conclusion found by several studies that fuel consumption could be decreased as the rapid acceleration rate is reduced (e.g., Ericsson 2001; af Wåhlberg 2007; Rodríguez et al. 2016). Harsh acceleration causes higher fuel consumption and CO_2e emissions,

Table 6 Regression results for multiple regression model (where *** and ** denote respectively the statistical significance at 1% and 5% level)

Independent variables	Fuel consumption (dependent variable)
c	0.066
t-statistic	(35.121)***
P-value	0.000
Harsh deceleration	−0.002
t-statistic	(−0.811)
P-value	0.417
Harsh acceleration	−0.030
t-statistic	(−9.932)***
P-value	0.000
Over 20 mph legal speed limit	−0.0137
t-statistic	(−4.078)***
P-value	0.000
Over 30 mph legal speed limit	−0.019
t-statistic	(−9.174)***
P-value	0.000
Over 40 mph legal speed limit	−0.001
t-statistic	(−0.162)
P-value	0.872
Over 50 mph legal speed limit	−0.004
t-statistic	(−0.658)
P-value	0.511
Over 60 mph legal speed limit	0.020
t-statistic	(1.273)
P-value	0.203
Over 70 mph legal speed limit	0.003
t-statistic	(0.096)
P-value	0.923
Harsh cornering	−0.034
t-statistic	(−14.348)***
P-value	0.000
Over rpm	−0.010
t-statistic	(−2.345)**
P-value	0.019
Excessive speeding	0.022
t-statistic	(11.640)***
P-value	0.000
No. of observation	4391
Adjusted R-squared	0.488
F-statistic	350.283

mainly due to a richer fuel-to-air ratio needed to avoid engine knocks and overheating of the cylinder head, which increases fuel consumption and CO_2e emissions. Furthermore, this richer fuel-to-air ratio persists even after the harsh acceleration behavior has ceased, resulting in greater fuel consumption and CO_2e emissions compared to gentle acceleration (Larsson and Ericsson 2009).

On the contrary, Table 6 denotes that there is no statistically significant relation between harsh deceleration and increased fuel consumption. This result is in agreement with the study by Wang et al. (2008). Although harsh deceleration shows a less notable influence on fuel consumption, it does influence fuel consumption indirectly. Deceleration events do not consume fuel directly, but forward momentum would be wasted each time the driver brakes (Natural Resources Canada 2021). In other words, harsh deceleration indirectly causes increased fuel consumption because it requires much more engine power to reach the desired speed compared to coasting. In some extreme cases, harsh deceleration leads to vehicles completely stopping. Instantaneous fuel consumption would reach the highest level when vehicles restart again since the engine needs to significantly increase its torque to overcome the effect of static friction (Rouphail et. al. 2000). However, all these effects on fuel consumption are, in fact, embodied in acceleration events. Therefore, the result of Table 6 displays harsh deceleration barely relating to increased fuel consumption.

Furthermore, the impact of the harsh cornering score on higher fuel consumption is found to be significantly negative, which means that fuel consumption will increase dramatically if drivers behave more aggressively when turning the vehicle. It is worth mentioning that harsh cornering causes more fuel consumption compared with harsh acceleration to some extent on straight roads. This is because vehicles require much more power to overcome extra rolling resistance forces during cornering, compared to straight acceleration (Olofson 2015). As Fedor (2018) suggested, harsh cornering, which means higher lateral acceleration, would increase extra rolling resistance forces and eventually dramatically increase fuel consumption. Moreover, it is apparent that harsh cornering would cause increased acceleration and deceleration events (rates). Therefore, for more aggressive drivers, harsh cornering affects fuel consumption not only by increasing additional resistance forces to roll, but also by increasing the harsh acceleration and deceleration behavior.

Regarding the relationship between over rpm score and higher fuel consumption, the results indicate that over rpm does impact fuel consumption to a certain degree, but it is not as strong as the behavior of harsh acceleration and cornering. Revolutions per minute is a tachometer that shows how fast the engine spins as the vehicle speeds up or slows down. The relationship between rpm and fuel consumption is quite similar to the relationship between speed and fuel consumption, which is displayed as a U shape. In other words, fuel consumption would reach the highest level when rpm is too low or too high. This result resembles the study by Lee et al. (2011).

The relationship between exceeding 20 and 30 mph legal speed limit scores and fuel consumption is strongly negative, which means fuel consumption can be reduced significantly if drivers adhere to the legal speed limit of 20 and 30 mph. On the other hand, the results depict that there were no statistically significant relations between excess speeding over 40, 50, 60 and 70 mph legal speed limits and fuel consumption. This result contradicts the conclusion of the report by the European Environment Agency (2020). This report suggested that obeying the legal speed limit on highways, which is normally 70 mph (GOV.UK 2021b), would result in a significant decrease in fuel consumption.

However, the effects of compliance with the legal speed limit in built-up areas, which usually range from 20 to 30 mph (GOV.UK 2021b), are unclear because the lower legal speed limits in these areas aim mainly to provide a safer and quieter local environment. One possible reason could be that areas with 20 and 30 mph legal speed limits have higher traffic congestion levels compared to areas where the legal speed limit is between 40 and 70 mph (Wilson et al. 2013). In the UK, 20 mph legal speed limit is enforced in residential areas, for example near schools, and 30 mph legal speed limit is applied in neighborhood streets (GOV.UK 2021b). The variation in vehicle speed would increase as driving occurs in such highly congested areas. As mentioned above, high congestion does increase fuel consumption due to increasing stop and go driving events. To exceed legal speed limits in these circumstances would substantially increase acceleration and deceleration events (rates) and eventually increase fuel consumption. By comparison, to exceed higher legal speed limits, such as 40, 50, 60 and 70 mph limits, the variation in speed change is less because of lower levels of traffic density. Therefore, the relationship between exceeding the legal speed limit at 40, 50, 60, and 70 mph and higher fuel consumption tends to be smaller (Carsten et al. 2008).

However, the relationship between excessive speeding scores and higher fuel consumption is positive, which means that fuel consumption decreases as excessive speeding behavior increases. This result is inconsistent with previous studies in which excessive speeding is regarded as inefficient driver behavior that causes higher fuel consumption (Servin et al. 2006). Excessive speeding behavior refers to drivers who exceed the legal speed limit. In this case, it is considered the average behavior of non-adherence to all legal speed limits, 20–70 mph. One possible explanation could be that most excessive speeding behavior in this case occurred with lower legal speed limits, especially over 30 mph legal speed limit, which is demonstrated in Table 7.

With increased excess-speed behavior at the lower legal speed limit level, fuel efficiency actually increases in response. This evidence was supported by

Table 7 Descriptive statistics of data regard of over speed limit score

Over legal speed limits score	Mean (%)	Median (%)	Maximum (%)	Minimum (%)	Standard deviation (%)
Over 20 mph	92.034	100	100	4	21.37
Over 30 mph	68.758	91	100	1	36.38
Over 40 mph	91.725	100	100	4	20.51
Over 50 mph	97.903	100	100	8	10.51
Over 60 mph	99.629	100	100	8	4.59
Over 70 mph	99.92	100	100	15	2.21

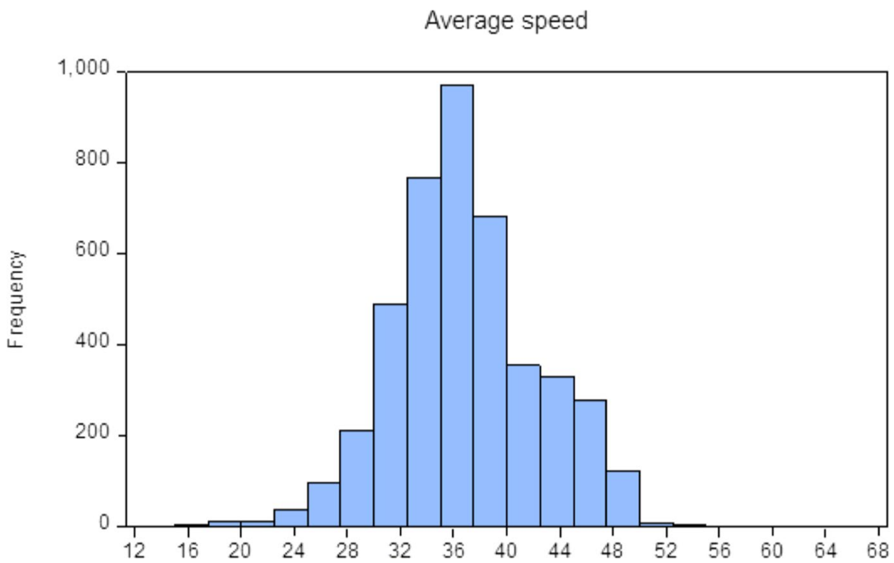

Fig. 4 The frequency distribution of the average vehicle speed

El-Shawarby et al. (2005), who used field data to demonstrate that fuel consumption and CO_2e emissions per unit distance would reach the optimal point when the average speed of freight vehicles ranges from 37 to 60 mph. Figure 4 represents the frequency distribution of the average vehicle speed.

As Fig. 4 shows, the average speed of selected vehicles in this case ranges from 16 to 55 mph. At the same time, a recent study by Davis et al. (2012) argued that fuel efficiency would reach the optimal point at a higher vehicle speed level compared with previous studies. For example, previous studies by the Federal Highway Administration found that the best fuel efficiency would be achieved when the speed reaches 35 to 40 mph. However, a more recent study from the Federal Highway Administration found that the optimal speed for the same vehicle is at a point higher than 35 to 40 mph (Davis et al. 2012). Since there is a lack of information for excessive speeding behavior regarding area-specific in this case, it is rather more difficult to define. Therefore, it is surprising that excessive speeding behavior reveals a relatively positive relationship to reducing fuel consumption.

5 Conclusion

In analyzing real-world telematics data, we identified key aspects of driver behavior. Our research findings can be bifurcated into two categories. First, we corroborate conclusions drawn from prior studies in the field, as follows:

- The behavior of harsh acceleration has a strongly negative influence on fuel consumption and CO_2e emissions due to a richer fuel-to-air ratio. Despite the behavior of harsh deceleration that does not significantly affect fuel consumption, it should be carefully considered, since it increases acceleration events (rates).
- The behavior of harsh cornering shows an even worse consequence in fuel consumption due to extra rolling resistance forces. Moreover, the behavior over rpm, which is easily ignored compared with the behavior of harsh acceleration and cornering, also has a relatively strong influence on fuel consumption.

Second, we present a novel finding that highlights a specific driver behavior frequently overlooked in previous research:

- When driving above set legal speed limits, fuel consumption increases dramatically when drivers do not adhere to lower legal speed limits of 20–30 mph. This is because the level of traffic congestion is much higher in these areas. On the other hand, the behavior of driving over the legal speed limits in higher set speed level limit areas of 40 to 70 mph shows only a limited influence on extra fuel consumption.

The findings of this work can provide useful information for both freight providers and drivers during their daily operations. Avoiding poor driver behavior as much as possible provides significant benefits economically (fuel consumption saving) and environmentally (CO_2e emissions reduction). It is important to note that the behavior of the freight driver is less fickle compared to the behavior of the private driver, even though their driving routes may be relatively similar. In other words, changing the behavior of the freight driver has more potential benefits since other external factors, mainly the driving environment and traffic-related factors, would not significantly interact with the behavior of the driver. As Payne (2013) established, driver behavior is difficult to change in a short time; in fact, it can sometimes take years to alter. Therefore, to obtain a stable result in altering driver behavior, certain related devices can be applied for freight trucks; for example, ISA (intelligent speed adaptation) speed-warning devices, which are designed to help drivers adjust their vehicle speed to below set legal speed limits (Warner and Aberg 2008), and other direct feedback devices. However, these devices may not have an effect if drivers choose to ignore the instructions. Therefore, logistics companies can introduce rewards and punishments for their drivers based on their driving scores. Meanwhile, policymakers may consider enforcing stricter regulations on driving above set legal speed limits at 20 and 30 mph, given that this behavior has a much stronger influence on fuel consumption at lower speed levels.

At the same time, this research has some limitations. First, compared to other factors (especially driving environment, traffic, and operations-related factors), driver-related factors are relatively 'new' (in other words, the effects of driver behavior are generally not studied individually) in the green road freight transport research area. Therefore, there are no fuel consumption models specifically designed and developed for driver-related factors, which obviously restricts the scope of this research. Meanwhile, despite the collected data containing many variables to quantify driver behavior, several important inputs, such as gear selection and idle time, are ignored. As discussed previously, gear selection among different drivers can lead to a considerable difference in fuel consumption, as much as 20% higher, with the same average speed and under the same route (Ding 2000), as idling time does. Furthermore, other important external factors that directly affect driver behavior have not been considered.

As Ericsson (2000) acknowledged, driver behavior is affected by driving environment-related factors, including road type, and traffic-related factors, such as traffic congestion. To be more specific, acceleration and deceleration rates for the same driver are significantly higher in the urban driving environment with traffic peak periods because the number of stop/go events is higher. However, in this investigation, we did not distinguish which driver behavior is caused by the surrounding driving environment (traffic- and environmental factors) or even operational factors (for example, the pressure of the delivery time window). Regarding these limitations, further work could examine the variables not considered in this study and seek to clearly differentiate which driver behavior is caused by external factors and which is caused by drivers themselves. Finally, although non-aggressive (or eco-friendly) driver behavior does have positive impacts on fuel consumption saving and CO_2e emissions reduction, it might lead to negative impacts economically (delayed delivery time, more drivers and vehicles required, and extra costs on driver aid equipment). Therefore, future studies should evaluate the trade-off between positive and negative impacts in this area.

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Declarations

Conflict of interest The authors declare that there is no conflict of interest regarding the publication of this paper.

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