IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received June 30, 2021, accepted July 27, 2021, date of publication August 3, 2021, date of current version October 19, 2021.

*Digital Object Identifier 10.1109/ACCESS.2021.3102222*

# A Landscape of Research on Bus Driver Behavior: Taxonomy, Open Challenges, Motivations, Recommendations, Limitations, and Pathways Solution in Future

**ALI MOHAMMED[1], MUHAMAD RAZUHANAFI MAT YAZID[1], B. B. ZAIDAN[2], A. A. ZAIDAN[2], SALEM GARFAN[2], R. A. ZAIDAN[2], H. A. AMEEN[3], Z. H. KAREEM[4], AND R. Q. MALIK[4]**

[1]Department of Civil Engineering, Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia (UKM), Bangi, Selangor 43600, Malaysia
[2]Department of Computing, Faculty of Arts, Computing and Creative Industry, Universiti Pendidikan Sultan Idris, Tanjong Malim, Perak 35900, Malaysia
[3]Department of Computer Techniques Engineering, Al-Mustaqbal University College, Hillah 51001, Iraq
[4]Department of Medical Instrumentation Techniques Engineering, Al-Mustaqbal University College, Hillah 51001, Iraq

Corresponding author: Muhamad Razuhanafi Mat Yazid (razuhanafi@ukm.edu.my)

This work was supported by the Fundamental Research Grant Scheme (FRGS) under Grant 1/2019/TK08/UKM/02/1.

**ABSTRACT** Driver behavior is a concerning issue in the area of intelligent transportation system (ITS). Driver behavior is a significant key player in a wide range of unpleasant events during the ride, such as accidents or crashes, traffic congestion, harsh braking, and acceleration/deceleration. Influencing factors of driver behavior have been explored in several studies. It is imperative to investigate these factors in order to provide a comprehensive analysis and to categorize them on the basis of a coherent taxonomy. With that, this study conducted a systematic review on prior studies that focused on bus driver behavior, particularly in the ITS. This study also established a taxonomy on the topic of driver behavior in multiple areas of ITS and their classifications. Different databases, namely ScienceDirect, Web of Science, and IEEE Explore, were utilized to obtain relevant articles from 2008 to 2021 (15 April). Several filtering and scanning stages were performed according to the exclusion/inclusion criteria on all 2,803 articles obtained; however, only 87 articles met the criteria. The final set of articles were categorized into a taxonomy. The first part of the taxonomy focuses on five main factors that influence driver behavior: environmental, demographic, habit, vehicle, and on-road routine factors. The second part of the taxonomy discusses the mapping of data collection methods on the basis of four categories: real-time data collection, survey, simulation, and benchmark. Discussion and analysis were provided to highlight the critical literature gaps on bus driver behavior in the ITS, involving the use of real-time data collection, which is imperative for acquiring highly accurate and sophisticated data. This multi-field systematic review has exposed new research opportunities, motivations, challenges, limitations, and recommendations and highlighted the need for the synergistic integration of interdisciplinary works. Overall, this study presented pathways solution in future direction on the basis of three sequenced phases, namely design, labeling and validation, and machine learning. This study can serve as a guide for future researchers, as it addressed the ambiguities in the ITS-driver behavior domain and provided valuable information on these ITS-driver behavior trends.

**INDEX TERMS** Intelligent transportation system, ITS, bus, behavior, driver behavior, bus driver.

## I. INTRODUCTION

Intelligent transportation system (ITS) is one of the research areas that attempt to incorporate the latest information technologies into the domain of transportation for various advantages [1], [2]. Such advantages include reducing traffic congestion, preventing accidents or crashes, and facilitating vehicle flow [3]. For that, a wide range of technologies can be exploited, such as the Global Positioning System (GPS), mobile network, Radio Frequency Identification (RFID), and

The associate editor coordinating the review of this manuscript and approving it for publication was Maurice J. Khabbaz.

other communication technologies by providing, sharing, and exchanging information about road safety, congestion, and other valuable knowledge [4]. ITS has been explored in a considerable number of studies, where various aspects of road, vehicle, and driver have been tackled. Although each aspect has considerable implications on transportation, the aspect of driver behavior is significant, as a driver can significantly influence the ride. A driver plays a considerable role in unpleasant road events, such as traffic congestion or fatal accidents, where human errors, sensation-seek, aggressiveness, and other human-involved factors are likely to be engaged [5].

As a remarkable component of public transportation, buses serve as a main instrument of public transport in many cities throughout the world [6], primarily due to its cost-effectiveness, flexibility, and wide coverage of services [7]. Buses are deemed the safest for long-distance travel, as compared to cars. Various studies have revealed that travelling via cars is more dangerous than travelling via buses, particularly distances of over 100 million person-kilometers are involved. Despite the high degree of safety for buses, empirical studies on bus accidents in developing countries have remained scarce. Moreover, the safety features of buses have created general public perceptions of lower traffic congestion and air pollution as well as improved road safety [8].

Meanwhile, driver behavior remains a chief concern in road safety policy and research [9]. The propensity to accelerate during driving is a possible candidate to measure driver behavior. Although the propensity to accelerate may be a stronger accident involvement indicator, this concern has been rarely deliberated in literature. The considerable role of a driver in various unpleasant events, such as traffic congestion and fatal accidents, is an undeniable fact, where human errors, sensation-seek, aggressiveness, and other human-involved factors are likely to be engaged [5].

The distinctive feature of a driving process lies in the dynamic control that requires cooperation between the body and mind. The driving process is generally complicated, as the traffic conditions are heterogeneous [10]. Accident records indicate low variances in driver behavior within a short period during an accident. In the case of driver faults, the major concern is the encroaching nature of bus accidents that involve passengers and road users. Besides that, personality attributes, vehicle condition, environment, decision making, psychological traits, and driving style contribute to the inclination of a driver to cause an accident [10]. For instance, associating information of driving style to accident statistics and speed limit were found to facilitate precise actions that can minimize bad driving behavior [6].

Moreover, certain drivers, such as bus drivers, critically affect a larger number of lives. A bus driver should have adequate and accountable driving behavior considering the popularity of bus as a public transport and its advantages in decreasing traffic congestion and serving larger populations that cannot afford individual cars [11]. Besides that, geographic location is another major aspect where culture, weather, or roads can affect driver behavior. There has been an increasing number of bus accidents in the last decade [12]. This increase is considerably associated with driver behavior, in which the majority of accidents are linked to aggressiveness, such as harsh acceleration, brake, or manoeuvring [13]. With that, this study conducted a systematic literature review on prior studies that focused on bus driver behavior. An extensive review was conducted on prior studies that tackled driver behavior in order to model influencing factors of driver behavior.

This study presented a systematic mapping of the key findings on the evaluation approaches of bus driver behavior. The main purpose was to determine the approaches used in these prior studies, particularly the features of these approaches, such as their origin, nature, and mode of execution. Through this mapping, this study presented conclusions on the state of the art in this field and contributed to the development and improvement in the evaluation approaches of bus driver behavior. Prior studies explored driver behavior as well; the differences of the current study from prior studies were highlighted in this paper, reflecting the significant contributions of the current study in the field. To be more specific, prior studies focused on simulation models that are available for signalized and unsignalized intersections using cellular automata (CA) models, and driver behavior was studied as a foregone conclusion [14]. Another systematic review focused on the issue of driver distraction in the context of advanced Driver Assistance Systems (DAS) [15]. To date, no systematic review on the evaluation of bus driver behavior has been conducted. As a result, the purpose of this systematic mapping was to report, classify, and characterize the characteristics of the evaluation approaches used to assess bus driver behavior. Furthermore, the current study applied systematic review protocol, taxonomy of critical factors, mapping of data collection methods, discussion of previous studies (i.e. motivations, challenges, limitations, and recommendations), and substantial analysis (i.e. experiment settings and data collection sensors).

The paper is organized as follows: Section 2 describes the search method for article survey; Section 3 presents the taxonomy of critical factors; Section 4 offers the mapping of data collection methods; Section 5 discusses motivations, challenges, limitations, and recommendations; Section 6 focuses on substantial analysis; Section 7 illustrates the future direction of the proposed pathway solution; Section 8 presents the limitations of study; Section 9 concludes the overall study.

## II. SEARCH METHOD

A systematic review protocol was applied in this study. The importance of a systematic review is determined by what is performed and discovered and the accuracy of reporting in the prior systematic review The reporting content of systematic reviews varies, as it does with other publications, restricting readers' ability to determine the motivations, challenges, limitations, and recommendations of such reviews [13]. A systematic (also known as ''structured'')

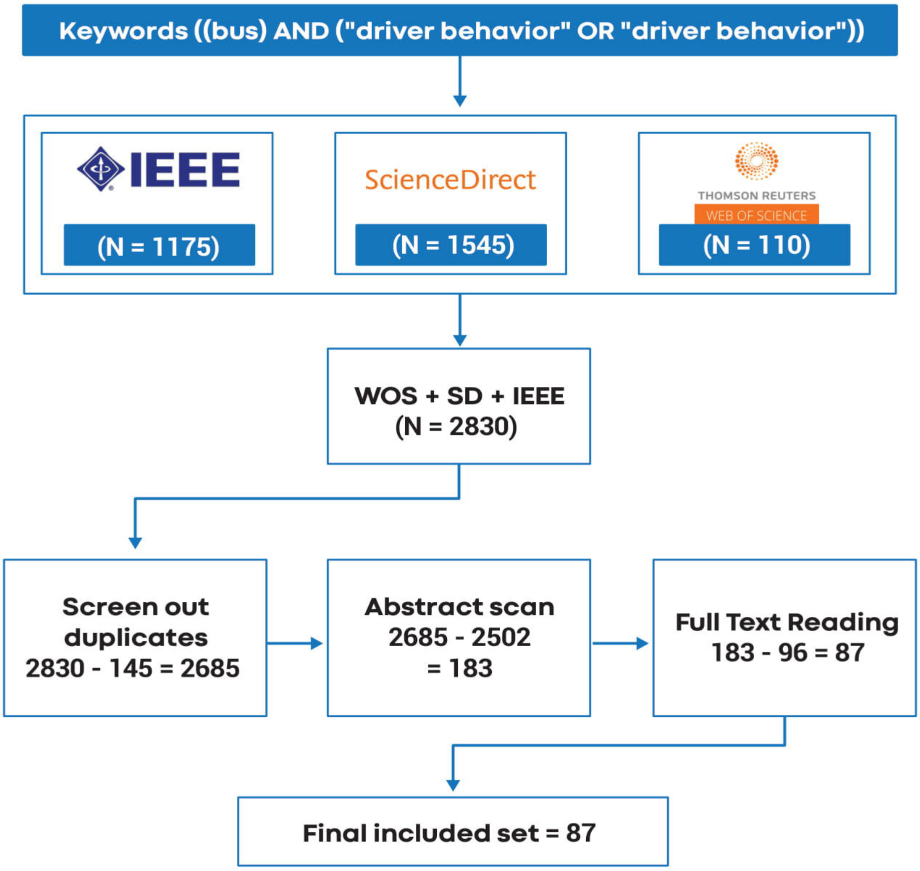


**FIGURE 1.** Search method.

literature review (SLR) has emerged as a promising technique for evaluating prior studies. High-quality SLRs aid entrepreneurs and policymakers in making informed decisions, as well as researchers in synthesizing relevant literature. SLRs have continuously gained attention due to its increasing popularity within the overall management domain, and early papers established rules and recommendations on how to perform similar review papers in the field. Its popularity in the management domain has almost completely replaced the conventional review approach. Transparency in data collection and data synthesis, which result in higher degrees of objectivity and reproducibility, are the key benefits of a SLR. The knowledge map and the diverse perspectives and disciplines contribute to the elaboration of view in this regard. It lays the foundation for creating a dynamic research field across these disciplines [14].

### *A. STEPS OF SYSTEMATIC LITERATURE REVIEW (SLR) METHOD*

1- The study covered the keywords of "bus" and "driver behavior". Additionally, this study focused on articles written in English. The following digital databases were selected to gather relevant articles from highly reliable journals in the domains of transportation engineering and communication engineering sciences and technologies: (1) ScienceDirect, (2) IEEE Explore, and (3) Web of Science (WOS). These databases cover scientific and technical literature and provide extensive insights on researchers' efforts in a wide yet relevant areas of disciplines. Articles were selected from these literature sources.

2- Thereafter, screening and filtering were performed in three iterations (Figure 1):

(A) In the first iteration, duplicate articles were excluded, and articles published from 2008 to 15 April 2021 were collected using Endnote software.
(B) In the second iteration, articles were filtered according to title and abstract, and articles that were not within the scope of the domains of interest were excluded.
(C) In the third iteration, articles were filtered by full text reading, and articles that were not within the scope of the domains of interest and did not meet the criteria were excluded.

The search on ScienceDirect, IEEE Xplore, and Web of Science databases was conducted in January 2018. A mix of keywords in different forms were used using the following one query text: ((bus) AND ("driver behavior" OR "driver behavior")).

3- This study used additional options in the search of relevant articles and excluded the chapters of books and reports from the search selection.

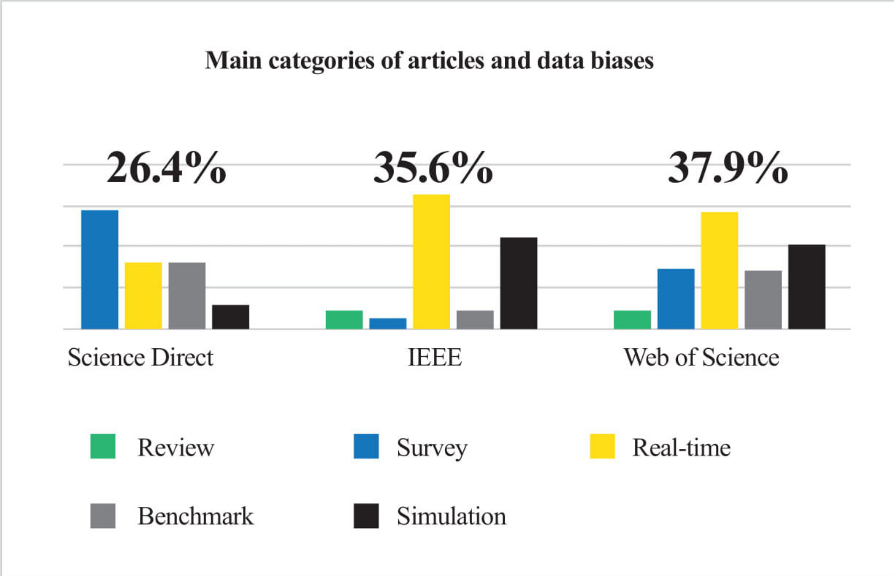


**FIGURE 2.** Distributed Articles in Databases.

4- Any duplicate articles from the search were removed. Additionally, articles that did not meet the inclusion/exclusion criteria were removed through three iterations of filtering and screening. The exclusion criteria are as follows:

(A) Articles are written in a language other than English.
(B) For other buses, articles focused on the controller area network or CAN bus) protocol.
(C) Articles focused on cars, instead of buses.
(D) Bus was only listed as an example.
(E) Driver behavior was only used as an example.

Alternatively, considering the focus of this study on bus driver behavior, the inclusion criteria are as follows:

(A) Articles on the influence of environmental, habitual, vehicle, demographic, and on-board routine factors on bus driver behavior;
(B) Articles on data collection methods related to bus driver behavior.

As shown in Figure 1, the final set of articles consisted of a total of 87 articles. Full text reading was performed, and the articles were analyzed in Microsoft Word. Articles were classified in detail using taxonomy and a large collection of highlights and comments to simplify further steps. Different categories (and subcategories), namely simulation, survey, real-time, benchmark, and review, were suggested. All categories were classified in the form of texts, depending on the author's preferred style. The data collection and relevant information were saved using Microsoft Word. All articles from various sources were fully analyzed to provide an overview on the subject. The current study addressed the following questions:

1) What are the most important factors that influence bus driver behavior?
2) What are the most popular data collection mapping methods?
3) What are the most popular motivations, challenges, limitations, and recommendations from prior studies?
4) What variables did the prior studies use?
5) What sensors did the prior studies use to collect driving data?
6) What options can be offered to potential researchers in terms of pathways?
7) What are the potential weaknesses that researchers should be aware of in this field?

### B. SEARCH DISTRIBUTION RESULTS

One of the contributions of this study included realizing the research trends through content analysis of some key journals in the field of driver behavior. Figure 2 and Figure 3 illustrate the trends of publications from three major databases from 2008 to 2021 (15 April).

As shown in Figure 2, ScienceDirect, IEEE Xplore, and Web of Science databases accumulated many research works. The outcomes of the review were categorized into five main categories: simulation, survey, real-time, benchmark, and review. The distribution of the five main categories of results from ScienceDirect, IEEE Xplore, and Web of Science databases were 26.4%, 35.6%, and 37.9%, respectively.

Figure 3 illustrates the number of publications from 2008 to 2021 (15 April), which were included in the current review. The outcomes of the review were categorized into five main categories: review, benchmark, survey, simulation, and real-time. A total of 87 articles were published from 2009 to 2021, and no articles were published in 2008. Interestingly, articles that were categorized under real-time category recorded the highest rate during this timeline of publication. Simulation represented the second category in the publication. On the other hand, articles that were

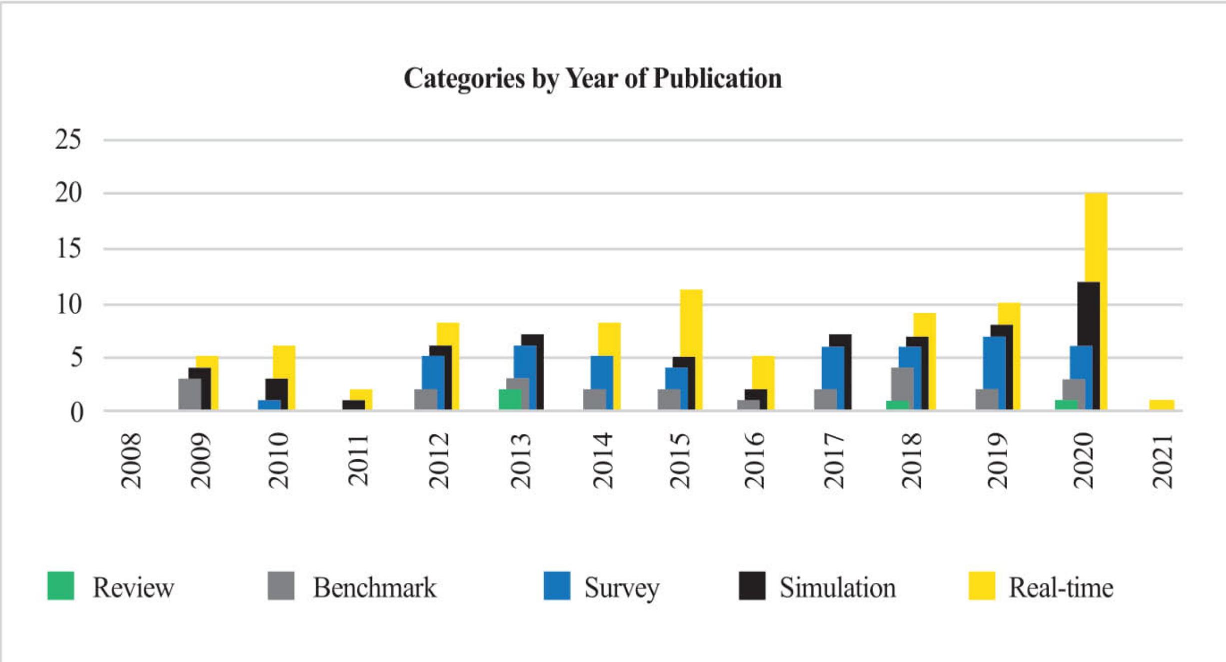


**FIGURE 3.** Number of Articles in each Category According to the Year of Publication.

categorized under benchmark category came in third. Articles that were categorized under review category recorded the lowest rate among these publications, which highlighted the need to conduct the current review.

## III. TAXONOMY OF CRITICAL FACTORS AND STATISTICAL INFORMATION OF ARTICLES

In this regard, focusing on the driver behavior is deemed a great opportunity to determine the current taxonomy. This section discusses the taxonomy of critical factors (Section 3.1).

### A. TAXONOMY OF CRITICAL FACTORS

This study aimed to propose a taxonomy of critical factors that were extracted from literature. Figure 4 shows five categories of factors that may influence driver behavior: environmental, demographic, habit, vehicle, and on-road routine factors. The following subsections address each factor independently.

#### 1) ENVIRONMENTAL FACTOR

This category of environmental factor is associated with different aspects that may influence driver behavior. This category consists of six main aspects of environmental factor, which are discussed in the following subsections.

##### a: TIME/LIGHTNING

The time of travel, such as day or night, is considered in the review to identify its relationship with driver behavior. The influence of day lighting in relation to bus drivers who cause accidents in Melbourne, Australia was studied, which revealed that working long hours on night shifts increases the likelihood of bus drivers causing accidents [16]. Another study showed a significant relationship between crashes and night-time driving for large trucks, but the rates for buses were lower [17]. On the other hand, a significant correlation between increasing speed and night-time shifts of bus drivers in Malaysia was identified using a benchmark dataset [13]. A study in Ghana assessed the severity of accidents for buses and mini buses and found higher rates of accidents during weekends and night time [8]. Focusing on bus driver behavior in Tehran, Iran, a study examined the influence of daytime and other factors and showed the significant influence of darkness on driver visibility [18]. Accordingly, the demand for guardrail during night time is high. The study also showed that the presence of guardrail during night time is more important than widening the road shoulder.

##### b: POLLUTION

Apart from that, this study also analyzed how air pollution, such as carbon dioxide ($CO_2$) or ground-level ozone ($O_3$), influence driver behavior. Using a simulation experiment (case study) with real-time data collection of GPS, a study in Finland examined the influence of fuel consumption and its link to the increase of $CO_2$ and demonstrated the significant influence of driver activities, such as acceleration and braking, on the increase of fuel consumption [19]. Another study in Europe examined the influence of air pollution on driver behavior and found a relationship between air pollution and aggressiveness using a benchmark dataset of Milan transport agency Progetto E-Moving (AMAT) [20].

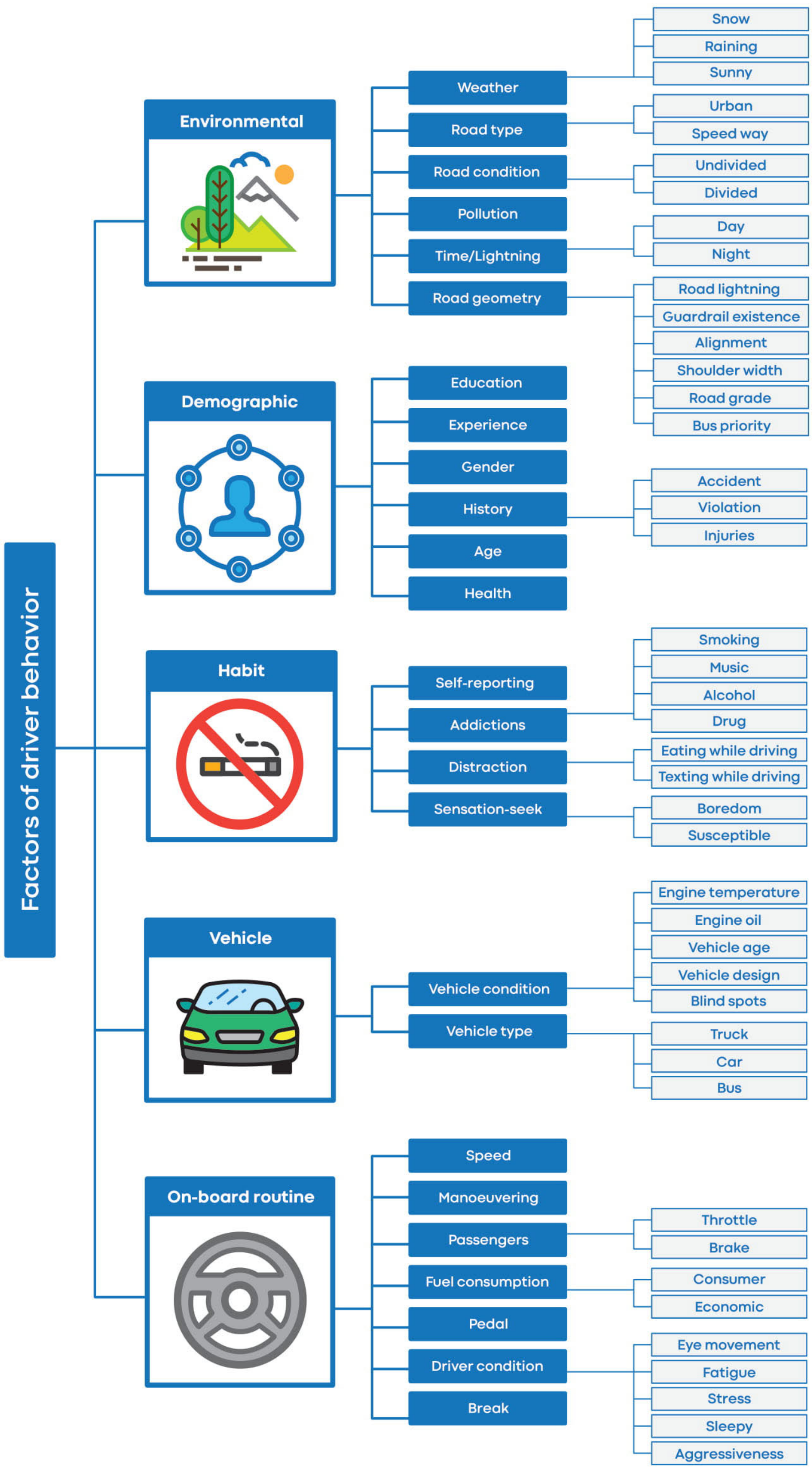


**FIGURE 4.** Taxonomy of critical factors.

### c: ROAD TYPE

The road type (divided and undivided) was specifically addressed. A study examined the responses of different drivers towards urban roads in Florida, United States of America (USA) and revealed the tendency of drivers to accommodate collisions when the road taper length was reduced [21]. Another study examined the influence of road type in relation to bus accidents and concluded that bus drivers are less likely to be at fault for accidents on divided roads [16]. The variances of desirable speed according to different vehicle types on diverse road types were studied, which revealed that vehicles on curb lanes had lower speeds than those on inner lanes [22].

### d: ROAD GEOMETRY

Road geometry involves road alignment, shoulder width, bus priority, road lightning, and guardrail existence. Focusing on bus priority, an experimental study was conducted on bus accident factors in Melbourne, Australia using the Traffic Incident Management System database and revealed that the majority of bus accidents in such roads came from hitting stationary objects [23]. A study found a significant correlation between road geometry (i.e. road lightning and guardrail existence) and driver behavior in Washington, USA [24]. In a study for probability of crashes for commercial motor vehicles in South Korea, multiple factors were studied [17]. Road geometry, specifically bus lane, was identified as one of these factors. The study used the benchmark data of the Traffic Accident Analysis System database. The non-existence of bus lane showed a great probability of crashes for bus drivers. In another study, the effects of different sub-factors of road geometry on bus driver behavior in Tehran, Iran were examined [18]. The experimental results showed that, although guardrail existence was not generally significant for the segments with wide shoulders, it surprisingly affected the bus driver behavior on the segments with a narrow shoulder. Another study on accidents involving bus and mini buses were conducted in Ghana, which revealed the significant reduction of accidents through the existence of road shoulder [8]. An experimental study was conducted on the influence of road grades on driving behavior in Atlanta, USA [25]. For this study, an OBE of GPS was utilized to measure acceleration. The results reported different driver behaviors according to the degrees of road grade. Meanwhile, a survey study was conducted on the influence of curves on driving behavior in China [26]. Driver Behavior Questionnaire (DBQ) was utilized to investigate the opinions of drivers. Drivers were classified into moderate and aggressive on the basis of the acceleration rates at curves. The National Highway Traffic Safety Administration [27] reported that 5,987 pedestrians were killed in traffic crashes in USA, which was an increase of 9% in total fatalities from 2015. Furthermore, a report issued by Federal Highway Administration [28] unveiled about 48,000 bicyclists and 65,000 pedestrians injured in accidents per year. Signals and marks appeared visible at "semi-controlled" passenger crossings. Still, the inconvenience to pedestrians and cars was said to be primarily due to the "discussion" among the parties involved to establish who concedes [29]. This study presented a unique technique based on multi semi-Markov modeling techniques to examine motorcyclists' delays and encounters with commuters. As part of a Markov chain, motorists awaiting conduct may be split into a sequence of route choices. In the Markov chain, every route choice is treated as an individual difference between two variables. It is important to obtain data of road grades, which can be utilized to enhance roadway design applications and various transportation vehicles performance analysis. Various road grade values substantially influence the working performance of heavy-duty vehicles. For example, truck speed performance is remarkably decreased by grade length and steep grade. As a result, road grades can be a promising indication for road safety analysis. Different studies revealed evidence of significantly lower rate of accidents on flat grade sections as compared to sharp grade sections [25].

### e: ROAD CONDITION

Road condition includes high-speed or urban ways. A prior study examined the influence of road condition on driver behavior in terms of pedal throttle and fuel consumption in China [30]. In the study, two types of road condition were considered: high-speed way and urban driving cycles. The results showed a link between high fuel consumption and accelerating on the urban driving cycles. Meanwhile, a quantitative survey study was conducted on the indicators of risky bus driving in Malaysia, which revealed a significant relationship between road condition and safe bus trips [31] . For instance, expressways are safer than arterials. As for the study on accidents involving buses and mini buses in Ghana, wet and rough roads were found to have higher rates of accidents [8]. Various strategies and applications have been established to tackle such problem, extending from infrastructure (e.g. dedicated bus lanes) to ITS applications (e.g. transit signal priority). On the other hand, an intersection area plays a vital role in urban traffic movement because they accommodate various movements for pedestrians and automobiles in the same area on the basis of time-sharing [32]. There are three main types of intersection area: roundabout, unsignalized, and signalized areas. The performance of signalized area is typically more preferred than the other two types [33]. The measurement of real-time performance is significant for agencies to maintain and sustain their roadways during the rainy season. The maintenance brought by infrastructure can be rather costly and scant in rural areas [34].

### f: WEATHER

Environmental factor also involves weather conditions, such as rainy, snowfall, and sunny. A prior study reported that adverse weather conditions like rain and snow have significant impact on bus driver in terms of bus accidents in Melbourne, Australia [16]. A study in South Korea found the impact of adverse weather conditions on driver behavior and the probability of crashes for different vehicle types (i.e. car, bus, and truck) [17]. In another study, the impact of snowfall on multiple criteria, including the probability of crashing and driver behavior, in Michigan, USA was studied [35]. The statistical results showed the tendency of most drivers to lower their speed limit during snowfall.

### 2) VEHICLE FACTOR

The vehicle itself can influence driver behavior, where its type or condition affects the decision made during the driving. The following subsections discuss aspects that are related to the vehicle factor.

#### *a: VEHICLE TYPE*

Vehicle type, such as car, bus, or truck, potentially influences driver behavior. A simulation experiment was conducted to identify driver behavior in relation to traffic congestion in Giza, Egypt [36]. The case study showed that specific vehicle type, such as mini bus, is the main reason for traffic congestion. Meanwhile, a study on bus driver in relation to fuel consumption in Lisbon, Portugal [37] showed that fuel consumption varies across different types of vehicle. Fuel consumption is higher for larger vehicles like bus. For instance, large bus (i.e. greater than 12 meters) was reported to be linked to higher probability of bus drivers being at fault for accidents [16]. Another study examined undesirable driving behavior and reported significant influence of vehicle type on driver behavior in undesirable events (e.g. extreme brake or hard acceleration) [38]. The results showed that mini bus drivers experience higher undesirable events than other vehicle drivers. In another study, free-flow speed variances in relation to different vehicles in Chennai, India were examined [22]. Free-flow speed refers to desirable speed that a driver would have without any influencing factor. The study showed free-flow speed variances across different vehicles—for examples, motor bikes recorded the highest flow-free speed for two-wheel vehicles (including scooters and mopeds), while SUV and sedan vehicles recorded the highest flow-free speed for four-wheel vehicles. Meanwhile, the types of bus in Lisbon, Portugal were addressed in another study on energy consumption behavior of driver [39]. The study showed that greater size of fleet in the bus contributes higher fuel consumption. Different commercial vehicles in terms of crash probability were examined in South Korea [17]. The study reported that taxis, buses, and large trucks recorded higher likelihood of being involved in crashes. The length of vehicle can affect the number of blind spots associated with driver behavior. In the study on bus drivers being at fault for accidents, the length of the bus was examined [16]. A greater vehicle length indicates many blind spots. Based on the results, a significant correlation was observed between the increase of blind spots and at-fault accidents among bus drivers. Another study examined vehicle type in terms of evacuation situations for buses [40] using a traffic simulation tool known as AIMSUN [41] for data collection. The results showed that bus fleet allows many people to safely evacuate. A quantitative survey study on anxiety among bus and taxi drivers was conducted, which revealed higher anxiety levels among taxi drivers than bus drivers [42].Snowfall has a significant effect on traffic safety because it impacts drivers behavior and vehicles performanceMoreover, snowfall negatively impacts transportation infrastructure. Depending on the severity, snowfall may reduce on-road visibility, pavement friction, vehicle balance and operations [35]. For example, non-commercial vehicles tend to have a large amount of flexible time schedule, which contributes to lower crash probability. In contrast, commercial vehicles, such as buses or trucks, are more likely to be involved in crashes due to their required work time schedule. Besides that, an experimental study was conducted to examine the influence of road grades on driving behavior in Atlanta, USA using an OBE of GPS to measure acceleration [25]. The results showed that heavy-duty vehicle drivers (e.g. bus drivers) tend to reduce their acceleration at high-grade roads.

#### *b: VEHICLE CONDITION*

Vehicle condition includes vehicle design, vehicle age, engine temperature, or oil status. A study examined the impact of vehicle condition (i.e. oil level and engine temperature) and other factors on bus driver performance using simulated data from Michigan, USA [43]. The study revealed both oil level and engine performance as significant predictors of bus driver performance. Meanwhile, a qualitative survey study involved bus transportation managers to investigate bus safety trip issues in Italy [44]. Based on the results, significant characteristics related to the bus design were found to be associated with safe bus trips, such as automatic door opening and sustainable internal materials. Two survey studies also examined the relationship between bus design and safety in Malaysia [12], [45]. Specific bus design characteristics, such as the façade structure and cover roof door, were revealed to play a significant role in providing safer bus trips. In another study, the probability of bus drivers being at fault for accidents in Melbourne, Australia was examined [16]. The study found that drivers with new buses (i.e. less than 10 years) were less likely to be at fault for accidents. On the other hand, an experiment on bus driver behavior in Lisbon, Portugal was conducted [46]. During the experiment, drivers were supplemented with a sound feedback that would alarm them when they performed undesirable events, such as sudden brake or hard acceleration. The results showed that new bus drivers (i.e. less than 10 years) tend to perform undesirable events when there were no feedback sounds. The crash probability for commercial motor vehicle in South Korea was studied [17]. The study then concluded that vehicles of 10 years or older have a higher probability of conducting crashes.

### 3) DEMOGRAPHIC FACTOR

For this factor, the demographic features of drivers were analyzed: age, gender, education, experience, and history.

The subsequent subsections discuss these aspects in further detail.

#### *a: HISTORY*

The history of driver involves the numbers of accidents, violations, and injuries. This study analyzed this history to identify any relative patterns to driver behavior. A study on the relationship between speed changes and history of crashes among bus drivers in Uppsala city, Sweden showed surprisingly findings [47]. The three-year experiment involved two groups of bus drivers. The first group had historical crashes, and the second group had no historical crashes. Both groups demonstrated gradual deceleration over time. This suggests that drivers do not learn from crashes, but rather, from their time experience. On the other hand, another study utilized the history of accidents and traffic violations instead to examine risky driving behaviors among drivers in Mashhad, Iran [48].

#### *b: AGE*

This study also analyzed how the age of driver can impact driver behavior. A study on the probability of bus drivers being at fault for accidents concluded that drivers of age above 60 years with experience of driving a bus for less than two years are most likely to be at fault for accidents [16]. Using DBQ, a survey was conducted among drivers in Mashhad, Iran to examine risky behaviors [48]. The results associated risky behaviors with young drivers. Another study examined critical features associated with car crashes in Iran and linked car drivers of below 20 years of age to sensation-seek feature that resulted in most of the car crashes [49].

#### *c: GENDER*

This study also analyzed how the gender of driver can impact driver behavior. A study in Melbourne, Australia reported that most of the accidents where bus driver is at-fault were operated by male drivers [16]. Using DBQ, the study on risky behaviors among drivers in Mashhad, Iran similarly revealed that male drivers demonstrate risky behaviors [48]. Another quantitative survey study was conducted on anxiety behavior among bus and taxi drivers in Taiwan, which showed that female drivers have less anxiety than male drivers [42].

#### *d: EXPERIENCE*

This study addressed the influence of experience of driver on drive behavior. One of the prior studies focused on the experience of driver by conducting a three-year experiment related to speed changes [47]. The results showed that most drivers tend to lower their speed most of the time. This proves the significant role of experience in terms of improving driving style. A qualitative survey (interview) was conducted among bus transportation managers to investigate bus safety trip issues in Italy [44]. The results showed that experienced bus drivers ensure safe bus trips. An experimental study on driving behavior in undesirable events in Lisbon, Portugal was conducted using an OBE of data logger (VDO-FM2000 Plus) to monitor pedal throttle and braking [38]. The results showed that inexperienced drivers tend to exhibit harsh braking and acceleration, as compared to experienced drivers. Goh *et al.* [16] found that bus drivers with experience of less than two years were more likely to be involved in at-fault accidents. Another survey study revealed the preference of users or commuters for a driver with experience of more than five years to ensure the safety of their ride [50]. The safety of bus passengers in relation to bus driver behavior was examined [51]. The quantitative survey results showed a significant relationship between experience of driver and the safety of passengers. Using DBQ, a survey on driver behavior in Serbia was conducted [52]. The study focused on the experience of driver as a main factor and demonstrated that drivers with no experience are likely to be involved in accidents, violations, and lapses. Similarly, using DBQ, a survey on driving behavior was conducted among bus drivers in Hefei, China [53]. The study showed a significant correlation between the experience of driver and safe bus trips.

#### *e: EDUCATION*

This study also analyzed how education can impact driver behavior. A simulation case study was conducted to examine the influence of driver behavior on fuel consumption in Finland [19]. Using an OBE of GPS, the study showed that providing training and reward to drivers can significantly improve driver behavior in relation to fuel consumption. A similar study on the influence of driver behavior on fuel consumption was conducted, which revealed that providing training sessions to bus drivers can help to reduce fuel consumption [54]. An experimental study examined the relationship between bus driver behavior and fuel consumption using a real-time data collection technique of OBD via data logger (VDO-FM2000 Plus) (to examine speed limit) [37]. The study used a case study in Lisbon, Portugal, and showed that giving training and reward to drivers can improve driver behavior in enhancing fuel consumption. Using DBQ, a survey on risky behaviors among drivers in Mashhad, Iran was conducted [48]. An association between risky behaviors and young, male drivers with low education level was observed. In another study, user expectation towards sightseeing buses in Thailand revealed that most commuters gave less priority on the education level of driver and more concerned about other aspects [50]. Meanwhile, a study on driver behavior in Lisbon, Portugal found that the effectiveness of training and education plays a vital role in reducing undesirable events by drivers, such as harsh acceleration and sudden brakes [38].

#### *f: HEALTH*

The final aspect of demographic factor involves the health of driver, and the study analyzed its influence on driver behavior. In another study, a quantitative survey on the impact of health-related problems of drivers and drive behavior in Taiwan was conducted [55]. The study found a significant association between adverse health-related problems of drivers (e.g. fatigue) and risky behaviors. Another study proposed a system to investigate the health status of bus driver in Porto, Portugal [9]. The system focused on the stress level of bus driver, which can be detected from the driving style.

#### 4) HABIT FACTOR

The current study also analyzed how habit factor influences driver behavior. The following subsections discuss different aspects of habit factor.

##### *a: DISTRACTION*

This aspect focuses on the situation (distractor) of driver while driving, such as texting or eating, which may affect concentration on road. Focusing on bus, a study utilized the Adaptive Cruise Control (ACC) to examine the impact of time gap by using a simulator [56]. ACC is a system that is implemented in many vehicles where an automatic process of applying brake or deceleration takes place in serious situations. However, ACC leaves a time gap for the driver to intervene. The study demonstrated variances in time gaps among the bus drivers, where certain drivers were distracted with secondary tasks. Focusing on the commercial motor vehicle driving behavior and risky indicators in USA, the study examined the impact of distraction such as eating or texting while driving using a benchmark dataset [57]. The results proved that such distraction are associated with accidents. In another study, speeding indicators among bus drivers in Malaysia were examined using a benchmark dataset [13]. The study linked eating while driving to increasing speed limit. A collision warning system in relation to driving style was proposed in another study [58]. The study utilized distraction such as eating or texting while driving and classified driving style into abnormal and normal classes on the basis of driver status using a benchmark dataset of real-scene.

##### *b: ADDICTIONS*

The other aspect of habit factor focuses on addictions, such as alcohol, drugs, music, or smoking, which may be present in any vehicle driver. In a questionnaire survey, users revealed smoking and alcohol drinking as their priorities in ensuring that their desired drivers do not have such addictions [50]. A study on speeding indicators for bus drivers in Malaysia was conducted [13]. A benchmark dataset was utilized to analyze the speeding limits of different drivers, and the results linked smoking to increasing speed. In another study, alcohol drinking was identified as one of the significant factors that may lead to severe crashes and accidents by commercial motor vehicle drivers [17]. A study to model the severity in bus and mini bus accidents in Ghana was conducted [8]. The study found a significant correlation between alcohol drinking by bus drivers and dangerous accidents. Moreover, music was identified as another habit of driver that can affect the performance of driver. Using simulated data from Michigan, USA, the study examined the impact of different factors on bus driver performance and found that interaction with music by driver considerably contributed to the prediction of bus driver performance [43].

##### *c: SELF-REPORTING*

Driver behavior in terms of reporting accidents was also examined in this study. A prior study reported that determining the recorded crashes is a more reliable source than self-reporting, where numerous drivers tend to not report their accidents [59]. In another study, self-reporting was significantly linked to stress [60]. This indicates that the highest level of stress can minimize self-reporting, where driver may be subjected to various stressful factors, such as time pressure and long shifts. A quantitative survey on the impact of health-related problems of drivers and driver behavior in Taiwan was conducted [55]. The study associated high levels of fatigue and stress with a few self-reporting and self-criticism characteristics. Using DBQ, a survey on driver personality in relation to bus safety in Italy was conducted [61]. The study identified self-reporting as an important characteristic in any driver for safe bus trip plans.

##### *d: SENSATION-SEEK*

This subsection addresses the influence of sensation-seek habit in driver on driving style. Using DBQ, a survey was conducted in Italy to investigate the influence of driver personality on bus safety [61]. The results showed that sensation-seek significantly affected the safety of bus trip plans (if the bus drivers have sensation-seek habit). In another study on sensation-seek habit among bus drivers in Karnataka, India [10], high levels of boredom, susceptibility, and disinhibiting were found to be significantly correlated to the probability of dangerous crashes. Another study on the relationship between sensation-seek habit by drivers and involvement in accidents in Iran also revealed similar findings [49]. The study found a significant relationship between sensation-seek habit and the probability of making crashes. The study also identified important factors that may influence sensation-seek habit, such as age, marital status, education level, and accident history of driver.

#### 5) ON-BOARD ROUTINE FACTOR

This factor is associated with the daily routine activities of driver. Such activities are related to acceleration, brake, manoeuvring, fuel consumption, and other aspects.

##### *a: SPEED*

As for this factor, acceleration and speed limit performed by driver were studied. In a study on driver behavior in Bangkok, Thailand, a scoring system that can provide score for each participating driver on the basis of their speed limit was proposed [62]. Another study examined driver behavior at intersections in Shanghai, China using an OBE of GPS (to monitor speed and time gaps) and showed variances in speed limit according to traffic signal lights (red, green, and yellow-dilemma zones) [63]. Meanwhile, an experimental study on fuel consumption was conducted [19]. The study identified harsh acceleration as one of the causes for high fuel consumption. In another study, speed limit was utilized to determine comfortable travel plan [64]. The study concluded high speed limit as one of the uncomfortable riding experiences. A system to classify driving style in Turkey was proposed in another study [65]. The study utilized a smartphone to monitor acceleration by the driver and showed different classes of aggressiveness. In Spain, a study classified driving style on the basis of acceleration using an OBD of RPM (to monitor speed limit) [66]. Based on the results, multiple categories of aggressiveness for driving style were observed. On the other hand, a study proposed a system to classify driving style in Lithuania [67]. The study utilized an OBE of GPS to observe the acceleration rates. The driving style was then classified into aggressive and normal. An experimental study on classifying driver behavior in Thailand was also conducted [68]. The study also utilized an OBE of a smartphone to observe acceleration and showed different classes of aggressiveness for driving style. Similarly, a classification system of driving style in Hungary was presented [69]. The study utilized a simulation paradigm to simulate acceleration and successfully showed different categories of driving style. Focusing on driving style classification of bus drivers in Sweden, two OBE auxiliaries, including GPS and CAN bus, were utilized to monitor acceleration in a study [70]. The driving style was similarly divided into two classes: normal and aggressive. Using a benchmark dataset to examine acceleration, a system to classify driving style in Thailand was presented [71]. Multiple aggressiveness categories were presented. Another classification study on driving style was conducted in China [72]. The study utilized an OBE of GPS to observe the speed limit. The results showed four categories of aggressiveness: defensive, weak defensive, weak aggressive, and aggressive. An experimental study was conducted to score driving behavior using an OBD measurement of RPM (to measure speed) [73]. The study presented a system that can score drivers based on their acceleration. In another study, a system was proposed to classify bus driver behavior into multiple classes of aggressiveness based on fuel consumption [74]. The study utilized a simulation technique to measure acceleration. The classification results were subsequently incorporated into an adaptive system that suits a working flow of a hybrid electronic engine to reduce fuel consumption. Using DBQ, a survey study on the influence of curves on driving behavior in China was conducted [26]. Based on the gathered views, the study classified the drivers to moderate and aggressive groups on the basis of their acceleration rates at curves. In today's world, new measures continuously undergo development to assess driving risk from naturalistic driving with the help of new technologies like GPS [75].

#### b: BRAKE

This factor involves analyzing driver behavior in terms of braking. The style of braking and the number of brakes were considered. In one of the studies, a rule-based system was proposed to provide score for drivers in Bangkok, Thailand [62]. For that, the study considered the number of brakes as one of the features that can identify the pattern of driving. Meanwhile, another study focused on the factors of comfortable travel plan [64]. The study identified the number of brakes by driver as one of the significant factors that directly affect the comfort level of riding. Harsh braking was noted to have extreme impact on the riding experience. Sudden or hard braking is always known for its undesirable impact. Another study examined harsh braking and its exact causes using simulated datasets [76]. The study found visual looming cues as significant factors that affect harsh braking, where the urgency of the given rear-end scenario's kinematics is involved. In another study, an experimental study on traffic conflict indicators was conducted in Malaysia [77]. A set of OBE auxiliaries, which included a camera recorder and GPS, were utilized to monitor the braking behavior. The results showed a significant relationship between braking and most traffic conflicts, including crashes and traffic congestion.

#### c: MANOEUVRING

This subsection discusses the influence of manoeuvring on driver behavior. A prior study considered the number of manoeuvring as one of the significant features that indicate driving pattern [62]. Similarly, another study on modeling comfortable travel plan also considered the number of manoeuvring. The results showed that high number of manoeuvring leads to an uncomfortable riding experience. An experimental study on the influence of driver behavior on standing passengers in bus was conducted using manoeuvring as indicator [78]. Using a benchmark dataset, the study reported high probability of passenger falling during harsh manoeuvring.

#### d: PASSENGERS

This subsection reviews driver behavior in relation to on-board passengers. Most vehicles would have a few passengers on-board, except for bus drivers. Bus is the only motor-wheel vehicle that contains a considerable number of passengers. Driving a bus is challenging [60]. A bus driver is subjected to time pressure, long shifts, and responsibility of passenger safety. These factors contribute to higher stress level for a bus driver. Many studies have linked a high level of stress for a driver and involvement in accidents [79]. A survey study on modeling the feasibility of bus school trips in Vadodara, India was conducted [80]. The statistical analysis of survey data revealed that the high number of passengers affects driver behavior. In another survey study to model bus driver behavior in Santiago, Chile, bus drivers were interviewed [81]. Bus passengers were found to significantly affect the stress level of bus driver. This notion has been frequently depicted, where drivers identify poor treatment from bus passengers. Drivers prefer to be assessed based on their performance, rather than consumer satisfaction.

### e: PEDAL

This subsection focuses on driver behavior in relation to the pedal style, including throttle or brake pedals. One of the earlier studies attempted to profile driver behavior by addressing the pedal pressure by driver in order to provide a biometric driver recognition system [82]. The study considered different features to profile driver behavior, including the brake and throttle pedal pressure. Both features were found to significantly influence the pattern of driving. An experimental study on the influence of bus driver behavior on fuel consumption was conducted in Lisbon, Portugal using a real-time data collection technique of OBD via VDO (to examine the brake and throttle pedal pressure) [37]. The study demonstrated the significant impact of harsh throttle and brake pressure on high fuel consumption. Another study on driver behavior was also conducted in Lisbon, Portugal [38]. In the aforementioned study, a sound feedback was implemented for public transports, such as buses. Such sound feedback would alarm the driver in undesirable events, such as sudden brake or hard acceleration. The results showed that drivers spent a long time in such undesirable events without receiving sound feedback. In another study on driver behavior and its role on fuel consumption, high fuel consumption from hard acceleration or pedal throttle by driver was observed, especially in urban driving cycles [30]. Another study reported increase in the probability of conducting crashes when drivers violated the speed limits [17]. Based on this finding, transportation authorities are encouraged to toughen the enforcement for this type of violation. An experiment on bus driver behavior in Lisbon, Portugal revealed fuel consumption as one of the major issues [46]. The study noted that acceleration, RPM, and aggressiveness by driver significantly affect fuel consumption. Considering that a wide range of studies have correlated harsh pedal pressure to fuel consumption, an experimental study in Chongqing, China focused on a specific zone, specifically the bus stop, with the aim to optimize the bus driving performance [83]. Such aspect witnessed critical behaviors of bus drivers. The study developed a new system that can guide bus drivers on pedal pressure (whether to throttle or brake). The system improved bus driving performance in terms of pedal pressure.

### f: FUEL CONSUMPTION

This study also analyzed driver behavior in relation to energy or fuel consumption. In one of the prior studies, the influence of bus driver behavior on fuel consumption was examined [84]. The study utilized a benchmark dataset, and the results revealed aggressiveness (e.g. harsh braking and acceleration) as the main reason for high fuel consumption. An experimental study was conducted to classify economical driving behavior among bus drivers in Italy using an OBE of GPS to monitor the speed limit [85]. The results showed a significant correlation between high speed limit and high fuel consumption. A simulation case study examined the influence of driver behavior on fuel consumption in Finland using an OBE of GPS and similarly identified harsh acceleration and braking as the main reasons for high fuel consumption [19]. In order to reduce fuel consumption rate, the study showed that giving training and reward to drivers would significantly improve driver behavior in relation to fuel consumption. An experimental study on the influence of bus driver behavior on fuel consumption in Lisbon, Portugal was conducted using a real-time data collection technique of OBD via VDO (to examine speed and braking behaviors of driver) [37]. Likewise, the study indicated that training and rewarding would contribute to the improvement in driver behavior in terms of fuel consumption. Besides that, different vehicle sizes showed variances in fuel consumption. Finally, the study also demonstrated the significant correlation between aggressiveness (i.e. harsh braking and acceleration) and high fuel consumption. In another study, driver behavior in relation to fuel consumption in Sweden was examined through a field trial [54]. The results showed that giving sound feedback with training can contribute to fuel-consumed events, such as harsh acceleration. Another experimental study in Lisbon, Portugal was conducted to model the relationship between bus driver behavior and fuel consumption using an OBE of VDO [38]. The study showed that training can significantly enhance bus driver behavior in undesirable events (e.g. harsh acceleration or braking) that cause high fuel consumption. In Idaho, USA, an experimental study was conducted on efficient fuel consumption for fleet vehicle using real-time data collection techniques, including OBD via RPM and OBE via GPS (to measure speed and distances) [86]. The study proposed an interfaced system that can prompt driver on their speed limit and distances. The proposed system showed improvement on driver behavior in terms of fuel consumption. Another study focused on the relationship between fuel consumption and driver behavior [30]. One of the assessed driver behaviors included pedal throttle, which was found to significantly affect fuel consumption. Meanwhile, in Lisbon, Portugal, the study examined the influencing factors of efficient energy consumption for bus transit in urban and suburban ways and reported a significant relationship between bus type and energy consumption [39]. In particular, the study linked the increase in fleet size to higher fuel consumption. For the initiation of a large, sophisticated system for buses in European countries, driver behavior in terms of energy consumption and technologies that can reduce fuel consumption were examined [87]. The study utilized multiple experiments in large European cities, such as London, Paris, Rome and Madrid, and two main OBD measurements, including Heating Ventilation and Air Conditioning and Internal Combustion Engine (ICE), to monitor both speed and fuel consumption. The study found that providing a computer-based system to prompt drivers on their speed limit and distances can reduce fuel consumption. On the other hand, another study proposed a system to classify bus driver behavior into multiple classes of aggressiveness in relation to fuel consumption [74]. The study utilized a simulation technique to measure the acceleration of each driver. The results of the classification were then incorporated into an adaptive system that suits a working flow of a hybrid electronic engine to reduce fuel consumption. In the study, the rate of transportation sector recorded 30.57% of the overall fuel consumption wherein the rate of highway transportation recorded 97.72% of fuel consumption. Thus, from an eco-driving perspective, the reduction of carbon emission and improvement in the quality of surrounding air can be achieved if bus companies consider effective and fundamental energy improvement strategies. Another study proposed a hierarchical predictive energy management strategy (HP-EMS) according to driver behavior and type [88]. Moreover, driving vehicles based on eco-driving values and techniques have noteworthy effect on reducing both carbon emission and fuel consumption. Although the present new generation vehicles are industrialized by certain types of developed mechanical and technical characteristics, driver behavior is still an essential factor that affect fuel consumption [89].

#### *g: DRIVER CONDITION*

This study also addressed driver in-board situation in relation to emotion, position, energy, and eye movement. Focusing on driver condition and speed limit, an experimental study was conducted to characterize driver behavior in Porto, Portugal [90]. For this purpose, two health-related devices (ECG and Vital Jacket) were utilized to detect specific information regarding driver condition. GPS was utilized to identify speed limit. The results showed a significant relationship between acceleration and the level of stress. In another experimental study on the fatigue level of bus drivers in Hangzhou, China, an implanted camera was utilized to monitor the face and eye movements of bus drivers [91]. The study showed that detecting these movements can significantly contribute to the determination of the fatigue level of bus driver. A quantitative survey study on the impact of fatigue and stress on drivers in Taiwan demonstrated the significant relationship of fatigue and stress with health problems [55]. In Porto, Portugal, a mobile sensing system was proposed to predict the level of stress for bus drivers [9]. Meanwhile, an experimental study was conducted to examine bus driver behavior in Singapore, specifically in terms of facial expression [92]. The study utilized an OBE of camera recording to monitor the eye movement of driver. The proposed detection system can identify the fatigue level of bus driver. In another study on vehicle type and driver condition, evacuation situations from buses were addressed [40]. The level of stress was examined in relation to the driver condition. The study showed that it is difficult to successfully accomplish evacuation when the bus driver experiences high level of stress. In Bogotá, Colombia, a study examined the stress implications on rapid bus drivers [2]. The study found that the majority of bus accidents are linked to stressed drivers and fatigue is a major indicator of high level of stress. A survey study on the influence of organizational aspect on bus driver behavior in Tehran, Iran was conducted [93]. Both Driver Safety Culture Questionnaire (DSCQ) and Public Transport DBQ (PTDBQ) were utilized in the study and a strong relationship between long working hours and high level of stress and fatigue by driver was reported. Another survey study on commercial motor vehicle driver behavior was conducted [94]. The study found a relationship between long working hours and less sleep hours, which generally leads to driver fatigue. The influence of organizational aspect on bus driver behavior was also examined in a survey study in South Korea [95]. The study utilized a questionnaire to explore the opinions of bus drivers. The results showed that drivers with low level of perceived organizational justice encountered major crashes. A questionnaire survey was conducted in Taiwan to examine the influence of organizational climate on bus driver behavior [96]. The results showed a significant relationship between organizational climate and bus driver stress. In another study, a collision warning system was proposed on the basis of driving style [58]. The study utilized driver condition to monitor the fatigue level. The driving style was classified into abnormal and normal classes on the basis of the driver status via a benchmark dataset of real-scene. The advanced driver assistance system (ADAS) and driver state monitoring system (DSMS) are deemed significant and remarkable because they assess and promote precise exchange of driving rights between humans and machines. The two sets of real-time warring data obtained from these two sophisticated systems were used to govern the wide-ranging ability indicators of driver [97].

## IV. MAPPING OF DATA COLLECTION METHODS

The collection of data on traffic, driver, or even the vehicles is a crucial step to analyze significant perspectives of transportation. This section provides a detailed discussion on data collection methods. This study focused on real-time data collection method. GPS can be used with a smartphone fixed in a vehicle for navigation. Figure 5 shows the main categories of data collection methods.

### *A. REAL-TIME DATA COLLECTION*

This part focuses on several transportation aspects in relation to real-time data collection. These aspects include information on vehicles, traffic road, and humans. Firstly, the aspect of vehicles serves to monitor the movement of specific vehicles, including the speed limit, brake, and manoeuvring. Secondly, the aspect of traffic road considers monitoring of traffic congestion and road width or length. Thirdly, the aspect of humans includes drivers, passengers, or even any transportation officers, where their behaviors may be subjected to analysis. Two categories of tools are involved in the real-time data collection for the aforementioned aspects: on-board equipment and diagnostic and roadside equipment [98]. These categories are explained in the following subsections.

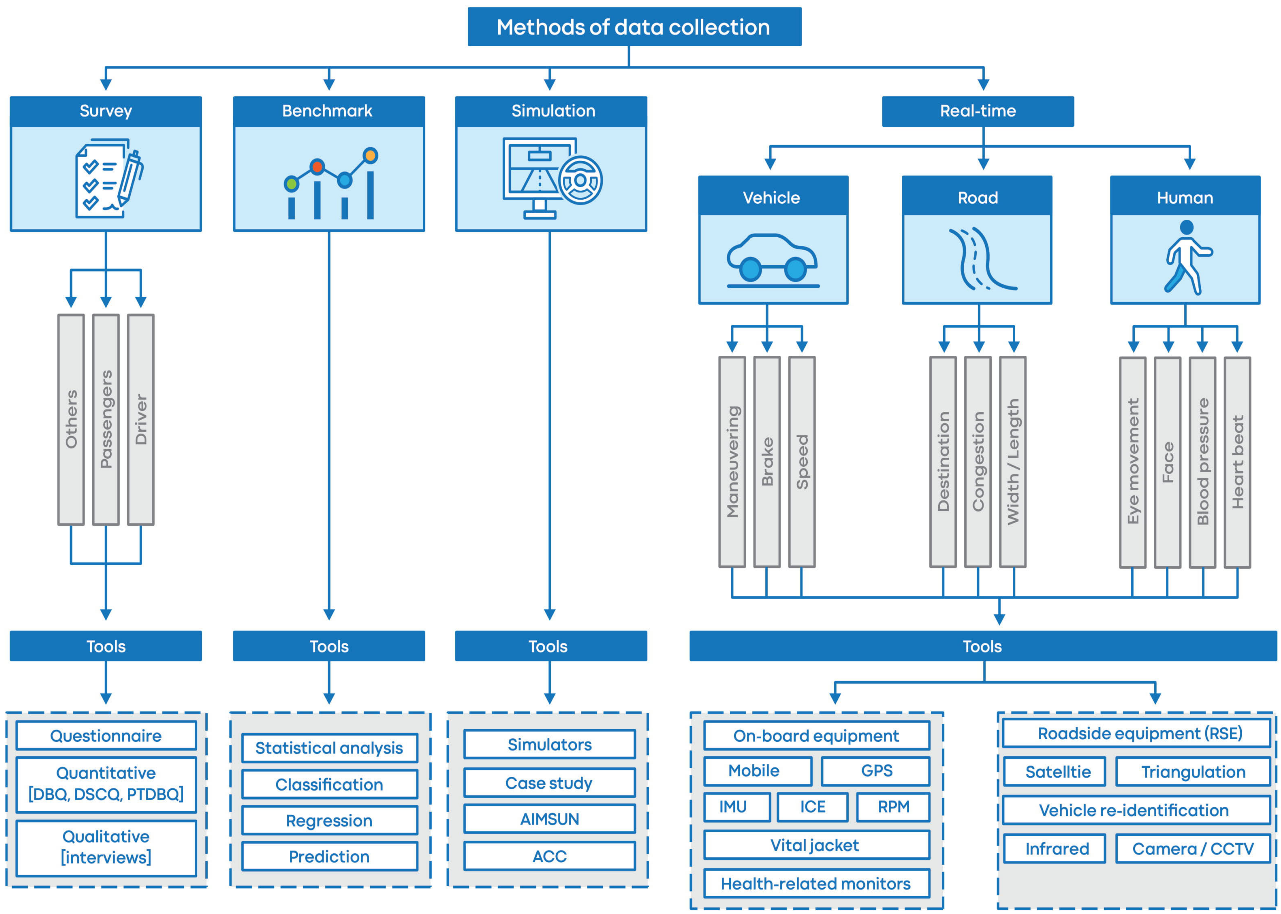


**FIGURE 5.** **Methods of data collection.**

### 1) ON-BOARD EQUIPMENT AND DIAGNOSTICS (OBE AND OBD)

For this category of tools, multipurpose sensors or devices are planted inside the vehicle to monitor specific measurements, such as the speed limit, movements inside the vehicle, or driver condition [63]. There are two categories of these devices: (1) diagnostics (OBD) that already exist in any vehicle, such as revolutions per minute (RPM) or ICE, and (2) auxiliary equipment (OBE) that is implanted in the vehicle, such as GPS or mobile. The first type of sensors includes health-related monitors, where the driver, passenger, or other involved human can be studied in terms of their blood pressure or heart beating—for example, an electrocardiogram (ECG) [9]. Using ECG, a prior study investigated driver behavior during the driving routine [90]. The second type of sensors includes wearable vest or jacket, where the driver or passenger is assigned for experimenting specific body movements during a trip plan [9]. Such movement information can be captured by the sensor vest worn by the driver or passenger. In one of the studies, Vital Jacket was utilized to measure the stress level of drivers [9]. The third device is the GPS, which can exploit satellite communication to locate the position of vehicle [99]. GPS can be built-in and supplemented with a smartphone in the vehicle. In both cases, information produced by GPS can be used to collect data on road condition, distances, speed limit, and other useful information. Another OBE device is the inertial measurement unit, which is a device implanted in the vehicle to measure the longitudinal speed with a sampling frequency of 25 Hz [85]. Finally, the fifth device is the mobile phone. With the exponential development in mobile networks, including 3G and 4G, the mobile network technology can also be examined for data collection. Acceleration, positioning, and other useful information can be detected using the mobile phone [100]. Although some professional tools like remote photoplethysmography (rPPG), which is used to measure or monitor heart rate in drivers, turbulences still occur during driving, such as kinematics and driver behavior. CNN and LSTM applications systems were developed to categorize and evaluate bus driver features, such as engine speed pedaling, lane change endeavors, deceleration, and corner turn [101], [102]. For field tests in Nanjing, China, a real-time differential global navigation satellite system DGNSS tracking feature for buses was developed, along with the lane-level guidance system centered on a vehicle-mounted terminal. The bus data processing primarily completes management and analysis based on the GPS/DBS data, which elucidate bus status, vehicle trajectories, individual driving behaviors, and road conditions [103].

#### 2) ROADSIDE EQUIPMENT (RSE)

As for this category of tools, network technologies that are implanted alongside the roads can be utilized to collect information on the location or other characteristics [63]. The first network technology is the roadside camera or CCTV. This technique is applied to implement cameras on specific roads to collect visual images or videos of the road conditions [104]. Multiple criteria may be present for this technique, such as the accuracy of images or videos. The footages may need to undergo a verification task to ensure data accuracy. The ways to utilize these cameras vary. Some cameras are fixed to the monitor a specific and constant target. In other cases, cameras may be designed to move while recording. The captured images or videos by the cameras can be processed via human or designed software for image processing. The camera may target driver, passenger, road, or even vehicle in terms of movement or other characteristics [8]. These cameras can be implemented for facial or vehicle license plate recognition. Such cameras can be also used to monitor the eye movement of driver. The second technique to collect data is the infrared or specifically, the infrared beams, which consist of a transmitter and a receiver [105]. The infrared devices are deployed in carriageway edges. The transmitter sends an infrared beam, and the reviver captures the beam. With a light-based technology, four beams can be utilized to sense a crossing vehicle. Once the beams break, the receiver can detect interrupting vehicles, specifically the speed, lane, and direction. The detection can also determine the vehicle type (whether it is a bicycle, car, or truck). The second technique involves triangulation, which mainly depends on the signals produced by mobile phones from inside the vehicles. Since the beginning of the 21$^{st}$ century, vehicles start to have a driver with at least one mobile phone that can be used as a traffic probe [106]. The mobile tower data can detect the signal of a movable mobile phone inside the moving vehicle through the triangulation technique. The accuracy of the detection significantly relies on the distance between antennas. The third network technique is the vehicle re-identification, which utilizes mounted detectors that are deployed over the road [107]. This technique can read a unique serial number of a given vehicle in a particular location and re-identify such vehicle in another location. Accordingly, the detector can estimate the traveling distance, time, and speed limit. The device for such process can be a Bluetooth or RFID. Finally, the fourth technique involves the satellite communication, which can be used to collect data by capturing images and aerial photographs of a specific location or area [108]. These images are processed via specific measurements to describe geographical objects. Triangulation is then incorporated to assemble the collected images to improve the accuracy and consistency of information.

### B. SURVEY DATA COLLECTION

This part focuses on collecting transportation-related information from those who may be involved in the process, such as driver, passenger, or transportation management officers. This data collection method aims to obtain the respondents' opinions, viewpoints, and feedback, which are then analyzed to identify patterns. The primary tool of survey involves questionnaire. There are two main types of questionnaire: quantitative and qualitative questionnaires. A quantitative questionnaire aims to survey a large number of respondents by giving them direct questions. On the other hand, a qualitative questionnaire focuses on the quality of the collected information, where a series of interview sessions may be conducted with fewer respondents, as compared to the number of respondents in quantitative questionnaire, but with richer information [109]. In literature, different parties have been surveyed on transportation issues. A questionnaire involving drivers was conducted to evaluate risky driving behavior [48]. In another study, bus passengers were surveyed on their opinions of their desired bus driver and characteristics of preferred driving style of bus driver [50]. Meanwhile, bus transportation managers were surveyed to investigate the safety issues of bus trip plans [44]. The study questioned the managers on two important criteria: driver experience and vehicle type and characteristics. The aforementioned studies considered quantitative questionnaire, specifically a transportation-related questionnaire known as DBQ. However, other questionnaires include DSCQ and PTDBQ [93]. Apart from quantitative questionnaire, qualitative questionnaire has been utilized in several other studies. For instance, bus drivers in Santiago, Chile were interviewed to model their behaviors [81]. The purpose of the current study was to scrutinize the relationships involving different types of driver behavior (inattention errors, errors, and violations), demographic information (mobility, age, and driving experience), traffic accidents, and self-assessment [110].

### C. SIMULATION DATA COLLECTION

This part focuses on simulation software or other measurements that can be used to simulate specific situations to collect data. In this sense, the driver or passenger may undergo a simulation experiment to investigate their reaction or behavior. ACC has been implemented in various modern vehicles [56]. ACC enables vehicles to take automatic actions in serious situations (e.g. near-crash), such as deceleration or brake. ACC has been utilized as a simulation to observe driver behavior in specific situations [56]. In another study, a driving simulation known as AIMSUN was utilized to examine bus driver and passengers in terms of evacuation situations [40]. Another type of simulation involves case study, where researchers tend to simulate an actual location as a special case. A case study approach was applied, in which the map segment in the city of Giza, Egypt, was utilized [36]. Another study reported that simulation in transportation field offers high-quality data with less-risky probabilities obtained from critical situations [21]. Examining these critical situations where drivers are exposed to unacceptable level of risks provide real-time data for assessment. Accordingly, simulation provides convenient solutions for such cases. However, there are multiple drawbacks of simulation, such as different levels of data accuracy between simulated and real-world cases. This mechanism does not consider more serious issues, such as lightning (i.e. day and night time) or driver personality.

### D. BENCHMARK

This part is the easiest and cost-free way to obtain data. Such mechanism depends on the collected, tested, and verified data by previous researchers. Benchmark datasets can also be acquired from legal authorities, such as transportation department databases [35]. Apart from database records, benchmark data from field trial are also utilized in studies, where transportation operators conduct experiments [54]. In this regard, researchers can obtain datasets regarding drivers, traffic roads, vehicles, and other characteristics to accommodate further analysis. The common benchmark datasets include the Analysis of Naturalistic External (ANNEXT) and the Second Strategic Highway Research Program (SHRP 2) datasets [111]. These datasets contain a wide range of driver and vehicle information in terms of crashes and near-crashes. After obtaining the datasets, researchers tend to use statistical analysis, such as regression, classification, or prediction, by applying different algorithms to categorize the data. For instance, a scoring system was proposed in a study to provide a score for each driver on the basis of multiple criteria, such as speed limit and number of brakes and manoeuvring, using benchmark dataset of ANNEXT [62].

## V. DISCUSSION OF LITERATURE

This section presents the most relevant challenges motivations, recommendations, and limitations found in the previous studies. The challenges in the past studies dealt with various concerns related to data collection management, energy consumption, drivers' health conditions, safety, system complexity and algorithm, and gender differences. The motivational factors of the past studies include enhancing the energy conservation awareness among drivers, improving driving performance and traffic flow, reducing accidents, enhancing road safety, better usability of lighting and brakes, reducing the stress level and fatigue of bus drivers, useful driving habits, better vehicle conditions, and classification of drivers. This section also presents the recommendations related to driver behavior, energy management strategies, and road safety. Last but not least, it discusses the limitations found in the previous studies.

### A. CHALLENGES

Although transportation studies have offered numerous benefits, no perfect solutions have been established. Studies are concerned about the challenges in transportation and driver behavior. The main challenges are discussed in the following subsections. Figure 6 presents the classification of challenges.

#### 1) CONCERN ON DATA COLLECTION MANAGEMENT

Challenges in data collection are part of a permanent, inevitable condition in the journey of research that may necessitate a long period of observation, supervision, or care and interfere with the physical, time, and measurements. The current study included different aspects of challenges included. For example, low GPS signals or app malfunction are among the most significant challenges in data collection because these issues may result in missing a few seconds of speed data [75]. Sites and the nature of roads, such as the mountainous roads, affect the GPS signals [112]. With data gathered from highway trips, the trip on the arterial street cannot reflect the real data process in terms of bus driver behavior. [32]. Other critical issues include test time restrictions, test equipment, and regulations of the bus company. Weather condition, such as rainy weather, is another significant challenge in data collection. Video recording can be carried out during clear weather, but rainy weather hampers the process of recording the vehicle speed [22], [39]. The measurements of driver behavior are significantly different for every participating driver due to the different schedule and hours of work involved—in this case, negative driver behavior may be underestimated [22]. Significant challenges of GNSS include the following [99]: (a) pseudorange errors that originate from urban multipath settings, making it difficult to accurately estimate the urban-wide bus speed and trajectory; (b) missing GNSS positioning data in non-line-of-sight urban scenarios; (c) low-frequency sampling and estimations from GNSS measurements; (d) real-time projections of multiple bus lines around the urban areas.

Time loss has been a concern of many researchers. It is also a considerable challenge in data collection for transportation studies due to the traffic signals and unsafe activities of passengers in terms of boarding and alighting, which may lead to frequent delay trip [30]. The methods of data collection that are associated with time loss are lacking, particularly the techniques of boarding and alighting, which result in substantial loss of data. Emission rate and the process of fuel consumption are also essential elements that are related to time [12]. Data on braking may also be lost or inaccurate, particularly in severe weather when the driver is forced to brake often. As a result, it is difficult to assess driver behavior in such conditions [34]. The diversity of stress-related driver behavior may be attributed to health condition [1], [9], emergency [40], and job hassles [55], making data collection a challenge. Researchers should standardize the cardiac metrics per driver [9], as drivers may behave differently during normal traffic [3]. At-fault crashes are an inherent obstacle in the collection of accurate data; these crashes increase the cost of the data collection systems, such as Automatic Crash Notification [35], [44]. Another concern about the absence of precise systems and algorithms via unreliable data resources places data in jeopardy because the evaluation of

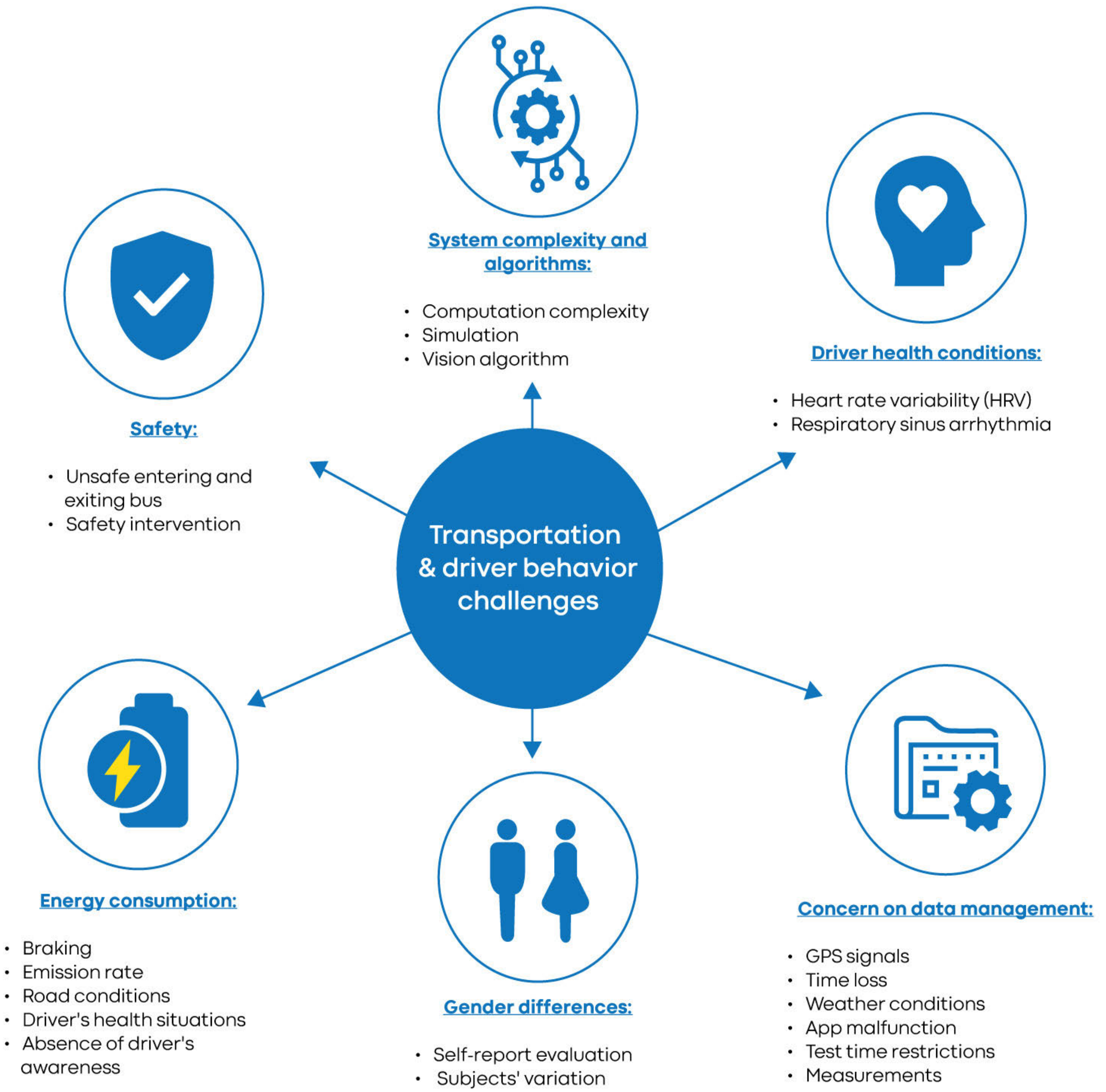


**FIGURE 6.** Classification of categories on challenges.

driver behavior is based on human perception, rather than technology-based precise sensors—this often results in inaccurate recording or unreliable judgment [17].

### 2) CONCERN ON ENERGY CONSUMPTION

Another significant concern is that drivers may cause problems in energy consumption [25]. When it comes to driver behavior, braking is identified as one of the most significant challenges to achieve energy-efficient consumption [12], [19]. The risks associated with emission rate and air pollution must be understood. The risks related with the use, potential abuse, and deceleration and acceleration of buses are increased when drivers are unaware; thus, the increase in energy consumption should be recalculated by considering various drivers situations, such as health condition, nature of road, and weather conditions [2], [20], [25], [30]. Complications from external factors like cargo, passengers, amount of traffic, vehicle type, or road geometry are autonomous of the driver, but have substantial impact on fuel consumption [19].

### 3) CONCERN ON DRIVER HEALTH CONDITIONS

The problems related to services for the health problems of driver pose significant pressure and challenges to the global healthcare systems. Health conditions, such as heart rate variability (HRV) [9] and respiratory sinus arrhythmia [101], cause problems in driver behavior. Lack of or ineffective model and mismanagement of application system that is connected to checking and monitoring driver behavior may lead to overlooking the significance of hazardous driving predictors for the healthcare and public policies [49].

#### 4) CONCERN ON SAFETY

Secure driving process is still being developed. Surveillance and observation processing are widely exploited to address issues related to safety and observation of driving process. Due to the lack of a safety system, the services did not consider the elderly in order to resolve issues linked to safety and supervision of the driving process [99]. Certain unsafe practices and processes may affect the safety of passengers. For example, during the boarding and alighting, doors are kept open during the trip to accommodate more passengers or to save more time [7]. Besides that, bus drivers are not willing to stop the bus. Other example includes the dangers of distracted driving [57]. An appropriate procedure must be applied to avoid risky processes that can affect safety [57]. Programs to increase the awareness of drivers and passengers on risky behaviors are inadequate [7]. Furthermore, safety interventions are also another concern that affects the behavior of the participating drivers and managers.

#### 5) CONCERN ON SYSTEM COMPLEXITY AND ALGORITHMS

Communication glitches may occur in numerous devices from manufacturers or companies that adopt diverse standards and techniques. Besides that, communication problems across the devices during data collection may also occur because these systems use various sensors and networking gadgets from numerous manufacturers [44] many computational processes are needed specially when GPS signal covers wide range of area. Thus, as the complexity of the simulation process increases, so does the number of steps needed in terms of time. [36]. Eyes Tracking Algorithms have been used to record driver behavior. However, there may be data loss in the system when the vehicle moves. Some features are added into the algorithm, but the system may still lose the target data [91]. Vision algorithm is another complicated system that is designated to monitor driver behavior in terms of eye movement and head turning. In many cases, this system produces an oblique view, which makes the system inapplicable. Furthermore, the image captured through such system has low resolution [92]. Apart from the lack of parameters, the results obtained from wavelet-based feature system generate high traffic volume, and the data cannot be processed [71]. In one of the prior studies, one of the challenges associated with managing a simulation was simulation sickness experienced by the simulation participants [18]. Although most algorithm system experiments involved driving on straight roads, certain studies noted driving on curves as another key challenge, depending mainly on the radius of the roundabout and vehicle speed [56]. The combination of multiple datasets is another issue to be considered to produce a single velocity profile with the best fuel efficiency is a limited multi-criteria optimization problem [86]. Considering the notable increase in the cost of generating new real data collecting system, concerns still remain in the quantification of the advantage cost ratios of these systems in regard to their impact on refining safety, reliability, and profitability [44]

#### 6) CONCERN ON GENDER DIFFERENCES

It is significant to highlight the necessity to translate the gathered evidence on psychosocial work participants. In many studies, the subjects or participants were mostly men. Moreover, analysis often exclude the consideration of gender differences. On the other hand, there have been limitations in the quality of intervention studies due to biases in terms of variation of subjects and self-report assessment [2].

### *B. MOTIVATIONS*

The advantages of using transportation based on driver behavior are apparent and compelling. This subsection lists a few benefits reported in literature, which are grouped into different categories. Figure 7 presents the classification of categories on motivations.

#### 1) BENEFITS RELATED TO INCREASING ENERGY CONSERVATION AWARENESS OF DRIVER

Previous studies indicated various indicators in driver behavior that result in fuel consumption, such as aggressiveness [37], [74], harsh braking [84], acceleration [38], pedal throttle [30], and bus type [39]. The nature of efforts to reduce fuel consumption varies with promising results. Studies have noted lower fuel consumption among drivers who receive more training sessions [19], [54]. However, other studies have argued to provide computer-based system to guide drivers in terms of their speed and distance to reduce fuel consumption instead [86], [87]. Rewarding and training the drivers have been noted to reduce fuel consumption [19]. Furthermore, another study noted that 30% of fuel consumption was mainly associated with driver behavior [19]. Another study concluded that private mobility increases fuel consumption and the rate of pollution, as compared to the massive usage of public transportation system, particularly in terms of the fuel ratio per passenger and per kilometers [85]. On the hand, studies have revealed the impact of various aspects of eco-driving, including driver characteristics, weather condition, and driving behavior, on fuel consumption. Furthermore, the increase of vehicle fuel efficiency has become a key research field due to its substantial impact on the usage of fossil fuel and global carbon repercussions [86]. In the evaluation of driver behavior, various control systems, such as controller area network (CAN bus) of public transports or LSTM deep learning predictor controller, cloud computing platform, and sensors have been developed to categorize and evaluate the eco-driving performance of bus drivers and to characterize driver behavior by engine speed, deceleration, pedaling, corner turn, and lane change endeavors [72], [73], [102].

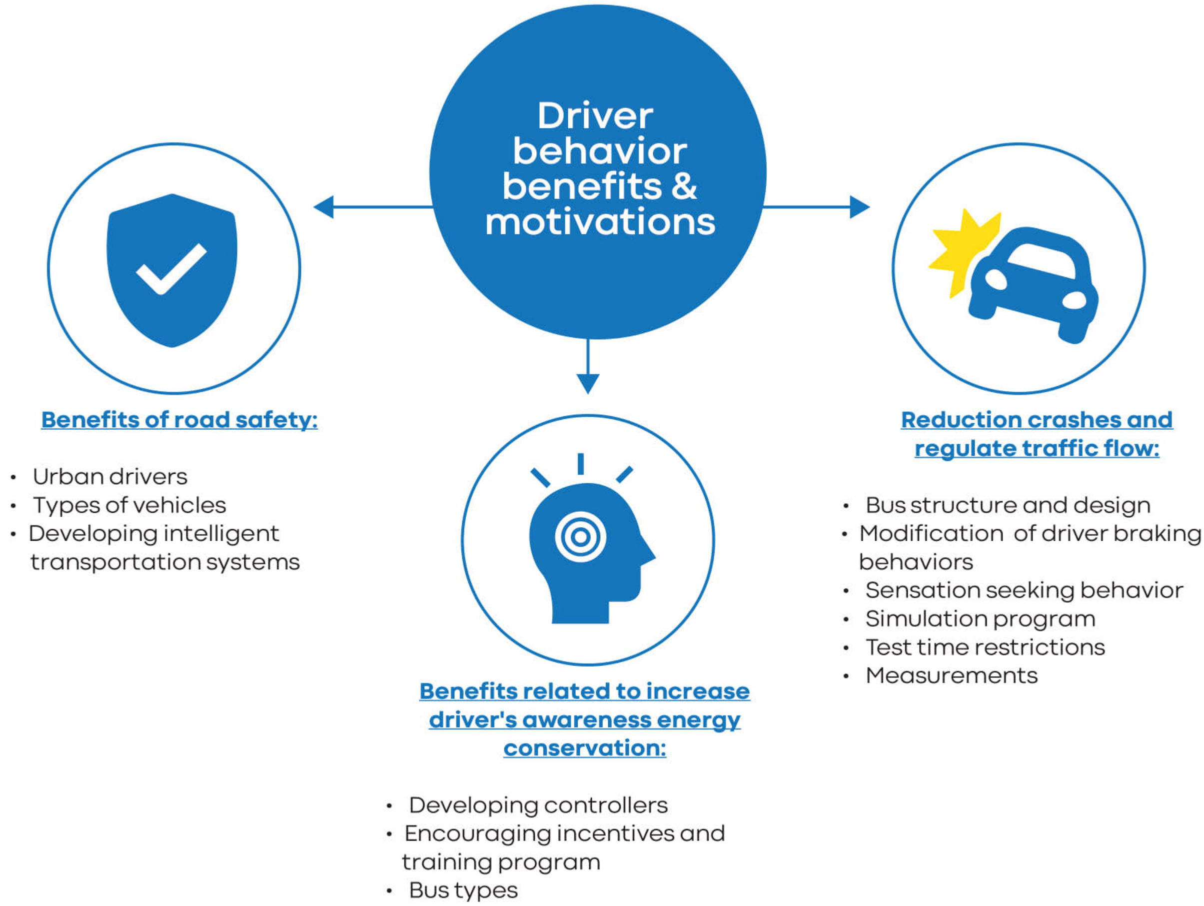


**FIGURE 7.** Classification of categories on motivations.

### 2) BENEFITS RELATED TO IMPROVING DRIVER BEHAVIOR, DECREASE CRASHES, AND AMELIORATE TRAFFIC FLOW

The range of driver performance measures is broadened to encompass a variety of parameters. About 90% of road crashes across the world is associated to human errors [53]. In these critical situations, drivers may be distracted by other secondary tasks that result in shorter time-gap for making decisions [56]. For instance, multimedia is turned on [43]. Furthermore, there have been many cases of drivers preferring to be evaluated based on their performance, rather than depending on consumer satisfaction [81]. A system that identifies optimized driving parameters to guide bus drivers for efficient performance was proposed [83]. Inexperienced drivers indicate low performance and may lead to accidents, violations, and lapses [52]. Bus performance, such as engine temperature and oil level, can be good predictors of driver performance [43]. Another study revealed that all drivers have gradual decrease in speed over time, regardless of their accident history [47]. In particular, drivers of age 60 years above with experience of less than two years are most likely to be at fault for accidents [16]. Another study proposed a better façade design with standard modular system that is significant for quality production and fabrication in terms of commerce was proposed to reduce the risk of accidents [45]. The Zuckerman Sensation Seeking Scale (ZSSS) was found to be effective in analyzing the influence of sensation seeking on accident reduction among Indian bus drivers [10]. On the other hand, developing a simulation program for traffic flow regulation may improve traffic behavior and flow, minimize accidents, and ensure environmental sustainability, which can be used as a carrier to examine the input and estimation of road condition information and infrastructure development [48], [61], [93], [97]. The use of GPS for lane-level positioning, with higher precision and lower complexity, has been studied in various studies. Meanwhile, the precise positioning of a BeiDou navigation satellite system (BDS) intuitively describes the driving trajectory, speed, and acceleration values of a bus operated by its corresponding driver—for example, Wei *et al.* implemented a decentralized automobile remote positioning based on multiple accessible navigation satellite systems and mobile networks [103].

### 3) BENEFITS OF ROAD SAFETY

It is essential to understand and perceive the influencing factors of professional urban bus driver behavior in order to maintain road safety [52], [63], [110]. Vehicle type is also considered a fruitful area of research given its significant influence on road safety and number of accidents [12], [23], [31], [35], [44], [49], [50]. The development of ITS can improve road safety, transportation efficiency, and transit signal priority [32], [55], [83], [87], [97].

#### 4) LIGHTING

Road and bus conditions in terms of lighting play a vital role in influencing driver behavior. Darkness has been noted to influence driver behavior, especially cases of non-existent guardrail [18]. Lighting and guardrail existence affect driver behavior [24]. On the other hand, the case of longer night-shift hours potentially increases the possibility of being at-fault for accidents among bus drivers [16]. With traffic congestion, narrow, dark roads increase the stress level of driver, affecting driver behavior [9]. Another study found a significant rapport between driving at night and crashes among large truck drivers, but the likelihood of such occurrence among bus drivers was found lower [17]. Assessing roadway features, such as guardrail existence, roadway geometry, and shoulder width, and how these variables can influence driver behavior, particularly during day and night (in relation to lighting circumstances) is deemed noteworthy [18], [85].

#### 5) BRAKE

Driving style can be recognized through pedal pressure. Harsh braking and maneuvering are some of the cues of driver aggressiveness. Furthermore, such practices extremely affect the riding experience [64]. Studies have also indicated the tendency of inexperienced drivers to have higher harsh braking and acceleration [38]. In some road conditions, such as crashes, congestion, and traffic conflicts, lead to repeated use of brake [77]. In addition, visual looming allusions have been identified as the most substantial elements that influence harsh braking [76].

#### 6) STRESS LEVEL OF BUS DRIVERS

Different cues of stressed drivers can be seen through driver behavior during the driving process. A study linked acceleration to stress [90]. On the other hand, fatigue is also considered as another main indicator of high stress level [2]. Stress and fatigue are also mainly linked to health problems [55]. In the context of stressed driver behavior, long working hours cause fatigue and stress [2], [93]. The number and behavior of passengers can increase the stress level of bus driver as well [80], [81]. Workplace environment also has significant impact on the stress level of driver [96]. A stressed driver may likely minimize self-reporting [60]. Driving a bus or truck is a stressful job, and work load can cause aberrant behavior or health problems, affecting driver behavior [55].

#### 7) DRIVER FATIGUE

A verity of parameters of driver fatigue can be noticed through the face and eye movement [91], [92]. Minimizing self-reporting and self-criticism in driver features also clearly indicate a high level of fatigue [55], [113]. Several studies [2], [68], [92] investigated the relationship of workload, fatigue, and unsafe risky behavior among Bus Rapid Transit (BRT) drivers.

#### 8) VEHICLE DESIGN AND DRIVER EXPERIENCE

Studies have proved the significant relationship between the safety of trip and specific bus characteristics, such as automatic door opening, material, façade structure, and other external and internal architecture of bus [44], [45]. Moreover, driver experience has a deep link with the nature and safety of bus trip [44]. On the other hand, many commuters prefer to travel with a driver who has more experience and are less concerned about the education level of driver [50]. Conversely, younger male drivers who have lower education level and less experience were found to exhibit risky behavior, affecting the safety of the trip [48], [51]. Bus safety is associated with drivers who exhibit less sensation-seek and high self-reporting features [53]. Another study confirmed a significant correlation between driver experience and safer bus trips [61].

#### 9) ROAD TYPE AND CONDITION

The degree of safety is also associated with the road type and condition. In one of the prior studies, bus drivers were found to be less likely at-fault for accidents at divided roads [16]. Arterials are said to be more dangerous than expressways [31]. Other kinds of road condition, such as non-existence of bus lane [17] or curved, wet, or rough roads, can increase the probability of crashes. Rain and snow are strongly linked to driver behavior, increasing the probability of crashes as well [16], [17]. Besides that, bus condition influences the probability of collision. In another study, commercial vehicles like buses and trucks are likely to crash during snow due to their time schedule and unclear vision of the road ahead [35]. Older buses are more likely to be at-fault for accidents [16]. Moderate and aggressive driver behaviors can be recognized based on their speed at curves [26]. Another study indicated variances in acceleration by drivers at intersections [63].

#### 10) HABIT

Studies have verified the relationship between alcohol drinking and accidents [8]. Smoking and alcohol use are the highest parameters of accidents [50]. Eating and smoking while driving as well as other driver habits contribute to the increased bus speed [13]. Gender of driver presents a new trend in literature. Female drivers are said to exhibit less anxiety as compared to male drivers [42]. Uncomfortable riding experience is also noted to be significantly associated with high speed limit [64].

#### 11) VEHICLE

Traffic accidents are mainly influenced by different road structure and typologies of vehicles. A prior study proposed the higher likelihood of buses, taxis, and large trucks in making crashes [17]. The probability of risk and making

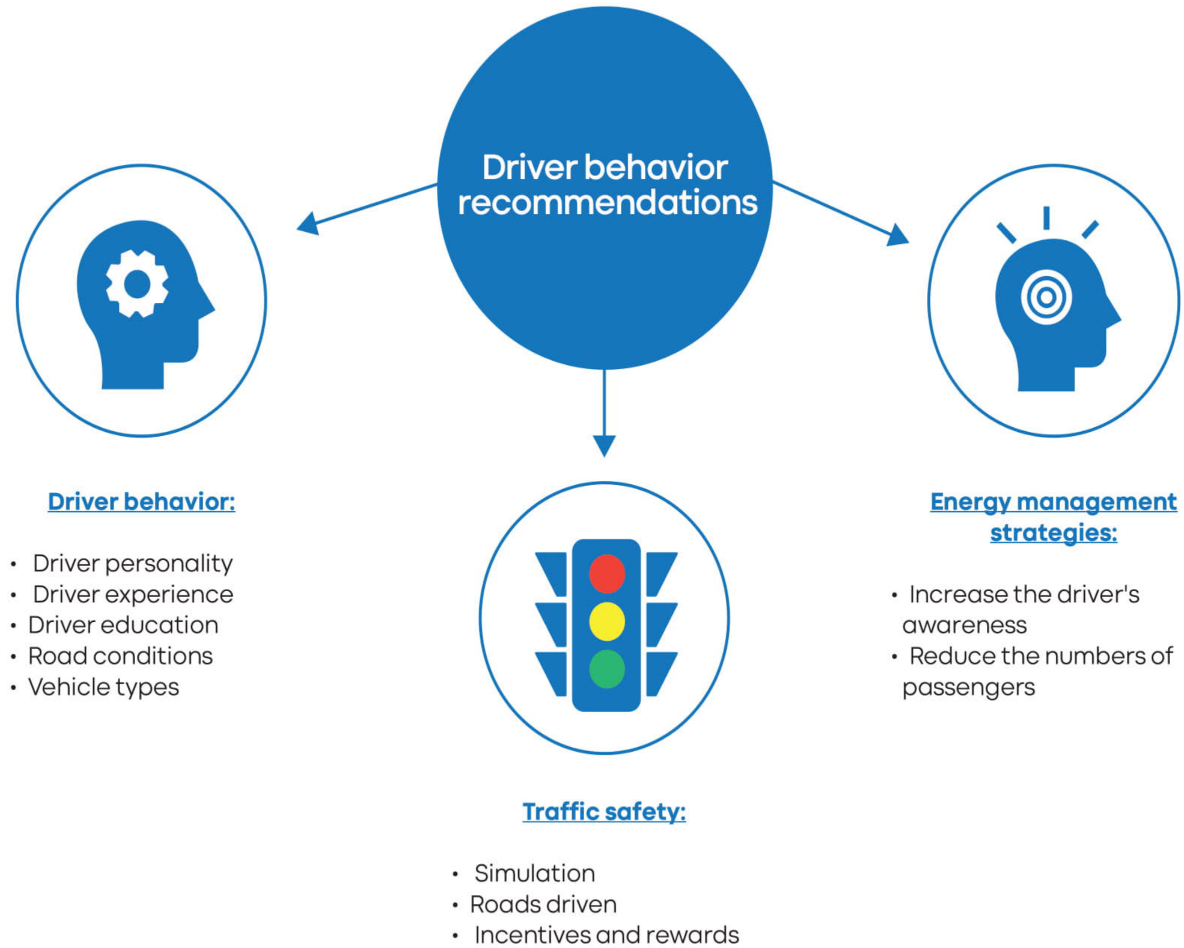


**FIGURE 8.** Categories of recommendations based on Driver behavior.

congestion mainly correlated to mini-buses, as compared with the other types of buses [36], [38]. The relationship between façade structure and other external design of bus, such as cover door, can be seen vividly in terms of bus safety [12]. Additionally, blind spots have been noted to be significantly correlated with the probability of causing accidents [16]. Festive seasons are substantially linked to bus accidents. For example, studies have noted express bus drivers in Malaysia as the likely type of bus drivers who cause accidents during festive seasons [13], [77].

#### 12) DRIVER CLASSIFICATION

The classification of driver behavior can potentially assist law makers and amend the current instructions. However, there are only two main types of driver behavior classification based on their driving style: normal and abnormal [58]. The various attributes that drivers can score include acceleration/deceleration and average trip length [73]. Besides that, studies have revealed that driving style can also be classified into normal and aggressive [67], [70]. Meanwhile, multiple aggressiveness is another prevailing characteristic of driving style [66]–[69]. Apart from the multiple aggressiveness attributes of driver behavior, namely defensive, weak defensive, weak aggressive, and aggressive, are significant features of driving style as well [72].

### C. RECOMMENDATIONS

This subsection presents the most significant recommendations from prior studies that address the challenges and simplify the safe and effective transportation driving activities comprising sensors, devices, and applications based on driver behavior (see Figure 8).

#### 1) RECOMMENDATIONS OF DRIVER BEHAVIOR

This subsection provides significant recommendations for bus drivers and driving agencies as well as considers the prediction of driver behavior, the appropriate driving style, and the commitment to operating times. The behavior of bus drivers is highly affected by the light conditions at night. In-depth research is recommended in this domain to address this issue and further analyze the correlation between mental effort and driving performance [18]. Employing video and audio are substantially useful to record and character-

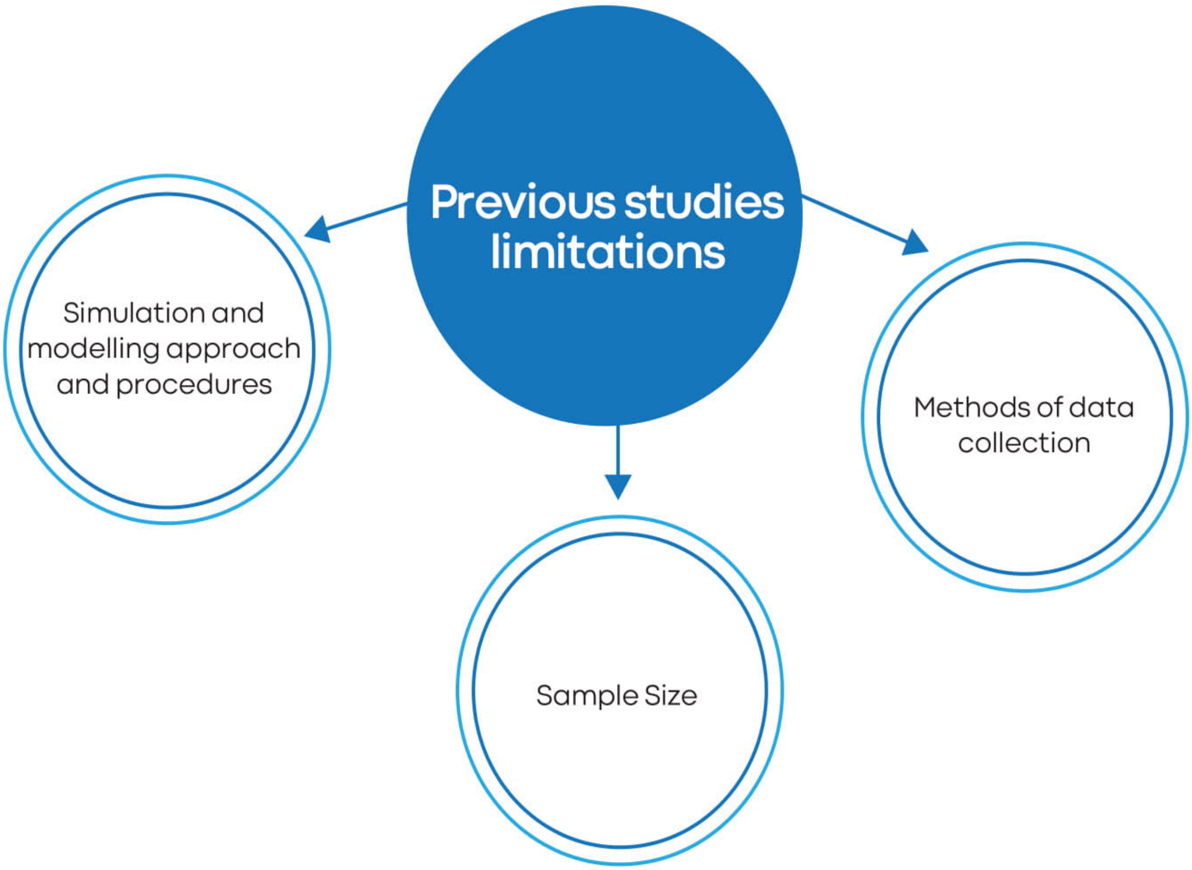


**FIGURE 9.** Categories of limitations.

ize driver behavior [90]. With the significant increase of accidents involving intercity buses, there is an urgent need to investigate intercity bus driver behavior [51]. There is a need for in-depth research on the effects of various vehicle types on the drivers' response and behavior [92]. Meanwhile, the implementation of a policy or evaluation system for the intercity bus drivers to have a co-driver has been proposed to avoid fatigue-related crashes and assist drivers to adopt attentive behavior [31]. In many circumstances, it is recommended to conduct longitudinal research in terms of acceleration as a prevalent driver behavior, taking into account the driver's education level, training hours, and the number of accidents, which may improve the overall understanding of these topics [60].

#### 2) RECOMMENDATIONS OF ENERGY MANAGEMENT STRATEGIES

Various companies and governmental agencies have started to introduce and provide improved programs on energy conservation [43]. One of the recommendations to manage traffic data is to increase data collection methods and the number of passengers for improved precision of future power demand estimates and energy management strategies [33]. Formative training, eco-driving training, and driver monitoring system development are also suggested to provide promising outcomes and increase drivers' awareness in reducing fuel consumption [43]. Despite the rapid development of the internet of vehicles, a significant amount of traffic information can be accessible through energy management mechanisms, but it is challenging to improve the efficiency of control strategies to familiarize with the driving cycles and different drivers. Thus, continuous research on all these interactions is desirable [74]. Case company is recommended to recruit drivers with high salary to mitigate issues related to working days, passenger load, and longer overtime hours.

#### 3) RECOMMENDATIONS OF TRAFFIC SAFETY

Providing instructions and imposing rigorous checking on the license of reckless drivers potentially offer optimistic results [50]. Work zone design and assessment, particularly taper configuration in urban terrain, are other aspects that should benefit from further evaluation [21]. A system to adopt traffic safety is also recommended to remind drivers of traffic conflicts and accidents and to promote positive traffic culture, rather than creating the fear of hazard [110]. More studies in similar contexts are needed to provide better interpretation of the performance under different circumstances [7]. It is significant to establish incentive assessment system and afford monthly material- and mental-based rewards to outstanding drivers in order to promote good practices of traffic safety

**TABLE 1. Experiment settings.**

| | Author | Location | Road Type | | Gender | | Study Type | | | | | Parameters | | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Expressway | Inside City | Male | Female | Experiment | Benchmark | Simulation | Survey | Review Study | Age | Acceleration | Anthropometric | Breaking | Body Functions | Collision | Distance | Driving Time (Day/Night) | Day of Week | Driver Habit | Deceleration | Fuel | Experience (Year) | Location | Number of Passengers | Crashes | Travel Cost | Travel Time | Road Type | Reaction Time | Road Geometry | Sensation-Seek | Speed | Velocity | Vehicle Maintenance | Vehicle Design | Vehicle Identification | Fatigue | Stress |
| 1 | [9] | Porto, Portugal | | ✓ | ✓ | | ✓ | | | | | ✓ | | ✓ | | ✓ | | | | | | | | ✓ | | | | | | | | | | | ✓ | | | | | |
| 2 | [40] | Greece | ✓ | | | | ✓ | | | | | | ✓ | | | | | | | | | ✓ | | | | | | | | | | | | ✓ | | | | | | |
| 3 | [21] | Florida, USA | | ✓ | ✓ | ✓ | ✓ | | | | | | | | | | ✓ | | | | | | | | | | | | | | | | | ✓ | | | | | | |
| 4 | [35] | Michigan, USA | | ✓ | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | ✓ | | | | ✓ | | | | | | |
| 5 | [18] | Tehran, Iran | | ✓ | ✓ | | ✓ | | ✓ | | | | | | | | | ✓ | | | | | | | | | | | | ✓ | | ✓ | | ✓ | | | | | | |
| 6 | [54] | Sweden | | | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 7 | [56] | Taiwan | ✓ | | | | ✓ | | | | | | ✓ | | | | | | | | | | | | | | ✓ | | | | | | | ✓ | | | | | | |
| 8 | [43] | Michigan, USA | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 9 | [39] | Lisbon, Portugal | | | | | | ✓ | | | | | | | | | | ✓ | | | | | | | | | | | | | | | | ✓ | | | | | | |
| 10 | [47] | Sweden | | | | ✓ | | ✓ | | | | | | | | | | ✓ | | | | | | | | | | | | | | | | ✓ | | | | | | |
| 11 | [22] | Chennai, India | | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | ✓ | | ✓ | | | | | | |
| 12 | [10] | Karnataka, India | | | | | | | | ✓ | | | | | | | | | | | | | | | | | ✓ | | | | | | ✓ | | | | | | | |
| 13 | [8] | Ghana | | | | | | ✓ | | | | | | | | | | | | ✓ | | | | | | | ✓ | | | | | | | | | | | | | |
| 14 | [76] | Sweden | | | | | ✓ | | | | | | | | | | | | | | | | | | | | ✓ | | | | | | | | | | | | | |
| 15 | [82] | Japan | | | | | ✓ | | | | | | ✓ | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | |
| 16 | [62] | Thailand | | | | | ✓ | | | | | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | |
| 17 | [63] | China | | | | | ✓ | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | ✓ | | | | | | |

behavior [53]. Besides that, a system to manage driving at night is recommended and can be achieved by improving the street lighting and traffic signage and illuminating road markings [31]. A system to develop simulation by taking into consideration of the weather variations and day or night driving is also recommended as another good platform to improve traffic control and safety [18].

Future initiatives should focus on improving kinematic mode-based velocity and acceleration estimations for different road conditions. Besides that, studies should consider defining bus driver behavior trends and the evaluation of intelligent bus systems, such as traffic light control, bus route planning, and constructive congestion management using assessment methods. The majority of bus vehicle tracking methods concentrate on algorithms and technology, but the application domain is rarely described [103].

### D. LIMITATIONS

Although prior studies accomplished some promising results, some limitations were identified, which are discussed in this subsection (see Figure 9).

Firstly, the sample size in most of the prior studies did not represent the general population and research community [60]. The most prevalent samples utilized in prior studies included bus drivers [44], [86], vehicle classes [10], and factors that affect driver behavior [60]. Secondly, the methods of data collection, such as reflective self-report assessments, can be inundated with biases [2], [9], [52], [53], [55], [61], [93], [95]. Thirdly, there are limitations to the simulation and modelling approaches and procedures—for example, they ignore error in the observed module and focus only on the psychological purposes, instead of the physiology. One of the prior studies noted computational complications [43], while certain studies only considered interaction vehicle-road [36], [70], [90]. Furthermore, some simulations did not reflect the lights in the bus for driving at night, particularly with wet road surface, which affect and impair drivers' forward vision [18]. Due to the inappropriate use of gender in prior studies [24], [42], [48], [53], [70], [81], [96], differences were noted as another limitation, as gender is an important demographic variable.

## VI. SUBSTANTIAL ANALYSIS

This section consists of two main parts: experiment settings and data collection sensors. The following subsections summarize all 87 articles.

### A. EXPERIMENT SETTINGS

This subsection presents the relevant data of 81 articles according to research location, road type, gender, study type,

**TABLE 1.** *(Continued.)* Experiment settings.

| | Author | Location | Road Type | | Gender | | Study Type | | | | | Parameters | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Expressway | Inside City | Male | Female | Experiment | Benchmark | Simulation | Survey | Review Study | Age | Acceleration | Anthropometric | Breaking | Body Functions | Collision | Distance | Driving Time (Day/Night) | Day of Week | Driver Habit | Deceleration | Fuel | Experience (Year) | Location | Number of Passengers | Crashes | Travel Cost | Travel Time | Road Type | Reaction Time | Road Geometry | Sensation-Seek | Speed | Velocity | Vehicle Maintenance | Vehicle Design | Vehicle Identification | Fatigue | Stress |
| 18 | [84] | Canada | | | | | | | ✓ | | | | ✓ | | | | | | | | | | | | | ✓ | | | | | | | | | ✓ | | | | | |
| 19 | [36] | Giza, Egypt | | | | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 20 | [85] | Italy | | | | | ✓ | | | | | | ✓ | ✓ | | | | | | | ✓ | | | | | | | | | | | | | ✓ | | | | | | |
| 21 | [90] | Portugal | | | | | ✓ | | ✓ | | | | ✓ | | | | | | | | | | ✓ | ✓ | ✓ | | | | | | | | | ✓ | | | | | | |
| 22 | [91] | China | | | | | ✓ | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | ✓ | | | | ✓ | | |
| 23 | [19] | Finland | | | | | ✓ | | | | | | | | ✓ | | | ✓ | | | ✓ | | ✓ | | | | ✓ | | | | | | | ✓ | | | | | | |
| 24 | [86] | USA | ✓ | | | | ✓ | | ✓ | | | | | | | | | ✓ | | | | | ✓ | | | | | | | | | | | ✓ | | | | | | |
| 25 | [80] | India | | | ✓ | ✓ | | | | ✓ | | ✓ | | | | | | ✓ | | | | | | | | | | ✓ | | | | | | | | | | | | |
| 26 | [37] | Portugal | | | | | | ✓ | | | | | ✓ | | ✓ | | | | | | | | | | | | | | | | | | | ✓ | | | | | | |
| 27 | [2] | Colombia | | | ✓ | | | | | ✓ | | | | | | | | | | | ✓ | | | | | | | | | | | | | | | | | | ✓ | ✓ |
| 28 | [48] | Iran | | | ✓ | ✓ | | | | ✓ | | ✓ | | | | | | ✓ | | | ✓ | | | ✓ | | | ✓ | | | | | | | | ✓ | | | | | |
| 29 | [44] | Italy | | | | | | | | ✓ | | | | | | | | | | | | | | ✓ | | | | | | | | | | | | ✓ | ✓ | | | |
| 30 | [55] | Taiwan | | | ✓ | ✓ | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | ✓ | ✓ | | | |
| 31 | [87] | Europe | | | | | | | | | ✓ | | ✓ | | | | | | | | ✓ | | | | | | | | | | | | | | | | | | | |
| 32 | [12] | Malaysia | | | | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | | | ✓ | | | |
| 33 | [23] | Australia | | | | | | ✓ | | | | | | | | | | ✓ | | | | | | | ✓ | | ✓ | | | | | | | | | | | | | |
| 34 | [16] | Australia | | | ✓ | | | ✓ | | | | ✓ | | | | | | | | | | | | | | | ✓ | | | | | | | ✓ | | | | | | |
| 35 | [81] | Chile | | | ✓ | | | | | ✓ | | | | | | | | | | | | | | | | | | ✓ | | | | | | | | | | | | |
| 36 | [50] | Thailand | | | ✓ | ✓ | | | | ✓ | | ✓ | | | | | | | | | ✓ | | | ✓ | | | | | | | | | | | | | | | | |

and parameters (i.e. age, acceleration, anthropometric, braking, body functions, collision, distance, driving time, day of week, driver habit, deceleration, fuel, experience, location, number of passengers, crashes, travel cost, travel time, road type, reaction time, road geometry, sensation-seek, speed, velocity,vehicle maintenance, vehicle design, vehicle identification, fatigue, and stress) used in data collection.

As shown in Table 1, when it comes to the percentage of factors for parameters in prior studies, speed represented 40% of the case studies, which is the highest rate among the parameters. Acceleration (34%) is the second-highest parameter, followed by crashes (17%). The remaining parameters are as follows: distance (14%); age (12%); driver habit (10%); velocity (9%) and vehicle identification (9%); experience (8%); fuel (7%) and location (7%); stress (6%) and road type (6%); deceleration (5%), vehicle maintenance (5%), and road geometry (5%); vehicle design (3%); collision (2%), anthropometric (2%), travel cost (2%), and travel time (2%); fatigue (1%), sensation-seek (1%), reaction time (1%), number of passengers (1%), day of week (1%), drive time (1%), and body functions (1%). Meanwhile, as for road type, inside city recorded 7% whereas expressway recorded 10%. As for gender, the male category recorded 44%, while the female category recorded 17%. As for the geographical distribution of the designated articles on ITS revealed that the most productive authors were from USA (14%) and China (14%), followed by India (6%), Iran (6%), Portugal (6%), Sweden (6%), and Taiwan (6%); Thailand (5%); Italy (3%) and Turkey (3%); Australia (2%), Europe Union (2%), and South Korea (2%); Chile (1%), Canada (1%), Colombia (1%), Egypt (1%), Finland (1%), Ghana (1%), Greece (1%), Hungary (1%), Japan (1%), Lithuania (1%), Serbia (1%), Singapore (1%), and Spain (1%).

### B. DATA COLLECTION SENSORS

This subsection presents relevant sensors used in real-time data collection. As shown in Table 2, GPS recorded the highest percentage of usage (69.4%), followed by camera (23.0%); OBD (19.4%) and accelerometer (19.4%); gyroscope (5.5%) and Inertial Measurement Unite (IMU) (5.5%); laser radar (2.7%), electrocardiography (ECG (2.7%), magnetometer (2.7%), gravity sensor (2.7%), eye detector (2.7%), VCR (2.7%), microphone (2.7%), microwave (2.7%), barometric (2.7%), bio-sensor (2.7%), steering wheel (2.7%), engine control unit (ECU) (2.7%), VDO (2.7%),

**TABLE 1.** *(Continued.)* **Experiment settings.**

| | Author | Location | Road Type | | Gender | | Study Type | | | | | Parameters | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Expressway | Inside City | Male | Female | Experiment | Benchmark | Simulation | Survey | Review Study | Age | Acceleration | Anthropometric | Breaking | Body Functions | Collision | Distance | Driving Time (Day/Night) | Day of Week | Driver Habit | Deceleration | Fuel | Experience (Year) | Location | Number of Passengers | Crashes | Travel Cost | Travel Time | Road Type | Reaction Time | Road Geometry | Sensation-Seek | Speed | Velocity | Vehicle Maintenance | Vehicle Design | Vehicle Identification | Fatigue | Stress |
| 37 | [38] | Portugal | | | | | | ✓ | | | | | ✓ | | ✓ | | ✓ | | | | | | | | | | | | | | | | | ✓ | | | | | | |
| 38 | [30] | China | | | | | ✓ | | | | | | | | | | | ✓ | | | | | | | | | | | | | | | | ✓ | | | | | | |
| 39 | [61] | Italy | | | | | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | ✓ |
| 40 | [20] | Europe | | | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | ✓ | | | | | | | ✓ | | |
| 41 | [17] | Korea | ✓ | ✓ | | | | ✓ | | | | | | | | | | | | | | | | | | | ✓ | | | | | | | | | | | | | |
| 42 | [52] | Serbia | | | | | | | | ✓ | | | | | | | | | | | | | | | | | | | | ✓ | | | | | | | | | | |
| 43 | [42] | Taiwan | | | ✓ | ✓ | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | ✓ |
| 44 | [45] | Malaysia | | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 45 | [83] | China | | | | | | ✓ | | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | ✓ | | | | | |
| 46 | [77] | Malaysia | | | | | | | | | ✓ | | ✓ | | | | | | | | | | | | | | | | | | | | | | ✓ | | | | | |
| 47 | [68] | Thailand | | | | | ✓ | | | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 48 | [69] | Hungary | | | | | ✓ | | ✓ | | | | ✓ | | | | | ✓ | | | | | | | | | | | | | | | | ✓ | | | | | | |
| 49 | [57] | USA | | | | | | ✓ | | | | | ✓ | | | | | | | | | | | | | | | | | | | | | ✓ | | | | ✓ | | |
| 50 | [92] | Singapore | | | ✓ | ✓ | ✓ | | ✓ | | | | | | | | | | | | ✓ | | | | | | | | | | | | | | | | | | | |
| 51 | [64] | China | | | | | | | ✓ | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 52 | [65] | Turkey | | | | | ✓ | | | | | | ✓ | | | | | | | | | ✓ | | | | | | | | | | | | ✓ | | | | | | |
| 53 | [67] | Lithuania | | | | | ✓ | | | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 54 | [70] | Sweden | | | | | ✓ | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | ✓ | | | | | | |
| 55 | [49] | Iran | | | ✓ | ✓ | | | | ✓ | | ✓ | | | | | | | | | ✓ | | | ✓ | | | ✓ | | | ✓ | | | | | | | | | | |

Vital Jacket (2.7%), GIS (2.7%), and photoplethysmography (PPG) (2.7%).

## VII. PATHWAYS SOLUTION IN FUTURE DIRECTION

Referring to the taxonomy of critical factors in this study (Section III), the main focus include habit (addictions), on-board routine (brake, passengers, and speed), and environment (time/lightning, road type, and weather). Based on the mapping of data collection methods (Section IV), real-time data collection from vehicle serves to obtain information in regard to speed and braking events using GPS in mobile and quantitative questionnaire survey among passengers.

Considering the aforementioned discussion on the factors of driver behavior and data collection methods, the use of real-time data collection is imperative to acquire highly accurate and sophisticated data. The combination of other data collection methods and real-time data collection is recommended to improve the accuracy of the acquired data. Apart from data collection methods, significant factors that should be considered in the analysis of driver behavior include speed limit and braking, where it was associated to various unfavorable outcomes, such as excessive fuel consumption, aggression, crashes, and accidents. The framework of the current study was set to articulate the identified gaps in literature, presenting three phases. The first phase refers to the design. The examination of the techniques aims at investigating possible tools for data collection on bus driver behavior, such as human, GPS, OBD, sensor, and camera. Data collection by GPS is proposed as the appropriate tool to identify speed, duration, distance, latitude, longitude, and altitude of the bus trip. Multiple paradigms are applicable in the navigation information collection, suggesting the suitability of mobile technology. Finally, a wide range of navigation mobile applications are compared to precisely select the appropriate application for data collection on bus driver behavior. The second phase refers to labeling and validation, with the aim to standardize the collected data from the selected application in the previous phase. A questionnaire aims to label the driver style (whether it is aggressive or not). Statistical analysis is conducted. Lastly, the third phase refers to machine learning, with the aim to utilize the gold-standard dataset, which is finalized in the previous phase for the prediction of models. In this manner, the gold-standard dataset undergoes a feature extraction task, where features such as braking, speed, and other significant characteristics are determined. Thereafter, a data splitting task is applied

**TABLE 1.** ***(Continued.)* Experiment settings.**

| | Author | Location | Road Type | | Gender | | Study Type | | | | | Parameters | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Expressway | Inside City | Male | Female | Experiment | Benchmark | Simulation | Survey | Review Study | Age | Acceleration | Anthropometric | Breaking | Body Functions | Collision | Distance | Driving Time (Day/Night) | Day of Week | Driver Habit | Deceleration | Fuel | Experience (Year) | Location | Number of Passengers | Crashes | Travel Cost | Travel Time | Road Type | Reaction Time | Road Geometry | Sensation-Seek | Speed | Velocity | Vehicle Maintenance | Vehicle Design | Vehicle Identification | Fatigue | Stress |
| 56 | [71] | Thailand | | | | | ✓ | | | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 57 | [31] | Malaysia | ✓ | | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | ✓ | | ✓ | | | | |
| 58 | [13] | Malaysia | | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | | ✓ | | | | | | |
| 59 | [51] | Malaysia | | | | | ✓ | | | | | | | | | | | ✓ | | | | | | | ✓ | | | | | | | | | ✓ | | | | | | |
| 60 | [72] | China | | | ✓ | ✓ | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | ✓ | | | | | | | | |
| 61 | [24] | USA | | | | | ✓ | | ✓ | | | | ✓ | | | | | | | | | | | | ✓ | | | | | | | | | | ✓ | | | | | |
| 62 | [66] | Spain | | | ✓ | ✓ | ✓ | | ✓ | | | | ✓ | | | | | | | | | | | | | | | | | | | ✓ | | ✓ | | | | | | |
| 63 | [93] | Tehran, Iran | | | | | | | | ✓ | | ✓ | | | | | | | | | | | | | | | ✓ | | | | | | | | | | | | | |
| 64 | [53] | China | | | ✓ | ✓ | | | | ✓ | | ✓ | | | | | | | | | | | | ✓ | | | ✓ | | | | | | | | | | | | | |
| 65 | [73] | Turkey | | | | | ✓ | | | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | ✓ | | | | | |
| 66 | [94] | USA | | | | | | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 67 | [95] | South Korea | | | | | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 68 | [96] | Taiwan | | | ✓ | ✓ | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | ✓ |
| 69 | [74] | China | | | | | | | ✓ | | | | ✓ | | ✓ | | | | | | | | | | | | | | | | | | | | ✓ | | | | | |
| 70 | [58] | China | | | | | ✓ | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | | | | ✓ | | |
| 71 | [25] | USA | | | | | ✓ | | | | | | ✓ | | | | | | | | | | | | | | | | | | | | | ✓ | | | | | | |
| 72 | [26] | China | | | | | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | ✓ | | | | | | |
| 73 | [78] | Sweden | | | ✓ | ✓ | | ✓ | | | | | ✓ | | | | | | | | | | | | ✓ | | ✓ | | | | | | | | | | | | | |
| 74 | [32] | USA | | | | | | | ✓ | | | | ✓ | | | | | | | | | | | | | | | | ✓ | | | | | ✓ | | | | | | |

to prepare two sets of training and testing. The training set will be used as an example set for a classifier. In this manner, the classifier will be trained on such example data before being put to the test on the testing set, where drivers are classified into aggressive or normal on the basis of the extracted features. Finally, multiple prediction models are implemented, and the selection criteria to filter them are based on the accuracy of prediction. Figure 10 shows these phases.

### A. PHASE 1: DESIGN

The data collection of bus driver behavior in Malaysia has been criticized. This phase aims to design appropriate data collection technique. Five common tools used to collect information on bus driver behavior are analyzed. The tools include camera, sensor, human, OBD, and GPS. Camera and sensors have been criticized in different studies due to the awareness of bus drivers—this affects the biasness of data collection [114]. Accordingly, a tool that involves minimal awareness of bus drivers should be utilized to obtain precise real-time data. Thus, an inclusion has been performed to contain GPS as a tool that facilitates data collection of bus drivers' speed and braking. Nonetheless, obtaining navigation information is not limited to one or two techniques. Such information can be acquired through via OBD technologies. However, the majority of buses in Malaysia are not compatible with such equipment. Bus companies are not allowed to incorporate OBD for their buses. When OBD is used, it will not be a naturalistic drive by the bus driver. Accordingly, another method has been proposed, which involves the use of a mobile application that can attain information on the pointnumber,speed, duration, altitude, latitude, distance, and time.

### B. PHASE 2: LABELING AND VALIDATION

Once the desired mobile application has been identified from the previous phase, this phase serves to apply the data collection using the identified mobile application. Experiments are conducted by enabling the mobile application to capture the point number, speed, duration, altitude, latitude, distance, and time within a bus trip. The collected data through the mobile application are further pre-processed to clean noisy data. Two main noisy data are determined, namely missing values and duplicate records. Missing values refer to records where the mobile application is unable to read the speed or braking information. Duplicate records refer to replicated readings by

**TABLE 1.** Experiment settings.

| | Author | Location | Road Type | | Gender | | Study Type | | | | | Parameters | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Expressway | Inside City | Male | Female | Experiment | Benchmark | Simulation | Survey | Review Study | Age | Acceleration | Anthropometric | Breaking | Body Functions | Collision | Distance | Driving Time (Day/Night) | Day of Week | Driver Habit | Deceleration | Fuel | Experience (Year) | Location | Number of Passengers | Crashes | Travel Cost | Travel Time | Road Type | Reaction Time | Road Geometry | Sensation-Seek | Speed | Velocity | Vehicle Maintenance | Vehicle Design | Vehicle Identification | Fatigue | Stress |
| 75 | [29] | USA | | ✓ | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | ✓ | | |
| 76 | [97] | China | | | | | ✓ | | ✓ | | | | | | | | | | | | ✓ | ✓ | | | ✓ | | | | | | | | | | | | | ✓ | | |
| 77 | [14] | India | | | | | | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 78 | [33] | USA | | | | | | ✓ | | | | | | | | | | | | | | | ✓ | | | | | | | ✓ | | | | ✓ | | | | | | |
| 79 | [75] | Iran | | | ✓ | | ✓ | | | | | ✓ | ✓ | | | | | | | | | | | | | | ✓ | | | | | | | ✓ | | | | | | |
| 80 | [101] | Malaysia | ✓ | | | | ✓ | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 81 | [110] | China | | | ✓ | ✓ | | | | ✓ | | | ✓ | | | | | | ✓ | | | | | ✓ | | | ✓ | | | | | | | ✓ | | | | | | |
| 82 | [34] | USA | | | | | ✓ | | | | | | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | |
| 83 | [89] | Turkey | | | | | ✓ | | ✓ | ✓ | | | | | | | | ✓ | | | | | ✓ | | | | | | | | | | | ✓ | | | | ✓ | | |
| 84 | [7] | India | | | | | ✓ | | | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | | | ✓ | | |
| 85 | [102] | Malaysia | ✓ | | | | ✓ | | ✓ | | | | ✓ | | ✓ | | | | | | | ✓ | ✓ | | | | | | | | | | | | | | | | | |
| 86 | [103] | | | ✓ | | | ✓ | | | | | | ✓ | | | ✓ | | | | | | | | | | | | | ✓ | ✓ | | | | | ✓ | | | ✓ | | |
| | | Percentage | 9% | 7% | 34% | 17% | | | | | | 12% | 34% | 2% | 9% | 22% | 2% | 14% | 1% | 1% | 10% | 5% | 7% | 8% | 7% | 1% | 17% | 2% | 34% | 7% | 1% | 5% | 1% | 40% | 10% | 5% | 3% | %10 | 1% | 6% |

the mobile application. A quantitative questionnaire survey is conducted to obtain feedback from bus passengers and determine driving style of the bus driver (aggressive or normal). Based on the feedback, the bus driver is labeled as either aggressive or normal. Finally, a statistical analysis using IBM SPSS is conducted to obtain the average label for drivers. After completing the statistical analysis, the outcome can be seen as a gold-standard dataset that is ready for training and testing purposes.

### C. PHASE 3: MACHINE LEARNING (GOALS TO BE ACHIEVED FROM ML)

This step is intended to apply multiple machine learning models after obtaining gold-standard dataset from the earlier stages. The steps are as follows:

1- Based on a set of characteristics, models seek to train the computer to predict any driving style (whether it is aggressive or natural). The labeling of machine learning comes from the interpretation of driver behavior questions based on passengers' questionnaire responses during the same journey. The characteristics of gold-standard dataset are collected and prepared for learning. Feature extraction is the term used for this step.

2- Following that, the extracted features are grouped with the corresponding driver ID before splitting into two groups: training and testing. The driver IDs and respective characteristics, as well as the classes of drivers are included in the training package (i.e. aggressive or normal). This type of aggregation enables a classification algorithm for learning from the features and their relationships according to the groups.

3- The testing package, on the other hand, only includes the driver IDs and corresponding attributes, but without classes. Based on the given features and the training model, the classification algorithm is assigned to predict the class mark for each driver. As a proof of concept, popular classification algorithms, including Support Vector Machine (SVM) [115], Decision Tree (DT) [113], [116], and Nave Bayes (NB) [44], [112], are considered. These algorithms are popular and demonstrate superior performance as compared to other algorithms. The numeric features of SVM are vectorized in a 2D space. The SVM then produces a separator that can correctly separate the data points into the respective groups (aggressive and normal), known as a hyper plane [115]. Meanwhile, NB employs a probabilistic model in which the likelihood of each feature corresponds to one of the com-

**TABLE 2. Real-time data collection sensors.**

| | Author | GPS | Camera | OBD | Gyroscope | Accelerometer | Magnetometer | Gravity Sensor | Eye Detector | VCR | Microphone | Microwave Radar | Laser Radar | ECG | IMU | Barometric | Bio-Sensor | Steering Wheel | ECU | VDO | Vital Jacket | PPG | Compass | GIS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | [9] | ✓ | | | | | | | | | | | | | | | | | | | ✓ | | | |
| 2 | [39] | ✓ | | | | | | | | | | | | | | | | | | | | | | |
| 3 | [22] | | ✓ | | | | | | | | | | | | | | | | | | | | | |
| 4 | [63] | ✓ | ✓ | | | | | | | | | | | | | | | | | | | | | |
| 5 | [85] | ✓ | | | | | | | | | | | | | ✓ | | | | | | | | | |
| 6 | [90] | ✓ | | ✓ | | | | | | | | | | ✓ | | | | | | | | | | |
| 7 | [91] | ✓ | ✓ | | | | | | | | ✓ | ✓ | ✓ | | | | | | | | | | | |
| 8 | [19] | ✓ | | | | | | | | | | | | | | | | | | | | | | |
| 9 | [86] | ✓ | | ✓ | | | | | | | | | | | | | | | | | | | | |
| 10 | [37] | | | | | ✓ | | | | | | | | | | ✓ | | | | | | | | |
| 11 | [87] | | | ✓ | | | | | | | | | | | | | | | | | | | | |
| 12 | [38] | ✓ | | | | | | | | | | | | | | | | | | | | | | |
| 13 | [30] | ✓ | | ✓ | | | | | | | | | | | | | | | ✓ | | | | | |
| 14 | [83] | ✓ | | | | | | | | | | | | | | | | | | | | | | |
| 15 | [77] | ✓ | ✓ | | | | | | | ✓ | | | | | | | | | | | | | | |
| 16 | [68] | | ✓ | | | | | | | | | | | | | | ✓ | ✓ | | | | | | |
| 17 | [92] | | ✓ | | | | | | ✓ | | | | | | | | | | | | | | | |
| 18 | [64] | ✓ | | | | ✓ | | ✓ | | | | | | | | | | | | | | | | |
| 19 | [65] | | | | ✓ | ✓ | ✓ | | | | | | | | | | | | | | | | | |
| 20 | [67] | ✓ | | | | ✓ | | | | | | | | | | | | | | | | | | |
| 21 | [70] | ✓ | | | | | | | | | | | | | ✓ | | | | | | | | | |
| 22 | [87] | | | ✓ | | | | | | | | | | | | | | | | | | | | |
| 23 | [38] | ✓ | | | | | | | | | | | | | | | | | | ✓ | | | | |
| 24 | [72] | ✓ | | | | | | | | | | | | | | | | | | | | | | |
| 25 | [66] | ✓ | | ✓ | | ✓ | | | | | | | | | | | | | | | | | | |
| 26 | [73] | ✓ | | | ✓ | | | | | | | | | | | | | | | | | | | |
| 27 | [25] | ✓ | | | | | | | | | | | | | | | | | | | | | | |
| 28 | [29] | | ✓ | | | | | | | | | | | | | | | | | | | | | |
| 29 | [97] | | ✓ | | | | | | | | | | | | | | | | | | | | | |
| 30 | [33] | ✓ | | | | | | | | | | | | | | | | | | | | | | |
| 31 | [75] | ✓ | | | | | | | | | | | | | | | | | | | | | | |
| 32 | [101] | | | | | | | | | | | | | | | | | | | | | ✓ | | |
| 33 | [34] | ✓ | | | | | | | | | | | | | | | | | | | | | | |
| 34 | [89] | ✓ | | ✓ | | | | | | | | | | | | | | | | | | | | |
| 35 | [102] | | | | | ✓ | | | | | | | | | | | | | | | | | | |
| 36 | [103] | ✓ | | | | | | | | | | | | | | | | | | | | | | ✓ |
| | Percentage | 69.4% | 23.0% | 19.4% | 5.5% | 19.4% | 2.7% | 2.7% | 2.7% | 2.7% | 2.7% | 2.7% | 2.7% | 2.7% | 5.5% | 2.7% | 2.7% | 2.7% | 2.7% | 2.7% | 2.7% | 2.7% | 2.7% | 2.7% |

puted groups [17], 118], [117]. When a class has a high likelihood, it is chosen as a predicted class. On the other hand, DT generates tree-like rules in which the characteristics are analyzed hierarchically in terms of a particular threshold [113]. Every node calculates the likelihood of the driver being violent or not. On the basis of this probability, the surfing through other features are calculated.

4- The final stage involves determining the heights accuracy between the algorithms [118] as well as the lowest mean absolute error (MAE), mean square error (MSE), and root mean square error (RMSE) [119]. These represent the objectives of using machine learning and pathways solutions.

## VIII. LIMITATIONS OF STUDY

Although the current study presented promising results, there were several limitations, which are discussed in this section. Firstly, the database sources utilized in the current review are reliable and cover a wide range of research areas, resulting in a substantial number of articles for reviewed. However, it was time-consuming to filter, process, and analyze these articles. This was deemed as one of the key limitations of systematic review. Secondly, the rapid growth in these research areas restricted the timeliness of the review. Thirdly, a schematic diagram of the study activities on ITS based on bus driver behavior did not essentially reflect the actual use of application effects. The findings of the current study represent the responses of the research community in order to

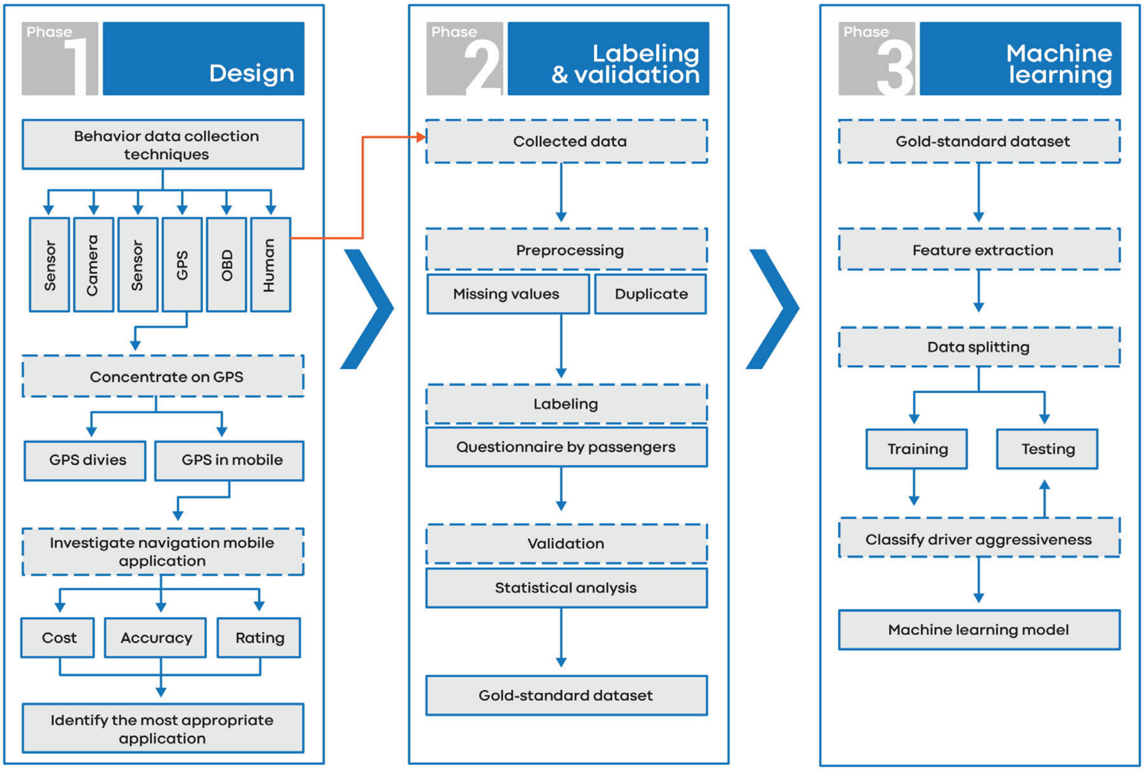


**FIGURE 10.** Pathways solution in future direction.

present a clear picture of bus driver behavior as an emerging topic. The findings can help bus designers, bus drivers, and relevant authorities in the adoption of appropriate solutions to reduce accident rates and improve bus services.

## IX. CONCLUSION

This study presented a systemic literature survey on influencing factors of bus driver behavior in terms of a taxonomy of critical factors. The proposed taxonomy of critical factors presented five main factors of driver behavior, including environmental, vehicle, demographic, habit, and on-board routine factors. One of the study's findings is mapping data collection methods existed in current literature. Four main methods were identified, namely, real-time data collection, survey, simulation and benchmark.

The current study aimed to contribute a better understanding on the survey and classification of relevant research efforts. The research efforts in this field were classified into four classes, namely taxonomy of critical factors, mapping of data collection methods, substantial analysis, and studies conducted on bus driver behavior. Through concentrated reading and analysis of the reviewed articles, valuable information on the motivations, challenges, recommendations, and limitations related to bus driver behavior were obtained.

This study determined the correlative gaps of data collection procedures and factors that affect driver behavior. Moreover, this study identified factors and important aspects related to road safety that were not discussed in the previous studies. In conclusion, researchers of bus driver behavior may be overwhelmed by the large number of related articles available, but the structure introduced by the taxonomy of critical factors and mapping of data collection methods in this study can provide significant insights and clear overview of bus driver behavior in ITS for researchers to identify additional challenges and research gaps. As for the future direction in research, the proposed framework in this study can be implemented and tested to address the above-mentioned research gaps.

## REFERENCES

[1] Y. R. B. Al-Mayouf, O. A. Mahdi, N. A. Taha, N. F. Abdullah, S. Khan, and M. Alam, "Accident management system based on vehicular network for an intelligent transportation system in urban environments," *J. Adv. Transp.*, vol. 2018, pp. 1–11, May 2018.

[2] S. A. Useche, V. G. Ortiz, and B. E. Cendales, "Stress-related psychosocial factors at work, fatigue, and risky driving behavior in bus rapid transport (BRT) drivers," *Accident Anal. Prevention*, vol. 104, pp. 106–114, Jul. 2017.

[3] W. Zhai, Y. Jiang, and S. Ji, "Research on the application of data mining algorithms in intelligent transportation," *Int. J. Adv. Pervas. Ubiquitous Comput.*, vol. 11, no. 2, pp. 1–10, Apr. 2019.

[4] S.-h. An, B.-H. Lee, and D.-R. Shin, "A survey of intelligent transportation systems," in *Proc. 3rd Int. Conf. Comput. Intell., Commun. Syst. Netw.*, Jul. 2011, pp. 332–337.

[5] A. Bolovinou, A. Amditis, F. Bellotti, and M. Tarkiainen, "Driving style recognition for co-operative driving: A survey," in *Proc. 6th Int. Conf. Adapt. Self-Adaptive Syst. Appl.* Greece: Citeseer, May 2014, pp. 73–78.

[6] D. Zhang, Q. Xiao, J. Wang, and K. Li, "Driver curve speed model and its application to ACC speed control in curved roads," *Int. J. Automot. Technol.*, vol. 14, no. 2, pp. 241–247, Apr. 2013.

[7] S. Dandapat, K. Bhattacharyya, and B. Maitra, "Quantifying factors influencing urban bus passenger boarding and alighting dynamics in an emerging economy," *J. Transp. Eng., A, Syst.*, vol. 146, no. 6, Jun. 2020, Art. no. 04020040.
[8] E. F. Sam, S. Daniels, K. Brijs, T. Brijs, and G. Wets, "Modelling public bus/minibus transport accident severity in Ghana," *Accident Anal. Prevention*, vol. 119, pp. 114–121, Oct. 2018.
[9] J. G. P. Rodrigues, M. Kaiseler, A. Aguiar, J. P. Silva Cunha, and J. Barros, "A mobile sensing approach to stress detection and memory activation for public bus drivers," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 6, pp. 3294–3303, Dec. 2015.
[10] A. Verma, N. Chakrabarty, S. Velmurugan, P. Bhat B, and D. Kumar H. D, "Sensation seeking behavior and crash involvement of Indian bus drivers," *Transp. Res. Procedia*, vol. 25, pp. 4750–4762, Jan. 2017.
[11] Y. Yan and Y. Fan, "Influence of the driver style difference in the acceleration process on the energy consumption of the EV bus," in *Proc. Int. Conf. Eng. Adv. Technol.*, May 2017, pp. 2672–2680.
[12] M. Y. Shaharudin, M. A. H. A. Balkhis, M. S. Mujir, and O. H. Hassan, "Conceptual framework of design study on façade of hi-deck bus using FRP composite," in *Proc. IEEE Bus., Eng. Ind. Appl. Colloq. (BEIAC)*, Apr. 2012, pp. 121–124.
[13] M. Ahmad, Z. H. Zulkipli, W. A. Batcha, N. F. Paiman, S. M. Faudzi, I. Othman, and M. R. Osman, "An observational study on speeding among Malaysian express bus drivers," *J. Soc. Automot. Eng. Malaysia*, vol. 1, no. 2, pp. 94–102, 2017.
[14] M. K. Singh and K. R. Rao, "Cellular automata models for signalised and unsignalised intersections with special attention to mixed traffic flow: A review," *IET Intell. Transp. Syst.*, vol. 14, no. 12, pp. 1507–1516, Dec. 2020.
[15] A. P. Hungund, G. Pai, and A. K. Pradhan, "Systematic review of research on driver distraction in the context of advanced driver assistance systems," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 25, Apr. 2021, Art. no. 036119812110041.
[16] K. Goh, G. Currie, M. Sarvi, and D. Logan, "Factors affecting the probability of bus drivers being at-fault in bus-involved accidents," *Accident Anal. Prevention*, vol. 66, pp. 20–26, May 2014.
[17] H.-C. Park, D.-K. Kim, S.-Y. Kho, and P. Y. Park, "Cross-classified multilevel models for severity of commercial motor vehicle crashes considering heterogeneity among companies and regions," *Accident Anal. Prevention*, vol. 106, pp. 305–314, Sep. 2017.
[18] S. S. Gilandeh, M. H. Hosseinlou, and A. J. Anarkooli, "Examining bus driver behavior as a function of roadway features under daytime and nighttime lighting conditions: Driving simulator study," *Saf. Sci.*, vol. 110, pp. 142–151, Dec. 2018.
[19] H. Liimatainen, "Utilization of fuel consumption data in an ecodriving incentive system for heavy-duty vehicle drivers," *IEEE Trans. Intell. Transp. Syst.*, vol. 12, no. 4, pp. 1087–1095, Dec. 2011.
[20] M. Gibson and M. Carnovale, "The effects of road pricing on driver behavior and air pollution," *J. Urban Econ.*, vol. 89, pp. 62–73, Sep. 2015.
[21] J. F. Morgan, A. R. Duley, and P. A. Hancock, "Driver responses to differing urban work zone configurations," *Accident Anal. Prevention*, vol. 42, no. 3, pp. 978–985, May 2010.
[22] S. Balakrishnan and R. Sivanandan, "Influence of lane and vehicle subclass on free-flow speeds for urban roads in heterogeneous traffic," *Transp. Res. Procedia*, vol. 10, pp. 166–175, Jan. 2015.
[23] K. C. K. Goh, G. Currie, M. Sarvi, and D. Logan, "Bus accident analysis of routes with/without bus priority," *Accident Anal. Prevention*, vol. 65, pp. 18–27, Apr. 2014.
[24] S. H. Hamdar, L. Qin, and A. Talebpour, "Weather and road geometry impact on longitudinal driving behavior: Exploratory analysis using an empirically supported acceleration modeling framework," *Transp. Res. C, Emerg. Technol.*, vol. 67, pp. 193–213, Jun. 2016.
[25] H. Liu, M. O. Rodgers, and R. Guensler, "The impact of road grade on vehicle accelerations behavior, $PM_{2.5}$ emissions, and dispersion modeling," *Transp. Res. D, Transp. Environ.*, vol. 75, pp. 297–319, Oct. 2019.
[26] Z. Deng, D. Chu, C. Wu, Y. He, and J. Cui, "Curve safe speed model considering driving style based on driver behaviour questionnaire," *Transp. Res. F, Traffic Psychol. Behaviour*, vol. 65, pp. 536–547, Aug. 2019.
[27] J. Chang, "Summary of NHTSA heavy-vehicle vehicle-to-vehicle safety communications research," Transp. Res. Board, USA, Tech. Rep. S2-S06-RW-1, 2016.
[28] Z. B. Haber, I. De la Varga, B. A. Graybeal, B. Nakashoji, and R. El-Helou, *Properties and Behavior of UHPC-Class Materials*. Washington, DC, USA: Federal Highway Administration. Office of Infrastructure, 2018.
[29] Y. Zhang and J. D. Fricker, "Multi-state semi-Markov modeling of recurrent events: Estimating driver waiting time at semi-controlled crosswalks," *Analytic Methods Accident Res.*, vol. 28, Dec. 2020, Art. no. 100131.
[30] H. Ma, H. Xie, D. Huang, and S. Xiong, "Effects of driving style on the fuel consumption of city buses under different road conditions and vehicle masses," *Transp. Res. D, Transp. Environ.*, vol. 41, pp. 205–216, Dec. 2015.
[31] T. H. Law, M. S. Daud, H. Hamid, and N. A. Haron, "Development of safety performance index for intercity buses: An exploratory factor analysis approach," *Transp. Policy*, vol. 58, pp. 46–52, Aug. 2017.
[32] P. Anderson and N. Geroliminis, "Dynamic lane restrictions on congested arterials," *Transp. Res. A, Policy Pract.*, vol. 135, pp. 224–243, May 2020.
[33] H. Liu, M. O. Rodgers, F. Liu, and R. Guensler, "Bayesian approach in estimating the road grade impact on vehicle speed and acceleration on freeways," *Transportmetrica A, Transp. Sci.*, vol. 16, no. 3, pp. 602–625, Jan. 2020.
[34] H. Li, J. C. Wolf, J. K. Mathew, N. Navali, S. D. Zehr, B. L. Hardin, and D. M. Bullock, "Leveraging connected vehicles to provide enhanced roadway condition information," *J. Transp. Eng., A, Syst.*, vol. 146, no. 8, Aug. 2020, Art. no. 04020073.
[35] G. Heqimi, T. J. Gates, and J. J. Kay, "Using spatial interpolation to determine impacts of annual snowfall on traffic crashes for limited access freeway segments," *Accident Anal. Prevention*, vol. 121, pp. 202–212, Dec. 2018.
[36] A. Naiem, M. Reda, M. El-Beltagy, and I. El-Khodary, "An agent based approach for modeling traffic flow," in *Proc. 7th Int. Conf. Informat. Syst. (INFOS)*, Mar. 2010, pp. 1–6.
[37] G. O. Duarte, G. A. Gonçalves, and T. L. Farias, "Vehicle monitoring for driver training in bus companies—Application in two case studies in Portugal," *Transp. Res. D, Transp. Environ.*, vol. 18, pp. 103–109, Jan. 2013.
[38] C. Rolim, P. Baptista, G. Duarte, T. Farias, and Y. Shiftan, "Quantification of the impacts of eco-driving training and real-time feedback on urban buses driver's behaviour," *Transp. Res. Proc.*, vol. 3, pp. 70–79, Jul. 2014.
[39] J. de Abreu e Silva, F. Moura, B. Garcia, and R. Vargas, "Influential vectors in fuel consumption by an urban bus operator: Bus route, driver behavior or vehicle type?" *Transp. Res. D, Transp. Environ.*, vol. 38, pp. 94–104, Jul. 2015.
[40] M. Kostovasili and C. Antoniou, "Simulation-based evaluation of evacuation effectiveness using driving behavior sensitivity analysis," *Simul. Model. Pract. Theory*, vol. 70, pp. 135–148, Jan. 2017.
[41] J. Barceló and J. Casas, "Dynamic network simulation with AIMSUN," in *Simulation Approaches in Transportation Analysis*. Spain: Springer, 2005, pp. 57–98.
[42] Y.-W. Huang, P.-C. Lin, and J. Wang, "The influence of bus and taxi drivers' public self-consciousness and social anxiety on aberrant driving behaviors," *Accident Anal. Prevention*, vol. 117, pp. 145–153, Aug. 2018.
[43] B. T.-W. Lin and S.-L. Hwang, "Effect prediction of time-gaps for adaptive cruise control (ACC) and in-vehicle tasks on bus driver performance," *Saf. Sci.*, vol. 50, no. 1, pp. 68–75, Jan. 2012.
[44] S. Cafiso, A. Di Graziano, and G. Pappalardo, "Road safety issues for bus transport management," *Procedia Social Behav. Sci.*, vol. 48, pp. 2251–2261, Jan. 2012.
[45] M. Y. Shaharudin, M. A. H. Al Balkhis, M. S. Mujir, and O. H. Hassan, "Line, shape and trend of innovative façade design of high deck bus for medium scale coachbuilder," in *Proc. IEEE Bus. Eng. Ind. Appl. Colloq. (BEIAC)*, Apr. 2013, pp. 202–204.
[46] C. Rolim, P. Baptista, G. Duarte, T. Farias, and J. Pereira, "Real-time feedback impacts on eco-driving behavior and influential variables in fuel consumption in a Lisbon urban bus operator," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 11, pp. 3061–3071, Nov. 2017.
[47] A. E. A. Wåhlberg, "Changes in driver celeration behaviour over time: Do drivers learn from collisions?" *Transp. Res. F, Traffic Psychol. Behav.*, vol. 15, no. 5, pp. 471–479, Sep. 2012.
[48] A. M. Moghaddam and E. Ayati, "Introducing a risk estimation index for drivers: A case of Iran," *Saf. Sci.*, vol. 62, pp. 90–97, Feb. 2014.

[49] Z. Rahemi, N. M. Ajorpaz, M. Sharifi Esfahani, and M. Aghajani, "Sensation-seeking and factors related to dangerous driving behaviors among Iranian drivers," *Personality Individual Differences*, vol. 116, pp. 314–318, Oct. 2017.
[50] V. Ratanavaraha and S. Jomnonkwao, "Model of users? Expectations of drivers of sightseeing buses: Confirmatory factor analysis," *Transp. Policy*, vol. 36, pp. 253–262, Nov. 2014.
[51] H. L. Khoo and M. Ahmed, "Modeling of passengers' safety perception for buses on mountainous roads," *Accident Anal. Prevention*, vol. 113, pp. 106–116, Apr. 2018.
[52] M. Maslać, B. Antić, K. Lipovac, D. Pešić, and N. Milutinović, "Behaviours of drivers in Serbia: Non-professional versus professional drivers," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 52, pp. 101–111, Jan. 2018.
[53] Z. Zhang, T. Ma, N. Ji, Z. Hu, and W. Zhu, "An assessment of the relationship between driving skills and driving behaviors among Chinese bus drivers," *Adv. Mech. Eng.*, vol. 11, no. 1, Jan. 2019, Art. no. 168781401882491.
[54] H. K. Strömberg and I. C. M. Karlsson, "Comparative effects of eco-driving initiatives aimed at urban bus drivers—Results from a field trial," *Transp. Res. D, Transp. Environ.*, vol. 22, pp. 28–33, Jul. 2013.
[55] C.-F. Chen and Y.-L. Kao, "The connection between the hassles–burnout relationship, as moderated by coping, and aberrant behaviors and health problems among bus drivers," *Accident Anal. Prevention*, vol. 53, pp. 105–111, Apr. 2013.
[56] T.-W. Lin, S.-L. Hwang, and P. A. Green, "Effects of time-gap settings of adaptive cruise control (ACC) on driving performance and subjective acceptance in a bus driving simulator," *Saf. Sci.*, vol. 47, no. 5, pp. 620–625, 2009.
[57] J. S. Hickman and R. J. Hanowski, "An assessment of commercial motor vehicle driver distraction using naturalistic driving data," *Traffic Injury Prevention*, vol. 13, no. 6, pp. 612–619, 2012.
[58] Y. Yuan, Y. Lu, and Q. Wang, "Adaptive forward vehicle collision warning based on driving behavior," *Neurocomputing*, vol. 408, pp. 64–71, Sep. 2020.
[59] J. Reason, A. Manstead, S. Stradling, J. Baxter, and K. Campbell, "Errors and violations on the roads: A real distinction?" *Ergonomics*, vol. 33, nos. 10–11, pp. 1315–1332, Oct. 1990.
[60] L. Dorn, L. Stephen, A. A. Wåhlberg, and J. Gandolfi, "Development and validation of a self-report measure of bus driver behaviour," *Ergonomics*, vol. 53, no. 12, pp. 1420–1433, Dec. 2010.
[61] L. Mallia, L. Lazuras, C. Violani, and F. Lucidi, "Crash risk and aberrant driving behaviors among bus drivers: The role of personality and attitudes towards traffic safety," *Accident Anal. Prevention*, vol. 79, pp. 145–151, Jun. 2015.
[62] S. Boonmee and P. Tangamchit, "Portable reckless driving detection system," in *Proc. 6th Int. Conf. Electr. Eng./Electron., Comput., Telecommun. Inf. Technol.*, May 2009, pp. 412–415.
[63] Y. Jiao, Y. Xiaoguang, Z. Tong, M. Danno, and M. Miyaji, "Chinese driver behavior characteristics research at intersection based on intelligent vehicle-infrastructure integration experimental platform," in *Proc. 2nd Int. Conf. Intell. Comput. Technol. Autom.*, Oct. 2009, pp. 523–528.
[64] C. Song, J. Wu, M. Liu, H. Gong, and B. Gou, "RESen: Sensing and evaluating the riding experience based on crowdsourcing by smart phones," in *Proc. 8th Int. Conf. Mobile Ad-Hoc Sensor Netw. (MSN)*, Dec. 2012, pp. 147–152.
[65] H. Eren, S. Makinist, E. Akin, and A. Yilmaz, "Estimating driving behavior by a smartphone," in *Proc. IEEE Intell. Vehicles Symp.*, Jun. 2012, pp. 234–239.
[66] J. E. Meseguer, C. T. Calafate, J. C. Cano, and P. Manzoni, "DrivingStyles: A smartphone application to assess driver behavior," in *Proc. IEEE Symp. Comput. Commun. (ISCC)*, Jul. 2013, pp. 000535–000540.
[67] V. Vaitkus, P. Lengvenis, and G. Zylius, "Driving style classification using long-term accelerometer information," in *Proc. 19th Int. Conf. Methods Models Autom. Robot. (MMAR)*, Sep. 2014, pp. 641–644.
[68] P. Phumphuang, P. Wuttidittachotti, and C. Saiprasert, "Driver identification using variance of the acceleration data," in *Proc. Int. Comput. Sci. Eng. Conf. (ICSEC)*, Nov. 2015, pp. 1–6.
[69] A. Mihaly and P. Gaspar, "Driver categorization based on vehicle motion and trajectory data," in *Proc. 16th IEEE Int. Symp. Comput. Intell. Informat. (CINTI)*, Nov. 2015, pp. 101–105.
[70] J. Carmona, M. A. de Miguel, D. Martin, F. Garcia, and A. de la Escalera, "Embedded system for driver behavior analysis based on GMM," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2016, pp. 61–65.
[71] N. Virojboonkiate, P. Vateekul, and K. Rojviboonchai, "Driver identification using histogram and neural network from acceleration data," in *Proc. IEEE 17th Int. Conf. Commun. Technol. (ICCT)*, Oct. 2017, pp. 1560–1564.
[72] C.-P. Hwang, M.-S. Chen, C.-M. Shih, H.-Y. Chen, and W. K. Liu, "Apply scikit-learn in Python to analyze driver behavior based on OBD data," in *Proc. 32nd Int. Conf. Adv. Inf. Netw. Appl. Workshops (WAINA)*, May 2018, pp. 636–639.
[73] G. Kar, B. Asiroglu, and F. S. Bir, "Scotto: Real-time driver behavior scoring using in-vehicle data," in *Proc. IEEE 89th Veh. Technol. Conf. (VTC-Spring)*, Apr. 2019, pp. 1–5.
[74] X. Tian, Y. Cai, X. Sun, Z. Zhu, and Y. Xu, "An adaptive ECMS with driving style recognition for energy optimization of parallel hybrid electric buses," *Energy*, vol. 189, Dec. 2019, Art. no. 116151.
[75] B. Khorram, A. A. Wåhlberg, and A. Tavakoli Kashani, "Longitudinal jerk and celeration as measures of safety in bus rapid transit drivers in Tehran," *Theor. Issues Ergonom. Sci.*, vol. 21, no. 5, pp. 577–594, 2020.
[76] G. Markkula, J. Engström, J. Lodin, J. Bärgman, and T. Victor, "A farewell to brake reaction times? Kinematics-dependent brake response in naturalistic rear-end emergencies," *Accident Anal. Prevention*, vol. 95, pp. 209–226, Oct. 2016.
[77] J. M. Diah and N. Q. A. Hamidun, "The methodology review of traffic safety monitoring by using video recording for express bus in Malaysia," in *Proc. IEEE 14th Int. Colloq. Signal Process. Appl. (CSPA)*, Mar. 2018, pp. 1–6.
[78] A. P. Silvano and M. Ohlin, "Non-collision incidents on buses due to acceleration and braking manoeuvres leading to falling events among standing passengers," *J. Transp. Health*, vol. 14, Sep. 2019, Art. no. 100560.
[79] A. H. Taylor and L. Dorn, "Stress, fatigue, health, and risk of road traffic accidents among professional drivers: The contribution of physical inactivity," *Annu. Rev. Public Health*, vol. 27, no. 1, pp. 371–391, Apr. 2006.
[80] S. M. Dave, D. P. Raykundaliya, and S. N. Shah, "Modeling trip attributes and feasibility study of co-ordinated bus for school trips of children," *Procedia Social Behav. Sci.*, vol. 104, pp. 650–659, Dec. 2013.
[81] I. Tiznado, P. Galilea, F. Delgado, and M. Niehaus, "Incentive schemes for bus drivers: The case of the public transit system in Santiago, Chile," *Res. Transp. Econ.*, vol. 48, pp. 77–83, Dec. 2014.
[82] A. Wahab, C. Quek, C. K. Tan, and K. Takeda, "Driving profile modeling and recognition based on soft computing approach," *IEEE Trans. Neural Netw.*, vol. 20, no. 4, pp. 563–582, Apr. 2009.
[83] Q. Han, L. Zeng, Y. Hu, L. Ye, Y. Tang, J. Lei, and X. Zhang, "Driving behavior modeling and evaluation for bus enter and leave stop process," *J. Ambient Intell. Humanized Comput.*, vol. 9, no. 5, pp. 1647–1658, Oct. 2018.
[84] S. Zorrofi, S. Filizadeh, and P. Zanetel, "A simulation study of the impact of driving patterns and driver behavior on fuel economy of hybrid transit buses," in *Proc. IEEE Vehicle Power Propuls. Conf.*, Sep. 2009, pp. 572–577.
[85] V. Manzoni, A. Corti, P. De Luca, and S. M. Savaresi, "Driving style estimation via inertial measurements," in *Proc. 13th Int. IEEE Conf. Intell. Transp. Syst.*, Sep. 2010, pp. 777–782.
[86] D. Wijayasekara, M. Manic, and D. Gertman, "Data driven fuel efficient driving behavior feedback for fleet vehicles," in *Proc. 8th Int. Conf. Hum. Syst. Interact. (HSI)*, Jun. 2015, pp. 75–81.
[87] M. V. Corazza, U. Guida, A. Musso, and M. Tozzi, "From EBSF to $EBSF_2$: A compelling agenda for the bus of the future: A decade of research for more attractive and sustainable buses," in *Proc. IEEE 16th Int. Conf. Environ. Electr. Eng. (EEEIC)*, Jun. 2016, pp. 1–6.
[88] M. Li, H. He, L. Feng, Y. Chen, and M. Yan, "Hierarchical predictive energy management of hybrid electric buses based on driver information," *J. Cleaner Prod.*, vol. 269, Oct. 2020, Art. no. 122374.
[89] E. Evin, M. B. Aydin, and G. Kardas, "Design and implementation of a CANBus-based eco-driving system for public transport bus services," *IEEE Access*, vol. 8, pp. 8114–8128, 2020.
[90] J. G. P. Rodrigues, F. Vieira, T. T. V. Vinhoza, J. Barros, and J. P. S. Cunha, "A non-intrusive multi-sensor system for characterizing driver behavior," in *Proc. 13th Int. IEEE Conf. Intell. Transp. Syst.*, Sep. 2010, pp. 1620–1624.

[91] W. Qing, S. BingXi, X. Bin, and Z. Junjie, "A PERCLOS-based driver fatigue recognition application for smart vehicle space," in *Proc. 3rd Int. Symp. Inf. Process.*, Oct. 2010, pp. 437–441.
[92] B. Mandal, L. Li, G. S. Wang, and J. Lin, "Towards detection of bus driver fatigue based on robust visual analysis of eye state," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 3, pp. 545–557, Mar. 2017.
[93] H. Mokarami, S. S. Alizadeh, T. R. Pordanjani, and S. Varmazyar, "The relationship between organizational safety culture and unsafe behaviors, and accidents among public transport bus drivers using structural equation modeling," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 65, pp. 46–55, Aug. 2019.
[94] H. S. Stern, D. Blower, M. L. Cohen, C. A. Czeisler, D. F. Dinges, J. B. Greenhouse, F. Guo, R. J. Hanowski, N. P. Hartenbaum, G. P. Krueger, M. M. Mallis, R. F. Pain, M. Rizzo, E. Sinha, D. S. Small, E. A. Stuart, and D. H. Wegman, "Data and methods for studying commercial motor vehicle driver fatigue, highway safety and long-term driver health," *Accident Anal. Prevention*, vol. 126, pp. 37–42, May 2019.
[95] S. J. Kim and E. K. Chung, "The effect of organizational justice as perceived by occupational drivers on traffic accidents: Mediating effects of job satisfaction," *J. Saf. Res.*, vol. 68, pp. 27–32, Feb. 2019.
[96] H.-K. Chen, H.-W. Chou, J.-W. Su, and F.-H. Wen, "Structural interrelationships of safety climate, stress, inattention and aberrant driving behavior for bus drivers in Taiwan," *Transp. Res. A, Policy Pract.*, vol. 130, pp. 118–133, Dec. 2019.
[97] T. Wang, Y. Chen, X. Yan, W. Li, and D. Shi, "Assessment of drivers' comprehensive driving capability under man-computer cooperative driving conditions," *IEEE Access*, vol. 8, pp. 152909–152923, 2020.
[98] R. Prabha and M. G. Kabadi, "Overview of data collection methods for intelligent transportation systems," *Int. J. Eng. Sci.*, vol. 5, no. 3, pp. 16–20, 2016.
[99] T. Guo, K. Iwamura, and M. Koga, "Towards high accuracy road maps generation from massive GPS traces data," in *Proc. IEEE Int. Geosci. Remote Sens. Symp.*, Jul. 2007, pp. 667–670.
[100] S. Wang, C. Chen, and J. Ma, "Accelerometer based transportation mode recognition on mobile phones," in *Proc. Asia–Pacific Conf. Wearable Comput. Syst.*, 2010, pp. 44–46.
[101] P.-W. Huang, B.-J. Wu, and B.-F. Wu, "A heart rate monitoring framework for real-world drivers using remote photoplethysmography," *IEEE J. Biomed. Health Informat.*, vol. 25, no. 5, pp. 1397–1408, May 2021.
[102] A. Cura, H. Kucuk, E. Ergen, and I. B. Oksuzoglu, "Driver profiling using long short term memory (LSTM) and convolutional neural network (CNN) methods," *IEEE Trans. Intell. Transp. Syst.*, early access, Jun. 8, 2020, doi: 10.1109/TITS.2020.2995722.
[103] Y. Yang, J. Yan, J. Guo, Y. Kuang, M. Yin, S. Wang, and C. Ma, "Driving behavior analysis of city buses based on real-time GNSS traces and road information," *Sensors*, vol. 21, no. 3, p. 687, Jan. 2021.
[104] C. Wilson, C. Willis, J. K. Hendrikz, R. Le Brocque, and N. Bellamy, "Speed cameras for the prevention of road traffic injuries and deaths," *Cochrane Database Systematic Rev.*, no. 10, pp. 1–72, Oct. 2010.
[105] K. Ozbay, H. Yang, and B. O. Bartin, "Calibration of an infrared-based automatic counting system for pedestrian traffic flow data collection," Transp. Res. Board, USA, Tech. Rep. 10-3574, 2010.
[106] J. Firnkorn, "Triangulation of two methods measuring the impacts of a free-floating carsharing system in Germany," *Transp. Res. A, Policy Pract.*, vol. 46, no. 10, pp. 1654–1672, Dec. 2012.
[107] K. Kwong, R. Kavaler, R. Rajagopal, and P. Varaiya, "Arterial travel time estimation based on vehicle re-identification using wireless magnetic sensors," *Transp. Res. C, Emerg. Technol.*, vol. 17, no. 6, pp. 586–606, 2009.
[108] K. Jacobsen, "High resolution satellite imaging systems—An overview," *Photogrammetrie Fernerkundung Geoinf.*, vol. 2005, no. 6, p. 487, 2005.
[109] H. Alshenqeeti, "Interviewing as a data collection method: A critical review," *English Linguistics Res.*, vol. 3, no. 1, pp. 39–45, Mar. 2014.
[110] W. Han and J. Zhao, "Driver behaviour and traffic accident involvement among professional urban bus drivers in China," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 74, pp. 184–197, Oct. 2020.
[111] T. Victor, M. Dozza, J. Bärgman, C. N. Boda, J. Engström, C. Flannagan, J. D. Lee, and G. Markkula, "Analysis of naturalistic driving study data: Safer glances, driver inattention, and crash risk," Transp. Res. Board, USA, Tech. Rep. S2-S08A-RW-1, 2015, Art. no. 0309274230.
[112] F. T. Al-Dhief, N. M. A. Latiff, N. N. N. A. Malik, N. S. Salim, M. M. Baki, M. A. A. Albadr, and M. A. Mohammed, "A survey of voice pathology surveillance systems based on Internet of Things and machine learning algorithms," *IEEE Access*, vol. 8, pp. 64514–64533, 2020.
[113] Z. M. Yaseen, M. F. Allawi, A. A. Yousif, O. Jaafar, F. M. Hamzah, and A. El-Shafie, "Non-tuned machine learning approach for hydrological time series forecasting," *Neural Comput. Appl.*, vol. 30, no. 5, pp. 1479–1491, 2016.
[114] A. Tavakoli, S. Kumar, X. Guo, V. Balali, M. Boukhechba, and A. Heydarian, "HARMONY: A human-centered multimodal driving study in the wild," *IEEE Access*, vol. 9, pp. 23956–23978, 2021.
[115] L. Li, S. You, C. Yang, B. Yan, J. Song, and Z. Chen, "Driving-behavior-aware stochastic model predictive control for plug-in hybrid electric buses," *Appl. Energy*, vol. 162, pp. 868–879, Jan. 2016.
[116] V. Naosekpam and R. K. Sharma, "Machine learning in 3D space gesture recognition," *Jurnal Kejuruteraan*, vol. 31, no. 2, pp. 243–248, 2019.
[117] A. Mosavi, S. Shamshirband, E. Salwana, K.-W. Chau, and J. H. M. Tah, "Prediction of multi-inputs bubble column reactor using a novel hybrid model of computational fluid dynamics and machine learning," *Eng. Appl. Comput. Fluid Mech.*, vol. 13, no. 1, pp. 482–492, Jan. 2019.
[118] A. Shahsavar, H. Moayedi, A. H. A. Al-Waeli, K. Sopian, and P. Chelvanathan, "Machine learning predictive models for optimal design of building-integrated photovoltaic-thermal collectors," *Int. J. Energy Res.*, vol. 44, no. 7, pp. 5675–5695, Jun. 2020.
[119] J. R. Cano, F. Herrera, and M. Lozano, "Using evolutionary algorithms as instance selection for data reduction in KDD: An experimental study," *IEEE Trans. Evol. Comput.*, vol. 7, no. 6, pp. 561–575, Dec. 2003.
[120] T. Chai and R. Draxler, "Root mean square error (RMSE) or mean absolute error (MAE)," *Geosci. Model Develop. Discuss.*, vol. 7, no. 1, pp. 1525–1534, 2014.