Accident Analysis and Prevention 133 (2019) 105300

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

# Toward an integrated traffic law enforcement and network management in connected vehicle environment: Conceptual model and survey study of public acceptance

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ARTICLE INFO

*Keywords:*
Traffic law enforcement
Transportation demand management
Connected vehicle
Driver performance monitoring

ABSTRACT

The increasing number of traffic accidents and their associated traffic congestion have prompted the development of innovative technologies to curb such problems. This paper proposes a novel score-based traffic law-enforcement and network management system (SLEM) that is based on connected vehicles (CV) technology. SLEM assigns a score to each driver which reflects her/his driving performance and compliance with traffic laws. The proposed system adopts a rewarding mechanism that rewards high-performing drivers and penalizes low-performing drivers who fail to obey the laws. The reward mechanism is in the form of a route guidance strategy that restricts low-score drivers from accessing certain roadway sections and time periods that are strategically selected in order to achieve an optimal traffic pattern in the network in which high-score drivers experience less congestion and a higher level of safety. A nationwide survey study was conducted to measure public acceptance of the proposed system. Another survey targeted a focused group of traffic operation and safety professionals. Based on the results of these surveys, a set of logistic regression models were developed to examine the sensitivity of public acceptance to policy and behavioral variables. The results showed that about 65.7 percent of the public and about 60.0 percent of professionals who participated in this study support the real-world implementation of SLEM.

## 1. Introduction

Traffic safety is a major concern around the world. About 7.3 million traffic-related accidents occurred in the United States in 2016. These accidents resulted in 40,327 fatalities, 3.144 million injuries, and an estimated $432 billion in economic losses (NSC, 2017; NHTSA, 2017). While many factors contribute to the occurrence of these accidents, human error and failure to obey traffic rules are among the top causes of the majority of these accidents. With regards to the multidimensionality of the traffic safety problem, a comprehensive approach that integrates education programs, law enforcement, and engineering technologies (also known as the EEE approach) is widely practiced in many cities around the world (Evans, 2004). Effort devoted to advancing engineering technologies for traffic safety applications can be generally classified into two categories: (a) driver-assisting technologies and (b) traffic monitoring and law-enforcing technologies (Smith, 2017). Driver-assisting technologies focus on reducing human errors that might contribute to accidents. For example, vehicles are increasingly equipped with bumper sensors that alert drivers so that they might avoid collisions with cars/objects in their blind spots. Law-enforcing technologies aim to develop platforms for traffic monitoring and reporting traffic law violations. These systems reduce dependence on police officers for traffic law enforcement tasks, which are expensive and occasionally put the officers in dangerous situations. Speed radars and red-light cameras, which are capable of video-recording a violating vehicle and issuing tickets that are sent directly to the driver's home/email addresses, are examples of automated law-enforcing technologies (Ahmed et al., 2016; U.S. Patent No. US7986339B2, 2011).

The acceleration toward smarter cities and infrastructure has increased the importance of developing innovative transportation technologies to improve mobility, safety, and law enforcement conditions. For example, the emergence of connected vehicles (CV) technology is expected to revolutionize traffic safety and mobility applications (Smith, 2017). Current research and development efforts focus on

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https://doi.org/10.1016/j.aap.2019.105300
Received 1 August 2019; Received in revised form 9 September 2019; Accepted 17 September 2019
Available online 01 October 2019

leveraging vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications to enhance traffic safety by providing better driving assistance capabilities. For example, dedicated short-range communication (DSRC) channels for vehicular communications have enabled the development of warning systems that keep drivers aware of their 360° surroundings. In addition, CV technology has been proposed to harmonize the traffic speed on freeways and to provide early warnings for drivers about building queues downstream of their current locations (Talebpour et al., 2013). It is generally estimated that CV technology could eliminate or mitigate up to 80 percent of minor crashes that take place at intersections, parking lots, or lane changes by enabling drivers to receive warning messages through V2V and V2I communications (NHTSA, 2016a). Another recent study concluded that out of the 6.3 million reported crashes which took place in 2015, CV technology could have averted 615,000 crashes and saved 1366 lives (NHTSA, 2016b).

Effort devoted to adopting CV technology for law enforcement applications is in its infancy. The idea is to integrate CV technologies in law-enforcement vehicles to improve data gathering, processing, and tracking of surrounding vehicles, with the goal of easing and increasing the efficiency of police officers' jobs (Microsoft, 2015). While the lack of supporting legislation and concerns about privacy invasion have slowed market readiness for these applications, there are strong indications that CV technology could benefit such applications. For example, automobile insurance companies have recently shown interest in using CV to develop systems for monitoring and profiling drivers' performance in terms of several driving aggressiveness measures (e.g., frequent lane changing, speeding, acceleration and deceleration rates, etc.). Obtaining this information enables insurance companies to design customized insurance policies with minimum loss risk (Händel et al., 2014). In addition, there has been considerable debate over current traffic penalties for violators of traffic laws, which include warnings, fines, driver's license suspensions, and jail time, and their effectiveness for curbing worsening trends in traffic law compliance. Intensive research in the last fifty years has concluded that improvements in future traffic conditions will depend on improving both driver performance and driver behavior (Lee, 2008).

In this context, this study conceptualizes an autonomous, score-based traffic law enforcement and management system (SLEM) that leverages CV technology. The system assigns a real-time score for each driver that reflects her/his monitored driving performance and traffic law compliance. Different from current systems that issue tickets to violating drivers, the proposed system adopts a reward mechanism that rewards high-performing drivers who comply with the traffic laws and penalizes low-performing drivers who fail to obey the laws. The proposed mechanism is in the form of a route guidance strategy that restricts low-score drivers from accessing certain roadway sections and strategically selected time periods. These restricted roadway sections and time periods would be selected such that high-score drivers experience less congestion and a higher level of safety while low-score drivers are instructed to follow alternative routes. The level of restriction could be designed to transform the traffic flow pattern in the network from an undesirable user equilibrium pattern to a system optimal pattern (Peeta and Mahmassani, 1995). As such, this system not only promotes safe driving but also reduces congestion in the network by achieving an efficient traffic distribution pattern in the network.

Traffic management strategies that adopt route restriction policies are not new. For example, the congestion pricing strategy specifies a toll for roadway segments to restrict access only to drivers willing to pay the imposed tolls (de Palma and Lindsey, 2011). Similarly, single occupancy vehicles are restricted from traveling on high occupancy vehicle (HOV) lanes (Abdelghany et al., 2000; Murray et al., 2001). The road rationing strategy adopted in several cities is another example of route restriction strategies, where vehicles are restricted from accessing some roads based upon the last digits of the license number on certain established days during certain periods (Han et al., 2010). In addition, the credit-based policy can be viewed as a restriction strategy, where each driver maintains a travel credit beyond which drivers are not allowed to travel in the network (Kockelman and Kalmanje, 2005; Yang and Wang, 2011). Finally, the incentive-based demand management strategy aims to reduce access to congested routes through providing incentives to drivers to avoid these routes (Ben-Elia and Ettema, 2011). Although these strategies have shown to be effective in reducing traffic congestion, their justice and equity remain an issue of heated debate.

Because of the novelty of SLEM, this research focused on understanding both public acceptance as well as the opinion of traffic system experts/professionals regarding the adoption of SLEM in their regions. To obtain information on public acceptance, a national survey with a sample of 1418 participants was designed and distributed across all 50 states and the District of Columbia (DC). The survey collected information on the participants' socioeconomic characteristics, their driving performance history, and their level of acceptance of the new system. Using this sample data, a logistic regression model was developed to determine significant variables that affect public acceptance of SLEM and to predict its level of acceptance under different policy and operation scenarios. Another survey was implemented at smaller scale to gather information on the views of traffic system experts/professionals of SLEM. The sample included experts from public agencies and consultants providing services to these agencies.

This study contributes to the literature in several ways. First, it introduces a score-based system that simultaneously aims to enhance traffic safety and reduce network congestion. It is also among the first attempts to study public acceptance of demand management strategies that are based on driver performance profiling and roadway access restrictions. Finally, a modeling framework in the form of a logistic regression model was developed to examine main factors that influence public acceptance of the real-world deployment of the system. The rest of this paper is organized as follows. The next section reviews different topics related to SLEM, including the history of performance-based driver profiling and the development of score-based systems. The conceptual model of the proposed SLEM is then described in Section 3. In Section 4, the survey design process and a brief description of the data collection procedure are presented. Sections 5 and 6 present the results and discuss the findings. The last section presents the conclusion and possible research extensions.

## 2. Literature review

Advances in telematics technology have focused considerable attention on the concept of monitoring and profiling drivers based on their driving performance for several applications, such as vehicle insurance and commercial/public transportation safety. For example, automobile insurance companies have recently introduced the Usage-Based Insurance (UBI) model, which issues insurance policies to drivers that reflect their vehicle usage and other known information concerning their driving performance. In addition, several technology companies have proposed a scoring system that can be used by owners of commercial vehicles and public transportation agencies to evaluate the performance of their drivers. As proposed in Händel et al. (2014), these scores combine several metrics that are monitored in real time (e.g., acceleration and braking, speeding, smoothness, swerving, etc.). For instance, the AXA Drive Coach application was developed to sense and analyze vehicle maneuvers, then assign scores to drivers based on these patterns (Tardy, 2015). Another driver scoring application, DriveSafe, applies pattern recognition techniques to detect driver distraction (Bergasa et al., 2014). Inspired by financial credit scores, the credit scoring services company FICO recently announced a new product called FICO® Safe Driving Score to establish a new driver characterization system that categorizes drivers based on their driving performance as shown in Table 1 below.

Three main approaches are used to monitor driving performance: physiological, in-vehicle sensing, and performance-based. The physiological-based approach is mainly used to evaluate the performance of

**Table 1**
Fico Safe Driving Score specifications ((FICO, 2019).

| | Target 1 | | Target 2 | |
|---|---|---|---|---|
| | Fleet Management | | Consumer and Novice Markets | |
| *Measuring Factors* | *Features* | *Benefits* | *Features* | *Benefits* |
| Speeding & Acceleration | Reinforce Safety Training | Cheaper Insurance Policies | Coaching Novice Drivers. | Proving Safe Driving Skills |
| Braking | Monitor, Engage and Coach | Better Fleet Safety Record | Monitor Experienced Drivers | Better Insurance Policies |
| Cornering | Reward and Incentive Programs | Cheaper Fleet Maintenance Fees | Remediation Coaching | To Prove Insurance Policy Worthiness |
| Cellphone Distraction | ———— | ———— | ———— | ———— |

commercial drivers. Sensors are physically attached to the drivers' bodies to acquire different bio-measures that can be used to assess the drivers' level of alertness or fatigue. Examples of these bio-measures include an electroencephalogram (EEG, brain activity), an electrooculogram (EOG, eye movement), and an electrocardiogram (ECG, heart rate) (Borghini et al., 2014). However, this approach is not widely accepted because drivers feel uncomfortable with these sensors attached to their bodies, especially if they are driving for long distances. The in-vehicle sensing approach aims to monitor drivers' alertness and evaluate their ability to maintain safe driving by installing sensors in the vehicle rather than attaching them to the drivers' bodies. For example, Liang et al. (2007) developed a platform to detect distracted drivers by monitoring eye movement and driving performance in a simulation environment. Cyganek and Gruszczyński (2014) performed field experiments to detect drivers' fatigue and drowsiness. Mbouna et al. (2013) examined visual feature monitoring schemes that monitor a driver's pupil and head position to detect drowsiness and distraction. Furthermore, a driver distraction detection experiment was conducted by Vicente et al. (2015) that monitored the driver's head pose and gaze. In addition to distraction and drowsiness, detection of the driver's emotional stress was also proposed by Gao et al. (2014), wherein facial recognition sensing was used to detect a driver's psychological state. An artificial neural network model was developed by Ye et al. (2017) to predict the driver's involvement in secondary distracting tasks such as calling, texting, and passenger interaction. Driving performance is also inferred by analyzing acceleration and braking pedal operations (Wahab et al., 2009). The IntelliSafe system introduced by Volvo is an example of a driver alertness detection system deployed in the real world (VOLVO, 2018). Finally, performance-based approaches monitor the vehicle's movements to assess driver performance. For example, vehicle movement data are used to infer information from the driver's braking and acceleration (Pentland and Liu, 1999) as well as lane changing and maneuvering (Kuge et al., 2000). Gonzalez et al. (2014) developed a model that detects driver aggressiveness by monitoring lateral and longitudinal accelerations and speed. Car following and headway distance data are also considered to measure driving aggressiveness (Miyajima et al., 2007).

The majority of the literature views the smartphone as the most affordable telematics tool for monitoring driver performance. Data on driving patterns could be acquired from the drivers' smartphones (e.g., accelerometers, magnetometers, GPS) to detect their risky performance and aggressiveness (Eren et al., 2012; Hong et al., 2014). These data can also be used to reveal additional information regarding the alertness of the driver (Dai et al., 2010). Smartphone applications have been developed to detect the activities of drivers and provide real-time suggestions to enhance their performance (Araújo et al., 2012). Evaluating the accuracy of driving performance systems that use smartphone data is already underway. For example, Paefgen et al. (2012) conducted a field study to evaluate a smartphone application for the assessment of driving performance during critical driving events and found that smartphones tend to overestimate the measurements of critical driving events. Castignani et al. (2013) considered an application for UBI driving scores and found that more effort is required to improve the accuracy of data gathered by smartphones. This work was extended by Castignani et al. (2015), who explored the SenseFleet drivers' profiling and scoring platform to detect risky driving events based on data that were collected independently from both a mobile device and the vehicle. Experimental results showed that SenseFleet was accurate in terms of differentiating between risky and calm driving. More recently, CV technology has been looked at as a plausible technology for monitoring and profiling driving performance (Chen et al., 2018). Based on data collected from a simulated CV platform, a machine-learning algorithm was proposed to profile drivers in terms of driving aggressiveness and assign them performance scores. The results from the developed model suggest that low-score drivers should follow safe drivers in order to enhance the highway safety and mobility conditions.

## 3. Conceptual model

This section introduces the conceptual model for SLEM. Several assumptions are considered for the system:

(a) A vehicle-to-infrastructure (V2I) secured connected system is established across the entire roadway network, which is capable of collecting high-frequency real-time data describing the location, movement direction, speed, acceleration, steering wheel angle, and tailgating distance for each vehicle on the road. The system can also obtain real-time information on the status of each traffic light. The system is connected to database describing the speed limit for all links and all mandatory signs in the network.
(b) SLEM is equipped with built-in rules that can be applied to reliably detect traffic law violations such as running a red light, violating the speed limit, tailgating, and performing a prohibited maneuver, etc.
(c) Each vehicle trip has an identified registered driver linked to it. Drivers have knowledge of SLEM and its functionality as an integrated law enforcement and traffic network management system.
(d) SLEM assigns each driver a score that reflects his/her average performance over a pre-defined period. This score is used to determine the driver's eligibility for route access for her/his current trip.
(e) Each driver can get a record of her/his violations in real-time along with instructions and incentives to improve his/her current score. Drivers who consistently fail to adhere to the traffic laws are subject to severe penalties ranging from imposing points on driver license to driving license suspension or jail time.

We defined $S$ as the list of possible score levels that a driver could be assigned such that $s_1 > s_2$ implies that drivers with score $s_1$ have a higher driving performance than those with score level $s_2$. Two dynamic traffic route assignment strategies are considered: (a) dynamic user equilibrium (DUE) and (b) dynamic system optimal (DSO) (Peeta and Mahmassani, 1995). Each pattern defines a set of superior routes for each origin-destination (OD) pair and departure time interval that are used by the drivers. The DUE pattern assumes that each driver selects the route that minimizes her/his travel time under a perfect information scenario. At equilibrium, no driver can improve her/his travel time by unilaterally changing her/his route. In the DSO routing strategy, drivers are assumed to fully comply with a route guidance strategy in which they are assigned to routes that minimize the total network travel time. Under the DSO equilibrium, no driver can improve his/ her marginal travel time by unilaterally changing his/ her route. A successful traffic management strategy would shift the traffic route assignment pattern in the network from the undesirable DUE pattern to the desirable DSO pattern. SLEM determines a route restriction scheme, which is defined in terms of the lowest (worst) score threshold for each route such that drivers with scores equal to or higher than this threshold are allowed to use this route. Assuming that drivers are choosing routes that minimize their travel time in the network, these thresholds are determined such that the traffic pattern in the network is transformed from DUE toward the DSO pattern. In other words, the threshold value for each route is strategically determined such that (a) the total travel time in the network is minimized, and (b) drivers with high scores are assigned high travel priority and may access faster routes in the network.

In this context, consider a roadway network $G(N, A, D)$, where $N$ is the set of nodes, $A$ is the set of links, and $D$ is the time-dependent traffic demand pattern estimated for the network for a pre-defined horizon $T$. This horizon is divided into $|T|$ departure time intervals. The vehicle demand $d_{ij}^{\tau} \in D$ for each OD pair $ij \in N$ and departure interval $\tau \in T$ is assumed to be given. Consequently, we define $d_{ij}^{\tau s}$ as the number of drivers traveling between an OD pair $ij$ in departure interval $\tau$ and belonging to score level $s \in S$.

Vehicles traveling between an OD pair in a given departure time interval are assigned to a superior set of routes that connect this OD pair. Each route $k \in K_{ij}^{\tau}$ is given a minimum score threshold $c_{ijk\tau}$. Drivers belonging to a score category $s$ that is less than $c_{ijk\tau}$ are restricted from using that route. Drivers who do not comply with the route access restrictions mandated by SLEM will have their scores further decreased and could be subject to other penalties. Fig. 1 illustrates an example of an OD pair with three routes. Drivers between this OD pair belong to three performance score levels ranked from the highest (s = 1) to the lowest (s = 3). In this example, the score level threshold for Route 1 is equal to 2, implying that drivers who have attained the score levels 1 and 2 are eligible to use this route. Similarly, the score level threshold for Route 2 is equal to 1, which limits the access of this route to drivers with the highest driving performance level.

We define $d_{ijk}^{\tau}$ as the number of vehicles that travel between OD pair $ij \in Z$ in departure interval $\tau \in T$ using route $k \in K_{ij}^{\tau}$. The level of congestion is defined for each route, which is measured in terms of the route travel time $tt_{ijk}^{\tau}(.)$. The portion of drivers who belong to score level $s \in S$ and use route $k \in K_{ij}^{\tau}$ is defined as $d_{ijk}^{\tau s}$.

The problem of determining the score thresholds $c_{ijk\tau}\ \forall\ i, j, k, \tau$ can be viewed as a version of the general network design problem (Farahani et al., 2013). A common formulation of this problem is in the form of a bi-level mathematical program. The upper-level problem determines the capacity allocated for each link, constrained by a given investment budget, that optimizes the overall performance of the network. The lower-level problem captures the demand distribution in the network in response to capacity adjustments. A similar bi-level model can be developed for SLEM, as presented in Eqs. (1)–(3).

Upper-Level Problem:

$$\text{Minimize} \sum_{ij} \sum_{k} \sum_{\tau} \left( \sum_{s \geq c_{ijk\tau}} d_{ijks}^{\tau} \right) . \ tt_{ijk}^{\tau} \tag{1}$$

Access priority constraints

Lower-Level Problem:

$$d_{ijks}^{\tau} \bullet (tt_{ijk}^{\tau} - u_{ij}^{\tau}) = 0\ \ \forall\ \ i, j, k, \tau,\ s \tag{2}$$

$$(tt_{ijk}^{\tau} - u_{ij}^{\tau}) \geq 0\ \ \forall\ \ i, j, k, \tau \tag{3}$$

Flow conservation constraints

The upper-level problem determines the optimal capacity allocated for the portion of the demand, $d_{ijks}^{\tau}$, belonging to each score level $s \in S$ through specifying the minimum score thresholds $c_{ijk\tau}\ \forall\ i, j, k, \tau$. These scores are determined such that the total travel time in the network is minimized as shown in (1). For each OD pair ij and departure interval $\tau$, the demand portions belonging to the different score levels on route k are summed up and multiplied by the travel time of route k. The demand allowed on route k must have a performance score that is higher than the threshold $c_{ijk\tau}$, that is $d_{ijks}^{\tau} = 0\ \forall\ i, j, k, \tau, s < c_{ijk\tau}$. Other constraints that should be considered for the upper-level problem include those that guarantee drivers with high scores receive higher priority to access faster routes in the network.

The lower-level problem represents the drivers' route choice behavior in response to the imposed score thresholds. As mentioned above, each driver is assumed to minimize her/his travel time under a perfect information scenario. This lower-level problem is represented by constraints (2) and (3), respectively. The variable $u_{ijk}^{\tau}$ is defined as the minimum travel time between the OD pair ij in departure interval $\tau$. These constraints ensure that the demand portion, $d_{ijks}^{\tau}$, is assigned to a subset of routes with minimum travel times that are equal to $u_{ijk}^{\tau}$. In addition, any route with a travel time greater than $u_{ijk}^{\tau}$ is not utilized. Other constrains that should be considered for the lower-level problem include the flow conservation constraints at the path and OD pair levels. Providing the full mathematical formulation and the solution algorithm of this problem is beyond the scope of this paper and is considered to be an extension of the work presented in this paper.

## 4. Survey design and implementation

A 32-question online survey was designed to measure public opinion about SLEM using Qualtrics software (see https://www.qualtrics.com). The survey was divided into three sections. The first section asked participants about their driving habits, such as their daily commuting distance, mode of commute, and whether they had previous accidents and/or violations. The second section collected information on the participants' opinion about SLEM and their main reasons for supporting or rejecting the system. The final section asked the participants for their demographic information, including their current city of residence. The survey was piloted in September 2017, using 20 participants to validate the overall quality of the survey, including completion time and clarity.

A short animation video clip was provided to explain the overall concept of a SLEM system.[1] A snapshot of this video clip is provided in Fig. 2. All survey participants were asked to watch the video before starting the second section of the survey. This video ensured that every participant received exactly the same information about the proposed system, thereby enhancing data accuracy and reducing bias.

The survey was distributed from March 1st to April 30th, 2018. Three approaches were used to recruit a representative sample. First, 45 students from three different engineering classes (two undergraduate and one graduate) were invited to participate voluntarily in the recruitment process. 32 students participated as recruiters. They recruited 376 valid participants from their family members and their network of friends who live in different states (an average of about 12 recruits per student). The second approach was to recruit participants face-to-face in public places such as coffee shops and shopping malls. These participants were asked to complete the survey either on the spot using a tablet, or alternatively, they were emailed or texted the survey link so they could complete the survey at their convenience. We also asked these participants to share the survey with their relatives and friends living in other states, if possible. This approach produced 97 valid responses were received. The third approach used an academic, research-

[1] Video link.

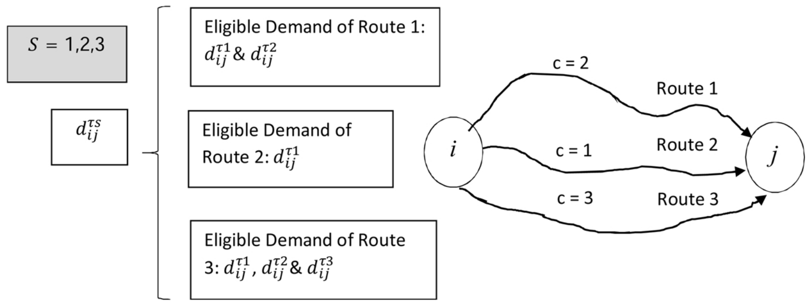


**Fig. 1.** Demand split among three routes with different score thresholds.


**Fig. 2.** Snapshots of the video used to demonstrate SLEM for the survey participants.

based online crowdsourcing platform (see https://prolific.ac). Online crowdsourcing platforms have been widely used as reliable methods for data collection (Rand et al., 2012). Previous researchers evaluated the reliability of these platforms by comparing their data with data collected using other traditional approaches, such as laboratory experiments and face-to-face interviews. They concluded that online crowdsourcing platforms generally produce results indistinguishable from other methods (e.g., Palan and Schitter, 2018). Through the online crowdsourcing platform used in this study, a total of 1009 participants were recruited from across the country, yielding 945 valid data points.

The result produced a convenience sample of 1672 participants, which, following the methodology proposed in Krejcie and Morgan (1970), satisfied the minimum sample size requirements. Participants responded from all 50 states and from the District of Columbia (DC). Eligible participants were U.S. residents who held a driver license (DL) during the last 3 years. Data were cleaned by removing duplicate, inconsistent, careless, and incomplete responses. The 1672 total responses were reduced to a total of 1418 valid responses, which still covered all 50 states and the DC area, as presented in Fig. 3.

Table 2 compares the sample with the U.S. population distribution for main demographic variables. 49.3 percent (n = 700) of the participants were female, 50 percent (n = 708) were male, and 0.7 percent (n = 10) of the participants identified themselves as another gender. Participants were aged 16 years or older, with an average age of 37.2 years. The age distribution of the sample slightly shifted towards younger age groups. The sample had a larger proportion of drivers aged 25–39 (47.2 percent) than the corresponding value in the U.S. population (20.3 percent). The sample also underrepresented drivers aged 60 or greater (6.5 percent) compared to the population value (21.3 percent) (U.S. Census Bureau, 2017a, 2018). Participants were divided among five different race/ethnic groups: White (77.5 percent), Black or African American (4.5 percent), American Indian or Alaska native (0.4 percent), Asian (8.8 percent), and other race or ethnicity (8.8 percent). The racial/ethnic sample matched the U.S. population closely, with the exception of the Black/African American sub-population and other race/ethnicity, where the sample proportion was smaller. Finally, the distribution of household incomes in the sample generally matched that of the population (U.S. Census Bureau, 2017b). Since enough data points were collected for each sub-population category as per Krejcie and Morgan (1970), it was concluded that the data were adequate for the purpose of the analysis conducted in this paper.

To examine the quality of the collected data, an internal consistency reliability test was conducted following the classical alpha test proposed by Cronbach (1951). The main purpose of Cronbach's alpha test is to measure the reliability of Likert scale surveys. The higher the value of alpha, the more reliable the data is. The general equation for Cronbach's alpha is given in Eq. (4) (Bland and Altaian, 1997):

$$\alpha = \left[1 - \frac{\sum_{i=1}^{k} s_i^2}{s_t^2}\right]\left(\frac{k}{k-1}\right) \tag{4}$$

where k is the number of items, $s_i^2$ is the variance of the $i^{th}$ item, and $s_t^2$ is the variance of the total score obtained by summing all items. A Cronbach's alpha score that is equal to 0.77 was obtained for the survey. According to Bland and Altaian (1997), a survey with satisfactory internal reliability should have a Cronbach's alpha score of 0.70 or above.

The second survey focused on obtaining experts' perspectives of

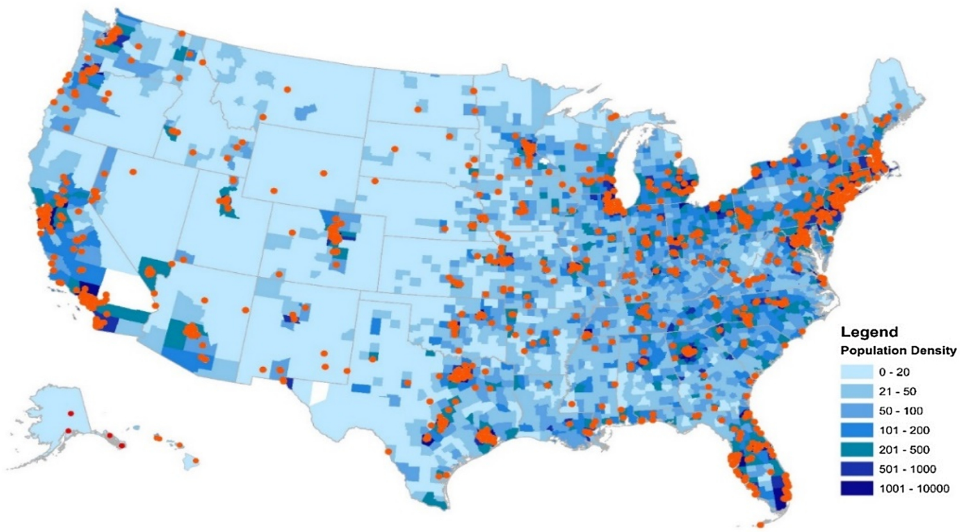


**Fig. 3.** Geocode locations of participants (in orange) across all 50 states (N = 1418). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

SLEM. Another short questionnaire was designed using the Qualtrics software to target professionals in the area of traffic operations, ITS, and safety. The survey included questions soliciting information on the expert's position, level of support for SLEM, and views about the effectiveness of SLEM at enhancing traffic safety and alleviating traffic congestion. Experts were also asked to list main obstacles that may prevent the adoption of this new technology in their regions. Finally, they were asked whether public agencies or private companies should operate such a system. The survey was distributed by email to more than 100 professionals who were identified from web-based professional networks (e.g., LinkedIn) and by visiting the websites of public agencies and consulting firms. Twenty responses were obtained from 10 different states covering 16 different cities. Participants mostly worked as senior traffic operations and safety engineers with expertise in ITS.

## 5. Results and analysis

The baseline data obtained from the first survey were first analyzed using preliminary descriptive statistics. Table 3 provides a summary of participants' demographic information. Most participants (54.5 percent) reported themselves as married or in a domestic relationship. In addition, about 45.5 percent of participants had at least one child. 37.5 percent of the participants reported a bachelor's degree as their highest level of education. Other participants reported their highest education to be some college (27.5 percent), a master's degree (22.4 percent), a doctoral degree (6.6 percent), or high school or less (5.9 percent). Respondents were mostly employed, either full- or part-time (57.7 and 17.5 percent, respectively). Ten percent were students, and only 7.9 percent reported being unemployed. Among the 1418 respondents, 69.5 percent lived in urban areas. The highest number of participants were from Texas (181 participants), California (169 participants), and New York (99 participants), respectively.

Table 4 includes a summary of the participants' commuting experience. About 35.5 percent of participants defined themselves as experienced drivers with more than 20 years of driving. In addition, 61.1 percent of the participants commuted 5 days or more weekly, and 80.7 percent of them commuted less than 25 miles daily. About 81.5 percent of the participants commuted alone, and only 4.9 percent carpooled. Almost one-third of the participants (32.7 percent) had one or more tickets in the last 5 years, and 32 percent also experienced at least one car accident during the same time period. In addition, 13.7 percent of individuals reported that they had points on their driver licenses. Speeding was reported as the most common ticket received by drivers (42.3 percent). Running a red light was the second most common traffic violation (7.3 percent).

Table 5 summarizes the participants' perception of congestion and their attitudes toward different actions to reduce traffic congestion. The majority (72.2 percent) of individuals agreed that congestion is a daily commute problem they face, and about 70.8 percent of them were willing to change their commuting routine to avoid this congestion. Changing their route is the most common action by individuals to avoid congestion (85.3 percent). The second most common action considered by the survey participants is changing the trip departure time (78.7 percent). Telecommuting is the third top action to avoid congestion (55.7 percent). Changing the travel mode and carpooling are the least favored actions among the participants, which was expected and aligned with previous studies (McKenzie, 2015). Based on the obtained data, incentives seem to have great influence on the participants' willingness to change their commuting behavior. Monetary rewards were the most desired option; 88.2 percent of participants agreed that monetary rewards could change their commuting behavior. Insurance discounts were the second most desired incentive chosen by participants (84.4 percent). In addition, 72.8 percent of the participants desired express lane access as an incentive to change their commuting

**Table 2**
Sample and population distribution of selected demographic variables (Nobs = 1418).

| Variable (Values) | Sample Distribution (%) | Population Distribution (%) |
|---|---|---|
| *Gender* (Female, Male)[a] | (50.0, 50.0) | (50.8, 49.2) |
| *Age* [years] (16-24, 25-39, 40-59, ≥ 60) | (16.6, 47.2, 29.7, 6.5) | (12.2, 20.3, 29.7, 21.3) |
| *Annual Household Income [USD]* (< 50k, 50k-99,999, 100k-149,999, ≥ 150k) | (36.8, 35.5, 14.1, 13.6) | (43.1, 29.3, 14.1, 13.6) |
| *Race/ Ethnicity* (White, Black/African American, Native American/Alaskan, Asian, Other)[b] | (77.5, 4.5, 0.4, 8.8, 8.8) | (76.6, 13.4, 1.3, 5.8, 2.9) |

[a] 10 participants who identified themselves to be other gender were considered females.
[b] Hawaiian\Islander races were considered Other.

**Table 3**
Summary of the demographics data of the survey participants.

| Variable | Percentage (%) |
|---|---|
| *Marital Status* (Married, Single, Divorced, Widowed, Separated) | (54.5, 38.8, 4.9, 0.9, 0.9) |
| *Number of Children* (None, 1, 2, 3, > 3 Children) | (54.5, 15.5, 18.3, 7.7, 4.0) |
| *Education* (No High School, High School Diploma, Some College, Bachelor's, Master's, Doctoral) | (0.2, 5.8, 27.5, 37.5, 22.4, 6.6) |
| *Employment* (Full-Time, Part-Time, Student, Unemployed, Retired, Disabled, Other) | (57.7, 17.5, 10.1, 7.9, 3.4, 0.7, 2.7) |
| *Urbanization* (Yes, No) | (69.5, 30.5) |

**Table 4**
Summary of the commute characteristics data of the survey participants.

| Variable | Percentage (%) |
|---|---|
| *Driving Experience [years]* (< 4, 4-10, 11-20, > 20) | (8.5, 29.5, 26.5, 35.5) |
| *Weekly Commuting [days]* (0, 1, 2, 3, 4, 5, > 5) | (11.5, 2.8, 5.5, 10.4, 8.8, 39.4, 21.6) |
| *Commute Distance [miles]* (< 5, 5-9, 10-14, 15-24, 25-39, 40-59, 60-79, > 80) | (22.0, 19.1, 19.5, 20.0, 11.0, 4.8, 1.8, 1.8) |
| *5-Years, Accidents (0, 1, 2, 3, > 3)* | (67.3, 23.2, 6.8, 1.8, 0.9) |
| *5-Years, Tickets* (0, 1, 2, 3, > 3) | (68.0, 21.6, 6.5, 2.7, 1.2) |
| *Commute Mode* (Drive Alone, Public Transportation, Carpool, Other) | (81.5, 6.6, 4.9, 7.0) |
| *Points on DL (No, Yes)* | (86.3, 13.7) |
| *Type of Ticket* (Speeding, Running a Red Light, Running a Stop Sign, Wrong Parking, Speeding & Running a Red Light, Other) | (42.3, 7.2, 4.0, 3.0, 3.3, 40.2) |

performance.

Fig. 4 shows a summary of participants' opinions regarding the three main aspects of SLEM that they were asked to evaluate. Answers were measured on a 5-point Likert scale including strongly agree, somewhat agree, neutral, somewhat disagree, and strongly disagree. First, participants were asked about SLEM's ability to enhance travel safety. 1062 participants (74.9 percent) agreed that such a system would enhance traffic safety in their regions. On the other hand, 147 participants (10.37 percent) did not think that such a system would achieve any improvement. The remaining 209 participants (14.74 percent) had neutral opinions.

Second, participants were asked to evaluate the system in terms of its fairness to drivers. A total of 756 participants (53.31 percent) reported that SLEM is fair to all drivers, and 412 participants (29.06 percent) think that SLEM is not fair. The remaining 250 participants (17.63 percent) had a neutral opinion about the fairness of the system. Third, participants were asked if they agree that the system would improve their driving performance. A total of 868 participants (61.21 percent) believed that the system would help them improve their driving performance, while 246 participants (17.35 percent) thought that the system would have no effect on their driving performance. The remaining 304 participants (21.44 percent) were neutral about the impact of the system on their driving performance.

Fig. 5 summarizes the main reasons participants either supported or rejected the idea of SLEM. In terms of supporting the system, most individuals supported SLEM because it could enhance traffic safety in their regions (N = 690, ˜74 percent). The other top two reasons are the system's ability to reduce congestion (N = 304, ˜32 percent) and its fairness in penalizing low-performing drivers and rewarding high-performing drivers (N = 223, ˜24 percent). As for why participants rejected the system, the majority of the participants indicated that a concern regarding invasion of privacy is the main reason for rejection (N = 354, ˜73 percent). Participants also rejected the system because they were not in favor of restricting their access to roadways (N = 125, ˜26 percent). Some participants also rejected the system because they thought that it would be hard to implement in the real world (N = 88, ˜18 percent).

These main reasons reported by the participants for rejecting SLEM are not surprising. Privacy is a common concern encountered in all CV applications. Effort is underway to ensure information security is unbreachable in all CV-enabled applications. Regarding roadway restrictions, SLEM is expected to be more acceptable because it restricts drivers from accessing some routes based on their driving performance rather than their income level, as implemented in the congestion pricing strategy, which could be viewed as inequitable (Ecola and Ligh, 2009).

**Table 5**
Summary of the congestion perception data of the survey participants.

| Variable | Strongly Disagree (%) | Somewhat Disagree (%) | Neutral (%) | Somewhat Agree (%) | Strongly Agree (%) |
|---|---|---|---|---|---|
| **General View of Driver's Performance** | | | | | |
| Congestion is a Commute Problem | 8.8 | 10.0 | 9.0 | 36.5 | 35.7 |
| Willingness to Change Commuting Routine | 1.6 | 5.4 | 22.2 | 37.9 | 32.9 |
| **Action to Avoid Traffic Congestion** | | | | | |
| Change Time | 4.3 | 10.9 | 6.1 | 43.6 | 35.1 |
| Change Route | 2.4 | 6.3 | 6.0 | 46.9 | 38.4 |
| Change Mode | 16.4 | 24.4 | 17.6 | 28.1 | 13.5 |
| Carpool | 20.4 | 25.7 | 16.2 | 27.3 | 10.4 |
| Telecommuting | 15.8 | 11.9 | 16.6 | 22.2 | 33.5 |
| **Incentives to Motivate Changing Commute Performance** | | | | | |
| Insurance Discount | 1.6 | 3.6 | 10.3 | 36.3 | 48.2 |
| Express Lane Access | 2.9 | 7.8 | 16.5 | 35.5 | 37.3 |
| Free Discounted Parking | 7.0 | 6.3 | 21.4 | 25.2 | 40.1 |
| Free Discounted Tolls | 5.6 | 5.9 | 21.4 | 27.0 | 40.1 |
| Discounted DL Renewal | 4.7 | 8.7 | 20.1 | 31.5 | 35.0 |
| Monetary Reward | 1.3 | 2.0 | 8.5 | 25.1 | 63.1 |

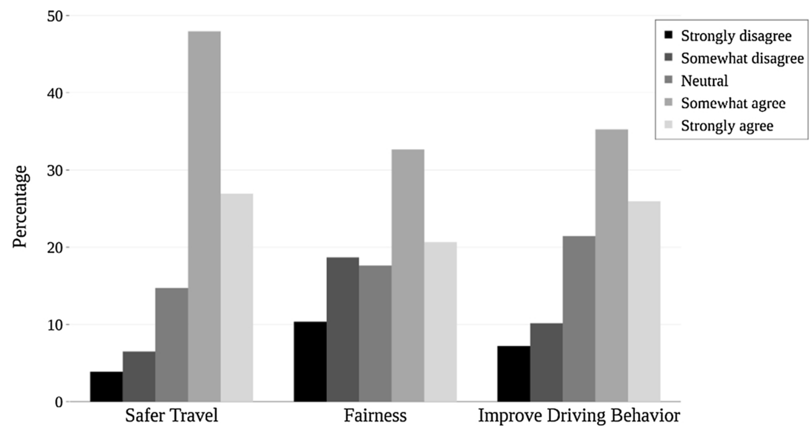


**Fig. 4.** Summary of the participants' opinion on different aspects of SLEM.

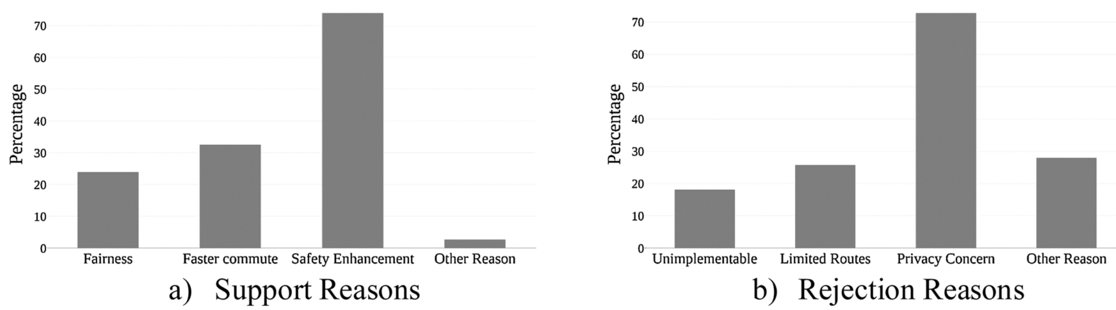


**Fig. 5.** The participants' main reasons for supporting and rejecting SLEM.

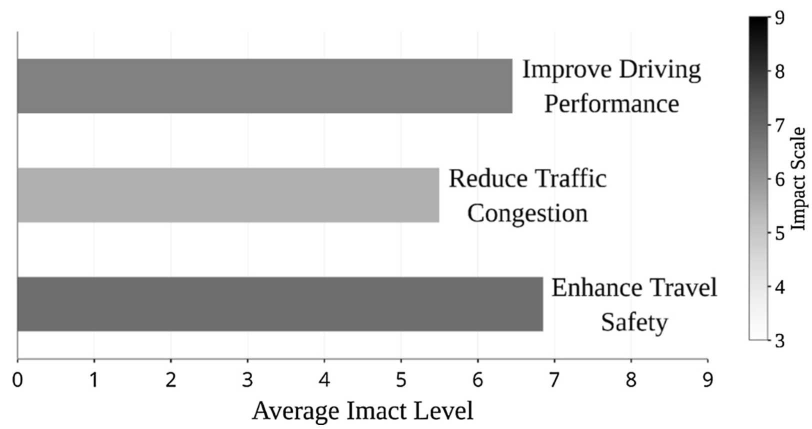


**Fig. 6.** Expert opinion of potential impacts of SLEM.

Next, we present the results regarding experts' perspectives of SLEM. Out of the 20 participants, 12 experts supported the concept of SLEM, and half of them indicated a strong support. Out of the eight experts who rejected the system, three experts indicated strong rejection. Fig. 6 summarizes the experts' perspectives on the effectiveness of SLEM. Experts were asked to give a score between zero (no impact) and 10 (very high impact) on their view of how SLEM can assist in improving the driving performance of the driver population, reducing traffic congestion, and enhancing traffic safety. Experts indicated that they expect the system to enhance the population's driving performance and traffic safety, with average scores of 6.45 and 6.85, respectively. However, they were less certain about the ability of the system to reduce traffic congestion, as indicated by an average score of 5.5. As for the experts' opinions on agencies that should administer such a system, about 65 percent of the experts indicated that public agencies should be in charge of operating such a system, while 15 percent thought that the private sector could operate the system. The remaining 20 percent indicated that public-private partnership could be an effective mechanism to successfully deploy and operate the system. Concern of privacy protection and ensuring fairness could explain the reason for the high percentage of experts who recommended that public agencies be involved in the operation of such a system.

## 6. Modeling public acceptance

In order to measure the level of support among the population and how their characteristics influence that support, a binary logistic regression model was developed (Chao-Ying et al., 2002). The model predicts the probability that an individual supports or does not support the deployment of SLEM by considering an array of independent variables, including the individual's commuting experience, traffic law violation history, familiarity with CV technology, and other demographic variables. The General Linear Model function in the R statistical computing environment was used to develop that model (Venables and

**Table 6**
Comparison among different model specifications.

| Coefficient | Full Model | Model 1 (Univariate) | Model 2 (Selection) | Model 3 (Stepwise) | Model 4 (Reduced) |
|---|---|---|---|---|---|
| Number of Variables | 34 | 29 | 20 | 17 | 11 |
| Number of Parameters | 116 | 85 | 78 | 52 | 28 |
| McFadden's $R^2$ | 0.18 | 0.16 | 0.15 | 0.15 | 0.11 |
| Nagelkerke $R^2$ | 0.29 | 0.26 | 0.25 | 0.24 | 0.19 |
| Hosmer-Lemeshow | 0.81 | 0.44 | 0.20 | 0.76 | 0.32 |
| Log-Likelihood | −741.48 | −761.04 | −769.32 | −770.27 | −806.37 |
| AIC | 1715 | 1692.08 | 1694.64 | 1644.55 | 1668.75 |
| BIC | 1895.39 | 1824.29 | 1815.96 | 1725.43 | 1712.30 |
| Corrected AIC (CAIC) | 1735.83 | 1703.06 | 1703.85 | 1648.59 | 1669.92 |
| Model Prediction Accuracy | 0.73 | 0.71 | 0.72 | 0.72 | 0.70 |

Ripley, 2002). The dataset from this study, which includes 1418 valid responses, was used to develop the model.

Several models were developed that differ in terms of their set of independent variables. Table 6 gives several goodness-of-fit measures for these models. The table also gives the prediction accuracy for each model. A review of these goodness-of-fit measures can be found in Harrell (2015). As shown in the table, the full model considers all available variables. Model 1, the purposeful model, was built by conducting a univariate analysis for each variable and choosing variables with a p-value $\leq$ 0.25 (Bursac et al., 2008). Model 2, the selection model, was built based on the best predictors used for the random forest (ensemble learning method) performed for the dataset. After we included all variables in the random forest model, we picked the top 20 predictors and used them to form the selection logit model. Model 3, the stepwise model, was built using backward elimination, which performs a stepwise model selection by the least Akaike Information Criterion (AIC) value (Venables and Ripley, 2002). As shown in the table, the stepwise model gives the best AIC, Bayesian information criterion (BIC), and $R^2$ values. A Hosmer-Lemeshow value of 0.76 indicates a good data fit for this model (Hosmer et al., 1997). The stepwise model includes variables that measure drivers' willingness to change their driving habits and also examines the set of actions that a driver is willing to take (e.g., change route, mode, or departure time). Model 4 uses a smaller number of predictors. That model includes only variables that measure the driver's willingness to change her/his commuting performance and ignores other variables that measure the driver's level of support for the set of actions she/he may consider. While eliminating a subset of the variables might worsen the value of the goodness-of-fit measure, developing a model with a reduced set of variables simplifies its application. For example, as shown in Table 6, though the AIC measure slightly increases from 1644.55 to 1668.75 in Model 4 compared to Model 3, reducing the number of variables from 17 to 11 makes the model more applicable. The prediction accuracy of this model is comparable to those of other models with a large number of variables.

Table 7 provides additional details on Model 4, the reduced model. The table lists the independent variables, estimated parameter(s) for each variable, and the measures of its significance. The odds ratio (OR) is a measure of association that reflects the effect that each independent variable has on the level of support of SLEM (OR value = 1, no effect; OR $<$ 1, less likely to support; and OR $>$ 1, more likely to support). Two demographic variables considered in the model are the household income and number of children. Other variables considered in this model include:

- Driver's opinion on the level of congestion encountered during her/his commute.
- Number of tickets issued in the past 5 years.
- Presence of any points on driver's license.
- Driver's willingness to change commuting behavior to reduce congestion.
- Driver's anticipation of her/his score if the new system were deployed (this variable gives information on the driver self-assessment of her/his driving performance).
- Driver's familiarity with the CV and telematics technology.
- Driver's acceptance of driving license suspension as a punishment for driving violation (this variable was used to imply the driver's level of acceptance to roadway access restriction).

Based on the model estimation results, respondents who reported congestion to be a commuting problem are 1.92 times more likely to support SLEM than those who did not (OR = 1.92, p = 0.004). Interestingly, respondents who are willing to change their commuting performance are significantly more willing to support SLEM (OR = 3.68, p = 0.01). Traffic law violation history is also a statistically significant variable, which implies that participants who have more violations tend to support SLEM more than those with no or fewer violations (OR = 1.23, p = 0.02). One possible explanation for this outcome is that drivers support SLEM because they believe that it could help them to seek a second chance to improve their driving performance over time and avoid monetary penalties.

Drivers who support DL suspension as punishment for violating drivers are also supportive of SLEM. Those who somewhat agreed with DL suspension are 3.32 times more likely to support the system than those who strongly disagreed, and those who strongly agreed are 4.55 times more likely to support the system (OR = 4.55, p = 0.007). In addition, participants who reported that they are familiar with CV technology are more likely to support SLEM than those who never heard of it before (OR = 1.4, p = 0.02). Furthermore, participants were asked to rate their expected driving score on a five-level Likert scale (poor, fair, good, very good, and excellent). As expected, those who rated themselves with lower scores showed less acceptance of SLEM than those who reported their scores to be excellent (OR = 0.05, p = 0.01). Variables such as number of commuting days and having points on drivers' license were not statistically significant in this model.

Fig. 7 summarizes different hypothesized scenarios based on the logit model presented in Table 7. Initially, the model predicted public acceptance of SLEM to be 81.2 percent. One can notice the difference between the acceptance rate reported by the model and that of the sample. This difference returns to the fact that the model does not have perfect prediction accuracy. As given in Table 6, the model has a prediction accuracy of 70% which means that there is a 30% chance that the model predicts a positive response to a participant who was reported in the sample to reject SLEM (i.e., negative response). We attempted to test the model performance under four scenarios. Each scenario was repeated 50 times to assure accuracy. In Fig. 7, the average value was plotted as a solid curve within the maximum and minimum bound, shown in shaded range. First, as shown in Fig. 7a, we increased the number of drivers who experience daily congestion from 72.2 percent (the base scenario) to over 95 percent and found that the acceptance of SLEM increased from 81.2 to 84.9 percent. Second, we tested the relationship between CV familiarity and the level of

**Table 7**
The logistic regression model results.

| Coefficient | Estimate | Odds Ratio | 95% CI | Z Value | P-Value |
|---|---|---|---|---|---|
| **Driving Experience *(Reference* = less *Than 4 Years)*** | | | | | |
| 4-10 Years | −0.68 | 0.51 | (-1.19, -0.2) | −2.70 | 0.01 |
| 11-20 Years | −0.83 | 0.44 | (-1.35, -0.33) | −3.20 | 0.00 |
| More Than 20 Years | −0.68 | 0.5 | (-1.21, -0.18) | −2.6 | 0.01 |
| **Weekly Commuting *[Days]*** | 0.05 | 1.05 | (-0.01, 0.11) | 1.54 | 0.12 |
| **Number of Tickets [Last 5 Years]** | 0.21 | 1.23 | (0.03, 0.39) | 2.30 | 0.02 |
| **Points on DL (Reference = No)** | | | | | |
| Yes | 0.39 | 1.48 | (-0.04, 0.84) | 1.76 | 0.08 |
| **Congestion is a Commute Problem *(Reference = Strongly Disagree)*** | | | | | |
| Somewhat Disagree | 0.31 | 1.36 | (-0.22, 0.84) | 1.14 | 0.25 |
| Neutral | 0.77 | 2.17 | (0.21, 1.34) | 2.69 | 0.01 |
| Somewhat Agree | 0.65 | 1.92 | (0.21, 1.09) | 2.88 | 0.00 |
| Strongly Agree | 0.34 | 1.41 | (-0.11, 0.79) | 1.51 | 0.13 |
| **Willingness to Change Commuting Routine *(Reference = Extremely Unlikely)*** | | | | | |
| Somewhat Unlikely | 0.40 | 1.49 | (-0.67, 1.5) | 0.73 | 0.47 |
| Neutral | 0.43 | 1.54 | (-0.54, 1.45) | 0.86 | 0.39 |
| Somewhat Likely | 1.02 | 2.77 | (0.04, 2.03) | 2.03 | 0.04 |
| Extremely Likely | 1.3 | 3.68 | (0.32, 2.32) | 2.58 | 0.01 |
| **DL Suspension as Punishment *(Reference = Strongly Disagree)*** | | | | | |
| Somewhat Disagree | 0.80 | 2.22 | (-0.54, 2.17) | 1.17 | 0.24 |
| Neutral | 1.09 | 2.99 | (-0.1, 2.33) | 1.78 | 0.07 |
| Somewhat Agree | 1.2 | 3.32 | (0.1, 2.35) | 2.12 | 0.03 |
| Strongly Agree | 1.52 | 4.55 | (0.42, 2.66) | 2.69 | 0.01 |
| **CVs Familiarity *(Reference = No)*** | | | | | |
| Yes | 0.34 | 1.40 | (0.05, 0.62) | 2.31 | 0.02 |
| **Expected Score *(Reference = Excellent)*** | | | | | |
| Poor | −3.05 | 0.05 | (-6.15, -0.77) | −2.46 | 0.01 |
| Fair | −1.67 | 0.19 | (-2.42, -0.93) | −4.41 | 0.00 |
| Good | −1.16 | 0.31 | (-1.53, -0.8) | −6.26 | 0.00 |
| Very Good | −0.72 | 0.49 | (-1.02, -0.42) | −4.7 | 0.00 |
| **Number of Children** | 0.17 | 1.19 | (0.05, 0.3) | 2.83 | 0.00 |
| **Household Income *(Reference = < $50,000)*** | | | | | |
| $50,000-$99,999 | 0.24 | 1.27 | (-0.04, 0.51) | 1.66 | 0.10 |
| $100,000-$150,000 | 0.58 | 1.79 | (0.18, 0.99) | 2.83 | 0.00 |
| > $150,000 | 0.68 | 1.98 | (0.25, 1.13) | 3.03 | 0.00 |
| **Outcome Levels** | | | | | |
| Support/Do Not Support | | | | | |

acceptance of SLEM. Based on the results in Fig. 7b, increasing the familiarity rate from 30 percent to over 92 percent increased the acceptance from 81.2 percent to approximately 92 percent. Third, as shown in Fig. 7c, increasing the proportion of safe drivers from 78.5 percent to over 95 percent increased the acceptance of SLEM from 81.2 percent to over 88.5 percent. Finally, as given in Fig. 7d, we increased the number of drivers who have an income of $100,000 or more from 27.8 percent to over 92 percent, which increased acceptance of SLEM from 81.2

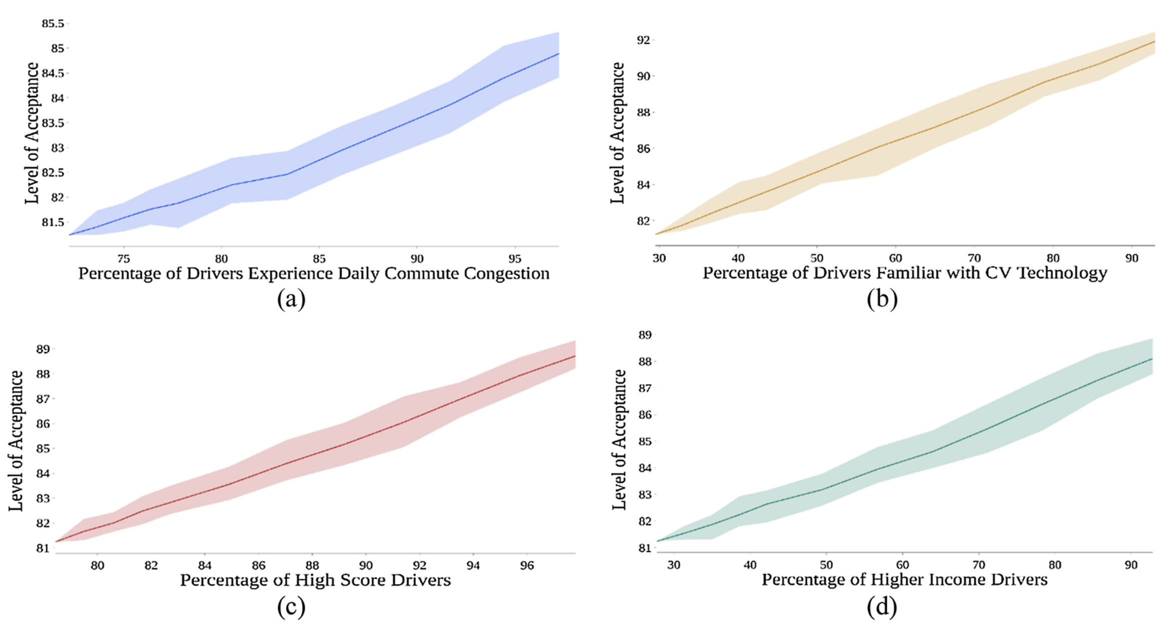


**Fig. 7.** The acceptance of SLEM under different operational scenarios.

percent to about 88.1 percent. Given that, income is usually correlated with level of education, this result implies that SLEM would be more accepted in communities with high level of education.

This analysis provides several insights about acceptance of SLMS. A broad spectrum of actions needs to be instituted by policymakers and institutions, including education and partnerships with transportation agencies and manufacturers to raise public awareness of the safety advantages of SLMS. Educating people about CV technology is a key element of achieving this goal, since this study revealed that more than 70 percent (N = 1000) of the participants were not aware of CV technology. Although acceptance of the SLMS was 65.7 percent, it is necessary to mention that 15.5 percent (N = 221) reported that privacy concerns were their only reason for rejecting this policy, which emphasizes the fact that raising awareness and educating the public could boost the acceptance of this policy to over 80 percent. In addition, about 2.19 percent (N = 31) of participants reported that they rejected the SLMS because they believed it could not be deployed. Addressing concerns over privacy and demonstrating an operational system could increase the public acceptance to over 83 percent.

Several issues related to the deployment of SLEM are worth discussion. First, the SLEM is an autonomous system with built-in traffic violation detection capabilities. These capabilities could be expanded through installation of appropriate sensors to detect other severe violations, such as driving under influence and hit-and-run incidents. Expanding these capabilities would significantly reduce dependence on traditional policing operations for enforcing the law against these felonies. Second, intensive research will be required to determine the weight of each detected traffic violation in the overall score assigned to each driver. These weights could vary by community or based on the prevailing traffic conditions in the network. For example, a single occupancy vehicle in an HOV lane might be assigned a higher penalty in the peak periods as compared to that assigned outside the peak periods. Third, the overall purpose of SLEM is to improve compliance with driving laws in a more equitable way. Therefore, differentiating between innocent and intentional violations is important for achieving public trust of SLEM. Fourth, the score could be extended to incorporate other factors in addition to driving performance. The score could include measures such as the vehicle's level of maintenance as an incentive for drivers to routinely maintain their vehicles. In addition, incentives could be offered for drivers to improve their scores. For example, drivers who reduce the total number of miles traveled, reduce their traveled miles in the peak period, increase their dependence on transit and non-motorized vehicles could be eligible for score improvements.

## 7. Conclusion

This paper presents a conceptual model and evaluates public acceptance of a novel score-based traffic law-enforcement and network management system (SLEM). The system assigns a real-time score for each driver that reflects their driving performance monitored over time. Different from current systems that issue tickets to violating drivers, the proposed system adopts a mechanism to reward high-performing drivers and penalize low-performing drivers. The mechanism is in the form of a route guidance system that restricts low-score drivers from accessing certain roadway segments that are strategically selected in the network. High-score drivers are rewarded by experiencing less congestion and a higher level of safety on these roadway segments, while low-score drivers are directed to use alternative routes.

To measure public acceptance of SLEM, a nationwide survey study was conducted. The results showed about 65.7 percent of the survey participants supported the implementation of SLEM in the real world. Traffic operation and safety experts supported the concept at a rate of 60 percent. Participants reported that their main reason for that support was an expected increase in roadway safety and reduction in traffic congestion. On the other hand, participants who did not support the new system indicated that concerns about privacy violations were their main reason for not accepting the system. Several logistic regression models were developed to examine the main variables that affect public acceptance. In general, drivers with higher income and those with children were supportive of the new system. In addition, drivers who (a) reported congestion as a commuting problem, (b) indicated that they are familiar with the CV technology, or (c) agreed that license suspension is an effective punishment were also highly supportive of the new system. This research can be extended in several directions. Effort is underway to develop a comprehensive mathematical formulation to model the system presented in this paper and to develop an efficient methodology for this mathematical model. In addition, sensitivity analyses to examine how public acceptance levels change with shifts in operation conditions and policy scenarios should be conducted.

## Declaration of Competing Interest

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

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