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On the Interest of Extending Internet of Behaviors to Internet of Habits: A Preliminary Exploration

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Abstract

We are investigating in this paper the issue of managing driving behaviors. In spite of the intensive research works that have addressed this issue, there is still a need for further investigations concerning the changing magnitude of the behaviors, their impact, as well as their inter-relations. Within this context, we are proposing in this paper a new approach for driving behavior management via the concepts of the Internet of Driving Behaviors (IoDB) and the Internet of the Driving Habits (IoDH). We are particularly aiming to inspect driving behavior scores and identify those repetitive aggressive conducts that are becoming long-lasting habits. In order to prevent and/or heal any driving habits that would increase road traffic risks and crashes, we are proposing the Invest-Prevent-Heal-Accompany process that uses the concepts of Confusion Driving Matrix and Confusion Behavior Matrix to investigate the reasons and causes of traffic homogeneity and driving scores. We explore the interest of the proposed approach using a dataset of 942 trips of 252 drivers collected from a governmental organization at Muscat city, Oman.

Keywords: Type your keywords here, separated by semicolons ;

1. Introduction

Numerous studies have reported alarming facts on the huge human and economic losses as well as on the heavy social impact of Road Traffic Crashes (RTCs) worldwide [19]. In order to deal with these facts, several works have investigated alternatives to predict, prevent, and mitigate the impact of RTCs. On the one hand, extending the existing road infrastructure is so far regarded as an expensive investment that will not necessarily accommodate the swift in-

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crease of transportation and mobility demands. On the other hand, increasing attention is being paid to extending the implementation of Intelligent Transportation Systems (ITSs), which have arisen as an auspicious solution to improve the quantity and the quality of road traffic flow as well as to enhance access to traffic and transport information with the help of next-generation technologies [6]. As an important target of ITS is related to the automation of car-driving activities, it is very important to create effective solutions for the identification and monitoring of driving behaviors. It was, indeed, recognized that these solutions are capable of improving road traffic and reducing its related risks [25]. The identification of driving behaviors has been investigated by a wide range of research works. These works have used numerous approaches relying, for example, on statistical analysis, empirical studies, artificial intelligence solutions, etc. (e.g., [12, 28]). The approaches have used data which are collected from four main sources [3]: Self-reporting questionnaires, video and image processing, instrumented cars, and dedicated mobile apps implemented on smartphones. In order to improve driving behaviors, several solutions have focused on providing drivers with feedback about their performance. Driving scores were recognized to be a relevant option that does not result into any significant cognitive burden to the driver [33]. In order to calculate these scores, many research works have proposed solutions to calculate these scores (e.g., [21, 27]). In spite of the complexity of this task resulting from the difficulty to quantify the factors impacting the driving behaviors, these solutions have presented encouraging results. Nevertheless, little efforts were spent on foreseeing the dynamics of these scores and the evolution of their related behaviors. More precisely, no existing work has addressed the issue of aberrant behaviors transforming into long-lasting driving habits. We argue that this issue is of paramount importance, particularly for any approach that attempts to prevent and/or eliminate aggressive behaviors.

To address the aggressive driving behavior transformation into aberrant driving habits, we propose in this paper to model the behaviors as a network of interacting and collaborating entities within the concept of Internet of Driving Behaviors (IoDB). The IoDB is responsible of identifying the driving behaviors and measuring their related scores. Based on their scores as well as their repetitions, some driving behaviors may metamorphose into habits. The monitoring of these habits will happen within the context of Internet of Driving Habits (IoDH). The IoDH is responsible of measuring the habit strengths and the application of appropriate actions to cure the aberrant driving routines. Our main contributions in this paper include: (1) Monitoring driving behaviors based on the concepts of Internet of Driving Behaviors and Internet of Driving Habits; (2) A solution for the untapped issue of driving behaviors transforming into driving habits; (3) Extending the notion of driver behaviors and habits to road behaviors and habits; and (4) A high level process of Inspect-Prevent-Heal-Accompany (IPHA) for the monitoring of driving behaviors and habits that uses the concepts of Confusion Driving Matrix and Confusion Habit Matrix. In the rest of the paper, Section 2 will outline the existing works that have addressed the issue of driving behaviors, driving scores, and driving habits. Section 3 will shed light on our proposed solution. Section 4 will be dedicated to our implementation and results.

2. Related work

Monitoring aberrant drivers' behaviors is the keystone toward safer driving activities [10]. These behaviors can be classified in several ways, such as positive and negative (e.g., [5]) or safe and unsafe (e.g., [9]). A wide range of approaches have been proposed for the identification of driving behaviors. For example, the authors in [34] have proposed a solution that detects abnormal driving behaviors in real-time. The solution uses traffic cameras, the YOLO algorithm, and Kalman filter to track the vehicles' locations via the analysis of consecutive images. The authors in [2] have run the Random Forest (RF) algorithm on two datasets (i.e. Strategic Highway Research Program 2 and Naturalistic Driving Study) and computed the risk profiles of drivers. The authors in [35] have proposed to identify normal and abnormal behaviors by applying the Serial-Feature Network (SF-Net) algorithm on data collected from smartphone inertial sensors (e.g., GPS, gyroscope). The authors in [4] have classified driving behaviors as bump, abnormal, and normal. To this end, they have run the k-Nearest Neighbor (KNN) and the Dynamic Time Warping (DTW) algorithms on smartphone generated data. The authors in [16] have proposed a Convolutional Neural Networks (CNN) approach to determine if driving styles are safe or aggressive by involving speed, signs and maneuver estimations. Furthermore, many research works have been interested in categorizing the drivers' aggressiveness levels (e.g., [37]). These approaches have mainly focused on setting up scores for driving behaviors. The scores are particularly important when they are shared with drivers since they can be comprehended more spontaneously, without any significant cognitive burden [33]. However, the calculation of these scores is not straightforward. According to [22],

this calculation is a two-type problem. In the first type, every segment of driving is categorized as one type from a predefined group of non-ordered driving styles. In the second type, the main goal is to categorize driving into ordered classes or compute a scalar score that sums up the level of risk. In order to calculate the driving scores, authors in [21] have considered some typical impact factors (including speeding, driving time, traffic flow, mileage, and traffic violations). They have then determined the weight of driving indexes using an improved EW-AHP. Authors in [27] have proposed a Safety Index (SI) for the driver where all main elements impacting road traffic crashes are taken into consideration. Authors in [33] have proposed an online scoring procedure that measures driving behaviors based on wheel speeds only. Scores range from 0 to 100, with 0 points and 100 points designate a steadily aggressive and a consistently non-aggressive driving behavior, respectively. The authors in [20] have proposed a model that aggregates drivers' driving data, extracts part of the aberrant behaviors as assessment index, and then applies the entropy weight method as well as the analytic hierarchy process to accordingly obtain and generate the index weight.
To improve the monitoring of driving behaviors, driving scores must be calculated continuously. However, there is no existing study that attempted to investigate if the repetition of the same aberrant behavior would lead to the creation of a longer-lasting abnormal practice. The reasons and results of repetitive behaviors have been explored intensively, mainly in psychology. In addition to appearing as a cognitive catalyst for decision-making [32], habitual behaviors were commonly linked to the frequency of past behaviors [13]. It was also reported that they partially include conscious cognitive assessment of individual's own behaviour [7]. Some research works (e.g., [1]) have highlighted that the chief characteristics of habitual behaviours include the absence of deliberate intent as well as a higher emphasize on environmental signals. Based on our investigations, we argue that driving habitual behaviors have been explored from the perspective of repeated actions and routines which are exhibited from the driver while driving or with respect to the origin and destination of his trips. However, we did not find any work that attempted to study the issue of aberrant behaviors transforming into risky driving habits.

3. Proposed solution

3.1. The Internet of Driving Behaviors

Number	Formula	Score details
(1)	$S(b,v) = \sum_{i=1}^{n} S(b_i, v)$	**Score of the driving behavior b during a specific trip v.** b_i is the ith time the behavior b was exhibited and $i = 1 \dots n$ is the total number of times the behavior b was exhibited
(2)	$S(v) = \sum_{b=1}^{m} S(v)$	**Score of a trip v.** $b = 1 \dots m$ is the total number of behaviors
(3)	$S(b) = \sum_{j=1}^{p} S(b, v_j)$	**Driving score for a specific behavior during all trips done by the driver.** v_i is the jth trip and $j = 1 \dots p$ is the total number of trips
(4)	$S_t(r) = \sum_{b=1}^{q} S_t(b, r)$	**Driving behavior for a given road section r at time t.** where $b = 1 \dots q$ is the total number of behaviors exhibited in r

Fig. 1. Examples of our proposed formulas to calculate driving scores

Driving behaviors have been investigated by a wide range of research works with a specific focus on human factors, like age, stress, and emotion. However, very little attention was given to the interconnection between driving behaviors. For this reason, we propose in this paper to deal with these behaviors as an interacted set of components that result into an Internet of Driving Behaviors (IoDB). The concept of IoB was addressed by several research works (e.g., [15, 11]). In these works, it was agreed that the IoT converts data to information, whereas the IoDB may convert knowledge into genuine wisdom [15]. It was also agreed that IoB combines the Internet of Things, behavioral science, and data science capabilities to ultimately discover insights about individual behaviors and thought patterns. In the specific context of transportation, we define the IoDB as a collection of entities, representing each a specific driver. An entity is responsible of analyzing the behaviors of the driver, investigating their interdependence, and generating any related assessments or scores. The behaviors are identified based on readings from different IoT devices. The main goal of the IoDB entities is to improve the driving experience and reduce driving risks. The structure of an IoDB entity (called IoDBe) is depicted in Figure 2 a. It includes a Perception Module to collect driving data. An Analysis Module will then apply the necessary analytics in order to identify and update the driving behaviors and scores of the driver. Driving behaviors (e.g., acceleration, braking, lane changing, cornering, etc.) can be assessed using several approaches proposed in the literature. In addition to identifying the driving behaviors, the Analysis Module will measure related driving scores. We are proposing in this paper to measure the driving scores from multiple perspectives (Figure 1). Based on the analytics results, the entity will identify the driving services that might be needed from peers or can be proposed to them. Driving services may include accommodating nearby drivers on the road by creating more space for them to change lanes. The request of provision of driving services will be planned, executed, and assessed by the Collaboration Module.

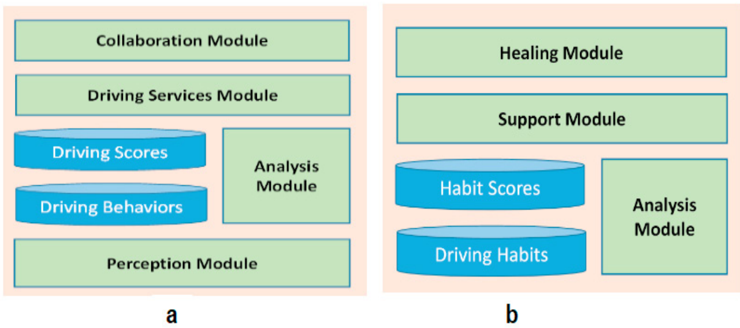

Fig. 2. (a) Structure of an IoDB entity, (b) Structure of an IoDH entity

The idea of the IoDB is to manage the driving behaviors of a given driver and their mutual intra-impacts and/or inter-impacts. The intra-impact refer the inter-relation of the driving behaviors of the same driver. The inter-impacts refer to the driving behaviors of neighboring drivers. For the sake of illustration, let us consider the example of the of Figure 3 where a specific trip may include a variety of driving behaviors. The same illustration can be done for all the trips done by a specific driving. A thorough investigation of these illustrations may reveal some relations between driving behaviors. The same investigation can be done for a specific road section and/or road pattern. In the same way, we can explore the options of impact between driving behaviors within the same spatial extent of the road section.

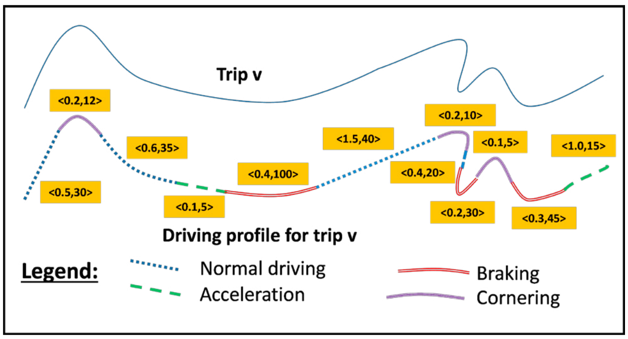

Fig. 3. Illustration of several driving behaviors of one driver with their duration and lengths over a single trip

3.2. The Internet of Driving Habits (IoDH)

Our thorough investigation of the literature is revealing that despite of the intensive investigation of driving behaviors and their related risks on road traffic and road crashes, there are no works that addressed the transformation of behaviors into driving habits. Habitual behaviors are described as automatic reactions prompted by triggers in the environment or by objectives stimulated in individuals' working memories [29]. The absence of reflections on the consequences of behaviors will make habitual behaviors to remain even when an intension of a contradicting goal is created [14]. Several works, particularly based on psychological theories (e.g., [29, 23]), have investigated the concept of habit. From a ubiquitous computing perspective, habits have been commonly referred to the detection and recognition of repetitive behavioral routines and patterns [30], sometimes with respect to designated user contexts [8]. In [36], the authors have used to define habits as the cognitive relations between behaviors and their triggering contexts. The authors have claimed that habits are reinforced via repetitive behaviors that depend in the context. Within the context of road traffic, measuring the strength of driving behaviors and their transitions to habits is still untapped. Modeling the habit strength of a particular driver driving behavior can assist initiatives to predict these behaviors more accurately and support any action to prevent and cure aberrant ones with personalized interventions. The assessment of habits and their strength is mainly achieved based on statistical analysis. Few attempts in the literature have presented computational models to account for the association between habit strength and repetition of behaviors (e.g., [17, 24, 26, 31]). Although these models have been developed for different fields, they result into similar habit dynamics patterns for the dynamics of habits. This result is found to be consistent with the empirical study presented in [18]. We propose to adopt in this paper the formal model presented in [26] and extend it as follows:

$$HS_{harshBraking}(t+1) = \begin{cases} HS_{harshBraking}(t) + HLP + 1, & \text{if } Behavior_{harshBraking} = 1 \\ HS_{harshBraking}(t) * HDP + 1, & \text{if } Behavior_{harshBraking} = 0 \end{cases}$$

In the model above, we replaced the Habit Gain Parameter (HGP) with the Habit Loss Parameter (HLP) reflecting the fact that aberrant behaviors will more likely to lead to risky behaviors. Furthermore, the parameter t refers to the occurrence number of the aberrant behavior (i.e. t=1 means the first time the behavior happened, t=2 the second time the behavior happened, etc.). In order to manage the driving habits, we rely on the concept of Internet of Driving Habits (IoDH). Within this network, every entity (called IoDHe) will have the structure represented in Figure 2 b. This structure includes an Analysis Module that will receive notifications from the driver's entity in the IoDB (i.e., IoDBe). The IoDBe will basically send a notification to the IoDHe including relevant information concerning the transformation of a driving behavior into a driving habit. The IoDHe will carry out the necessary operations in order to assess the strength of the habit and generate its related score. A Healing Module will then be triggered to set up the appropriate actions to cure the aberrant driving habit. This module may rely on the help of a Support Module to find solutions for the habit from peers.

3.3. From drivers' behaviors to roads' behaviors

We are interested in this section in the assessment of the driving behaviors in a given road section through their aggregation and the investigation of their associations and mutual impact. To this end, we propose to use Gini index to measure the purity of driving scores in the road section. When the Gini index gets closer to 1, the driving behaviors are quite similar, regardless of whether they are good or aggressive. When the Gini index gets closer to 0 this means that there is a random relation between the drivers' behaviors. This may mean, for example, that traffic is fluent in some road lanes and congested in others. For the sake of convenience, we propose to normalize the driving scores to make sure that they fit within the scale of [0-1] of the Gini index. When both curves (i.e. Gini and normalized driving scores) are superimposed (Figure 4 a), we can identify if further investigations about the driving behaviors, the road section, or both of them should be carried out. We reflect these thoughts in what we call Confusion Driving Matrix – CDM (Figure 4 b). In the matrix, which is applied for a specific time slot, the Random/Bad section means that the driving behaviors are not homogeneous, which may be a reason for the aggregated bad driving score and thus the aberrant behaviors. The Pure/Bad section means that the driving behaviors are homogeneously bad, for example, due to heavy road traffic, road constructions, or inconvenient road section pattern. The Random/Good section means that although the driving behaviors are not homogeneous, the aggregated driving score is good. This may be explained by a situation where some road lanes have fluid traffic and others are congested. Finally, the Pure/Good section suggests that no further investigations are needed. In order to make use of the concept of CDM, it is important to investigate this issue over time and explore the correlations between the results obtained. For example, if the Gini index is always bad as well as the driving scores then we may conclude that the problem is more likely to be related to the road shape. In this case, additional investigations of the CDM for similar road shapes may lead to the conclusion that the problem could be generalized to the road pattern. If the problem cannot be generalized to the road pattern then we may conclude that bad driving behaviors could be related to specific road traffic characteristics during specific periods of the day. The right decision about the road behavior could then be taken.

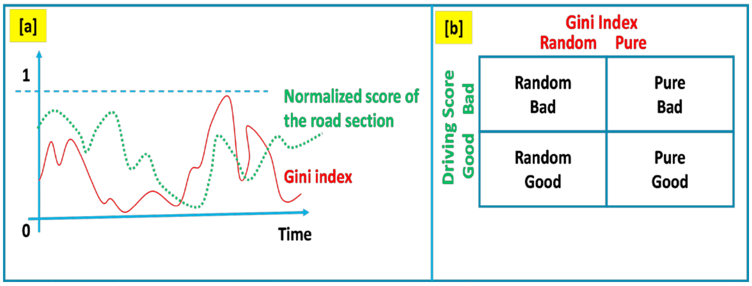

Fig. 4. [a] Superposition of the Gini index on the normalized driving scores; [b] Confusion Driving Matrix

3.4. From drivers' habits to roads' habits

Similarly to roads' behaviors, we are introducing in this paper the concept of road habit. This concept, which concerns a specific period of the day (e.g., from 8:00 am to 8:30 am), can be defined as the aggregation of the habits of the drivers who are crossing this road. The investigations of the habits over the whole period of the day for all the available data would reveal comparable results as for the road's behaviors. We can for example infer if good or bad driving habits are getting stronger or weaker at specific locations, specific times, specific road patterns, etc. Similarly to the CDM, we define the concept of Confusion Habit Matrix (CHM). The same investigations as for the CDM will be performed and published in a future work.

3.5. The Inspect-Prevent-Heal-Accompaniment (IPHA) cycle

The main purpose of investigating the issue of driving behaviors is to identify options to improve road traffic while reducing related risks and losses. We particularly focus in this paper on aberrant behaviors and habits. To this end, we propose an action plan where data about driving behaviors are collected and aggressive behaviors are identified. These behaviors will then be inspected to see if they are transforming into habits. Appropriate actions must be taken in order to prevent this transformation. The actions may, for example, include improving the road infrastructure, proposing training to drivers, applying personalized policies to drivers, etc. They will be specified based on the investigations of the drivers and road behaviors. If prevention actions are unsuccessful to avoid the aberrant driving behavior becoming a habit then further actions are needed to repair this behavior. In addition to removing driving points, mandatory trainings and/or preventions from driving at specific times and/or locations may be applied. During this step, related driving measures will be collected and continuously studied. When these measures show that the aberrant habit was broken over a predefined period as per current regulations (these regulations will differ from one country to another), driving restrictions which were earlier imposed on the driver can be lifted gradually and appropriate re-assessment of driving behaviors will be applied. These actions are done during the Accompaniment step where relevant feedbacks are given to the driver to support the transition back to normal driving behavior.

4. Preliminary experimental results

In order to explore the interest of our proposed framework, we conducted an experimental study based on a real trajectories dataset that has been collected in the city of Muscat, Oman. The objectives of the experiment is to explore if our proposed framework can generate habits from a set of real driving behaviours.

4.1. Dataset

Our dataset consists of 910748 GPS records of 252 drivers' trips collected over two years from July 2020 to January 2023 from a local governmental organization. Each data point consists of a geo-location (latitude, longitude), timestamp and driver-id. The data is heavily distributed in the northeast of Oman around the capital Muscat and small distribution in the southwest of Oman around Salalah. The sampling rate of the GPS ranges from 3 seconds to 1 minute.

4.2. Results

We report in Figure 5 numbers based on our dataset concerning the harsh braking per day and the harsh braking per hour, respectively. As we can see, the number of occurrences of this behavior is limited during Friday and Saturday, which corresponds to week-end. During the rest of the days of the weeks, this number is relatively high. On Figure 5 b, we can remark that the highest number of harsh braking events is happening around 9:00-10:00 am, which is commonly a very active road traffic time-slot in Muscat.

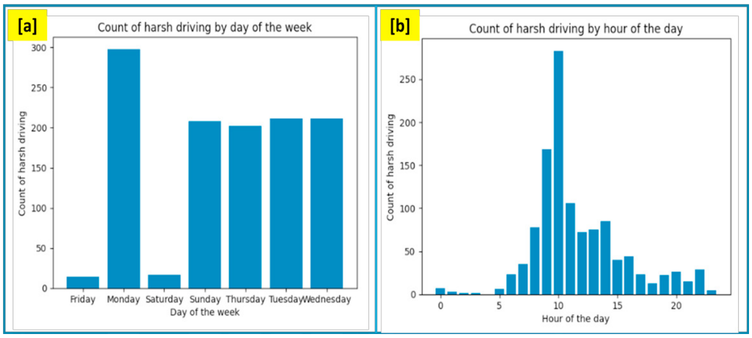

Fig. 5. [a] Harsh braking by day; [b] Harsh braking per hour

In Figure 6, we present the heats maps of harsh acceleration and harsh braking for one driver in two different regions of Muscat. In Figure 7 we illustrate the driving habits of a sample of three drivers: 1) a driver who doesn't have habits, 2) a driver who developed a habit and 3) a driver whose habit has been healed.

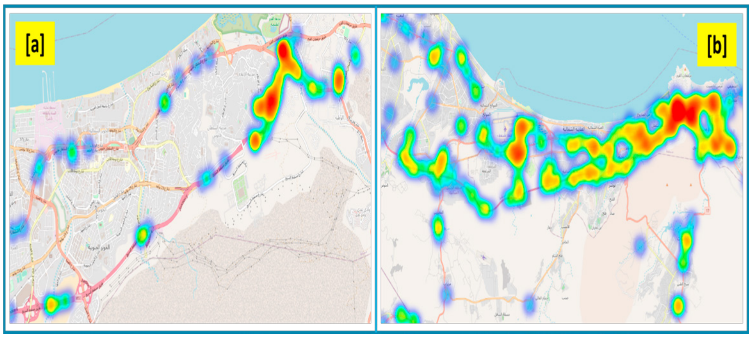

Fig. 6. For one driver and one trip: [a] Heat map of harsh acceleration; [b] Heat map for harsh braking

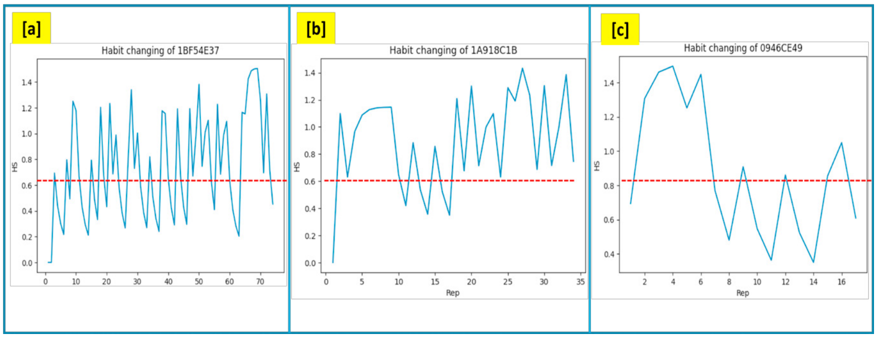

Fig. 7. Illustration of driving score: [a] fluctuating score; [b] behavior transforming into a habit; [c] Habit being cured (Remark – The dashed line represents the habit score threshold)

The investigation of driving scores computed from our dataset has revealed that a number of drivers have developed harsh braking and harsh acceleration habits. Although this number is limited, it confirms that aberrant driving practices can be developed over time. It is also confirms the need for additional investigation to predict, prevent, and cure them.

5. Conclusion

Monitoring driving behaviors has been recognized as a relevant alternative to improve road traffic and reduce related risks. Several research works have focused on the identification of these behaviors as well as their classifications. Specific attention was given to aberrant behaviors, including harsh braking, harsh acceleration, and harsh cornering. In order to measure the level of these abnormal behaviors and as well as their impact, many works have proposed solutions to calculate related scores. These scores are particularly important in providing drivers with simple relevant information that do not result into any specific cognitive burden. Our extensive review of the current literature revealed that the existing research works did not give any attention to the transformation of the aggressive behaviors into long-lasting practices. For this reason, we proposed in this paper to extend the investigation of driving behaviors to driving habits. Our main goal was to inspect aberrant behaviors that would become aberrant driving habits and prevent this transformation. To this end, we proposed to model the driving behaviors as an Internet of Driving Behaviors (IoDB) and model the driving habits as an Internet of Driving Habits (IoDH). We also proposed to investigate not only the drivers' driving behaviors and habits but also road behaviors and habits. We proposed the concepts of Confusion Behavior Matrix and Confusion Habit Matrix as well as the process of Inspect-Prevent-Heal-Accompany (IPHA) to manage the transitions between the IoDB and the IoDH. Our preliminary explorations confirmed the need to further investigate the formation of aberrant driving habits. Our future works will focus on implementing our proposed IoDB, IoDH, and the IPHA process to improve the monitoring of driving behaviors.

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