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Differences of Malaysian Bus Drivers Behaviours in Speeding, Acceleration and Deceleration Under Various Driving Conditions

Ali Mohammed
Department of Civil Engineering, Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia (UKM), Bangi, Selangor 43600, Malaysia.

Muhamad Razuhanafi Mat Yazid*
Department of Civil Engineering, Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia (UKM), Bangi, Selangor 43600, Malaysia.
Corresponding author: Muhamad Razuhanafi Mat Yazid

Abstract:

Understanding driver conditions through their driving behaviour are, therefore, the key element to ensure safe driving. Especially in this transition era, vehicles have gradually been equipped with various levels of automation systems. This study aims to investigate the significant difference in Malaysian express bus drivers' behaviours in terms of speeding, acceleration and deceleration. The study is comparing the behaviours between day/night, weekends/weekdays, and road type (east, north, south). The study employed a fully quantitative research design. The data were collected using the smartphone application "Digital Dashboard GPS Pro application" using GPS technology collect the data. The study was conducted in Malaysia. The data was collected from 36 bus express trips around. The data were analysed using SPSS. 23. The independent t-test analyses and one-way ANOVA were used to analyse the data. The findings showed there is no significant difference in express bus driving behaviours in terms of speeding, acceleration and deceleration between weekends and weekdays, and road type. However, the findings showed there is a significant difference in drivers' behaviours between day and night in terms of Overspeed. This research contributes significantly to the limited studies that examine the bus drivers' behaviours towards achieving road safety and avoiding road fatalities.

Keywords: Bus drivers' behaviours, speeding, acceleration, deceleration, significant difference.

Introduction

Road safety could lead to great driving by estimating the human behaviour of the drivers which could be affected on the number of road accidents in many places [1]. Moreover, 1.3 million fatalities and 50 million injuries were recorded every year over the world [2]. In this trend, the main reason for death among young people between the ages of 15 and 29 is road accidents [3]. Besides, traffic accidents were considered as the third cause of killing after cardiovascular and mental illnesses which were reported by the World Health Organization (WHO). For instance, in the United States, about $99 billion of medical treatment costs were caused by accident fatalities in 2010 [4]. Also, the aggressive behaviour of the driver such as fast driving, acceleration, and instance breaking could be affected on road safety [5].

To maintain road safety and get the final score of human driver behaviours, a powerful technique was used called Driver Monitoring and Analysis (DMA) which involved information gathering of aggressive behaviour of the driver, then this information will be passed through computer modelling to acquire the desired score. In addition, Driver Behavior Profiling (DBP) is considered as another technique for analyzing the behaviour of drivers which was used recently [6].
In addition, the cost of car insurance depends on the individual behaviour using different insurance policies such as Usage-Based Insurance (UBI), and Pay-HOW-YouDrive (PHYD) [7]. Consequently, the driver who has a high safety score could be awarded a low cost of car insurance. Also, behaviour profiling could provide useful information to estimate the cost of insurance such as gender and marital status of the drivers. On the other hand, freight management could use the analysis of the driver's behaviour on a real-time basis. So, the owners of freight businesses could understand the behaviour of their drivers. Moreover, the freight system could be connected to the safety score using smartphones to inform the driver about accidents, reckless, and unsafe driving on the roads [8]. The growth of urban cities as shown by the recent statistics from 746 million in 1950 to 3.9 in 2014 motivated the construction of a modelling system for driver behaviour in the last decades. Consequently, more people migrated to cities and the transportation infrastructure
Human error. As a result, Driver Behavior Modeling (DBM) was mainly used to predict driving manoeuvres, driver intent, vehicle and driver state, and environmental factors [9]. On the other hand, the Intelligent Transport System (ITS) is considered as one of the research fields that attempt to incorporate the latest information technologies into the transportation domain to show various advantages. These advantages involved decreasing traffic congestion, avoiding accidents, and vehicle flow facilitating. Thus, a large number of technologies could be found such as Global Positioning System (GPS), mobile network, Radio Frequency Identification (RFID) which serve road safety by sharing and exchanging the required information. ITS was involved in many studies which were related to the aspects of roads, vehicle, and driver behaviour. Thus, a driver played a considerable role in road events specifically in traffic congestion or fatal accidents [10]. Moreover, driver aggressiveness represents the main cause of traffic accidents, and the detection of such aggressive behaviour shows a significant application in ITS by developing the capability of detecting systems to improve traffic safety [11].

Literature Review

Inappropriate driving behaviours pose a serious threat to traffic safety. In a 2015 report published by the World Health Organization (WHO), more than one million people worldwide lost their lives as a result of issues related to non-safe driving conduct of individuals [12]. More specifically, the lack of a safe driving attitude and failure to obey traffic laws have contributed enormously to fatal accidents and injury accidents [13]. The threat of unsafe driving conduct, however, can be deflated with improvements in the data and techniques used for identifying and classifying driving behaviours [14]. With intelligent transportation systems (ITS) that can identify non-aggressive driving habits, highways can be devoid of traffic congestion (Peng, Fields, Rutkowski, Bowne, 2011). Apart from minimizing traffic accidents, identifying appropriate driving styles can also aid the reduction of energy consumption [15]. Previous studies have identified and classified driving behaviours with various sources of data. In [16] data for driving, classification was obtained from On-Board Diagnostics (OBD) systems. These computer systems are installed on vehicles to collect acceleration and speed data for driving classification [14]. Even though OBD technologies are reliable in collecting information for driving categorization, a considerable number of automobile owners do install them on their vehicles because they are intrusive, creepy, and expensive. These problems, nonetheless, can be overcome with the use of smartphones for data collection. Smartphones are portable and user-friendly, and they provide accurate speed data for driving classification using AI techniques. Researchers have also used several qualitative approaches to acquire data for driving classification. Recent studies also suggest that behaviour questionnaires can be utilized in identifying non-professional drivers and non-professional drivers [17]. While this qualitative method can help researchers to understand the emotions, sentiments, and motivations of individuals who engage in aggressive or non-aggressive driving behaviours [18], it is time-consuming and susceptible to bias [19][20]. A combination of smartphone data and questionnaire data has the potential to improve the classification of driving behaviours using machine learning techniques.

Related Work

The DB examination has been the subject of extensive research during the last few years. Traditionally, a driver-centric approach has been used to better identify the specific individual characteristics that lead to drivers' greater risk, with a particular focus on their DB. In order to capture the driver's physiological condition and driving ability in real-time scenarios [21] created a flexible alertness monitoring system. Various physiological measurements have been gathered in order to detect stress responses or forecast future values[22]. Other traits include motion sickness [23] and various psychological diseases such as Autism Spectrum Disorders, Attention-Deficit/Hyperactivity Disorder [24]and Bipolar Disorder [24] were evaluated in order to determine their impact on driving safety. The nature and breadth of a driver's psychosocial features, including personality qualities, have begun to be considered by road safety practitioners to better understand the risky conduct that contributes to crash involvement and violations. Analyzing driving profiles like age, gender, and other demographic variables is part of studying DB. In DB and safety research, senior drivers have received a lot of interest, especially in nations where the population is ageing. Relevant researchers focused to learn more about the contributions of easily measured age-related characteristics that may be used to construct evaluations and interventions to help people with driving impairments [25]. Ben-Ari and Yehiel investigated several demographics and personality traits using a multi-dimensional method to integrate sociodemographic and motivational aspects in order to present a more complete picture of DB [26]. Several attempts have also been made to look at the driver's operational decisions that could lead to unintended unsafe behaviors like vehicle handling or traffic maneuvering blunders.

Despite the fact that embedded vision sensors were used, a driver foot gesture modelling and prediction framework was proposed. parameters from the Controller Area Network for car sensors (CANbus). The states of the brake and acceleration pedals, for example, reveal information regarding the actions of the feet, Foot movement detected by vision-based sensors before and after a pedal press can provide useful information for a better semantic comprehension of driver states and for predicting when a pedal is pressed before it happens [27] A significant amount of research has been devoted to evaluating driver behaviour in dilemma zones, as they become very dubious and may make an incorrect judgment, which could result in a right angle accident or a rear-end collision. [28] investigated the formulations of the DVE three parameters, namely the driver, the vehicle, and the environment model, in order to design an inserted driver-vehicle interface with the goal of increasing the effectiveness and safety gains of advanced driver assistance systems while reducing workload and omissions caused by nomad gadgets and in-vehicle information systems. Driver features such as head, eye, and hand cues were used to determine the driver's activity level and evaluate the driver's performance in on-road conditions using a Support Vector Machine (SVM) classifier [29] Artificial Neural Networks [30], Logistic regression [31], and Dynamic Bayesian Networks have all been investigated in the field of sleepiness recognition [32].

Despite the relevance of these discoveries and their contribution to the literature, it appears that an effort to offer a fuller and more comprehensive picture of the harnessed ML approaches, as well as the measures accounted for DB evaluation, has yet to be made. We believe that this type of research is the most important to investigate because it lays forth a conceptual framework that incorporates numerous variables that influence a driver's behaviour in order to have a thorough understanding of the DB within the DVE system in which the drivers operate.

Naturalistic Driving Behaviour (real-time data collection)

Naturalistic driving data are important and indispensable resources for driver behaviour learning and understanding. Unlike other autonomous driving tasks (e.g., object detection, vehicle tracking, trajectory prediction, etc.) that have many well-annotated open-source datasets. A strict definition of naturalistic driving data is that data should be collected using participants' familiar vehicles with several cameras and sensors installed, which capture vehicle manoeuvres and driver behaviours in an unobtrusive style. However, such data collection will be costly and time-consuming to practice, as well as complex to coordinate. Therefore, only a few datasets fit this definition such as Strategic Highway Research Program 2 (SHRP 2) data. Naturalistic driving data is preferred because it is important to analyze driver's driving manoeuvres and reactions in real-world traffic scenarios.

The Currents Study

The study aims to answer the following research question

1. What is the significant difference in express bus drivers' behaviours in speed, acceleration, and deceleration between day/night, weekdays/weekends, and road type?

To answer the research question, the following hypotheses were formulated:
H1: There is no significant difference in bus drivers' behaviours between weekdays and weekends in terms of speed.

H2: There is no significant difference in bus drivers' behaviours between weekdays and weekends in terms of acceleration.
H3: There is no significant difference in bus drivers' behaviours between weekdays and weekends in terms of deceleration.
H4: There is no significant difference in bus drivers' behaviours between day and night in terms of speed.
H5: There is no significant difference in bus drivers' behaviours between day and night in terms of acceleration
H6: There is no significant difference in bus drivers' behaviours between day and night in terms of deceleration.
H7: There is no significant difference in bus drivers' behaviours between road types in terms of speed.
H8: There is no significant difference in bus drivers' behaviours between road types in terms of acceleration.
H9: There is no significant difference in bus drivers' behaviours between road types in terms of deceleration.

Methodology

The study employed a fully quantitative research design. The data were collected using the smartphone application "Digital Dashboard GPS Pro application" using GPS technology to collect the data for Malaysian express bus drivers' behaviours. The study was conducted in Malaysia. The data was collected from 36 bus express trips around Malaysia divided as follow: 18-day trips and 18-night trips, 18-weekend trips, 18 weekdays trip, 12 trips to the north, 12 trips to the south, and 12 trips to the east. The bus company were selected randomly. The data were analysed using SPSS. 23. The independent *t*-test analyses and one-way ANOVA were used to analyse the data. Generally, the incorporation of t-test allows an evaluation between the two sets of data, the data from the students as well as the teachers, to discover if they are substantially varied. However, the independent t-test was used to explore the significant difference between teachers and students' usage of digital technologies and digital literacy.

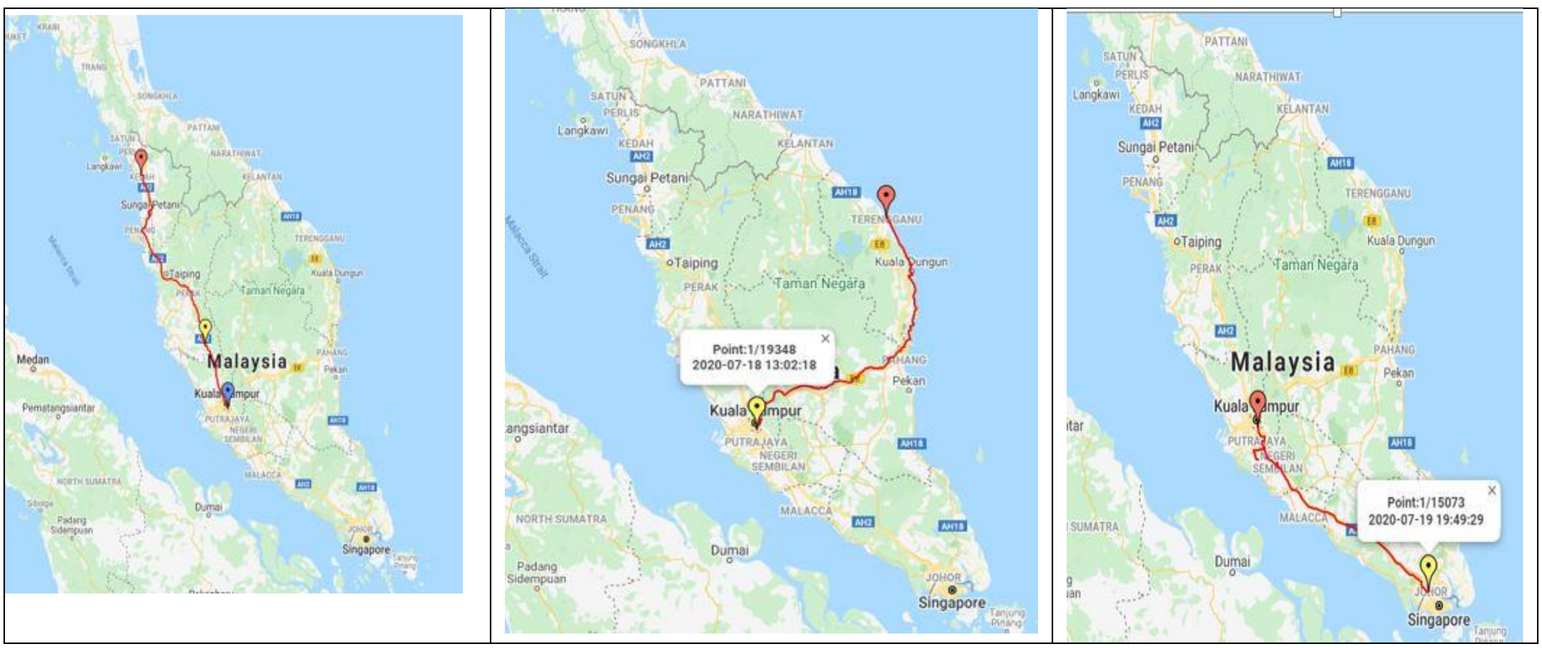

Figure 1. Sample of Road trips in Malaysia

Findings and Discussion

1. **Significant difference between Weekend and Weekdays (Hypotheses 1, 2, 3)**

This section presents the findings of the hypotheses (1,2,3), which is to investigate the significant difference in bus drivers' behaviours between weekend and weekdays. To test the hypotheses, the independent t-test was used. The results are presented in Table 1. As the table shows, the independent t-test shows that all the variables achieved a significant level as follows: in terms of speed ".807", acceleration ".0720", deceleration ".906". Therefore, based on the criteria of ($P > 0.05$) if the P-value is higher than 0.05 indicates that there is no significant difference between the sampled (weekend and weekday), it can be concluded that the null hypotheses regarding the use significant difference between bus drivers behaviours are supported and the alternative hypotheses are rejected.

Table 1. Significant difference in bus drivers' behaviours between weekdays and weekends

Paired Samples Test									
		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	Weekend (% over) – weekday (% over)	4.91667	46.66744	19.05	-44.057	53.89114	.258	5	0.807
Pair 2	Weekend (Aggressive DCC%) – weekday (Aggressive DCC%)	.000077	.00047	.0001	-.0004	.0005	.379	5	0.720
Pair 3	Weekend (Aggressive ACC%) – weekday (Aggressive ACC%)	-.000012	.00025	.0001	-.0002	.0002	-.124	5	0.906

Summary of Hypotheses 1, 2,3 testing

Situation	**P-value**	**Decision**
Weekend (% over) weekday (% over)	p-value =0.807>0.05	-Accept the null hypothesis -There are no significant differences between the mean (weekend, weekday)
Weekend (Aggressive DCC%) weekday (Aggressive DCC%)	p-value =0.720 >0.05	-Accept the null hypothesis -There are no significant differences between the mean (weekend, weekday)
Weekend (Aggressive ACC%) – weekday (Aggressive ACC%)	p-value =0.906 >0.05	-Accept the null hypothesis -There are no significant differences between the mean (weekend, weekday)

2. Significant difference between Weekend and Weekdays (Hypothesis 4,5,6)

This section presents the findings of the first hypothesis, which is to investigate the significant difference in bus drivers' behaviours between weekend and weekdays. To test the hypotheses, the independent t-test was used. The results are presented in Table 3. As the table shows, the independent t-test shows that all the variables achieved a significant level as follows: in terms of speed ".026", acceleration ".476", deceleration ".643". Therefore, based on the criteria of ($P > 0.05$) if the P-value is higher than 0.05 indicates that there is no significant difference between the sampled (day and night), it can be concluded that the null hypotheses regarding the significant difference of the speed between bus drivers behaviours are rejected and the alternative hypotheses are accepted. However, regarding the other hypotheses of acceleration and deceleration, it can be concluded that the null hypotheses regarding the use significant difference between bus drivers' behaviours are supported and the alternative hypotheses are rejected.

Table 3. The significant difference in bus drivers' behaviours between day and night

Paired Samples Test									
		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	Day (% over) - night (% over)	-19.39	15.1	6.16871	-35.25	-3.53	- 3.144	5	0.026
Pair 2	Day (Aggressive DCC%) - night (Aggressive DCC%)	- .00014	.00047	.00019	-.00064	.00034	-.771	5	0.476

Pair 3	Day (Aggressive ACC%) - night (Aggressive ACC%)	-.0001	.0005	.00023	-.00070	.00047	-.493	5	0.643

Table 4 Summary of hypotheses 4,5,6, testing

Situation	P-value	Decision
day(% over) - night (% over)	0.026< 0.05	-Reject the null hypothesis -There is a significant difference between the mean (day, night)
day (Aggressive DCC%) - night (Aggressive DCC%)	0. 476 >0.05	-Accept the null hypothesis -There are no significant differences between the mean (day, night)
day (Aggressive ACC%) - night (Aggressive ACC%)	0.643>0.05	-Accept the null hypothesis - There are no significant differences between the mean (day, night)

1. **The significant difference between Weekend and Weekdays (Hypotheses 1, 2, 3)**

This section presents the findings of the first hypothesis, which is to investigate the significant difference in bus drivers' behaviours between weekend and weekdays. To test the hypotheses, one-way ANOVA was used. The results are presented in Table 5. As the table shows, the one-way ANOVA shows that all the variables achieved a significant level as follows: in terms of speed ".214", deceleration ".334", acceleration ".569". Therefore, based on the criteria of (P > 0.05) if the P-value is higher than 0.05 indicates that there is no significant difference between the sampled (day and night), it can be concluded that the null hypotheses regarding the significant difference of the speed between bus drivers behaviours are rejected and the alternative hypotheses are accepted. However, regarding the other hypotheses of acceleration and deceleration, it can be concluded that the null hypotheses regarding the use significant difference between bus drivers' behaviours are supported and the alternative hypotheses are rejected.

One-way ANOVA						
		Sum of Squares	df	Mean Square	F	Sig.
Speed	Between Groups	1128.692	1	1128.692	1.757	0.214
	Within Groups	6424.023	10	642.402		
	Total	7552.715	11			
DCC	Between Groups	.000	1	.000	1.030	0.334
	Within Groups	.000	10	.000		
	Total	.000	11			
ACC	Between Groups	.000	1	.000	.347	0.569
	Within Groups	.000	10	.000		
	Total	.000	11			

Table 6. Summary of Hypotheses 7,8,9 testing

Situation	p-value	Decision
Speed	0.214>0.05	-Accept the null hypothesis -There are no significant differences between the means (weekend, weekday)

(Aggressive DCC%)	0.334>0.05	-Accept the null hypothesis -There are no significant differences between the means (weekend, weekday)
(Aggressive ACC%)	0.569>0.05	-Accept the null hypothesis -There are no significant differences between the means (weekend, weekday)

The type of buses and the number of drivers did not significantly influence speeding behaviours. Surprisingly. Speeding among bus drivers may be due to the feeling of being safe in a larger vehicle. This corresponded with previous studies which showed that drivers of larger cars felt better protected compared to drivers of smaller vehicles. In turn, they were likely to accept a higher level of risk (Wilde 1988, 2001). Furthermore, the presence of another driver in a bus did not provide any form of preventive action against speeding. This was supported by a study that showed that speed violations for buses with dual drivers were higher compared to single driven buses (Osman et al., 2009).

As for the journey factors, only 'the time of day' had a significant difference with speeding. Drivers were 2.5 more likely to speed during nighttime due to lack of enforcement and low traffic volume compared to during the day. Hence, they were more likely to display risky behaviours including speeding. This is worrying because in Malaysia, as in other developing countries, serious road accidents are more likely to occur at night. As reported by Norlen et al. (2009), accident data in 2006 revealed that bus crashes at night tend to be more serious and were associated with a higher number of fatalities and injuries. Due to the normal practice of Malaysian bus drivers, passengers were allowed to disembark outside the designated terminal, which was normally nearer to their intended destination. Bus operators and enforcement agencies have not seriously looked into this problem. According to Osman et al. (2010b), most of the bus operators audited did not conduct route and risk management which included ensuring that passengers embark and disembark at the assigned terminals. Another study conducted by Osman et al. (2011) found that the pre-departure inspection by enforcement agencies was limited to only checking documents and vehicle conditions."

Conclusion

This study aimed to investigate the significant difference in Malaysian express bus drivers' behaviours in terms of speeding, acceleration and deceleration. The study is comparing the behaviours between day/night, weekends/weekdays, and road type (east, north, south). The study employed a fully quantitative research design. The data were collected using the smartphone application "Digital Dashboard GPS Pro application" using GPS technology collect the data. The study was conducted in Malaysia. The data was collected from 36 bus express trips around. The data were analysed using SPSS. 23. The independent t-test analyses and one-way ANOVA were used to analyse the data. The findings showed there is no significant difference in express bus driving behaviours in terms of speeding, acceleration and deceleration between weekends and weekdays, and road type. However, the findings showed there is a significant difference in drivers' behaviours between day and night in terms of Overspeed. This research contributes significantly to the limited studies that examine the bus drivers' behaviours towards achieving road safety and avoiding road fatalities.

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