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Research Article

Driver violation analysis: IETT example*

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Abstract: This article discusses the importance of driver behavior analysis in improving public transportation safety. It specifically focuses on the case of Istanbul Metropolitan Municipality Istanbul Electricity Tram and Tunnel Operations General Directorate (IETT), which operates a large number of public vehicles in Istanbul, including buses, Metrobus, Beyoglu nostalgic tram, and Karakoy tunnel funicular system. The article highlights various technologies IETT uses to analyze driving behavior, such as GPS data analysis, bus telemetry data analysis, and driver behavior data analysis. It also presents an analysis of driver violation data obtained from a driver motion analysis system used by IETT to detect violations. The data shows that the most violated rule is seat belt fastening, followed by distraction, drowsiness, and other violations. The article suggests that analyzing driver behavior data can help identify areas where driver behavior can be improved, reduce the risk of accidents, and improve overall safety.

Keywords: Driver violation, Driving behavior, Driver motion analysis, urban transportation

Sürücü ihlal analizi: İETT örneği*

Özet: Bu makale, toplu taşıma güvenliğinin artırılmasında sürücü davranış analizinin önemini tartışmaktadır. Özellikle İstanbul'da otobüs, metrobüs, Beyoğlu nostaljik tramvayı ve Karaköy tünel füniküler sistemi gibi çok sayıda kamu aracını işleten İstanbul Büyükşehir Belediyesi İstanbul Elektrik Tramvay ve Tünel İşletmeleri Genel Müdürlüğü (İETT) örneğine odaklanmaktadır. Makalede, İETT'nin sürüş davranışını analiz etmek için kullandığı GPS veri analizi, otobüs telemetri veri analizi ve sürücü davranış veri analizi gibi çeşitli teknolojiler vurgulanmaktadır. Ayrıca, İETT tarafından ihlalleri tespit etmek için kullanılan bir sürücü hareket analiz sisteminden elde edilen sürücü ihlal verilerinin bir analizini de sunmaktadır. Veriler, en çok ihlal edilen kuralın emniyet kemeri takma olduğunu, bunu dikkat dağınıklığı, uyuşukluk ve diğer ihlallerin izlediğini göstermektedir. Makale, sürücü davranışı verilerinin analiz edilmesinin, sürücü davranışının iyileştirilebileceği alanların belirlenmesine, kaza riskinin azaltılmasına ve genel güvenliğin iyileştirilmesine yardımcı olabileceğini öne sürmektedir.

Anahtar Kelimeler: Sürücü ihlali, Sürüş davranışı, Sürücü hareket analizi, kentsel ulaşım

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1. Introduction

Urban transportation systems are essential to ensuring the mobility and connectivity of modern cities, supporting economic activities, and improving the quality of life for citizens. However, with the increasing demand for public transportation, safety concerns have become a critical issue for operators and policymakers. Among the myriad factors influencing transportation safety, driver behavior has emerged as a pivotal aspect due to its direct and measurable impact on accident rates, passenger satisfaction, and operational efficiency. Unsafe driving practices, such as failing to fasten seat belts, fatigue, distractions, and mobile phone usage, not only increase the likelihood of accidents but also compromise public trust in transportation systems.

In Türkiye, the Istanbul Electricity Tram and Tunnel Operations (IETT), managed by the Istanbul Metropolitan Municipality, operates one of the most extensive public transportation networks. Its diverse fleet includes buses, Metrobus lines, nostalgic trams, and funicular systems, serving millions of passengers daily. Given the complexity and scale of its operations, IETT faces unique challenges in maintaining high safety standards while meeting the mobility needs of Istanbul's 16 million residents. To address these challenges, IETT has embraced technological innovations, deploying GPS systems, telemetry devices, and in-vehicle cameras to monitor and analyze driver behavior in real time. These technologies enable the detection of risky behaviors, the identification of patterns, and the implementation of corrective actions to improve safety outcomes.

This study focuses on analyzing driver violations within IETT's transportation network by utilizing comprehensive datasets obtained from advanced driver monitoring systems. It explores common violations, such as seat belt non-compliance and fatigue-related distractions, and examines their correlation with external factors, including operator performance, time of day, and day of the week. To better understand the relationship between driver behaviors and accident probabilities, this study employs binomial logistic regression analysis. This statistical method allows for the identification of significant predictors and the estimation of accident probabilities under different scenarios. By leveraging this approach, the study provides actionable insights into the specific behaviors that most significantly increase safety risks.The study highlights the critical role of data analytics in identifying high-risk behaviors and providing actionable insights to reduce accident risks and enhance safety protocols. Moreover, it underscores the importance of proactive interventions, such as tailored training programs, optimized scheduling, and fatigue management systems, in fostering a safety-oriented culture within urban transportation.

In addition to contributing to local safety improvements, this research has broader implications for urban transit systems globally. By presenting a scalable framework for driver behavior analysis, the study offers valuable insights into the role of technology in advancing public transportation safety. It demonstrates how data-driven decision-making can be integrated into urban transit strategies to achieve sustainable, efficient, and passenger-centric mobility solutions. Furthermore, the findings serve as a guide for policymakers and transportation agencies seeking to adopt innovative approaches to enhance safety and operational performance in increasingly complex urban environments.

By situating driver behavior analysis within the broader context of urban transportation challenges and technological advancements, this study aims to inform stakeholders about best practices for ensuring safer, more efficient, and sustainable mobility systems. It emphasizes the need for collaboration among operators, passengers, and policymakers to build a resilient and safety-focused public transportation framework adaptable to the needs of diverse urban landscapes.

2. Literature Review

2.1 Driver training and simulation studies

One of the factors that affect driver behavior is the management practices of the enterprise. A study of Chinese bus drivers found that enterprises with better management practices had fewer incidents of risky driving behavior (Liu and Hansen, 2019). In the same article Information relevancy can also affect driving behavior, as highlighted by a simulator study on professional bus drivers, which demonstrated the effects of information relevancy on driving behavior. Another factor that affects driver behavior is the use of new technology. A study of driving behavior recognition methods based on vehicle multisensor information found that the use of sensors can provide accurate data on driver behavior, which can be used to improve safety. Similarly, modeling driver behavior in real-world scenarios using multiple noninvasive sensors can help identify patterns and areas that require improvement, as suggested by a study on the same topic (Li et al., 2013).

A gamification program to improve driver behavior, as suggested by a study on improving driver behavior using gamification (Helvaci et al. 2018). The program incentivized safe driving based on individual driver histories, promoting responsible behavior. Another study used a driving simulator to explore gap acceptance behavior. Findings revealed that acceptance time and distance varied based on driver experience and traffic density, highlighting the unpredictable nature of driver clearance behavior influenced by multiple factors (Farah et al., 2007). The other article discusses the use of mobile apps to improve driving behavior. A systematic mapping study allowed the researchers to analyze existing mobile applications. The results show that there are applications designed using various techniques to change the behavior of drivers. The gamification features of these apps are popular as they increase the frequency of users using the app and the motivation to improve their driving behavior (El hafidy et al., 2021).

An article touches on some of the issues to consider about the validity of driving simulators. The researchers warn that driving simulators may not fully reflect the real-world driving experience, and there may be some differences. Despite this, driving simulators offer many advantages, for example, they can check driving conditions and simulate special situations in a safe environment. As a result, the validity of driving simulators depends on the simulator's purposes, driver experience, and usage scenarios (Kaptein et al. 1996). The paragraph discusses how instructional conditions affect mental effort and performance. Suitable conditions lead to high performance with low mental effort, while unsuitable conditions result in the opposite. Finding the right teaching conditions is crucial for effective learning, although effectiveness may vary depending on tasks and individual differences (Paas and Van Merriënboer, 1993).

An article presents a new method for detecting driver maneuvers using a rule classifier. The proposed method uses a set of rules to classify driver maneuvers, such as lane changing, turning, and braking, based on the vehicle's speed, acceleration, and steering wheel angle. The authors evaluated the method on a dataset of real-world driving scenarios and compared its performance to other existing methods. The results showed that the proposed method achieved higher accuracy and stability in detecting driver maneuvers, making it a promising approach for real-world applications such as autonomous driving and driver monitoring systems (Porwik et al. 2022).

2.2 Risky driving behaviors and fatigue

Attitudes toward traffic safety also play a significant role in driver behavior. A study of bus drivers in China found that attitudes toward traffic safety were associated with risky driving behavior (Wang et al. 2022). Fatigue is another factor that can affect driver behavior. A study of bus rapid transport (BRT) drivers found that stress-related psychosocial factors at work, along with fatigue, were associated with risky driving behavior (D’souza, and Maheshwari, 2015). A methodological approach for studying public bus transit driver distraction was suggested by a study (D’souza, and Maheshwari, 2015) which involved monitoring driver behavior using various sensors and devices. Finally, analyzing driver behaviors during common tasks using a frontal video camera and CAN-Bus information can help identify violations and areas that require improvement, as suggested by a study on the analysis of driver behaviors during common tasks (Sathyanarayana et al. 2014).

The another article, the influence of road condition and age on the driver's secondary duties was investigated using an online method for driver load estimation. In the research, driving parameters such as drivers' reaction time, average speed, and standard deviation of speed were analyzed and the effects of age and distractions on driving performance were verified. The results showed that younger drivers drive at higher speeds than middle-aged and older drivers and that distractions negatively affect driving performance (Verwey, 2000).

An article proposes a method using a support vector machine (SVM) algorithm to detect the cognitive distractibility states of drivers in real time. This model detects changes in vehicle acceleration and steering control if a driver is distracted. Experiments show that the model can accurately detect driver distraction in real time. It is envisaged that this technology can be used to increase driver safety (Liang et al. 2007). The article explores measuring drivers' mental load by analyzing their biological data like brain waves, heart rate, and eye movements at various load levels. Findings indicate that increased mental load leads to changes in brain waves, higher heart rate, and decreased eye movements. These measurements could be useful for assessing driver strain in different conditions, potentially enhancing evaluations of driving performance (De Waard and Brookhuis, 1996). Another article presents a method for predicting risky driving events using explainable artificial intelligence techniques. This method aims to understand why the driver exhibits risky driving behaviors by using environmental data as well as driving behavior data. The authors note that this method improves the results of previous studies and could potentially have a major impact on driving safety in the future (Masello et al., 2023).

2.3 Device use while driving

The use of mobile phones while driving is also a significant concern for public transportation companies. A study of intra-city bus drivers in India found that there was a tendency to use mobile phones while driving (Ahmed et al., 2023). Similarly, the use of cell phones while driving is a common violation that can result in distracted driving and accidents, as indicated by the tendency of intra-city bus drivers to use cell phones while driving, using the ordered probit model (Shaaban et al, 2018). A study of distracted driving in commercial vehicles and buses found that distractions such as mobile phone use were a significant cause of accidents. Next to cell phones one common cause of distraction driving on the bus is the use of electronic devices, such as navigation systems, or entertainment systems, by the driver. Research has shown that the use of such devices while driving can increase the risk of accidents, particularly if the driver is texting, emailing, or browsing social media. Other potential sources of distraction for bus drivers include interacting with passengers, eating or drinking, and adjusting the vehicle's controls (Shaaban et al, 2018). The other article explores the effects of information relevancy on driving behavior (Nilsson et al., 2021). Another article analyzed the age of drivers and the effect of distractions on driving performance. 87 participants were made to drive with different distractions and their driving parameters were examined (Papantoniou, et al. 2017).

An article is a meta-analysis to examine the effects of mobile phones on driver performance. The study examined 48 studies examining the effect of mobile phone use on driving performance. The meta-analysis results showed that the use of mobile phones adversely affected the driver's reaction times, accelerator pedal use, steering wheel control, and vehicle following distance. It was also determined that the effects of mobile phone use on driving performance depend on factors such as age, gender, type of phone used, and driving conditions. The meta-analysis results showed that mobile phone use significantly affects driving performance and therefore it is important to prevent mobile phone use while driving (Caird et al. 2008).

Another study aims to investigate the effect of mobile phone use on driver performance. For this purpose, 20 participants (11 men, and 9 women with an average age of 20) were given driving tasks in the driving simulator accompanied by different levels of distraction (for example, using a mobile phone). The results showed that mobile phone use negatively affects driving performance. This effect is explained by reducing the time it takes for eyes to look at the road while driving and causing distraction from important objects in traffic. The researchers emphasize that these results pose a serious risk to the driving safety of mobile phone use (Strayer et al. 2003). The article demonstrates using driver modeling in the UTDrive research platform to detect and assess distractions. Parameters like eye movements, reaction time, and biometric data are analyzed to understand drivers' responses to distractions and their impact on driving performance. Results indicate that driver modeling is effective for distraction detection and evaluation (Hansen et al. 2017).

The article examines drivers' attitudes toward distraction-reduction strategies and their response to their flaws. Using driving simulations with various distractions, the study found that drivers are willing to use imperfect strategies but doubt their effectiveness. They express openness to better strategies for greater effectiveness and comfort. This research aids in understanding drivers' needs to combat distractions and supports the development of improved strategies (Donmez et al., 2006).

An article, the effect of cell phone conversations on driving performance is examined using a meta-analysis of 23 previous studies. According to the results of the meta-analysis, it has been determined that mobile phone conversations have a significant negative impact on driving performance, especially prolonging the reaction time, reducing driving speed, and increasing the risk of lane violation. However, it was concluded that the influence of some factors (eg, type of speech, journey time, driver experience) differs, and future studies should consider these factors. In addition, it was stated that hands-free devices also negatively affect driving performance, and therefore, the use of mobile phones while driving should be reduced as much as possible (Horrey and Wickens, 2006).

An article discusses whether hands-free phones are safer than handheld phones. In the experimental study, the performances of the participants in the driving simulator were compared while talking on hands-free and handheld phones. The results showed that hands-free phones improved driving performance, but were not safer than handheld phones. In addition, it has been found that phone use negatively affects driving performance in general (Ishigami and Klein, 2009). The other article explores the effect of cell phone conversations on driving performance. The researchers used a simulator to measure driving performance by allowing participants to make phone calls at various intervals. The results showed that cell phone calls caused a significant decrease in driving performance. This decrease was particularly evident in tracking, maneuvering, and vehicle control (Rakauskas et al., 2004).

In recent years, research has emphasized the critical role of public transportation drivers' behaviors in traffic safety. Aggressive driving behaviors, significantly influenced by demographic factors such as age, gender, and driving experience, are among the leading contributors to traffic accidents (Hamarat & Duran, 2020). Research in Türkiye identified three key categories of negative driving behaviors: errors, violations, and inattentiveness (Trafik Hizmetleri Başkanlığı, n.d.). the nally, fatigue and stress levels among public transportation drivers have been shown to significantly increase accident risks (Terzi, 2019). These findings underscore the importance of monitoring and improving driver behaviors through big data analytics and real-time monitoring systems. Particularly, big data-driven driver behavior models developed for fleet and public vehicles are regarded as effective tools for enhancing driving safety (Terzi, 2019). Moreover, advanced methods employing visual and vehicular sensors, as well as machine learning algorithms such as Graph Convolutional Recurrent Networks, have shown promising results in accurately detecting and mitigating hazardous driving behaviors (Adhikari, 2023; Khosravinia et al., 2023).

3. IETT Data Sets

IETT is responsible for managing all the rubber-tired public vehicles in Istanbul and operates a total of 6241 buses, including 3202 public sector buses and 3039 private sector buses. IETT has utilized artificial intelligence to analyze real-time driver violations detected by specialized in-vehicle cameras capable of performing detailed driver movement analysis. These advanced cameras are designed to monitor driver actions such as seat belt compliance, distracted driving, and fatigue. The data generated from these analyses is instantly recorded in the IETT database, enabling real-time monitoring and data-driven improvements in public transportation safety and efficiency. With the driver behavior analysis camera, smoking, talking on the phone, wearing seat belts, sleepiness, inattention, driver tracking with facial recognition, and inspections of drivers who work more than working hours are carried out. In IETT, analysis can be made on driving safety and driver performance evaluation by using 2 types of technological system data. These are data received from telemetry system devices in the entire fleet of IETT and data from in-vehicle camera systems. There is a telematics device in 6241 vehicles, and driver movement analysis systems are installed in 3039 vehicles.

3.1 GPS Data Analysis

IETT GPS data analysis involves analyzing the location data collected from the GPS devices installed in IETT buses. This data provides valuable insights into bus routes, travel times, and passenger behavior, which can be used to optimize bus routes and schedules to improve overall efficiency and effectiveness. Real-time monitoring of bus locations and performance allows IETT to quickly identify and respond to issues while tracking passenger behavior helps IETT adjust routes and schedules to better serve passengers and improve satisfaction. By leveraging the insights gained from this data, IETT can make data-driven decisions that lead to improved operations, reduced costs, and increased customer satisfaction.

3.2 Driver Behavior Data

Driver behavior data is crucial for analyzing safety in public transportation. Collected from cameras, it offers insights into driver habits like fatigue and distractions. Analyzing this data helps improve driver behavior, reducing accident risks and enhancing safety. Initially met with resistance, the project gained acceptance through passenger support and explanations of its safety aims. As a result, the institution's reputation improved and also gained public support.

4. IETT Data Analysis

The numerical data cited in this study were sourced from the institutional knowledge repository of the Istanbul Metropolitan Municipality, Directorate General of IETT (2023). These include internal operational records and data provided by the Information Technology Department. The graphs were created using Excel, while the logistic regression analyses were conducted using the Jamovi software.

Driver behavior analysis relies on data collected from in-vehicle cameras to monitor activities such as seat belt usage, distracted driving, fatigue, smoking, and mobile phone use. These insights help identify unsafe behaviors, enabling interventions to improve safety and reduce accidents. Real-time monitoring ensures immediate corrective actions, while long-term data analysis highlights areas requiring additional training. These efforts enhance road safety, optimize operations, and boost both passenger and driver satisfaction.

IETT employs approximately 14,000 drivers. Initially, the introduction of driver behavior monitoring cameras faced resistance from personnel, sparking criticism on social media. However, with strong passenger support and transparent communication about the project's safety goals, the institution successfully addressed concerns, gaining acceptance and public trust.

4.1 Violation Data

Our article presents an analysis of monthly data from April 2023 obtained from a driver motion analysis system used to detect driver violations. The analysis is presented in Figure 1, which displays the percentage and numerical distribution of driver violations. The data shows that the most violated rule is seat belt fastening, with 140,478 instances or 80% of all violations. Other violations include Distraction (look around alarm) with 8,036 instances or 5%, drowsiness with 24,063 instances or 14%, phone call alarm with 1,342 instances or 1%, and smoking alarm with 982 instances or 0%.

Table 1. Driver violations

Driver Violations	Total
Distraction (Look Around Alarm)	8036
Drowsiness	24063
Phone Call Alarm	1342
Seat Belt Not Fastening Alarm	140478
Smoking Alarm	982
Grand Total	174901

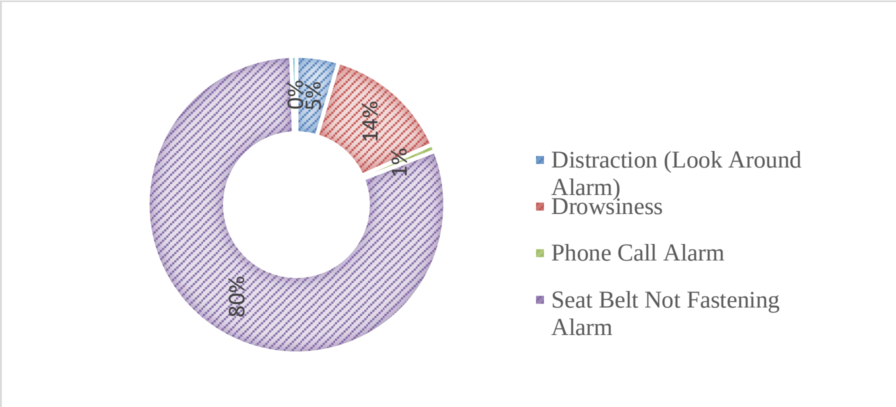

Figure 1. Driver violations percentages

4.1.1 Violation rates by the operator

The rate of driver violations by operators can be used as an indicator to measure the performance of an operator's drivers in obeying traffic rules. These rates may reflect how much an operator cares about driver training, what tools he uses to monitor compliance, and his sensitivity to passenger safety.

Figure 2 displays the distribution of these violations by the operator, with the majority of violations attributed to seat belts, and not fastening alarms. Particularly, the operators Mavi Marmara, Kent İçi İstanbul, and Özulaş have values ranging from 10% to 20%, making them the top violators of this rule. Drowsiness violations, on the other hand, are below 5%, with the highest violators being Mavi Marmara, Öztaş Ulaşım, and Özulaş operators.

In addition, rates of driver violations, according to operators, can help determine which lines or areas drivers commit more violations, helping to take preventive measures. This can be an important step in increasing the quality of public transportation service, increasing passenger satisfaction, and ensuring safety.

Table 2. Driver violations by operator-dependent

Operator	Distraction (Look Around Alarm)	Drowsiness	Phone Call Alarm	Seat Belt Not Fastening Alarm	Smoking Alarm	Grand Total
İst Halk Otobüs	651	2328	167	15497	169	18812
İst Özel Taşımacılık	145	762	107	9249	58	10321
İstanbul Çift Katlı Halk Otobüsleri	120	621	23	1256	20	2040
İstanbul Halk Ulaşım	827	1799	44	24542	35	27247
Kentiçi İstanbul	273	301	16	1286	11	1887
Mavi Marmara	1840	4874	150	36491	68	43423
Öztaş Ulaşım	1330	4469	281	12531	235	18846
Özulaş	1923	5273	241	21258	191	28886
Yeni İstanbul Halk Otobüsleri	927	3636	313	18368	195	23439
Grand Total	8036	24063	1342	140478	982	174901

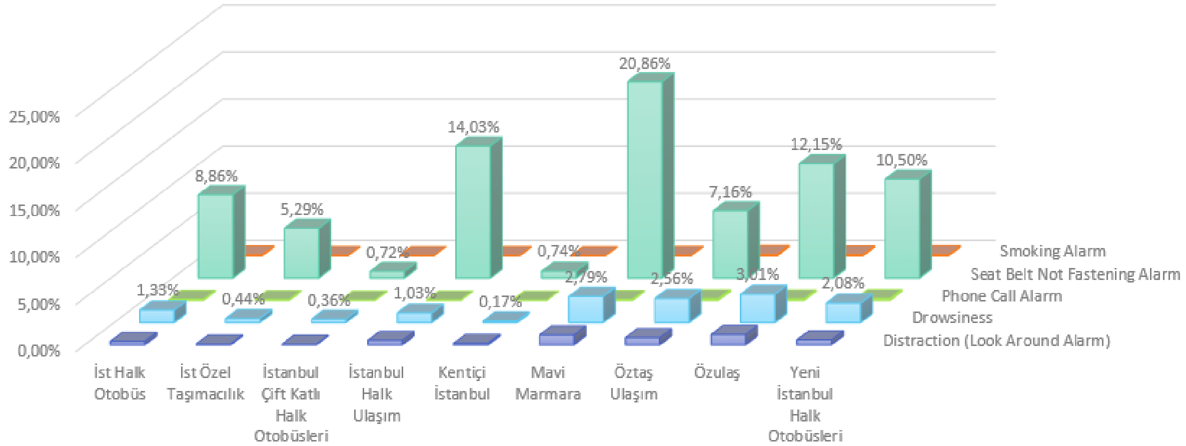

Figure 2. Driver violation percentages by operator-dependent

4.1.2 Violation rates by day of the week

The article presents an analysis based on one month of data from April 2023. As April is a spring month and the weather is warmer, there may be an increase in traffic on the roads. Figure 3 shows the percentage of driver violations on weekdays and weekends, indicating that drivers are more likely to violate rules related to drowsiness on weekends. This could be due to the accumulation of fatigue throughout the week, as well as the fact that roads are more congested on weekends. Overall, the most frequent violation is related to seat belt fastening.

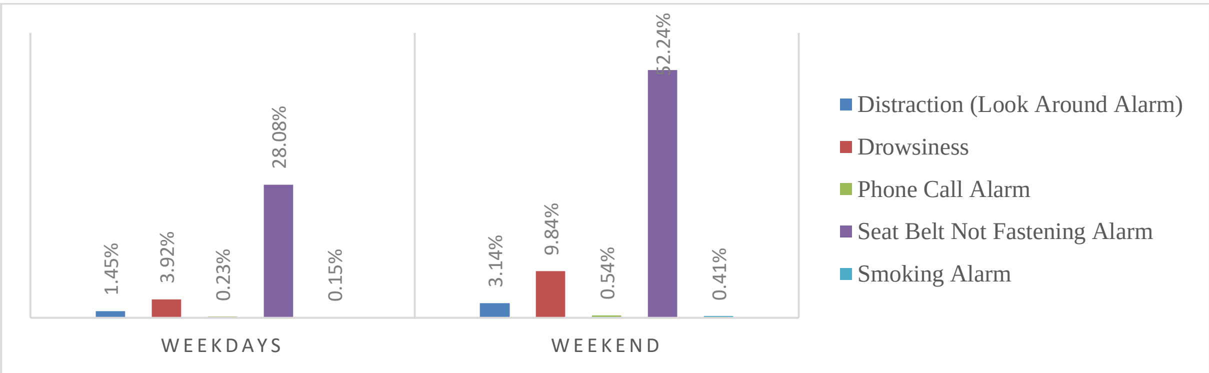

Figure 3. Driver violation percentages by weekdays and weekend

4.1.3 Violation rates by hour (average)

When analyzing the data on violation rates by hour (average), it becomes evident that violations tend to be higher during the peak morning hours on weekdays. This could be due to the increased traffic and congestion during this time, causing drivers to become more impatient and make reckless decisions. Additionally, people may be rushing to get to work or school and may be less mindful of traffic laws. It's also possible that law enforcement agencies are more active during these times, leading to more violations being reported. It's important to note that these trends may vary depending on the location and specific circumstances, but understanding the patterns can help inform traffic safety measures and enforcement strategies.

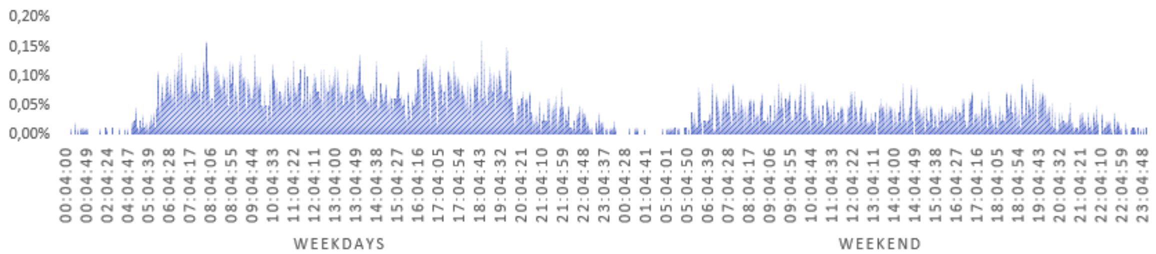

Figure 4. Driver's distraction graph

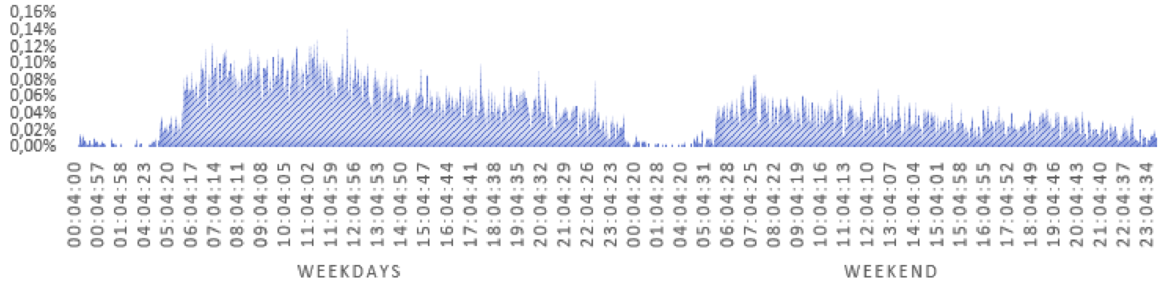

Figure 5. Driver's drowsiness graph

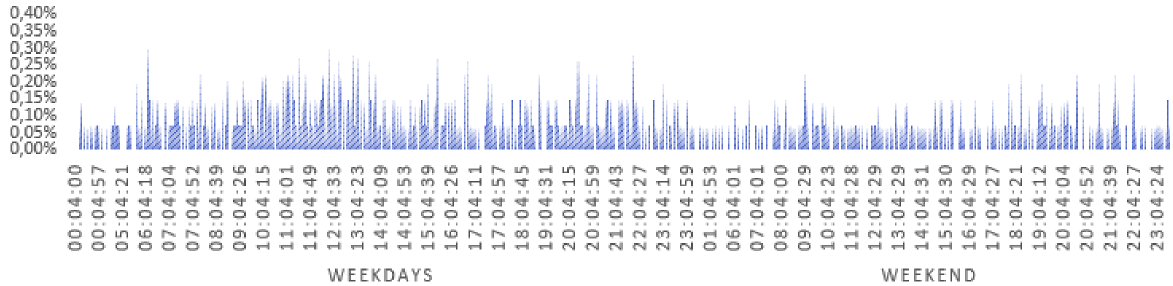

Figure 6. Driver's phone call alarm graph

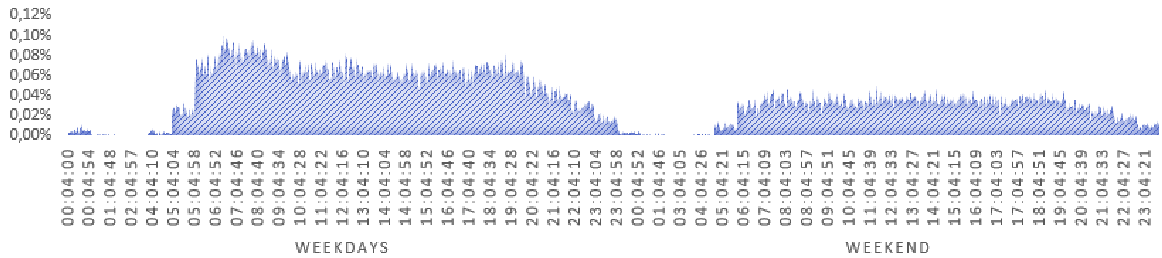

Figure 7. Driver's seat belt fastening alarm graph

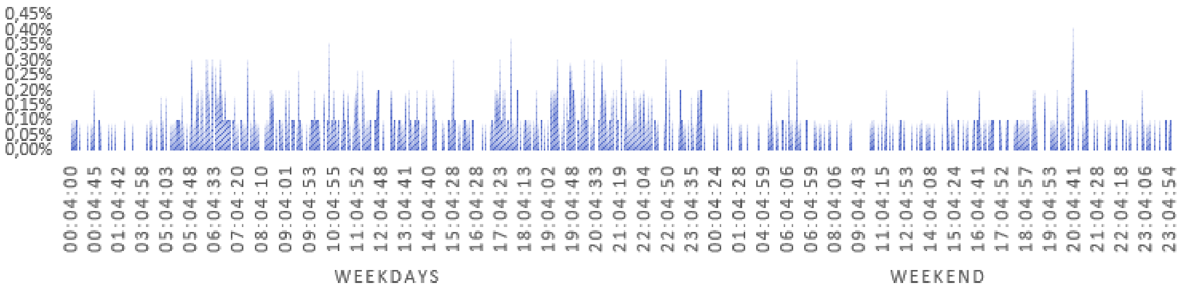

Figure 8. Driver’s smoking alarm graph

4.2 Accident Data

According to the analysis of the accident data for April 2023, the number of accidents that occurred can be categorized based on the type of crash. The data shows in Figure 7 that 84 crashes occurred due to crashing into each other within public buses, 265 crashes occurred due to crashing into another vehicle, and 14 crashes occurred due to damage by attack. In addition, 6 accidents occurred due to falling passengers, 5 due to collisions with pedestrians, and 5 due to hitting other vehicles. 3 accidents caused damage to passengers and 13 accidents where the vehicle went off the road. It is important to note that these numbers represent a snapshot of accident data for a single month and that the causes of accidents can vary widely. However, analyzing this data can help identify patterns and potential areas for improvement in road safety.

Table 3. Accident types

Accident Types	Total
Crashing into each other (within public buses)	84
Crashing into vehicle	265
Damage by attack	14
Falling passenger	6
Other vehicles hit us	5
Passenger damage	3
Pedestrian collision	5
Vehicle off the road	13
Grand Total	395

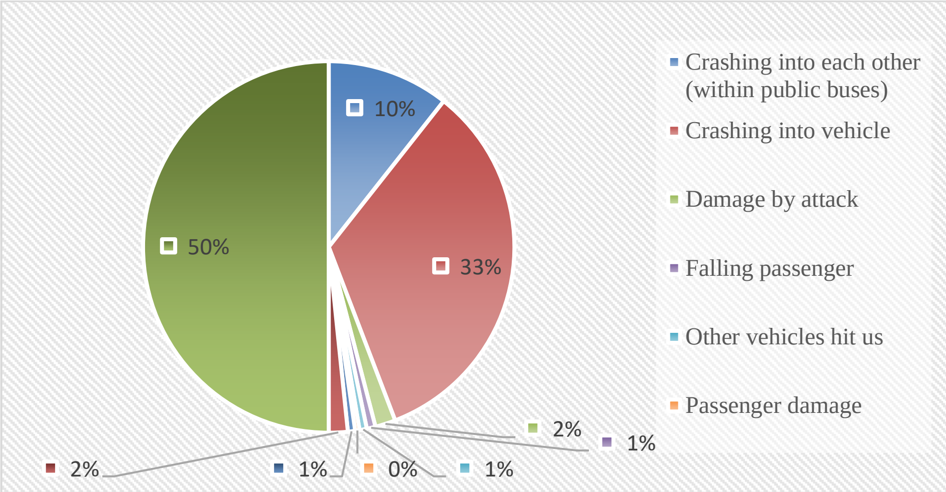

Figure 9. Accident types percentages

When the accident status in Figure 10 is analyzed according to accident types, 0 indicates no accident and 1 indicates an accident. This approach allows us to comprehensively examine the relationship between different types of accidents and their accident situations. Thanks to the assignment of these binary values, it is possible to evaluate the frequency and characteristics of accidents that occur in each type of alarm.

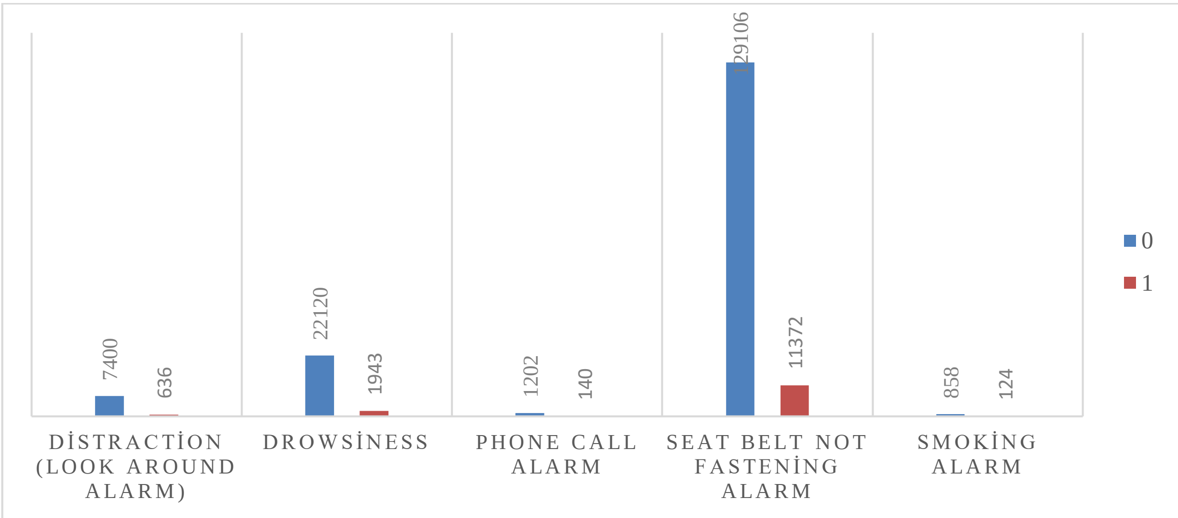

Figure 10. Accident status by accident types, 0 - there is no accident, 1- there is an accident

5. Estimating Accident Probability of Alarm Types with Binomial Logistic Regression Analysis

In an article reviewed, a binomial logistic regression model was used to examine the effect of independent variables such as drivers' sleepiness and fatigue level on rule violations. In this article, the following are mentioned about the reasons for using the binomial logistic regression model (Mahajan et al., 2019).

The nature of the dependent variable: The research analyzes a categorical dependent variable such as violations. Binomial logistic regression is a frequently preferred method for the analysis of such dependent variables. This model is used when the dependent variable is divided into two categories (violation or no violation).

Estimation of the effect of independent variables: Logistic regression is used to estimate the effect of independent variables on the dependent variable. In this article, it is desired to determine the effect of independent variables such as drivers' sleepiness and fatigue level on rule violations. The binomial logistic regression model is a suitable option for estimating these effects quantitatively and obtaining statistically significant results.

Our study aims to examine the relationship between driver alarm data and accidents using data collected by IETT. This analysis can help us understand the impact of driver distraction measures on accident rates and can guide the development of traffic safety policies. In this study, binomial logistic regression analysis was used on the dependent variable 'Accident Status' column. Binomial logistic regression is a statistical analysis method used in binary classification problems. Binomial logistic regression is a statistical analysis method used when the dependent variable is binary. This method evaluates the influence of independent variables to estimate the probability of the dependent variable.

In this model, the dependent variable named "Accident Status" has two values: 0 and 1. These values represent whether there has been an accident. Binomial logistic regression uses an argument called "Alarm Type" to predict this accident situation.

In Table 4., the "Model Fit Measures" section of the model has some criteria that evaluate the fit of the model. These:

Deviance: A statistical measure by which the fit of the model is measured.

AIC (Akaike Information Criterion): An information criterion that takes into account the fit and complexity of the model.

R^2: A measure of the explanatory power of the model.

McF: Another statistical measure that evaluates the fit of the model.

The "Model Specific Results" section contains model-specific results. This section displays the estimated coefficients and other statistical information for the dependent variable "Accident Status". The estimated coefficient (Estimate), standard error (SE), Z statistic, and p value of each independent variable are indicated. Estimated coefficients represent log ratios between status "Accident Status = 1" and status "Accident Status = 0".

Table 4. Binomial logistic regression by accident types

Predictor	Estimate	SE	Z	p
Intercept	-4.002	0.00946	-422.87	<.001
Alarm Type:				
Distraction (Look Around Alarm) – Seat Belt Not Fastening Alarm	-0.365	0.04101	-8.89	<.001
Drowsiness – Seat Belt Not Fastening Alarm	0.104	0.02479	4.20	<.001
Phone Call Alarm – Seat Belt Not Fastening Alarm	0.352	0.08613	4.09	<.001
Smoking Alarm – Seat Belt Not Fastening Alarm	0.201	0.09129	2.20	0.028

If explained through an example calculation. For example, when we want to predict "Alarm Type: Distraction (Look Around Alarm) – Seat Belt Not Fastening Alarm". In this case, the corresponding estimated coefficient is used to determine how the relevant alarm type affects the probability of the dependent variable "Accident Status". The estimated coefficients are represented as log odds (logistic regression coefficients).

In the example, the estimated coefficient for the alarm type "Distraction (Look Around Alarm) – Seat Belt Not Fastening Alarm" is given as -0.365. This coefficient affects the log odds value of the dependent variable "Accident Status" of the relevant alarm type. The log odds value represents the probability of an accident. To make an estimate, the log odds value is calculated using the corresponding estimated coefficient for a given "Alarm Type" value. Next, the logistic function is used to convert the log odds value to probability. The logistic function converts log odds to a probability value in the range [0, 1].

Distraction (Look Around Alarm) – Seat Belt Not Fastening Alarm:

Estimated coefficient: -0.365

Log Odds = Intercept + Alarm Type (Coefficients) = -4.002 + (-0.365) = -4.367

Accident probability: P(Accident Status = 1 | Alarm Type = Distraction) = 1 / (1 + exp(-Log Odds)) = 1 / (1 + exp(-(-4.367))) = 1 / (1 + 0.012) ≈ 0.988

Drowsiness – Seat Belt Not Fastening Alarm:

Estimated coefficient: 0.104

Log Odds = Intercept + Alarm Type (Coefficients) = -4.002 + 0.104 = -3.898

Accident probability: P(Accident Status = 1 | Alarm Type = Drowsiness) = 1 / (1 + exp(-Log Odds)) = 1 / (1 + exp(-(-3.898))) = 1 / (1 + 0.020) ≈ 0.980

Phone Call Alarm – Seat Belt Not Fastening Alarm:

Estimated coefficient: 0.352

Log Odds = Intercept + Alarm Type (Coefficients) = -4.002 + 0.352 = -3.650

Accident probability: P(Accident Status = 1 | Alarm Type = Phone Call) = 1 / (1 + exp(-Log Odds)) = 1 / (1 + exp(-(-3.650))) = 1 / (1 + 0.025) ≈ 0.976

Smoking Alarm – Seat Belt Not Fastening Alarm:

Estimated coefficient: 0.201

Log Odds = Intercept + Alarm Type (Coefficients) = -4.002 + 0.201 = -3.801

Accident probability: P(Accident Status = 1 | Alarm Type = Smoking) = 1 / (1 + exp(-Log Odds)) = 1 / (1 + exp(-(-3.801))) = 1 / (1 + 0.022) ≈ 0.977

Accident probabilities have been estimated under the following alarm types:

Distraction (Look Around Alarm) – Seat Belt Not Fastening Alarm: Estimated accident probability is approximately 98.8%.

Drowsiness – Seat Belt Not Fastening Alarm: The estimated probability of an accident is approximately 98.0%.

Phone Call Alarm – Seat Belt Not Fastening Alarm: Estimated accident probability is approximately 97.6%.

Smoking Alarm – Seat Belt Not Fastening Alarm: The estimated probability of an accident is approximately 97.7%.

According to these results, drivers with the "Distraction (Look Around Alarm)" alarm type have the highest accident probability (98.8%), while drivers with the "Phone Call Alarm" alarm type have the lowest accident probability (97.6%). It is seen from these probability results that all of them can increase the risk of accidents.

These results show the impact of different alarm types on the probability of an accident in the absence of seat belts. According to estimates, distractions, drowsiness, phone calls, or smoking, along with not using a seat belt, significantly increase the risk of an accident. The presence of these alarm types can cause drivers to distract themselves from the road or drive while drowsy. This increases the probability of causing an accident. These estimates are important for understanding the relationship between alarm types and seat belt use, and for encouraging drivers to avoid such risky behavior. These data can be used to improve traffic safety measures and prevent accidents.

6. Conclusion

In conclusion, ensuring the safety of drivers and passengers on the road is a critical issue, and the transportation industry has focused on improving driving behavior through the use of technology and interventions aimed at reducing the risk of accidents. The Istanbul Metropolitan Municipality Istanbul Electricity Tram and Tunnel Operations General Directorate (IETT) is a leading public transportation government service that provides various services, including buses. As with any public transportation service, IETT must prioritize the safety of its passengers and employees. Therefore, it is crucial to understand the driving behavior of bus drivers and identify any violations that may impact the safety of the passengers and the general public. IETT has implemented various technological systems, including telemetry system devices and in-vehicle camera systems, to analyze driving safety and driver performance. The data obtained from GPS and telemetry systems installed in buses and driver behavior cameras can provide valuable insights into bus routes, travel times, passenger and driver behavior, and bus performance. By analyzing this data, IETT can optimize bus maintenance schedules, reduce fuel costs, and improve overall efficiency and effectiveness.

The institution provides services with approximately 14,000 driver personnel. Initially, the driver personnel were uncomfortable with the inspections carried out with the driver behavior analysis camera, which was put into operation with the project. However, with the support of the passengers, the institution convinced the driver personnel by explaining on every platform that the project aimed to increase the safety of both passengers and driver personnel. The personnel involved in the project gained significant experience on the subject, and the institution's reputation has increased, and public support has been obtained.

In conclusion, IETT has implemented various technological systems to analyze driving behavior and ensure the safety of its passengers and employees. By analyzing the data obtained from these systems, IETT can optimize its operations, reduce costs, and increase customer satisfaction. Furthermore, analyzing driver behavior data can help IETT identify areas where driver behavior can be improved, reduce the risk of accidents, and improve overall safety on the road. With a population of approximately 16 million people in Istanbul, the systems that operate within the city have the potential to be integrated into many countries and cities. This means that the systems in place in Istanbul can serve as a model for other places to follow, due to the large and diverse population and the range of needs and challenges that come with it.

The findings of this study highlight significant patterns and trends in driver behavior, providing actionable insights for improving public transportation safety. One key takeaway is the critical role of integrating real-time monitoring systems to address high-risk behaviors such as seat belt violations, fatigue, and distractions. By identifying these behaviors promptly, transportation agencies can implement corrective measures that not only reduce accident rates but also enhance operational efficiency and public trust. Furthermore, the correlation between specific operator practices and violation rates underscores the importance of tailored training programs and stricter compliance monitoring.

Looking ahead, the data-driven approach adopted in this research lays the groundwork for developing predictive safety models capable of preempting potential incidents. These models, coupled with AI-powered intervention systems, can revolutionize public transportation by enabling adaptive scheduling, personalized driver feedback, and predictive maintenance of vehicles. Beyond safety improvements, these innovations have the potential to lower operational costs, reduce environmental impact through optimized routes, and improve passenger experiences, fostering a more sustainable urban transportation system. As global cities face increasing mobility challenges, the methodologies and technologies explored in this study can serve as a scalable blueprint for enhancing urban transit systems worldwide.

Future directions for improving driving safety in public transportation could include the integration of real-time data analytics and predictive modeling. By using real-time data, transportation agencies can identify safety risks and take proactive measures to prevent accidents and incidents. This could involve the use of sensors and other connected devices that can gather data on vehicle performance, road conditions, and traffic patterns in real-time. Also the development of more sophisticated machine learning algorithms that can analyze complex data sets, such as video footage from cameras mounted on buses or other vehicles. By analyzing this data, transportation agencies could identify patterns of driver behavior that may indicate a risk of accidents or other safety incidents. Furthermore, the use of artificial intelligence could also help improve driving safety in public transportation. AI-powered systems could be used to monitor driver behavior in real-time, alerting drivers when they are exhibiting unsafe behaviors or taking corrective action when necessary. Additionally, AI could be used to optimize routes and schedules to minimize the risk of accidents and reduce the potential for congestion and delays.

Researchers’ Contribution Statement

In the author's colophon, the researchers' contribution rates are indicated.

Conflict of Interest Statement, if any

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers’ bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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References

Adhikari, B. (2023). Using Visual and Vehicular Sensors for Driver Behavior Analysis: A Survey. *arXiv preprint arXiv:2308.13406*. Retrieved from https://arxiv.org/abs/2308.13406

Ahmed, S., Uddin, M. S., Feroz, S. I., Alam, M. R. B., Farabi, F. A., Uddin, M. M., & Rifaat, S. M. (2023, January). The tendency of intra-city bus drivers to use a cell phone while driving using ordered probit model. *Int AIP Conference Proceedings* (Vol. 2643, No. 1, p. 030007). AIP Publishing LLC.

Caird, J. K., Willness, C. R., Steel, P., & Scialfa, C. (2008). A meta-analysis of the effects of cell phones on driver performance. *Accident Analysis & Prevention*, 40(4), 1282-1293.

D’souza, K. A., & Maheshwari, S. K. (2015). A methodological approach for studying public bus transit driver distraction. *International Journal of Sustainable Development and Planning*, 10(2), 229-244.

De Waard, D., & Brookhuis, K. A. (1996). The measurement of drivers' mental workload.

Donmez, B., Boyle, L. N., Lee, J. D., & McGehee, D. V. (2006). Drivers’ attitudes toward imperfect distraction mitigation strategies. *Transportation research part F: traffic psychology and behavior*, 9(6), 387-398.

El hafidy, A., Rachad, T., Idri, A., & Zellou, A. (2021). Gamified Mobile Applications for Improving Driving Behavior: A Systematic Mapping Study. *Mobile Information Systems*, 2021, 1-24.

Farah, H., Polus, A., Bekhor, S., & Toledo, T. (2007). Study of passing gap acceptance behavior using a driving simulator. *Advances in Transportation Studies an International Journal*, 9-16.

Hamarat, B., & Duran, S. (2020). Factors Influencing Aggressive Driving Behaviors: A Case Study from Çanakkale Province. *Journal of Awareness*, 5(4), 503–514. Retrieved from https://dergipark.org.tr/tr/download/article-file/1390557

Hansen, J. H., Busso, C., Zheng, Y., & Sathyanarayana, A. (2017). Driver modeling for detection and assessment of driver distraction: Examples from the UTDrive test bed. *IEEE Signal Processing Magazine*, 34(4), 130-142.

Helvaci, S., Senova, A., Kar, G., & Gören, S. (2018). Improving driver behavior using gamification. In Mobile Web and Intelligent Information Systems: *15th International Conference, MobiWIS 2018,* Barcelona, Spain, August 6-8, 2018, Proceedings 15 (pp. 193-204). Springer International Publishing.

Horrey, W. J., & Wickens, C. D. (2006). Examining the impact of cell phone conversations on driving using meta-analytic techniques. *Human factors*, 48(1), 196-205.

Ishigami, Y., & Klein, R. M. (2009). Is a hands-free phone safer than a handheld phone? *Journal of safety research*, 40(2), 157-164.

Kaptein, N. A., Theeuwes, J., & Van Der Horst, R. (1996). Driving simulator validity: Some considerations. *Transportation research record*, 1550(1), 30-36.

Khosravinia, P., Perumal, T., & Zarrin, J. (2023). Enhancing Road Safety through Accurate Detection of Hazardous Driving Behaviors with Graph Convolutional Recurrent Networks. *arXiv preprint arXiv:2305.05670*. Retrieved from https://arxiv.org/abs/2305.05670

Li, N., Jain, J. J., & Busso, C. (2013). Modeling of driver behavior in real-world scenarios using multiple noninvasive sensors. *IEEE transactions on multimedia*, 15(5), 1213-1225.

Liang, Y., Reyes, M. L., & Lee, J. D. (2007). Real-time detection of driver cognitive distraction using support vector machines. *IEEE transactions on intelligent transportation systems*, 8(2), 340-350.

Liu, Y., & Hansen, J. (2019). Analysis of Driving Performance Based on Driver Experience and Vehicle Familiarity. *SAE International Journal of Transportation Safety*, 7(2), 175-190.

Mahajan, K., Velaga, N. R., Kumar, A., & Choudhary, P. (2019). Effects of driver sleepiness and fatigue on violations among truck drivers in India. *International journal of injury control and safety promotion*, 26(4), 412-422.

Masello, L., Castignani, G., Sheehan, B., Guillén, M., & Murphy, F. (2023). Using contextual data to predict risky driving events: A novel methodology from explainable artificial intelligence. *Accident Analysis & Prevention*, 184, 106997.

Nilsson, H., Mullaart, M., Strand, N., & Eriksson, A. (2021). The effects of information relevancy on driving behavior: A simulator study on professional bus drivers. *Cognition, Technology & Work*, 23, 429-437.

Paas, F. G., & Van Merriënboer, J. J. (1993). The efficiency of instructional conditions: An approach to combine mental effort and performance measures. *Human factors*, 35(4), 737-743.

Papantoniou, P., Antoniou, C., Pavlou, D., Papadimitriou, E., Yannis, G., & Golias, J. (2017). Exploratory analysis of the effect of distraction on driving behavior through a driving simulator experiment. *International Journal Transportation*, 5, 35-46.

Porwik, P., Orczyk, T., & Doroz, R. (2022, December). A Stable Method for Detecting Driver Maneuvers Using a Rule Classifier. In Intelligent Information and Database Systems: *14th Asian Conference, ACIIDS 2022*, Ho Chi Minh City, Vietnam, November 28–30, 2022, Proceedings, Part I (pp. 156-165). Cham: Springer International Publishing.

Rakauskas, M. E., Gugerty, L. J., & Ward, N. J. (2004). Effects of naturalistic cell phone conversations on driving performance. *Journal of safety research*, 35(4), 453-464.

Sathyanarayana, A., Boyraz, P., & Hansen, J. H. (2014). Effects of multitasking on drivability through can-bus analysis. *Smart Mobile In-Vehicle Systems: Next Generation Advancements*, 169-182.

Shaaban, K., Gaweesh, S., & Ahmed, M. M. (2018). Characteristics and mitigation strategies for cell phone use while driving among young drivers in Qatar. *Journal of Transport & Health*, 8, 6-14.

Strayer, D. L., Drews, F. A., & Johnston, W. A. (2003). Cell phone-induced failures of visual attention during simulated driving. *Journal of experimental psychology: Applied*, 9(1), 23.

Terzi, R. (2019). Big Data-Based Driver Behavior and Driving Models for Fleet and Public Transportation Vehicles (Doctoral dissertation). Gazi University, Institute of Science. Retrieved from https://avesis.gazi.edu.tr/yonetilen-tez/c1fbcddb-ec43-4e56-aa1b-0602eecffeef/

Trafik Hizmetleri Başkanlığı. (n.d.). The Role of Driver Behaviors in Accident Risk: Violations, Errors, and Inattentiveness. *Trafik Hizmetleri Başkanlığı Publications*. Retrieved from https://www.trafik.gov.tr/

Verwey, W. B. (2000). On-line driver workload estimation. Effects of road situation and age on secondary task measures. *Ergonomics*, 43(2), 187-209.

Wang, L., Wang, Y., Shi, L., & Xu, H. (2022). Analysis of risky driving behaviors among bus drivers in China: The role of enterprise management, external environment and attitudes towards traffic safety. *Accident Analysis & Prevention*, 168, 106589.