Distracted Driving Across Vehicle Types: A Comparative Analysis Between Two-Wheelers and Cars

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Abstract: Driver behaviour is pivotal in road safety, particularly for two-wheeler riders and car drivers navigating urban traffic environments. Driver distraction is a key contributor to accidents, as it diverts attention from the primary task of driving, increasing the likelihood of crashes. However, there is a scarcity of research which understands the distraction patterns of drivers and the influence of mode choice on distraction. This study addresses this gap by using an Eye Tracker to compare visual, manual, and cognitive distractions among two-wheeler riders and car drivers during peak and off-peak traffic conditions. The findings reveal that cognitive distractions account for 2.41% of travel time during peak hours for two-wheeler drivers, while manual distractions are more prevalent during off-peak hours (2.42%). In contrast, car drivers show significantly higher visual distractions, accounting for 7.58% during peak hours and 8.24% during off-peak hours, highlighting distinct distraction patterns across two vehicle types.

Key Words: Driver Distraction, Blink Rate, Eye Tracker, Two-wheeler, Car, Traffic conditions

1. INTRODUCTION

Traffic accidents are a major problem in both developing and developed countries. Each year, around 1.25 million people die in road crashes worldwide, making traffic accidents one of the leading causes of death, which results in significant human and financial losses Global status report on road safety (2023). Further, MoRTH (2022) reported that there were 461,312 total accidents in 2022 in India as compared to 412,432 in 2021 which makes a total increase of 11.9% in the total number of accidents; approximately 36.5% of these accidents result in Fatalities, and it describes that vulnerable road users are involving in majority of the fatalities, especially Two-wheelers. Driver behaviour constitutes one of the predominant factors contributing to the occurrence of accidents in a majority of the cases, including but not limited to speeding, aggressive driving, distraction, impaired driving, and fatigue which collectively account for approximately 93% of such incidents Viktorová, L., and Šucha, M. (2019). Driver distraction is one of the major factors causing road accidents, as reported by the National Highway Traffic Safety Administration (NHTSA), 25% of police reported crashes involve some form of driver inattention, Ranney *et al.* (2007). Driver distraction is defined as "when a driver is late in detection of information needed to finish the driving task safely as some event, activity, some person, inside or outside the vehicle, it serves to direct the driver's attention away from the driving duty" Young *et al.* (2007). NHTSA classifies distractions into 4 categories from the perspective of the function of a driver, i.e., Visual distraction, Cognitive distraction, Auditory distraction, and Biomechanical distraction, Ranney *et al.* (2007). In some of the studies, Tran *et al.* (2018), the authors classified distractions into three forms: Visual distraction, Manual distraction, and Cognitive distraction. In another study, Klauer, S. G. (2006), authors defined driver distraction as "a driver has to engage in a secondary task that is not necessary to perform the primary driving task" and the consequences of the driving performance were explained by Stutts *et al.* (2003).

Driver distraction can be investigated by conducting Naturalistic driving studies (NDS), simulator studies, or in some cases visual anticipation. To ascertain the manual and visual interactions with the navigation system and cell phone usage while driving, some studies used naturalistic driving data, Kuo *et al.* (2017). Using Vehicle dynamics sensor data from the Shanghai Naturalistic Driving Work (SH-NDS), China, another study aimed at distraction detection using the Long-Short term model (LSTM) model for phone usage detection Wang *et al.* (2022). In another study, the authors investigated a critical safety concern, i.e., how mobile phone distraction affects driving behaviour, Amini *et al.* (2023). Due to the difficulty in collecting data through NDS, some studies have employed driving simulators for understanding behaviour (Amini *et al*. 2023; Liang *et al.* 2024; Hoekstra-Atwood *et al.* 2017; Papantoniou *et al.* 2017). A driving simulator study has been conducted to understand the impact of visual distractions and analyse the mental workload across different durations of distraction, Liang *et al.* (2024). In another study, Hoekstra-Atwood *et al.* (2017), the authors have defined a relation between distractibility score and glance rate, and higher distractibility score linked to longer glances at stimuli. Further, another study observed that the reaction time of drivers varies by distraction type and age group, Papantoniou *et al.* (2017). Kuo *et al.* (2017) examined the head posture, gaze, pupil metrics, and eyelid opening in real time using the Driver Monitoring System (DMS) to classify the driver's attentional distractions. Hammond *et al.* (2019) have compared the naturalistic truck data distractions with that of naturalistic motor coach bus distractions, and they found fewer total distractions present in motor coach bus distractions. Though limited studies have been reported in understanding two-wheeler distractions, a study reveals that the distraction propensities of a motorized two-wheeler driver are significantly affected by time pressure. When drivers were under time pressure, their chances of getting distracted during a mobile phone conversation, texting, and talking to a pillion rider were 48%, 33%, and 77% respectively, Gupta et al. (2022). Another study Clabaux *et al.* (2014), highlighted the significant issues in powered two-wheeler and pedestrian interactions in urban traffic. Among the 11,787 Motorized Two-wheeler (MTW) drivers observed, 16.49% used mobile phones while driving. Most of these drivers (71.76%) were using these phones in hands-free mode, with devices like earphones, Bluetooth, or phones inside helmets. Similar study compared the gaze patterns of car drivers and two-wheeler drivers, and the authors concluded that the carriageway and mirror were the two features that most caught their attention.

By considering the above discussion, most of the distraction-related studies were conducted on heavy vehicles such as trucks and buses, and personalized vehicles like cars. Though the two-wheeler drivers are more vulnerable, very limited research has been reported to date on two-wheeler (motorcycle) driver distractions which are distinct from car driver distractions. Hence the present study aims to understand and compare two-wheeler driver distractive behaviours car rider distractions, to identify new approaches or techniques to reduce the fatalities and thus increase road safety. In this process, the study is capturing the driver's eye gaze movement i.e., the blink rate of a driver, and analysing the relationship between the blink rate and speed of vehicles in both cars and two-wheelers. Further, the study also identifies and classifies various distractions during travel. The next section explains the details of data collection and methodology followed in the study.

2. METHODOLOGY

A comprehensive methodology was adopted to understand two-wheeler and Car rider's distraction behaviour to enhance the safety of riders. The study is structured in three major sections: selection of study area, data collection, and data analysis.

2.1 Selection of Study Area

By designating the study area as Hyderabad, Telangana, the study stretch is selected by considering factors like urbanization, traffic flow, and the length of the stretch. The selected segment extends from Bahadurpally X roads to Dullapally X roads with a length of 8.8 km (Figure 1).

Figure 1. Selected Study Stretch

2.2 Study Equipment

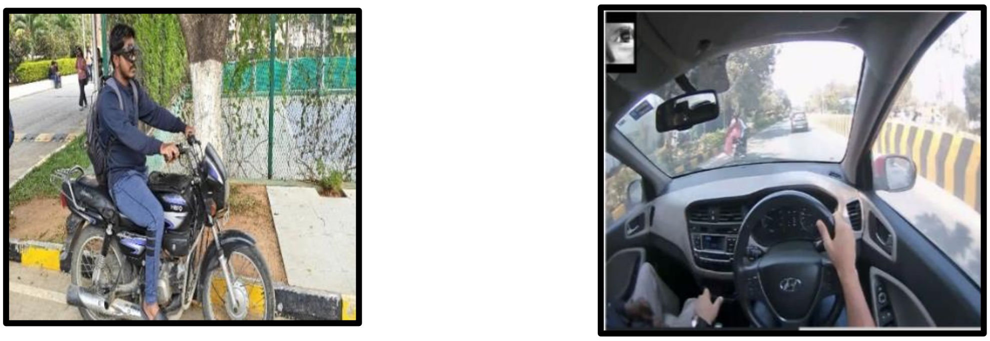
The Kexxu Eye Tracker is an advanced eye-tracking device designed for precise gaze analysis. It offers high accuracy in tracking eye movements, blink rates, and fixation points, making it a valuable tool for understanding cognitive load and distractions.

(a) (b) (c)

Figure 2. (a, b, c) Kexxu Eye Tracker

2.3. Data collection

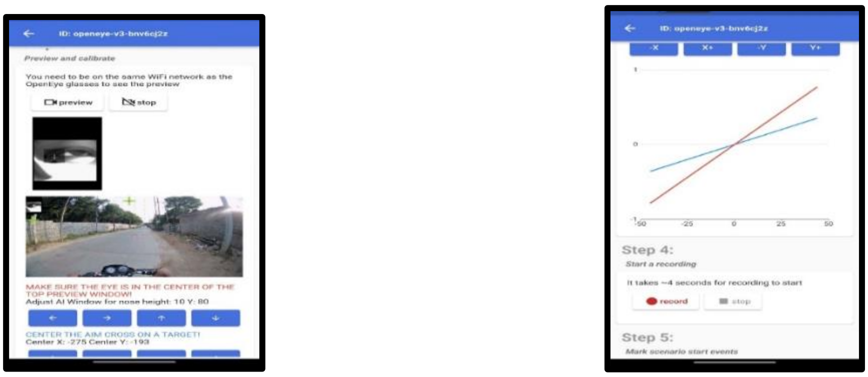
The Data Collection section involves 3 main components: the selection of participants, the selection of instruments, and the collection of data. In the present study, four participants with valid driving licenses and a minimum experience of three years in operating two-wheelers were involved. The participants were asked to drive two times in a day during both peak and off-peak hours using the same vehicle, and under similar weather conditions. A short-term Naturalistic Driving Study (NDS) has been performed using the instrumented vehicle. The Kexxu Eye Tracker is a sophisticated eye-tracking device with a variety of applications in traffic and driver behaviour research. It included features like real-time monitoring of pupil and gaze movements, area of interest monitoring, and generation of heat maps, among others. The instrument is relatively easy to wear like general reading glasses and it won't create any difficulty while driving. Figure 3 shows the instrument-fitted driver.



(a) (b)

Figure 3(a)& 3(b). Visual representation of Eye Tracker with the participant.

The workflow of the Eye Tracker starts with the setup phase and culminates in analysis. The first stage entails the installation of an eye tracker app into the participant's mobile or tab. Subsequently, a connection is to be established between the eye tracker to Kexxu devices and then the eye tracker to mobile through a QR code. The next step involves the calibration of the eye tracker, before use. The process of calibration is done by adjusting the AI camera window to fit over the eye and ensuring proper tracking. Once the calibration is done, its effectiveness can be verified by checking the preview. The eye tracker is now ready to wear by the driver and the data collection process can be initiated. Once the participant starts driving, it is necessary to drive the vehicle in a manner that is both natural and reflective of their customary driving style. Hence, to facilitate familiarity with the eye tracker, the driver has been asked to undertake pilot drives at various places while using the eye tracker. Once the experiment is stopped, the data files will be saved in the cloud. Further, basic analysis of data was provided in the Kexxu Editor through the YOLO model, such as driver's heat map, gaze plots, time of focus, etc. Figure 4 provides a visual representation of the eye tracker calibration process



(a) (b)

Figure 4(a) & 4(b). Visual representation of the process of calibration of an Eye tracker

3. DATA ANALYSIS & RESULTS

3.1 Blink Rate Analysis

This section analyses the influence of traffic flow on the blink rate of two-wheeler drivers and car drivers as presented in Table 1 and Table 2. The tables showing the data on average speeds maintained by the participants during peak and off-peak hours, along with their average blink rates. A high blink rate may indicate stress, anxiety, and distraction among drivers, all of which may contribute to significant safety hazards. From Table 1, it can be inferred that the average blink rate is higher during peak hours compared to off-peak hours. To further elucidate these findings, Figure 5 illustrates the variation in drivers' blink rates throughout their trips, offering additional insights into the relationship between traffic conditions and driver behaviour.

Table 1. Blink rate and Journey speeds of Two-Wheeler Drivers

	Peak Hour period		Off-Peak hour period	
	Speed (kmph)	Average Blink Rate per min	Speed (kmph)	Average Blink Rate per min
Driver 1	33.382	39.95	34.548	36.2
Driver 2	25.840	49.2	30.171	42.56
Driver 3	25.714	51.842	32.795	24.904
Driver 4	21.477	33.391	27.716	20.947
Average	**26.603**	**43.59**	**31.3075**	**31.15**

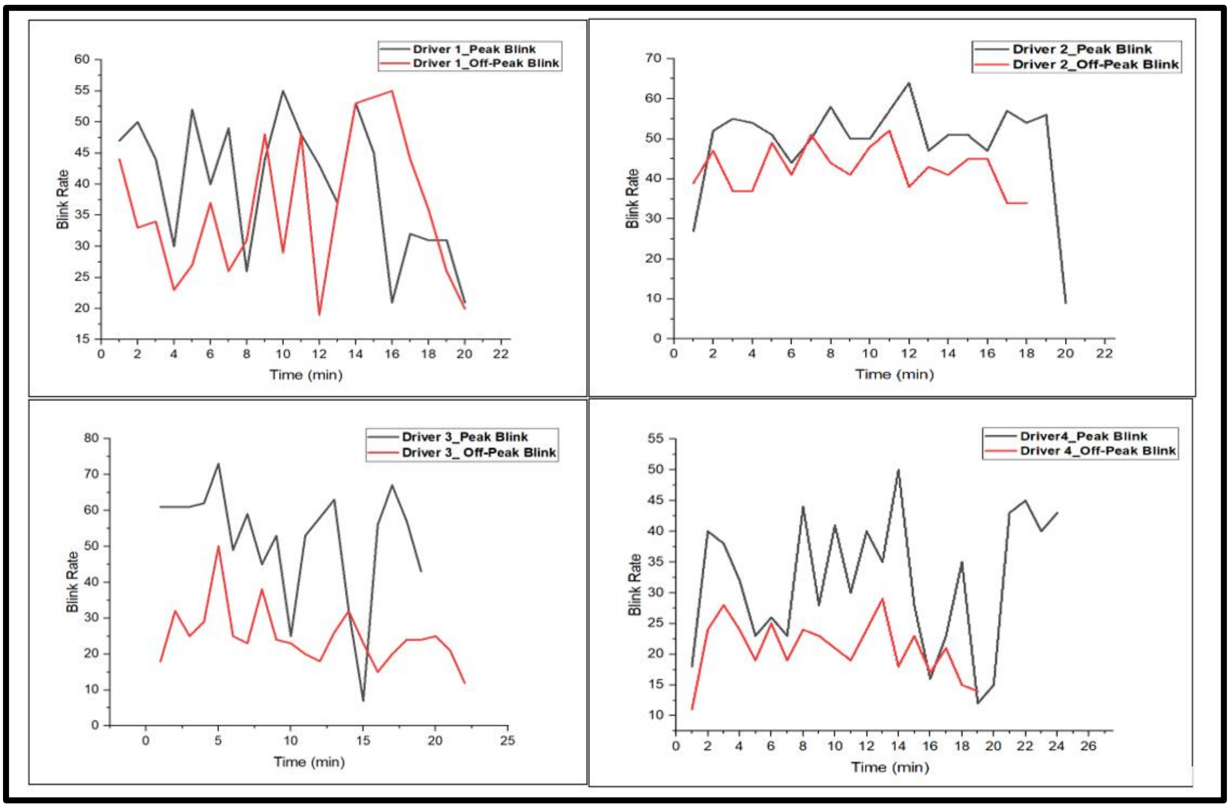


Figure 5. Blink rate variations of two-wheeler drivers (vs) time.

Table 2. Blink rate and Journey speeds of Car Drivers

	Peak Hour period		Off-Peak hour period	
	Speed (kmph)	Average Blink Rate per min	Speed (kmph)	Average Blink Rate per min
Driver 1	35.24	6.4	26.915	6.45
Driver 2	30.17	22.27	27.54	32.052
Driver 3	30.49	11.833	27.91	12.44
Driver 4	32.1	16.526	27.98	16.375
Average	**32**	**14.25**	**27.58**	**16.83**

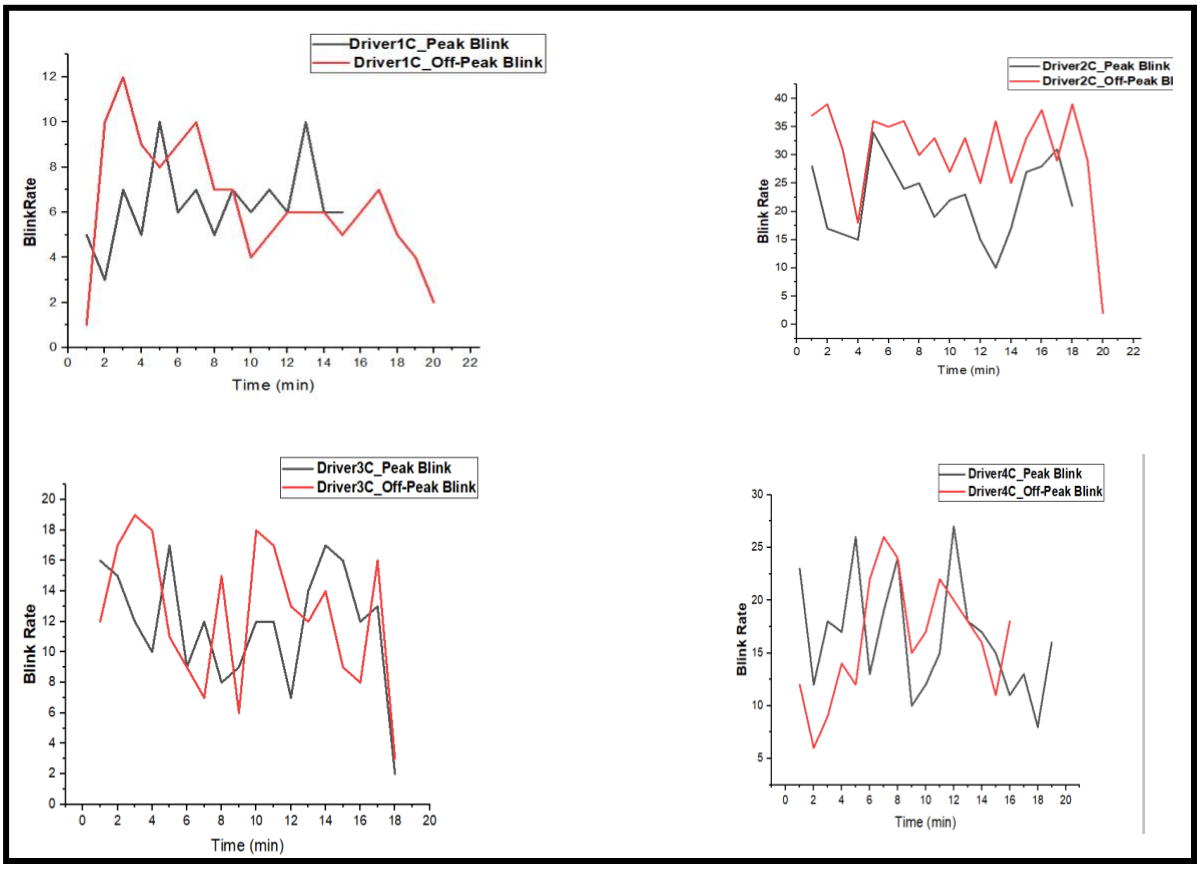


Figure 6. Blink rate variations of car drivers (vs) time.

The above plots (Figure 5 & Figure 6) illustrate the variation in blink rates of drivers, specifically two-wheeler riders and car drivers, during peak and off-peak periods. The data is plotted against time, showing minute-by-minute changes in blink rates. This analysis highlights how blink frequency fluctuates over time, comparing the differences between peak and off-peak conditions for both types of vehicle drivers. For car drivers, the average blink rate per minute is noticeably lower in comparison to two-wheeler riders. During peak hours, an inverse relationship is observed between speed and blink rate for both two-wheeler riders and car drivers. For two-wheelers, the average blink rate is higher when the speed is lower, indicating that reduced speed during congested conditions correlates with increased blink frequency.

Conversely, for cars, the speed is higher during peak hours, and the average blink rate per minute of the driver is comparatively lower. This indicates that car drivers maintain a lower blink rate when traveling at higher speeds, possibly due to heightened focus or reduced stress in faster-moving traffic. In contrast, two-wheeler riders exhibit a higher blink rate at lower speeds, potentially reflecting greater stress or fatigue in slower, stop-and-go conditions. These findings highlight distinct behavioural patterns between the two modes of transportation under varying traffic conditions. During off-peak hours, the relationship between speed and average blink rate per minute shows distinct patterns for two-wheelers and cars. For two-wheelers, both speed and average blink rate remain relatively stable, suggesting a consistent correlation between these variables under low-traffic conditions. Conversely, for cars, while the average blink rate per minute is significantly lower. This implies that car drivers are tend to maintain reduced blink rates as speed increases, further highlighting the distinct behavioural responses of two-wheeler riders and car drivers under varying traffic conditions.

3.2 Hypothesis Testing

To further examine the observed differences in blink rate and speed between two-wheeler drivers and car drivers, a statistical hypothesis test is conducted. Since the data does not necessarily follow a normal distribution, the Mann-Whitney U test—a non-parametric test—is employed to determine whether there is a significant difference in the distributions of blink rate and speed across the two modes of transport. This analysis aims to validate whether the variations in driving behaviour during peak and off-peak conditions are statistically significant.

Null Hypothesis (H_0): There is no significant difference in blink rates and speeds between car and two-wheeler drivers, regardless of peak or non-peak hours. This implies that their eye movement patterns and speed selection remain statistically similar across different traffic conditions.
Alternative Hypothesis (H_1): There is a significant difference in either blink rates or speeds between car and two-wheeler drivers, depending on peak or non-peak hours. This suggests that external conditions such as traffic congestion and road environment may influence their driving behaviours differently.

The observed significant difference in blink rates during peak hours suggests that two-wheeler and car drivers experience different levels of cognitive and visual distractions under high-traffic conditions. This result is consistent with previous research Cvahte Ojsteršek, T., & Topolšek, D. (2019) which highlights the external distractions, such as traffic density and traffic environment, influence visual cognitive distraction. To gain a deeper understanding of the impact of distractions under varying driving conditions, a detailed analysis of potential distraction sources (e.g., mobile phone use, roadside advertisements, etc) is explored in the next section under distraction analysis

Table 3. Mann-Whitney U Test Results

Measure	Peak/Off Peak	Vehicle	U Statistic	P-Value
Blink Rate	Peak	Car	0.0	0.029*
Speed	Peak	Bike	13.0	0.200
Blink Rate	Off Peak	Car	2.0	0.114
Speed	Off Peak	Bike	4.0	0.306

* Significant at 5%level

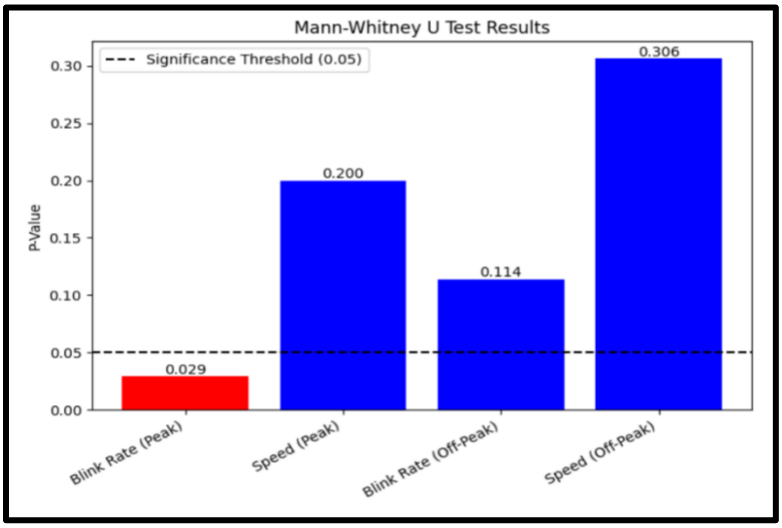


Figure 7. Graphical representation of Mann-Whitney U test results

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3.3 Distraction Analysis

The distractions identified through the eye tracker include visual distractions, manual distractions, and cognitive distractions. Visual distraction occurs when a driver glances away from the road; Manual distraction occurs when a driver may take their hands off the bike handle or car steering; and Cognitive distraction occurs when a driver's attention is diverted from the driving due to distractions such as thinking about something else or talking to someone. Cognitive distraction is directly correlated with the workload. The heatmaps are plotted based on the Area of Interest (AOI) in Figure 8 and these heatmaps help determine the various distracted activities of two-wheeler drivers and car drivers.

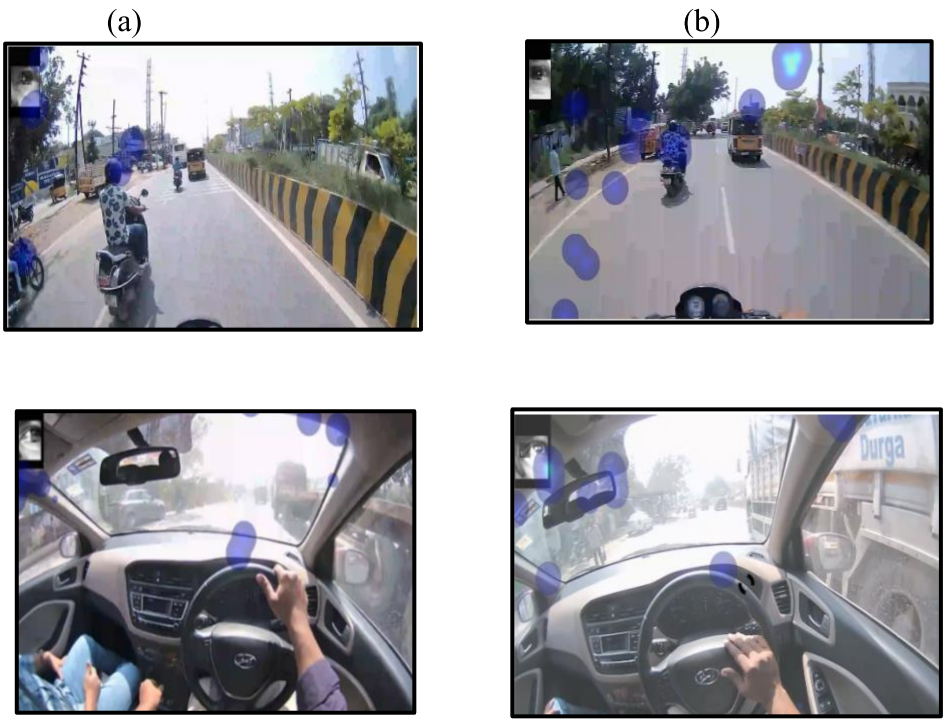

Figure 8. Dynamic Heatmaps of Drivers (a, b – Two-wheelers & c, d – Car drivers)

Based on the heatmaps generated by the eye-tracker, various distractions have been identified along with their respective durations. These distractions include: Visual distractions – Looking at the Hoardings, Street lights, Trees, Vehicles, & Pedestrians; Manual distractions – Taking hands off the two-wheeler handle; Cognitive distractions – Usage of mobile phone. Figure 9 illustrates the various distractions encountered by drivers during peak and off-peak hours for two-wheelers and suggests that visual distractions are relatively minimal for all drivers in both peak and off-peak conditions, while manual and cognitive are predominant among two-wheeler drivers.

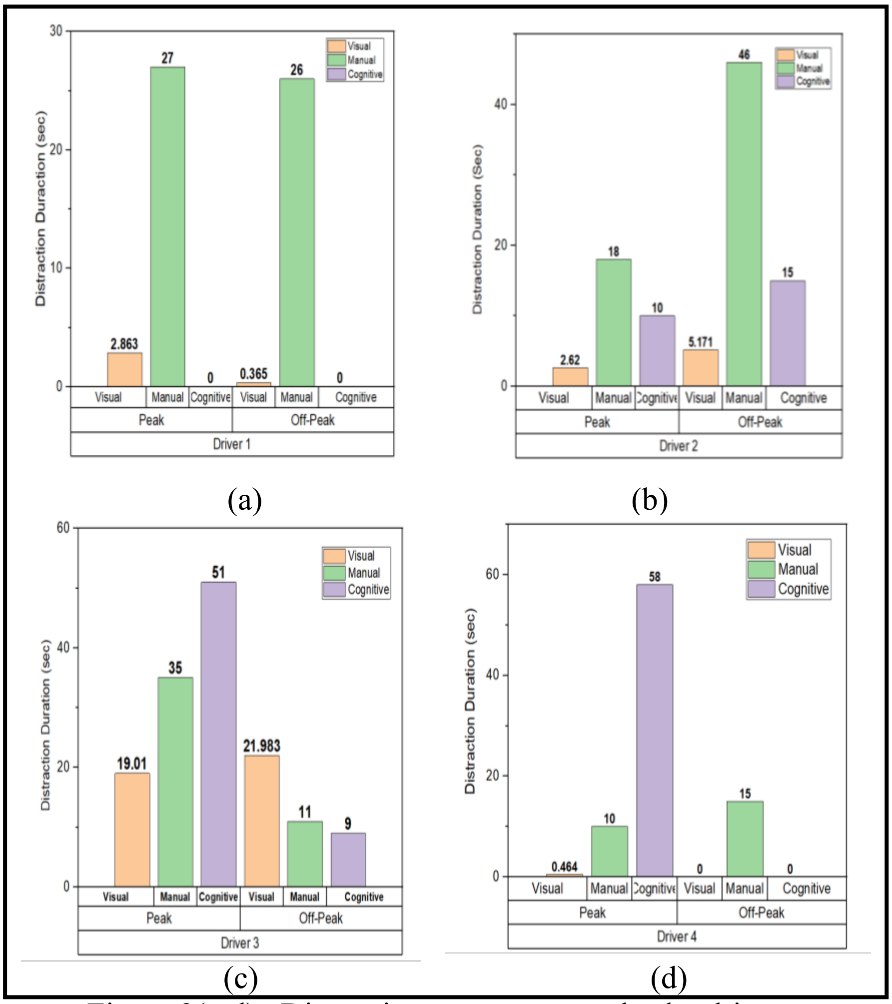

Figure 9(a-d). Distractions among two-wheeler drivers

Additionally, the study analyses the proportion of time drivers are distracted from driving, along with variations across different types of distractions. Table 4 presents the various distractions along with the percentage of time drivers engaged in each distraction. The data reveals that drivers spend 2.41% of their travel time on cognitive distractions, which is greater than the time spent on other distractions. In contrast, they are spending more than 2.42% of their travel time on manual distractions during off-peak hours. Figure 10(a-d) depicts various distractions observed in the drivers during peak hour and off-peak hour conditions for Car drivers.

Table 4. Various distractions as a percent of travel time(Two-Wheeler)

	Peak hour considerations (% of travel time)			Off-peak hour considerations (% of travel time)		
	Visual	Manual	Cognitive	Visual	Manual	Cognitive
Driver 1	0.25	2.36	0	0.0396	2.82	0
Driver 2	0.20	1.42	0.79	0.49	4.37	1.42
Driver 3	1.584	0.833	4.833	2.27	1.13	0.929
Driver 4	0.03	0.694	4.02	0	1.369	0
Average	**0.516**	**1.326**	**2.410**	**0.699**	**2.422**	**0.587**

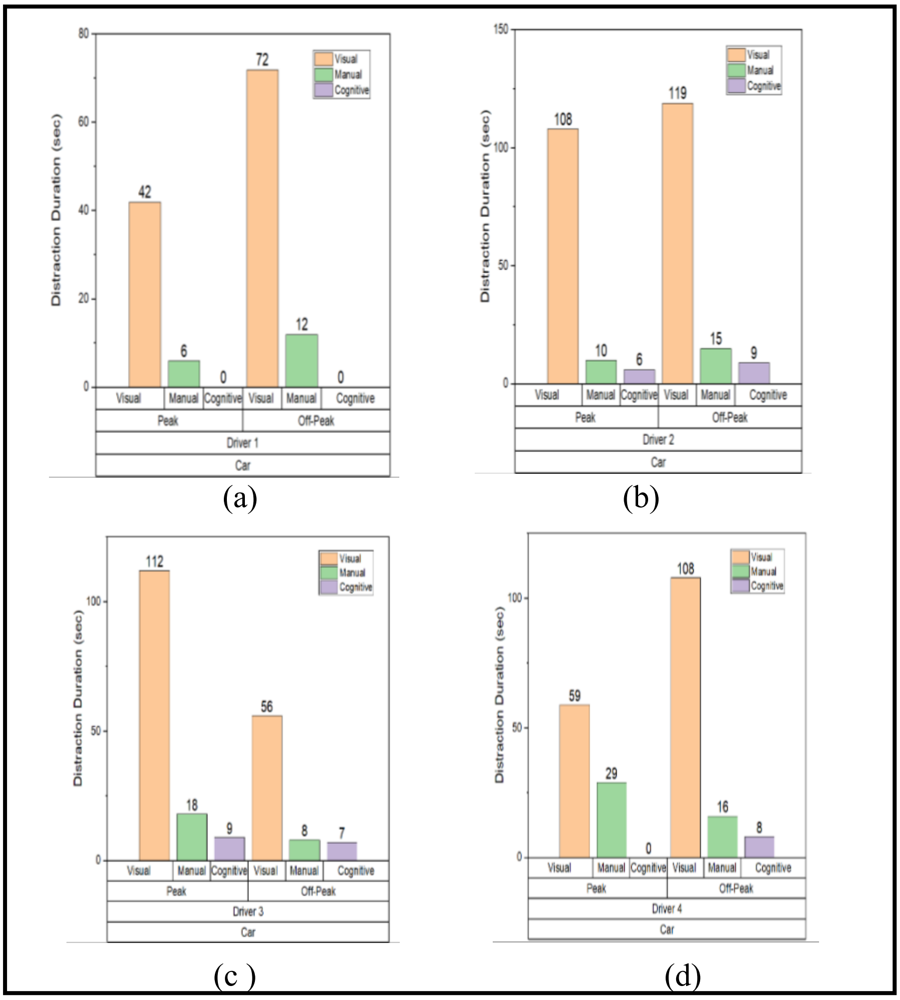

Figure 10(a-d). Distractions in Car drivers

Additionally, the study examines the percentage of time drivers are distracted from driving, as well as the variations across different types of distractions. Table 5 shows various distractions along with the percentage of time that drivers engaged in these distractions.

Table 5. Various distractions as a percent of travel time (Car)

	Peak hour considerations (% of travel time)			Off-peak hour considerations (% of travel time)		
	Visual	Manual	Cognitive	Visual	Manual	Cognitive
Driver 1	4.708	0.672	0	6.299	1.05	0
Driver 2	10	0.925	0.55	9.98	1.258	0.755
Driver 3	10.41	1.674	0.837	5.30	0.7583	0.663
Driver 4	5.24	2.575	0	11.38	1.685	0.843
Average	**7.58**	**1.46**	**0.34**	**8.24**	**1.187**	**0.565**

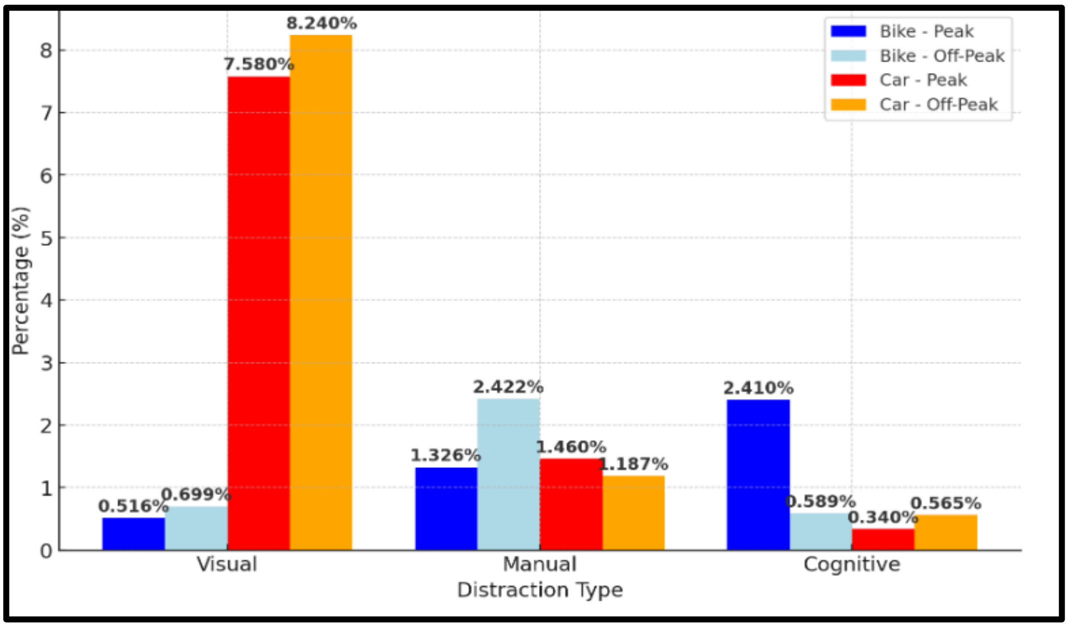

Figure 11. Comparison of car vs two-wheeler distractions during peak and off-peak hours

4. CONCLUSIONS AND FUTURE SCOPE

This study provides a comparative analysis of driver distractions in two-wheelers and cars using an eye tracker under both peak and off-peak traffic conditions. The findings highlight distinct distraction patterns across vehicle types. Two-wheeler drivers exhibit a 39% higher blink rate during peak hours compared to off-peak hours, indicating increased cognitive load and reduced attentiveness in congested conditions. In contrast, car drivers show an 18.10% higher blink rate during off-peak hours than in peak hour conditions, implying a potential decrease in alertness when traffic density is lower. The results further indicate a direct relationship between speed and blink rate, challenging the assumption that drivers are more attentive at higher speeds. Additionally, cognitive distractions dominate during peak hours for two-wheeler drivers, while manual distractions are more prevalent during off-peak hours. For car drivers, visual distractions remain consistently high across both traffic conditions (7.58% in peak and 8.24% in off-peak hours), emphasizing the need for targeted interventions. These differences underscore the importance of vehicle-specific safety measures, stricter enforcement of traffic laws, speed regulations, and driver awareness programs to mitigate distraction-related crashes.

While this study provides valuable insights into distraction patterns across different vehicle types, certain limitations offer scope for further research. Expanding the sample size and including a more diverse demographic of drivers could enhance the generalizability of the findings. Additionally, a detailed investigation into the relationship between blink rate, travel speed, and distraction severity could provide deeper insights into attentional demands across vehicle types. Future studies could also examine the impact of distractions on driving performance during different lighting conditions (day vs. night), varying road surface conditions, and different vehicle speeds. Furthermore, the integration of advanced technologies like Driver Monitoring Systems (DMS) in both two-wheelers and cars could be explored to assess their effectiveness in reducing distractions and improving driver awareness.

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