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Impact of level 2 automation on driver behavior: A study using association rules mining

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ABSTRACT

Driver distraction and reduced situational awareness pose significant risks in vehicles with Level 2 (L2) automation systems, such as adaptive cruise control and lane-keeping assistance. This study analyzed naturalistic driving data using Association Rules Mining (ARM) to investigate the impact of L2 automation on driver behavior. The dataset included 771 driving events categorized by L2 system activation status (active or inactive), intersection types, and hand positions on the steering wheel. Key variables were analyzed, such as eyes-off-road (EOR) time, off-road glance frequency and duration, and the influence of different driving conditions. The findings revealed that driver distraction, indicated by longer EOR times and more frequent off-road glances, is significantly higher when L2 systems are active. Additionally, drivers exhibit the highest levels of inattention with no hands on the wheel during L2 activation. These insights highlighted the need for improved driver-system interfaces. They targeted driver education to enhance the safety and effectiveness of L2 automation, ultimately contributing to safer roadways and better-informed policy decisions.

1. Introduction

1.1. Background

The rapid advancement of advanced driver assistance systems (ADAS) has significantly transformed vehicle technology (Nidamanuri et al., 2022). Level 2 (L2) automation systems, such as adaptive cruise control (ACC) and lane-keeping assistance (LKA), have gained widespread adoption (Kim et al., 2022; Luo, 2023; Utriainen et al., 2020). These systems offer the dual capabilities of controlling both steering and acceleration/deceleration under specific conditions, thereby assisting drivers in maintaining lane position and safe following distances. However, despite their potential to enhance convenience and safety, there are critical concerns regarding their impact on driver behavior. Atwood et al. (2019) and Blanco et al. (2015) have indicated that drivers using L2 systems tend to exhibit longer off-road glances, suggesting reduced situational awareness and increased reliance on the automation system. This reduced situational awareness can be problematic, especially considering that 3,308 crashes in the US during 2022 were caused by

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driver distraction or inattention NHTSA (2022). Beanland et al. (2013) emphasized that inattentive driving represents a major road safety problem, making it essential to understand the dynamics behind such driving behavior to ensure that L2 systems are safe and effectively reduce crashes.

Despite the widespread adoption and potential benefits of L2 automation systems, there remain significant gaps in understanding how these systems influence driver behavior, particularly in real-world driving conditions. Previous studies have provided insights into the effects of L2 systems on driver attention and engagement. Yet, critical questions remain unanswered regarding the specific behavioral patterns that emerge based on the activation status of the technology. For instance, while it is known that drivers tend to exhibit longer off-road glances with L2 systems, the underlying factors influencing these behaviors and their implications on road safety are not fully understood. Previous studies have examined driver behavior under L2 automation; however, they have not fully explored the effects of varying hand positions on wheel (both hands, one hand, no hands), driver distraction and attention in real-world scenarios. This study uniquely investigated the behavioral patterns using Association Rules Mining (ARM) to determine complex non-linear relationships between driver behavior and L2 system activation using naturalistic driving data. Unlike traditional statistical methods, ARM provides insights into hidden patterns, offering a novel approach to understand driver interactions with automation systems in diverse driving contexts. Many studies used regression models to investigate the relationship between specific outcomes and associated risk factors. However, these models often focus on overall average effects, potentially missing important variations within subgroups that possess distinct risk profiles. Consequently, interventions are designed with the average individual in mind, rather than related to the unique characteristics of different subgroups. This paper emphasized the strengths of rule-based analysis, which can identify subgroups with varying risk patterns without relying on predefined assumptions. By examining variables such as eyes-off-road (EOR) time, the frequency and duration of off-road glances, and the impact of different intersection types and road conditions, this study investigated the complex and non-linear relationships. Additionally, this study implemented the ARM on three subsets of the data representing both hands-on-wheel, one hand-on-wheel, and no hands-on-wheel driving behavior. Through this comprehensive analysis, the study aimed to provide an understanding of driver behavior under L2 automation, ultimately informing the development of safer and more intuitive automated driving systems.

1.2. Study Objectives and Hypotheses

This study aimed to understand how the activation status of L2 automation systems affects driver behavior in real-world scenarios. The research will use detailed naturalistic driving data to explore the behavioral patterns associated with active and inactive L2 systems. This will be achieved through ARM to analyze key variables such as EOR time, the frequency and duration of off-road glances, and the influence of various intersection types and road conditions. To better understand driver interactions with L2 systems, the study will evaluate three specific subsets of data representing both hands-on-wheel, one hand-on-wheel, and no hands-on-wheel driving behaviors. This study proposed the following hypothesis:

- Drivers exhibit longer EOR times and an increased frequency of off-road glances when L2 systems are active compared to inactive ones.
- Intersections and varying road conditions significantly influence driver EOR behavior, with different patterns emerging based on whether the L2 system is active or inactive.
- Hand position on the steering wheel (both hands, one hand, no hands) during L2 system activation affects the extent and nature of driver distraction, with no hands-on-wheel scenarios showing the highest levels of inattention.

The insights gained from this research are expected to inform the design and implementation of more intuitive and safer automated driving systems. Additionally, understanding the behavioral adaptations of drivers using L2 automation can guide the development of targeted driver education and training programs. Ultimately, the study aims to enhance the overall safety and effectiveness of L2 automated systems, contributing to improving traffic safety and driver support technologies. The study's unique focus on evaluating driver behavior across different hand positions on the steering wheel under varying L2 system activation statuses added insights into driver interactions with automated systems. Additionally, by analyzing the influence of intersection types and traffic conditions, this study provided practical insights to inform the design of more intuitive and safer automated driving systems. These contributions are expected to enhance the overall safety and effectiveness of L2 automation, ultimately leading to improved road safety and better-informed policy decisions.

2. Literature Review

The rapid advancements in vehicle automation technology have introduced various levels of driving automation, with L2 automation being one of the most prevalent. L2 automation systems, which include features such as adaptive cruise control and lane keeping assistance (LKA), allow the vehicle to control both steering and acceleration/deceleration under certain conditions. Despite these advancements, understanding how drivers interact with and adapt to these systems remains a critical area of research. Many studies have examined driver behavior under L2 automation, focusing on control transitions (Lee et al., 2023). One study analyzed glance behavior using data from autonomous vehicles (AVs), examining differences in driver-initiated overrides. Findings revealed that glance frequency influenced the overriding of L2 automation, suggesting a need for improved driver-system interfaces to support safe information extraction. Gershon et al. (2021) investigated how partial vehicle automation reshapes the driving task and driver behavior under L2 automation. The study analyzed fourteen participants' driving behavior data over one month between manual driving, ACC, and Super Cruise. Results revealed that 50 % of miles were driven using automation, with drivers initiating 9.98 transitions per trip on average, reflecting the differences in drivers' strategic, maneuver, and control decisions.

Driver expectations on L2 ADAS systems can affect the engagement and performance of the driver. Russell et al. (2021) investigated low and high-capability L2 vehicles to assess whether driver expectations align with the vehicle's actual capabilities. Findings revealed that mismatched expectations decreased driver engagement and performance, particularly during unexpected events. Another study examined driver behavior under L2, focusing on maintaining driver supervision during automated driving (Hecht et al., 2022). This research utilized a driving simulator study to test human–machine interface (HMI) concept using affective message framing. They found that participants using the HMI showed a stable road attention ratio. Mueller et al. (2020) highlighted the potential of L2 driving automation to reduce crashes but also identified risks related to driver disengagement. The study utilized methods to develop data-driven recommendations for system design that encourage driver engagement. Recommendations include attention reminders, countermeasures for sustained noncompliance, proactive methods for keeping drivers engaged, and clear communication of system limitations and driver responsibilities. Another study focused on driver behavior under L2 automation during non-critical take-over situations, such as lane-changing or overtaking (Madigan et al., 2018).

Previous studies have shown mixed results regarding the impact of L2 automation on driver behavior. For instance, A study aimed to understand how to secure driver supervision engagement and conflict intervention performance using highly reliable L2 automation (Victor et al., 2018). The study involved test-track experiments, analyzing the drivers' response to conflicts after 30 min of supervised automation. Results showed that while supervision reminders kept drivers' eyes on the path and hands on the wheel, 28 % of drivers still crashed despite these reminders, highlighting the importance of cognitive engagement and a clear understanding of system limitations. Another study examined various levels of automation (LOA) to improve human/machine performance during dynamic control tasks (Endsley and Kaber, 1999). The study involved simulation trials with different LOA, measuring effects on performance, situation awareness, and workload. Results indicated that while automation of task implementation improved performance under normal conditions, it affected performance recovery during system failures. Carsten et al. (2012) noted that drivers using L2 automation tend to exhibit longer glance durations away from the road, potentially increasing the risk of accidents.

Several studies have used ARM to investigate transportation safety and driver behavior. Kong et al. (2020) implemented ARM on naturalistic driving data to examine the speeding behavior of the drivers. In another study, Kong et al. (2021) have used the ARM tool to explore the near crash events based on naturalistic driving data. To explore the attributing factors in a hit and run crash, Das et al. (2021) have used ARM that identified several significant factors which have high likelihood of contributing to such crashes. Furthermore, recent studies have adopted the ARM to investigate the patterns of high-speed crashes, risky driving behavior crashes related to young drivers, and AV related crashes (Hossain et al., 2024; Labbo et al., 2024; Liu et al., 2024). Moreover, this methodology has also been used in several studies that investigated pedestrian crashes (Chakraborty et al., 2024; Hossain et al., 2023, 2022; Tamakloe and Adanu, 2024). Therefore, this study has implemented ARM to investigate and identify the complex pattern of driving behavior with the L2 automation system activation status.

This study examined driver behavior under active and inactive L2 automation conditions using a dataset from naturalistic driving environments. It explored the driving behavior of vehicles with L2 systems. Particularly, it evaluated the eye glance patterns of drivers and considered the placement of hands-on wheels while the L2 activation system was both on and off. Furthermore, to capture the behavioral pattern, ARM was applied to the dataset that highlighted the association rules of driving behavioral patterns for both hands-on-wheel, one hand-on-wheel, and no hands-on-wheel. By addressing these factors, this study aims to fill the gaps left by previous research, providing a more detailed and enhanced understanding of driver interactions with L2 systems. This approach sheds light on how drivers engage with L2 automation and offers practical insights for improving the design and safety of these systems, ultimately contributing to enhanced road safety and reduced driver distraction.

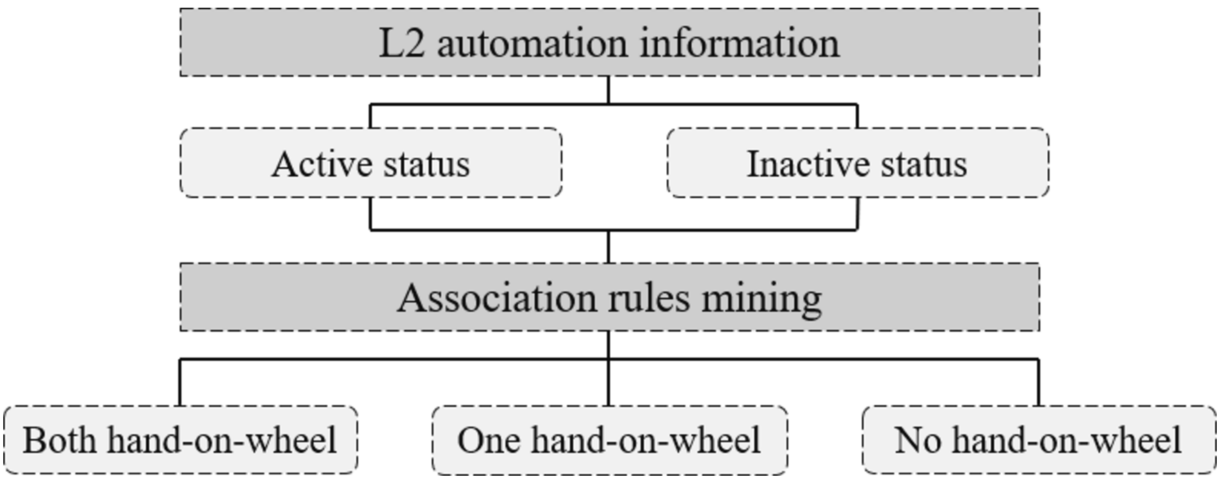


Fig. 1. Study design flow chart.

3. Methodology

3.1. Study design and data source

This study employed a quantitative research design, utilizing open-sourced naturalistic driving data collected by a university transportation center (Klauer and Anderson, 2023). The dataset comprises 771 driving events recorded on uncontrolled access roadways in Virginia, focusing on vehicles equipped with L2 automation systems. Each event is categorized based on the activation status of L2 systems (active or inactive), intersection types, and hand positions on the steering wheel (both hands, one hand, no hands). Furthermore, ARM is applied to investigate the attributes related to driving behavior based on hand position on the steering wheel. The study design is briefly illustrated in Fig. 1.

3.2. Association rules mining

In this study, ARM was employed to explore the underlying factors associated with driver behavior under varying conditions of L2 automation. Unlike traditional statistical modeling techniques commonly used in driver behavior analysis, ARM offers several distinct advantages. While statistical methods can provide insights into the individual effects of different variables on driver behavior, they are often constrained by predefined assumptions. Violations of these assumptions can lead to biased or inaccurate results (Mondal et al., 2020). In contrast, ARM overcomes these limitations and provides several key benefits such as identifying the hidden patterns between the variables in large datasets. This approach is particularly effective in analyzing driver behavior data, offering valuable insights that may not be readily apparent using traditional statistical methods. ARM allows for identifying complex and non-linear relationships among various factors, contributing to a more comprehensive understanding of driver behavior patterns and the impact of L2 automation on driver attention and engagement. Additionally, ARM demonstrates superior performance and flexibility in handling diverse data distributions and efficiently manages large datasets.

Additionally, ARM's efficient handling of big data makes it particularly suitable for analyzing large, complex datasets common in traffic safety and driver behavior research. By employing ARM in this study, this study aims to identify complex associations and patterns in driver behavior under different L2 automation statuses, thereby providing a deeper and more nuanced understanding of the factors influencing driver engagement and safety. ARM employs several algorithms, with the Classifications Based on Associations (CBA) algorithm being one of the most widely used. Introduced by Hahsler et al. (2019), the CBA algorithm employs a step-by-step approach to identify frequent item sets based on the principle that all subsets of a frequent item set must also be frequent.

The traditional ARM algorithm, such as Apriori, is widely used to discover frequent patterns and associations between variables in a dataset (Agrawal et al., 1993). These algorithms focus on identifying itemset that frequently occur together but are not explicitly designed for classification. The CBA algorithm differs from standard ARM algorithms by focusing on association rules specifically for classification. It combines association rule mining with classification, making it ideal for predictive modeling (Azmi et al., 2019; Yin and Han, 2003). This method allows for the extraction of recurring item groups within large datasets. In this context, the set of items $I = \{i_1, i_2, ..., i_m\}$ includes various aspects of driver behavior and L2 automation status, while the dataset $C = \{c_1, c_2, ..., c_n\}$ represents individual events or transactions, each containing a subset of items from *I*. A k-itemset is defined as an itemset with k items. An association rule is formatted as $Antecedent(A) \rightarrow Consequent(B)$, indicating that the presence of A increases the likelihood of B occurring. The study evaluates the strength and relevance of the identified rules using four key measures: support, confidence, lift, and coverage. Detailed explanations of these measures are provided in the following sections.

3.2.1. Support

Support quantifies how frequently an item set appears within a dataset. It measures the proportion of transactions that a rule covers relative to the entire dataset (Hahsler et al., 2005). Equation (1) expresses the mathematical representation of support.

$$\text{Support}, S(A \rightarrow B) = \frac{A \cap B}{N} \tag{1}$$

Where,

$S(A \rightarrow B)$ = support of the association rule $(A \rightarrow B)$,

$A \cap B$ = frequency of occurrences with both antecedent and consequent, and.

N = total frequency of occurrences.

3.2.2. Confidence

Confidence assesses the reliability of a rule by measuring how often it is true. It calculates the likelihood that the consequent (B) occurs in transactions where the antecedent (A) is present. A high confidence value indicates that B frequently occurs when A is present (Hahsler et al., 2005). The mathematical representation of confidence can be defined using Equation (2).

$$Confidence, C(A \rightarrow B) = \frac{S(A \rightarrow B)}{S(A)} \tag{2}$$

Where,

$C(A \rightarrow B)$ = confidence of the association rule $(A \rightarrow B)$,

$S(A \rightarrow B)$ = support of the association rule $(A \rightarrow B)$, and.
$S(A)$ support of antecedent $.A$

3.2.3. Lift

Lift measures the actual occurrence of both the antecedent (A) and consequent (B) compared to their expected co-occurrence if they were independent. It is the ratio of the observed frequency to the expected frequency. A lift value greater than 1 indicates positive dependence, meaning A and B appear together more often than expected, whereas a value less than 1 indicates negative dependence (Montella et al., 2011). The mathematical representation of lift can be defined using Equation (3).

$$Lift, L(A \rightarrow B) = \frac{C(A \rightarrow B)}{S(B)} = \frac{S(A \rightarrow B)}{S(A).S(B)} \tag{3}$$

Where,
$S(A \rightarrow B)$ = support of the association rule $(A \rightarrow B)$,
$S(A)$ = support of antecedent, and.
$S(B)$ = support of consequent.

3.2.4. Coverage

Coverage is the support of the antecedent A in the rule $(A \rightarrow B)$, i.e., $S(A)$. It indicates how often the rule can be applied. Coverage is simply the support of A and can be calculated as Equation (4).

$$Coverage, CO = S(A) \tag{4}$$

3.3. Data Description

The dataset includes naturalistic driving data from Virginia, primarily focusing on uncontrolled access roadways (Klauer and Anderson, 2023). Table 1 outlines the key variables used in analyzing L2 driving events, providing definitions and relevant descriptions for each variable. The data encompasses a substantial amount of driving events, with a total of 771 events recorded. These events are categorized based on the activation status of L2 automation systems, with 439 events having active L2 features and 332 events with inactive L2 features. The dataset includes detailed information on various driving contexts, such as intersection types, lead vehicle presence, and traffic density. It spans multiple driving scenarios, including no intersection (506 events), moving straight through an intersection (159 events), and turning through an intersection (106 events).

Additionally, the dataset captures a wide range of driver behaviors and conditions, such as eyes-off-road time, off-road glances, hand position on the steering wheel, and engagement in secondary tasks. Note that two definitions were considered to define EOR behavior. For EOR definition 1, only glances directed forward are defined as on-road. All other glance locations, such as the left or right mirror/window/windshield, rearview mirror, center stack, instrument cluster, eyes closed, over-the-shoulder (left or right), passenger, cell phone, portable media device, and interior object, are considered off-road. Conversely, for EOR definition 2, glances directly related to driving tasks are considered on-road. These include glances forward, to the left or right mirror/window/windshield, rearview mirror, and instrument cluster. All other glances not directly related to driving are considered off-road (*21, 22*). *"TotalEOR_1"* and *"TotalEOR_2"* represent the total eyes-off-road time, while *"OffRoadGlances_1"* and *"OffRoadGlances_2"* count the number of eyes-

Table 1
Definitions and Descriptions of Variables Used in The Analysis of L2 Driving Events.

Variable	Definition
L2 Status	L2 features are activated for the event or available but inactive for the event (Active: 439, Not active: 332)
Intersection	None = No intersection; Straight = moving straight through an intersection; Turn = Turning through intersection (None: 506, Straight: 159, Turn: 106)
TotalEOR_1 (seconds)	Total eyes off-road time for an event using EOR definition 1
OffRoadGlances_1 (count)	Number of eyes off-road glances for an event using EOR definition 1
TotalEOR_2 (seconds)	Total eyes off-road time for an event using EOR definition 2
OffRoadGlances_2 (count)	Number of eyes off-road glances for an event using EOR definition 2
LV	Lead vehicle category (Vehicle: 434, Vehicle at far: 169, No vehicle present: 166)
Total Glance_Sec (seconds)	Length of glance window that was evaluated in seconds
PercentEOR_1 (percentage)	Percent of event that had eyes off-road time using EOR definition 1
PercentEOR_2 (percentage)	Percent of event that had eyes off-road time using EOR definition 2
Active Mean Speed (mph)	Mean speed for an event when L2 systems were active
Traffic Density	Amount of ambient traffic present in an event
HOW_1	None = no hands-on-wheel; One hand = either right or left hand only; Both hands = both hands-on-wheel (None: 450, One: 193, Both: 128)
ST1	First secondary task observed in the event (No secondary task: 367, Cognitive task: 166, Vehicle related task: 132, Phone: 19)
LOS	Level of service (A1: 108, A2: 118, B: 447, C: 68)

off-road glances. The LV variable indicates the presence of a lead vehicle during the event. Additionally, *"Total Glance_Sec"* measures the length of the glance window evaluated in seconds. *"PercentEOR_1"* and *"PercentEOR_2"* denote the percentage of event time during which eyes were off-road.

Table 2 presents a detailed analysis of various driver behavior metrics under different conditions of L2 automation status (*"Active"* and *"Not Active"*) and hand positions (HOW_1: Both hands, None, One hand). The metrics include mean eyes-off-road time (MnEOR) and its standard deviation (SDEOR) for two different definitions (EOR1 and EOR2), mean and standard deviation of the number of off-road glances (MnORG and SDORG), and mean and standard deviation of total glance time (MnTG and SDTG). For events where the L2 system was active and both hands were on the wheel, the mean eyes-off-road time using EOR definition 1 (MnEOR1) was 6.27 s, with a standard deviation of 3.48 s. The mean number of off-road glances (MnORG1) was 7.62, with a standard deviation of 4.25. When no hands were on the wheel, the mean eyes-off-road time (MnEOR1) increased significantly to 8.56 s, with a standard deviation of 4.94 s, indicating higher distraction. With one hand on the wheel, the mean eyes-off-road time (MnEOR1) was 7.52 s, and the standard deviation was 4.01 s. In contrast, for events where the L2 system was not active and both hands were on the wheel, the mean eyes-off-road time (MnEOR1) was 4.72 s, with a standard deviation of 3.66 s, which is lower compared to when the L2 system was active. Overall, the table demonstrates that driver distraction, as indicated by longer eyes-off-road times and more off-road glances, tends to be higher when the L2 system is active, especially when drivers do not have their hands on the wheel.

Table 3 presents the descriptive statistics for key variables related to driver behavior during events with L2 automation status. *"TotalEOR_1"* and *"TotalEOR_2"*, which measure total eyes-off-road time, show mean values of 6.63 s and 3.62 s, respectively, indicating varying eyes-off-road durations. *"OffRoadGlances_1"* and *"OffRoadGlances_2"*, representing the number of eyes-off-road glances, have means of 7.65 and 3.58, respectively, suggesting frequent short and infrequent longer glances. *"TotalGlance_Sec"*, the total glance duration, is highly consistent with a mean of 29.97 s. *"ActMeanSpd"*, the mean speed during active L2 events, averages 44.54 mph, highlighting a common operating speed range. *"PercentEOR_1"* and *"PercentEOR_2"*, the percentages of event duration with eyes-off-road time, have mean values of 0.22 and 0.12, respectively, showing varying levels of eyes-off-road engagement.

4. Results

4.1. Density plots of driver behavior metrics

This section analyzes driver behavior metrics using density plots to explore the relationship between off-road glance durations, total glance durations, hand positions, and L2 automation status across all hand positions. The density plot (see Fig. 2a) analysis of off-road glances by hand position and L2 automation status reveals that the *"Active"* status of L2 automation correlates with longer off-road glance durations across all hand positions ("both hands", "none", and "one hand'). Specifically, when L2 automation is active, drivers tend to glance off-road for extended periods, peaking around 10–15 times (for *OffRoadGlances_1*, and slightly lower for *OffRoadGlances_2*), whereas, with L2 automation inactive, the distribution peaks earlier, around 5–10 times. This trend suggests that drivers may rely more on L2 automation, leading to increased off-road glances, potentially due to a perceived sense of security provided by the automation system, as supported by a previous study (Strayer et al., 2023). Conversely, the inactive L2 status is associated with lower off-road glances, indicating greater driver engagement. A similar trend is visible in Fig. 2(b).

Fig. 3(a) illustrates the distribution of *"TotalEOR_1"* durations across different hand positions on the steering wheel and the status of L2 (*"Active"* in blue and *"Not Active"* in yellow). For all hand positions, the data indicates that when L2 automation is active, drivers exhibit a broader and generally longer duration of eyes-off-road instances compared to when L2 automation is not active. Specifically, with both hands on the wheel, the *"Active"* status peak is around 5–10 s, whereas the *"Not Active"* status peaks sharply around 5 s. When no hands are on the wheel, the *"Active"* status again shows a broader distribution with a peak of around 10 s, compared to the sharper and shorter peak of the *"Not Active"* status of around 5–7 s. For the one hand-on-wheel position, the *"Active"* status shows a longer duration of eyes-off-road instances with a peak of around 10 s, while the *"Not Active"* status peaks around 5–7 s. A similar trend is visible in Fig. 3(b). Overall, the broader distributions and longer peak durations observed with active L2 automation imply that drivers feel more secure and are less vigilant about maintaining visual focus on the driving environment.

Conversely, when L2 automation is inactive, drivers exhibit shorter and more concentrated total EOR durations, possibly due to increased driver engagement and the need for increased attention to driving tasks (Solís-Marcos et al., 2018). The sharper and earlier peaks in the *"Not Active"* status highlight drivers' need to stay more alert and actively monitor the road when the L2 automation support is unavailable.

The density plot in Fig. 4 illustrates the distribution of *"TotalGlance_Sec"* for different hand positions on the steering wheel under

Table 2
Driver Behavior Metrics by L2 Automation Status and Hand Positions.

L2Status	HOW_1	MnEOR1	SDEOR1	MnEOR2	MnORG1	SDORG1	MnORG2	SDORG2	MnTG1	SDTG1
Active	Both	6.27	3.48	3.25	7.62	4.25	3.42	2.85	30.0	0.024
Active	None	8.56	4.94	4.72	9.29	4.5	4.29	3.61	30.0	0.018
Active	One	7.52	4.01	3.99	8.68	4.63	3.91	2.87	30.0	0.015
Not Active	Both	4.72	3.66	2.98	5.78	4.18	3.38	3.38	30.0	0.019
Not Active	None	4.57	3.1	2.32	5.79	4.57	2.68	3.19	30.0	0.018
Not Active	One	4.85	3.66	2.61	6.08	4.56	2.78	3.26	30.0	0.018

Table 3
Descriptive Statistics of L2 Automation Variables.

variable	missing	mean	sd	p0	p25	p50	p75	p100	hist
TotalEOR_1	0	6.63	4.92	0	3.0	5.67	9.38	25.5	
OffRoadGlances_1	0	7.65	4.75	0	4.0	7.0	11.0	22.0	
TotalEOR_2	0	3.62	4.26	0	0.68	2.27	5.0	25.5	
OffRoadGlances_2	0	3.58	3.42	0	1.00	3.00	5.0	18.0	
TotalGlance_Sec	0	29.97	0.02	29.87	29.95	29.97	29.98	30.0	
ActMeanSpd	332	44.54	15.77	0.69	35.25	48.98	56.55	78.95	
PercentEOR_1	0	0.22	0.16	0	0.1	0.19	0.31	0.85	
PercentEOR_2	0	0.12	0.14	0	0.08	0.08	0.17	0.85	

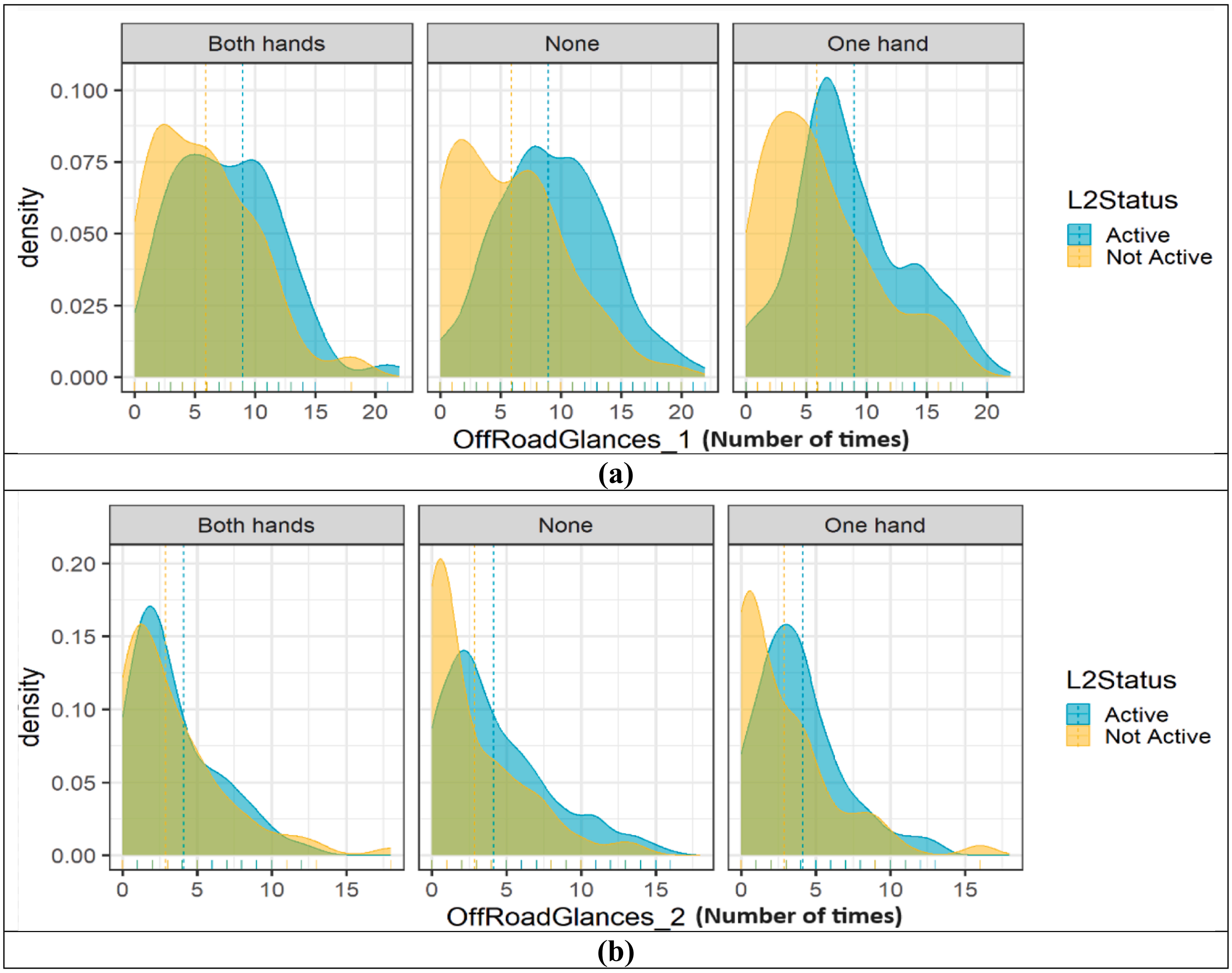


Fig. 2. Density plots of driver off-road glance behavior by L2 automation status and hand positions.

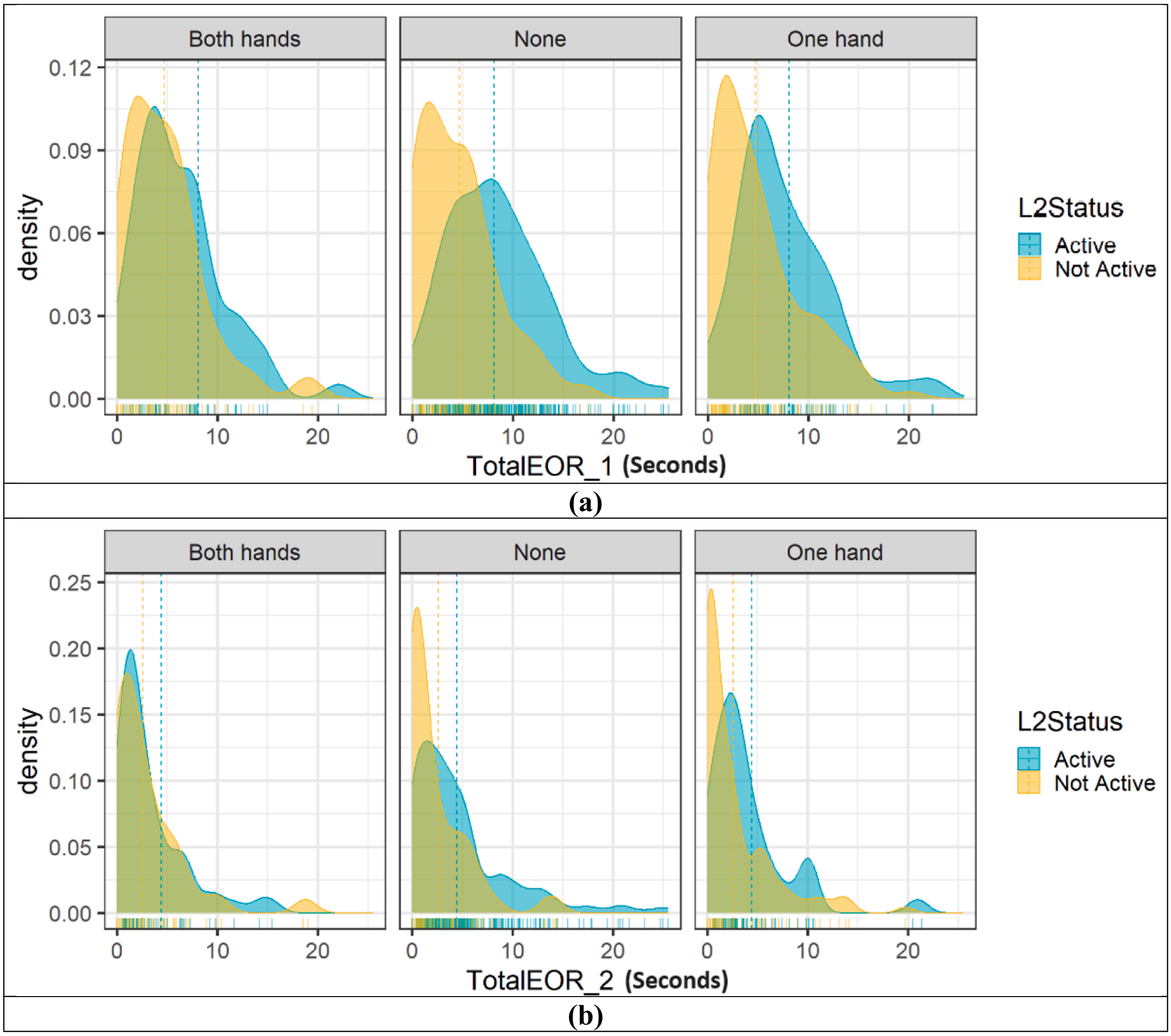


Fig. 3. Density plots of driver total EOR behavior by L2 automation status and hand positions.

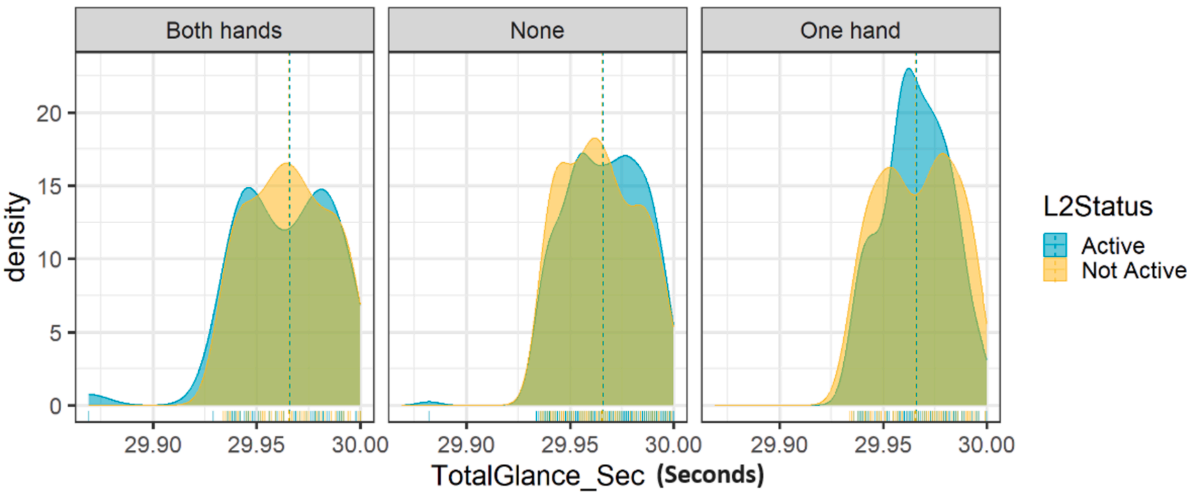


Fig. 4. Density plots of driver number of total glance behavior by L2 automation status and hand positions.

two conditions of L2 automation status. Across all hand positions, the total glance duration hovers closely around 30 s, suggesting a narrow range of variance. For both hands on the wheel, the density peaks slightly above 29.95 s for both active and inactive L2 status, with the inactive status showing a slightly broader distribution. When no hands are on the wheel, the peak again centers around 29.95 s, with the active L2 status showing a narrower distribution than the inactive status. With one hand on the wheel, the active L2 status shows a distinct, sharp peak slightly above 29.95 s, indicating a more consistent glance duration than the inactive status, which has a broader peak.

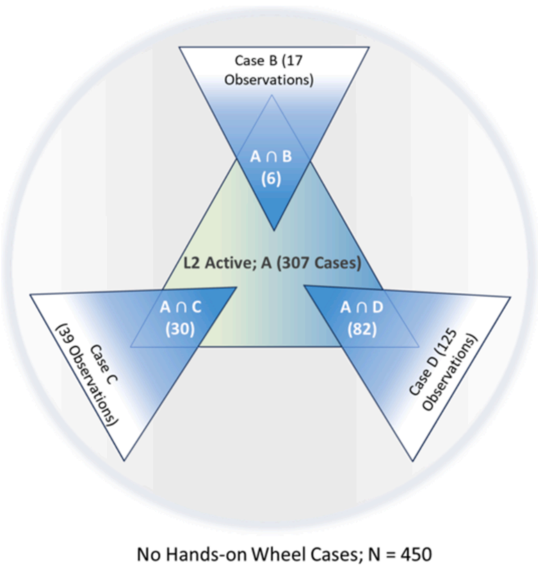
4.2. Association rules mining by hand position

This study utilized a robust rule-mining technique known as ARM to thoroughly examine driver behavior related to L2 automation and extract actionable insights. The dataset was categorized into three levels based on hand positions on the steering wheel: both hands, one hand, and no hands. Rules were generated for each category to uncover factors associated with these different hand positions. The analysis used the 'arulesCBA' package in R, employing the CBA algorithm to mine the data (Hahsler et al., 2019). This package differs from conventional association rules as it specifically focuses on creating classifiers by mining class association rules, where the consequent is restricted to the class attribute for predictive modeling. The generated rules were ranked according to their lift values, which indicate their significance. To enhance clarity and focus, only the most significant rules based on lift value are reported in this paper. For a complete understanding of the results, it is important to consider the number of items set in the rules. A two-item rule represents one antecedent and one consequent, while a three-item rule includes one antecedent and two consequents (Das et al., 2019). This study considered up to three items, ensuring that the findings were interpreted correctly and concisely.

Additionally, to investigate driver attentiveness, the driver's involvement in secondary tasks was selected as consequent. The association rules were selected based on lift values. A threshold of 1.15 in the lift values was selected for further explanation. The following section details the outcomes of the rule mining analysis. Fig. 5 shows a representation of an example of how support, confidence, coverage, and lift measures of an association rule are calculated.

4.2.1. Association rules for both Hands-On-Wheel

The association rules for both hands-on-wheel driving conditions, sorted by the lift values, are illustrated in Table 4. The rule (BH01a) with the highest lift value has an antecedent of {*L2Status* = *Not Active, OffRoadGlances_1* = *6*} and a consequent of {*ST1* = *Cognitive*}. This association rule examines the relationship between L2 automation status, off-road glance duration, and engagement in a secondary cognitive task. The support value indicates that this combination of L2 automation status and off-road glance duration occurs in 2.3 % of the data, providing insight into how common this specific scenario is within the dataset. The confidence value shows that when drivers are not using L2 automation and have glanced off-road for 6 s, there is a 50 % chance they are also engaging in a secondary cognitive task. The coverage value indicates that 4.7 % of the dataset meets the antecedent conditions (L2 status and glance duration). The lift value of 3.200 reveals that the likelihood of engaging in a cognitive task is 3.2 times higher when L2 automation is inactive, and the off-road glance duration is 6 s, compared to if these factors were independent. This rule suggests that drivers are more likely to engage in secondary cognitive tasks when L2 automation is off, and they have glanced off-road for 6 s. When the L2 system is inactive, the driver must manually control the vehicle, increasing cognitive load. Frequent off-road glances (6 in this case) may indicate the driver is checking mirrors, instruments, or surroundings to maintain situational awareness, leading to cognitive tasks such



For Rule NH04,
{L2Status=Active, Intersection=Turn → ST1=No Secondary Tasks}
Support = 0.013, Confidence = 0.667, Coverage = 0.02, Lift = 1.657

Case B = {No Secondary Task, Turn}
Case C = {No Secondary Task, Straight}
Case D = {No Secondary Task, None}

$$Support, S(A \rightarrow B) = \frac{6}{450} = 0.013$$

$$Coverage, CO = S(A) = \frac{9}{450} = 0.02$$

$$Confidence, C(A \rightarrow B) = \frac{6}{9} = 0.667$$

$$Lift, L(A \rightarrow B) = \frac{C(A\rightarrow B)}{S(B)} = \frac{S(A\rightarrow B)}{S(A).S(B)} = \frac{\frac{6}{450}}{\frac{9}{450}\cdot\frac{181}{450}} = 1.657$$

Fig. 5. An example of estimating association rules parameters.

Table 4
Top Association Rules for Both Hands-On-Wheel.

Rule No.	Antecedent	Consequent	S	Con	Cov	L
BH01a	{L2Status = Not Active, OffRoadGlances_1 = 6}	{ST1 = Cognitive}	0.023	0.500	0.047	3.200
BH01b	{Intersection = None, OffRoadGlances_1 = 1}	{ST1 = Cognitive}	0.023	0.500	0.047	3.200
BH02	{Intersection = None, LOS = A2}	{ST1 = Vehicle}	0.031	0.364	0.086	3.103
BH03a	{OffRoadGlances_1 = 4, OffRoadGlances_2 = 1}	{ST1 = No Secondary Tasks}	0.047	1.000	0.047	1.455
BH03b	{LV = Vehicle, OffRoadGlances_1 = 10}	{ST1 = No Secondary Tasks}	0.047	1.000	0.047	1.455
BH04a	{OffRoadGlances_2 = 5, LOS = B}	{ST1 = No Secondary Tasks}	0.039	1.000	0.039	1.455
BH04b	{Intersection = None, OffRoadGlances_1 = 3}	{ST1 = No Secondary Tasks}	0.039	1.000	0.039	1.455
BH05a	{TotalEOR_1 = 0}	{ST1 = No Secondary Tasks}	0.031	1.000	0.031	1.455
BH05b	{TotalGlance_Sec = 29.992}	{ST1 = No Secondary Tasks}	0.031	1.000	0.031	1.455
BH05c	{TotalGlance_Sec = 29.956}	{ST1 = No Secondary Tasks}	0.031	1.000	0.031	1.455
BH05d	{TotalEOR_2 = 0.867}	{ST1 = No Secondary Tasks}	0.031	1.000	0.031	1.455
BH05e	{TotalGlance_Sec = 29.942}	{ST1 = No Secondary Tasks}	0.031	1.000	0.031	1.455
BH05f	{Intersection = Straight,LOS = C}	{ST1 = No Secondary Tasks}	0.031	1.000	0.031	1.455

Note: BH = Both hands-on wheel, S = Support, Con = Confidence, Cov = Coverage, L = Lift.

as interacting with passengers or talking. This cognitive task may vary depending on the presence of intersections (Liao et al., 2016, 2015). In non-intersection scenarios, drivers were observed with minimal off-road glances. This indicates that the drivers may engage in brief cognitive tasks, such as speaking to a passenger or checking a device, as the driving environment is less complex.

Additionally, non-intersection areas with good traffic flow may allow the driver to focus on vehicle-related tasks such as adjusting the instrument panel or monitoring the vehicle systems without distraction from navigating intersections. The drivers were found to refrain from engaging in secondary tasks under certain conditions. The rule (BH03a) {*OffRoadGlances_1 = 4, OffRoadGlances_2 = 1 → ST1 = No Secondary Tasks*} indicates that the combination of initial frequent glances followed by fewer glances means the driver is quickly scanning surroundings before focusing on the road, indicating high engagement with driving and no secondary tasks. The presence of lead vehicles requires close monitoring. This vigilance reduces the likelihood of engaging in secondary tasks to maintain safe following distance and response time. Similarly, situations involving no intersections or straight paths through intersections, combined with a moderate or higher traffic density, necessitate continuous monitoring and adjustment, further reducing the initiation of secondary tasks (Lemonnier et al., 2020).

4.2.2. Association rules for one hand-on-wheel

The association rules for one-hand-on-wheel driving conditions, sorted by lift values, are reported in Table 5. The rules for one-hand-on-wheel driving demonstrate how drivers regulate their attention based on the complexity and demands of the driving environment. Several rules indicate that drivers engage in cognitive tasks under specific conditions. When total glance times are close to 30 s (Rules OH01, OH03a), drivers show a pattern of consistent, methodical monitoring. This behavior can be related to cognitive tasks like interacting with passengers, talking, or thinking about navigation and driving strategies.

Additionally, frequent off-road glances, particularly when combined with moderate traffic flow (LOS = B) or the absence of intersections, suggest an increased cognitive load (Werneke and Vollrath, 2012). In these situations, drivers may engage in cognitive tasks as they process information and make decisions while maintaining situational awareness. Some off-road glances (Rule OH06) correlate with cognitive tasks. This balance between monitoring the road and attending to cognitive tasks indicates that drivers manage their attention effectively, engaging in secondary cognitive activities while maintaining focus on driving. The rules suggest

Table 5
Top Association Rules for One Hand-On Wheel.

Rule No.	Antecedent	Consequent	S	Con	Cov	L
OH01	{TotalGlance_Sec = 29.99}	{ST1 = Cognitive}	0.016	1.000	0.016	4.825
OH02	{Intersection = None, OffRoadGlances_1 = 11}	{ST1 = Vehicle}	0.016	0.750	0.021	4.669
OH03a	{TotalGlance_Sec = 29.944, LOS = B}	{ST1 = Cognitive}	0.016	0.750	0.021	3.619
OH03b	{Intersection = None, OffRoadGlances_2 = 6}	{ST1 = Cognitive}	0.016	0.750	0.021	3.619
OH04	{OffRoadGlances_2 = 7}	{ST1 = Cognitive}	0.021	0.667	0.031	3.217
OH05	{OffRoadGlances_1 = 3}	{ST1 = Vehicle}	0.026	0.385	0.067	2.395
OH06	{OffRoadGlances_1 = 6}	{ST1 = Cognitive}	0.041	0.348	0.119	1.678
OH07	{OffRoadGlances_1 = 7}	{ST1 = No Secondary Tasks}	0.052	0.769	0.067	1.515
OH08	{L2Status = Active}	{ST1 = Vehicle}	0.093	0.234	0.399	1.455
OH09	{Intersection = Turn}	{ST1 = No Secondary Tasks}	0.145	0.667	0.218	1.313
OH10	{PercentEOR_2 = 0}	{ST1 = No Secondary Tasks}	0.140	0.643	0.218	1.266
OH11	{LOS = A2}	{ST1 = No Secondary Tasks}	0.109	0.636	0.171	1.253

Note: OH = One hand-on wheel, S = Support, Con = Confidence, Cov = Coverage, L = Lift.

drivers can afford to split their attention between driving and cognitive tasks in structured, less demanding scenarios. For example, on highways with moderate traffic flow, where the road is relatively predictable and there are fewer complex interactions with other vehicles. Similarly, long, straight road sections without frequent intersections offer a less cognitively demanding environment, allowing for tasks like adjusting the radio or briefly glancing at navigation. Additionally, when driving at constant speeds with cruise control active, the reduced need for acceleration or braking provides more flexibility for cognitive activities.

Certain conditions lead drivers to refrain from secondary tasks. When drivers exhibit many off-road glances, such as 7, they are likely fully engaged in monitoring their environment. This vigilance reduces the likelihood of engaging in any secondary tasks. Similarly, when the L2 is active, drivers tend to focus on vehicle-related tasks, such as adjusting settings or monitoring the system's performance. This behavior aligns with findings from previous studies that reported similar results (Zangi et al., 2022). This engagement in vehicle-related tasks comes at the expense of secondary tasks, reflecting the need for oversight and control. Complex driving scenarios, such as turning at intersections, require significant attention, leading to no secondary tasks as drivers navigate safely through these maneuvers. Likewise, zero percent eyes-off-road time indicates full attention to the road, preventing any engagement in secondary tasks. In scenarios with good traffic flow (LOS A2), drivers steadily focus on the driving environment, discouraging secondary task engagement. The need for continuous monitoring and adjustment in such conditions ensures that the driver's attention remains on the road.

4.2.3. Association rules for no hands-on wheel

The association rules for no hands-on wheel driving conditions, sorted by lift values, are illustrated in Table 6. The rules for driving with no hands on the wheel provide valuable insights into the conditions influencing whether drivers engage or refrain from secondary tasks. The rule (NH01) with the highest lift value was identified as {*Intersection = None, TotalGlance_Sec = 29.988 → ST1 = Cognitive*}. This rule can be interpreted as follows: In situations where no intersection is involved and the driver's total glance time is approximately 29.988 s, there is a 55.6 % likelihood that the driver is in a cognitive state. This combination of factors (no intersection and specific glance time) occurs in 1.1 % of all instances in the dataset, and this rule is about 2.358 times more likely to occur than by random chance, indicating a significant association between these conditions and the cognitive state of the driver. One interpretation of this rule is that when there are no intersections and the total glance time is approximately 30 s, drivers show a pattern of consistent and structured monitoring. This behavior can lead to cognitive tasks such as interacting with passengers. The engagement in cognitive tasks during less complex driving scenarios suggests that drivers balance their attention between the road and mental activities (Cantin et al., 2009), taking advantage of less demanding driving conditions to perform secondary cognitive tasks.

Several conditions can lead drivers to refrain from secondary tasks. When the L2 automated driving system is inactive, drivers maintain higher vigilance, especially in good traffic conditions (LOS = A2) (Noble et al., 2021). This increased attention to driving excludes secondary task engagement as drivers focus on compensating for the lack of automation support. Driving straight through intersections or turning with an active L2 system also requires significant attention (Ebadi et al., 2021; Reece and Shafer, 1995). These scenarios necessitate continuous monitoring of the driving environment, leading drivers to avoid secondary tasks to ensure safe navigation through these potentially complex driving maneuvers. Frequent off-road glances, such as having 14 glances, indicate intensive monitoring of the environment. This high level of engagement also prevents the initiation of secondary tasks, as drivers focus on maintaining situational awareness. When the percent eyes-off-road time is zero, drivers focus entirely on the road. This complete

Table 6
Top Association Rules for No Hands-On Wheel.

Rule No.	Antecedent	Consequent	S	Con	Cov	L
NH01	{Intersection = None, TotalGlance_Sec = 29.988}	{ST1 = Cognitive}	0.011	0.556	0.020	2.358
NH02	{L2Status = Not Active, LOS = A2}	{ST1 = No Secondary Tasks}	0.049	0.710	0.069	1.764
NH03	{Intersection = Straight, OffRoadGlances_2 = 4}	{ST1 = No Secondary Tasks}	0.016	0.700	0.022	1.740
NH04	{L2Status = Active, Intersection = Turn}	{ST1 = No Secondary Tasks}	0.013	0.667	0.020	1.657
NH05	{L2Status = Active, OffRoadGlances_2 = 8}	{ST1 = No Secondary Tasks}	0.016	0.636	0.024	1.582
NH06	{L2Status = Active, LOS = A1}	{ST1 = No Secondary Tasks}	0.038	0.607	0.062	1.509
NH07	{OffRoadGlances_2 = 4, LOS = B}	{ST1 = No Secondary Tasks}	0.031	0.560	0.056	1.392
NH08	{LV = Vehicle, far, LOS = A2}	{ST1 = No Secondary Tasks}	0.060	0.540	0.111	1.343
NH09	{L2Status = Active, OffRoadGlances_1 = 14}	{ST1 = No Secondary Tasks}	0.024	0.524	0.047	1.302
NH10	{L2Status = Not Active, PercentEOR_2 = 0}	{ST1 = No Secondary Tasks}	0.047	0.477	0.098	1.187
NH11	{L2Status = Active, OffRoadGlances_1 = 4}	{ST1 = No Secondary Tasks}	0.020	0.474	0.042	1.178
NH12	{LV = Vehicle, far, OffRoadGlances_2 = 3}	{ST1 = No Secondary Tasks}	0.016	0.467	0.033	1.160
NH13	{Intersection = Straight}	{ST1 = No Secondary Tasks}	0.087	0.464	0.187	1.154
NH14	{LOS = A1}	{ST1 = No Secondary Tasks}	0.058	0.464	0.124	1.154

Note: NH = No hands-on wheel, S = Support, Con = Confidence, Cov = Coverage, L = Lift.

attention to driving eliminates the possibility of secondary tasks, as any distraction could compromise safety.

Similarly, in scenarios with good traffic conditions (LOS = A1 and LOS = A2), drivers maintain a steady focus on the driving environment. The need for continuous monitoring and adjustment in such conditions ensures that the driver's attention remains on the road, discouraging secondary task engagement. The presence of a lead vehicle also requires drivers to maintain situational awareness. This continuous monitoring of the lead vehicle's movements and the surrounding traffic prevents secondary tasks, as drivers need to be ready to respond to any changes in the lead vehicle's speed or position.

4.3. Key findings

This analysis reveals crucial insights into driver behavior, focusing on the impact of L2 automation and hand position. It also examines how traffic complexity influences driver distraction and engagement with secondary tasks. The major findings from the analysis are described below:

- The study found that driver distraction, measured through eyes-off-road time and off-road glances, is significantly higher when L2 systems are active. This indicates increased reliance on the automation system and reduced situational awareness. This finding also verified the first hypothesis of the research, which assumed that drivers exhibit longer EOR times and an increased frequency of off-road glances when L2 systems are active compared to inactive ones.
- The presence of a lead vehicle necessitated continuous monitoring, reducing the likelihood of engaging in secondary tasks. Frequent off-road glances in the presence of a lead vehicle discouraged secondary task engagement. Additionally, it was found that intersections and varying road conditions significantly impact driver behavior, revealing distinct patterns depending on whether the L2 system is active or inactive. This finding also addressed the second hypothesis of this study, where it was assumed that different road conditions and level of service of roads will impact driver behavior.
- Association rules for both hands-on-wheel conditions indicate that drivers are more likely to engage in cognitive tasks when L2 automation is inactive, and they have moderate off-road glances. In less complex driving environments, such as non-intersection areas, drivers perform brief cognitive tasks with minimal off-road glances. Additionally, frequent initial off-road glances followed by fewer glances are associated with a reduction in secondary tasks, reflecting higher engagement with driving, especially in more complex scenarios.
- Association rules for no hands-on-wheel conditions reveal that drivers are likelier to engage in cognitive tasks, such as interacting with passengers when no intersections and glance times are significant. This suggests drivers balance their attention between the road and secondary activities in less complex scenarios. Conversely, drivers avoid secondary tasks when L2 automation is inactive, driving through intersections, or taking turns with active L2 automation. This finding addresses the final hypothesis of the study, where it was expected that the hand-on-wheel position of the driver would be impacted based on the activation status of L2 automation.

5. Conclusions

This study investigated the impact of L2 automation system activation on driver behavior in real-world driving conditions. By analyzing a dataset of 771 naturalistic driving events categorized by L2 system activation status, intersection types, and hand positions on the steering wheel, this research advances the understanding of how various factors influence driver distraction and secondary task engagement. An ARM with the CBA algorithm was utilized to explore the relationships between driver behavior and L2 system activation. The findings reveal that L2 automation significantly affects driver behavior, with system activation correlating with increased driver distraction, as indicated by longer eyes-off-road times and more frequent off-road glances. This suggests drivers rely excessively on automation, diminishing situational awareness. The study highlights the critical role of hand positioning on the steering wheel, showing that drivers who remove their hands from the wheel exhibit higher levels of distraction, especially when L2 systems are active. Moreover, a lead vehicle and complex traffic conditions reduced secondary task engagement, underscoring the importance of maintaining attention during challenging driving scenarios. Additionally, intersection types and traffic complexity significantly influence driver behavior, with drivers engaging more in cognitive tasks in simpler environments and focusing more on the driving task in complex situations.

These insights have several key applications for enhancing road safety and optimizing driver engagement with L2 automation systems. Developing improved driver-system interfaces could help maintain physical and cognitive involvement even with active L2 systems. Although L2 automation is continuously improving, there is a need for changes in the interfaces in autonomous vehicles. The interfaces should keep drivers more engaged and aware of their surroundings, even when automation is active. Adding more frequent alerts or reminders to pay attention could reduce distraction.

Additionally, advanced systems using eye-tracking and biometric sensors can alert drivers when they are not paying enough attention to the road, helping to prevent accidents. Integrating other safety systems, such as collision avoidance and emergency braking, can improve the technology. Targeted driver education programs should address the risks associated with hands-off driving and secondary task engagement, particularly in complex traffic scenarios. System design could incorporate more effective alerts or reminders for disengaged drivers. Furthermore, the study's findings can guide policymakers in formulating regulations to ensure safe automation practices and define operational limits for L2 systems, ultimately contributing to safer driving environments.

While this study provides valuable insights into driver behavior under L2 automation, it has several limitations. The data used is from a specific region, limiting the applicability of the results to other areas. Additionally, the reliance on naturalistic driving data introduces variability due to uncontrolled factors such as weather, traffic density, and individual driver differences, which can influence behavior and affect the consistency of the findings. The study also does not consider how driver behavior might change over time as they become more familiar with L2 automation systems, as long-term behavioral adaptations and learning effects were not captured in the dataset. Furthermore, the research focuses solely on L2 automation systems and does not explore higher levels of automation, which might have varying impacts on driver behavior.

CRediT authorship contribution statement

Rohit Chakraborty: Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis. **Syed Aaqib Javed:** Writing – original draft. **Subasish Das:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Data curation, Conceptualization. **Boniphace Kutela:** Writing – review & editing. **Md Nasim Khan:** Writing – review & editing, Writing – original draft.

Declaration of competing interest

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

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Data availability

The authors do not have permission to share data.

References

Agrawal, R., Imieliński, T., & Swami, A. (1993). Mining association rules between sets of items in large databases. *SIGMOD Rec., 22*, 207–216. https://doi.org/10.1145/170036.170072

Atwood, J. R., Guo, F., & Blanco, M. (2019). Evaluate driver response to active warning system in level-2 automated vehicles. *Accident Analysis & Prevention, 128*, 132–138. https://doi.org/10.1016/j.aap.2019.03.010

Azmi, M., Runger, G. C., & Berrado, A. (2019). Interpretable regularized class association rules algorithm for classification in a categorical data space. *Information Sciences, 483*, 313–331. https://doi.org/10.1016/j.ins.2019.01.047

Beanland, V., Fitzharris, M., Young, K. L., & Lenné, M. G. (2013). Driver inattention and driver distraction in serious casualty crashes: Data from the Australian National Crash In-depth Study. *Accident Analysis & Prevention, 54*, 99–107. https://doi.org/10.1016/j.aap.2012.12.043

Blanco, M., Atwood, J., Vasquez, H.M., Trimble, T.E., Fitchett, V.L., Radlbeck, J., Fitch, G.M., Russell, S.M., Green, C.A., Cullinane, B., Morgan, J.F., 2015. Human Factors Evaluation of Level 2 and Level 3 Automated Driving Concepts.

Cantin, V., Lavallière, M., Simoneau, M., & Teasdale, N. (2009). Mental workload when driving in a simulator: Effects of age and driving complexity. *Accident Analysis & Prevention, 41*, 763–771. https://doi.org/10.1016/j.aap.2009.03.019

Carsten, O., Lai, F. C. H., Barnard, Y., Jamson, A. H., & Merat, N. (2012). Control Task Substitution in Semiautomated Driving: Does It Matter What Aspects Are Automated? *Human Factors, 54*, 747–761. https://doi.org/10.1177/0018720812460246

Chakraborty, R., Das, S., & Khan, M. N. (2024). Uncovering pedestrian midblock crash severity patterns using association rules mining. *Transportmetrica A: Transport Science*, 1–48. https://doi.org/10.1080/23249935.2024.2379948

Das, A., Khan, M. N., Ahmed, M., Ghasemzadeh, A., & Gaweesh, S. (2019). Structural Equation Modeling Approach for Investigating Driver Behavior in Adverse Weather Conditions using Trajectory-level SHRP2 Naturalistic Driving Data. *Road Safety & Simulation (RSS Conference)*.

Das, S., Kong, X., & Tsapakis, I. (2021). Hit and run crash analysis using association rules mining. *Journal of Transportation Safety & Security, 13*, 123–142. https://doi.org/10.1080/19439962.2019.1611682

Ebadi, Y., Helm, A., Hungund, A. P., Roberts, S. C., McDermott, J. M., Epstein, J. N., & Fisher, D. L. (2021). Impact of L2 automated systems on hazard anticipation and mitigation behavior of young drivers with varying levels of Attention Deficit Hyperactivity Disorder symptomatology. *Accident Analysis & Prevention, 159*, Article 106292. https://doi.org/10.1016/j.aap.2021.106292

Endsley, M. R., & Kaber, D. B. (1999). Level of automation effects on performance, situation awareness and workload in a dynamic control task. *Ergonomics, 42*, 462–492. https://doi.org/10.1080/001401399185595

Gershon, P., Seaman, S., Mehler, B., Reimer, B., & Coughlin, J. (2021). Driver behavior and the use of automation in real-world driving. *Accident Analysis & Prevention, 158*, Article 106217. https://doi.org/10.1016/j.aap.2021.106217

Hahsler, M., Grün, B., & Hornik, K. (2005). arules - A Computational Environment for Mining Association Rules and Frequent Item Sets. *Journal of Statistical Software, 14*, 1–25. https://doi.org/10.18637/jss.v014.i15

Hahsler, M., Johnson, I., Kliegr, T., & Kuchař, J. (2019). Associative Classification in R: Arc, arulesCBA, and rCBA. *The R Journal, 11*, 254–267.

Hecht, T., Zhou, W., & Bengler, K. (2022). How to keep drivers attentive during level 2 automation? Development and evaluation of an HMI concept using affective elements and message framing. *Safety, 8*.

Hossain, A., Sun, X., Mahmud Zafri, N., & Codjoe, J. (2023). Investigating pedestrian crash patterns at high-speed intersection and road segments: Findings from the unsupervised learning algorithm. *International Journal of Transportation Science and Technology*. https://doi.org/10.1016/j.ijtst.2023.04.007

Hossain, A., Sun, X., Thapa, R., & Codjoe, J. (2022). Applying association rules mining to investigate pedestrian fatal and injury crash patterns under different lighting conditions. *Transportation Research Record, 2676*, 659–672. https://doi.org/10.1177/03611981221076120

Hossain, M. M., Abbaszadeh Lima, M. R., & Zhou, H. (2024). Severity analysis of secondary crashes on high-speed roadways: pattern recognition using association rule mining. *Transportation Research Record, 2678*, 919–931. https://doi.org/10.1177/03611981231223194

Kim, H., Song, M., & Doerzaph, Z. (2022). Is driving automation used as intended? Real-world use of partially automated driving systems and their safety consequences. *Transportation Research Record, 2676*, 30–37. https://doi.org/10.1177/03611981211027150

Klauer, C., Anderson, G., 2023. Evaluation of Eyes Off Road During L2 Activation on Uncontrolled Access Roadways (VTTI-00-031) [supporting dataset].

Kong, X., Das, S., Jha, K., & Zhang, Y. (2020). Understanding speeding behavior from naturalistic driving data: Applying classification based association rule mining. *Accident Analysis & Prevention, 144*, Article 105620.

Kong, X., Das, S., "Tracy" Zhou, H., & Zhang, Y. (2021). Patterns of near-crash events in a naturalistic driving dataset: Applying rules mining. *Accident Analysis & Prevention, 161*, Article 106346. https://doi.org/10.1016/j.aap.2021.106346

Labbo, M. S., Qu, L., Xu, C., Bai, W., Ayele Atumo, E., & Jiang, X. (2024). Understanding risky driving behaviors among young novice drivers in Nigeria: A latent class analysis coupled with association rule mining approach. *Accident Analysis & Prevention, 200*, Article 107557. https://doi.org/10.1016/j.aap.2024.107557

Lee, J., Kamaraj, A., Li, M., Domeyer, J., & Toyoda, H. (2023). *Drivers' Glance Behavior During Driver-Initiated Overrides of L2 Driving Automation*. Lee, John: A Comparison Between Intentional and Unintentional Overrides.

Lemonnier, S., Désiré, L., Brémond, R., & Baccino, T. (2020). Drivers' visual attention: A field study at intersections. *Transportation Research Part F: Traffic Psychology and Behaviour, 69*, 206–221. https://doi.org/10.1016/j.trf.2020.01.012

Liao, Y., Li, S. E., Wang, W., Wang, Y., Li, G., & Cheng, B. (2016). Detection of Driver Cognitive Distraction: A Comparison Study of Stop-Controlled Intersection and Speed-Limited Highway. *IEEE Transactions on Intelligent Transportation Systems, 17*, 1628–1637. https://doi.org/10.1109/TITS.2015.2506602

Liao, Y., Li, S. E., Wang, W., Wang, Y., Li, G., & Cheng, B. (2015). The impact of driver cognitive distraction on vehicle performance at stop-controlled intersections. In *in: 2015 IEEE Intelligent Vehicles Symposium (IV). Presented at the 2015 IEEE Intelligent Vehicles Symposium (IV)* (pp. 946–951). https://doi.org/10.1109/IVS.2015.7225806

Liu, P., Guo, Y., Liu, P., Ding, H., Cao, J., Zhou, J., & Feng, Z. (2024). What can we learn from the AV crashes? – An association rule analysis for identifying the contributing risky factors. *Accident Analysis & Prevention, 199*, Article 107492. https://doi.org/10.1016/j.aap.2024.107492

Luo, T. (2023). Study on Adaptive Cruise Control Systems of Passenger Vehicles and Solutions Based on V2X Technologies. In *in: 2023 4th International Conference on Computer Engineering and Intelligent Control (ICCEIC). Presented at the 2023 4th International Conference on Computer Engineering and Intelligent Control (ICCEIC)* (pp. 539–549). https://doi.org/10.1109/ICCEIC60201.2023.10426734

Madigan, R., Louw, T., & Merat, N. (2018). The effect of varying levels of vehicle automation on drivers' lane changing behaviour. *PLoS One1, 13*, e0192190.

Mondal, A. R., Bhuiyan, M. A. E., & Yang, F. (2020). Advancement of weather-related crash prediction model using nonparametric machine learning algorithms. *SN Appl. Sci., 2*, 1372. https://doi.org/10.1007/s42452-020-03196-x

Mueller, A.S., Reagan, I.J., Cicchino, J.B., 2020. Addressing Driver Disengagement and System Misuse: Human Factors Recommendations for Level 2 Driving Automation Design.

NHTSA, 2022. Distracted Driving | NHTSA [WWW Document]. URL https://www.nhtsa.gov/risky-driving/distracted-driving (accessed 7.23.24).

Nidamanuri, J., Nibhanupudi, C., Assfalg, R., & Venkataraman, H. (2022). A Progressive Review: Emerging Technologies for ADAS Driven Solutions. *IEEE Transactions on Intelligent Vehicles, 7*, 326–341. https://doi.org/10.1109/TIV.2021.3122898

Noble, A. M., Miles, M., Perez, M. A., Guo, F., & Klauer, S. G. (2021). Evaluating driver eye glance behavior and secondary task engagement while using driving automation systems. *Accident Analysis & Prevention, 151*, Article 105959. https://doi.org/10.1016/j.aap.2020.105959

Reece, D. A., & Shafer, S. A. (1995). Control of perceptual attention in robot driving. *Artificial Intelligence, Special Volume on Computer Vision, 78*, 397–430. https://doi.org/10.1016/0004-3702(95)00029-1

Russell, S., Atwood, J., Mclaughlin, S., 2021. Driver Expectations for System Control Errors, Driver Engagement, and Crash Avoidance in Level 2 Driving Automation Systems.

Solís-Marcos, I., Ahlström, C., & Kircher, K. (2018). Performance of an Additional Task During Level 2 Automated Driving: An On-Road Study Comparing Drivers With and Without Experience With Partial Automation. *Human Factors, 60*, 778–792. https://doi.org/10.1177/0018720818773636

Strayer, D. L., Cooper, J. M., Sanbonmatsu, D. M., & McDonnell, A. S. (2023). *A Multi-Method Approach to Understanding Drivers' Experiences and Behavior Under Partial Vehicle Automation*. Washington, DC: AAA Foundation for Traffic Safety.

Tamakloe, R., & Adanu, E. K. (2024). Critical patterns associated with vehicle-pedestrian hit-and-run casualty injury severity under different weather conditions: An association rule mining approach. *IATSS Research, 48*, 299–318. https://doi.org/10.1016/j.iatssr.2024.06.003

Utriainen, R., Pöllänen, M., & Liimatainen, H. (2020). The Safety Potential of Lane Keeping Assistance and Possible Actions to Improve the Potential. *IEEE Transactions on Intelligent Vehicles, 5*, 556–564. https://doi.org/10.1109/TIV.2020.2991962

Victor, T. W., Tivesten, E., Gustavsson, P., Johansson, J., Sangberg, F., & Ljung Aust, M. (2018). Automation Expectation Mismatch: Incorrect Prediction Despite Eyes on Threat and Hands on Wheel. *Human Factors, 60*, 1095–1116. https://doi.org/10.1177/0018720818788164

Werneke, J., & Vollrath, M. (2012). What does the driver look at? The influence of intersection characteristics on attention allocation and driving behavior. *Accident Analysis & Prevention, 45*, 610–619. https://doi.org/10.1016/j.aap.2011.09.048

Yin, X., & Han, J. (2003). CPAR: Classification based on Predictive Association Rules, in. In *Proceedings of the 2003 SIAM International Conference on Data Mining. Presented at the Proceedings of the 2003 SIAM International Conference on Data Mining, Society for Industrial and Applied Mathematics* (pp. 331–335). https://doi.org/10.1137/1.9781611972733.40

Zangi, N., Srour-Zreik, R., Ridel, D., Chassidim, H., & Borowsky, A. (2022). Driver distraction and its effects on partially automated driving performance: A driving simulator study among young-experienced drivers. *Accident Analysis & Prevention, 166*, Article 106565. https://doi.org/10.1016/j.aap.2022.106565