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How do drivers interact with in-vehicle information systems in everyday driving? Evidence from large-scale naturalistic data

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ABSTRACT

How do drivers interact with in-vehicle Information Systems (IVIS)? Driver distraction is one of the major contributors to road crashes, and IVIS interactions are a potential source of such distraction. Yet, little is known about when, how, and under which driving contexts drivers engage with IVIS in everyday driving. However, for safe system design and evidence-based regulation, we must understand which context factors shape IVIS engagement. To close this gap, we leverage large-scale naturalistic data collected from 669,493 customer trips across 79 countries, to characterize everyday IVIS interactions. Using mixed-effects models, we examine how environmental conditions, vehicle dynamics, road infrastructure, driving automation, and vehicle mileage affect how drivers engage with IVISs. Our results show that drivers interact approximately every five minutes, mostly at the start of their trip, and more frequently via physical buttons than touchscreen inputs. We further observe significant regional differences in how IVISs are used and show that engagement decreases with vehicle mileage. In partially automated conditions, drivers are more likely to initiate interactions, while increased driving dynamics lead to fewer and less complex engagements. Together, these findings extend existing evidence by demonstrating how multiple contextual factors simultaneously shape real-world IVIS engagement. They provide an empirical basis for context-aware IVIS design, evaluation, and regulation that more accurately reflects the diversity and variability of everyday driving behavior.

1. Introduction

As vehicles evolve into connected, intelligent platforms, in-vehicle Information Systems (IVISs) have become a central part of the driving experience. These systems offer information and entertainment to the driver, typically via a center-stack touchscreen and the instrument cluster. To interact with these systems, drivers have to divide their attention between the primary driving task and the secondary IVIS interaction (Metz et al., 2011), thereby increasing the potential for driver distraction (Zhong et al., 2024). Because driver distraction is one of the major contributors to road crashes, research, industry, and legislators share a common interest in reducing the distraction potential of IVISs. This motivates the development, evaluation, and oversight of usable and less distracting systems to reduce the need for mobile phone use while driving. Previous work indicates that drivers adapt their secondary task activities in response to the driving context, showing that factors such as vehicle dynamics, road infrastructure, and traffic conditions affect engagement in Non-Driving Related Tasks (NDRTs) (Christoph et al., 2019; Ebel et al., 2023a; Seaman et al., 2022). Accordingly,

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designing in-vehicle interfaces that are both safe and usable requires a holistic understanding of when, how, and under which driving conditions drivers engage with the IVIS (Harvey and Stanton, 2013). While previous research has addressed isolated aspects of driver distraction, empirical evidence capturing realistic everyday scenarios remains limited. Addressing this gap is essential for advancing scientific understanding, but also for informing system design and evidence-based regulation.

From a **research perspective**, understanding real-world IVIS use is essential for explaining how interaction behavior emerges from the interplay of driving context, system characteristics, and individual differences. While prior studies have examined how isolated factors, such as vehicle dynamics, task properties, or driving automation affect IVIS engagement (Ebel et al., 2022, 2023a; Zhong et al., 2024), evidence from everyday driving is needed to establish a coherent picture of when and how drivers engage with IVIS across diverse contexts. This knowledge would allow more targeted investigations and could inform study design, thereby providing a stronger empirical basis for theories of driver attention, multitasking, and secondary task engagement.

For **industry**, such an understanding is a prerequisite for designing IVISs that remain usable and safe across varying driving conditions (Stevens et al., 2002). Many current systems are still developed based on controlled test scenarios or design assumptions rather than empirical evidence of real-world use (Ebel et al., 2021). Grounding design decisions in naturalistic interaction patterns can support more user-centered interface designs (Ebel et al., 2020) and provide the foundation for adaptive user interfaces that respond meaningfully to contextual demand (Graefe et al., 2021; Masuhr et al., 2008; Walter, 2019). Without knowing when and how interaction occurs in everyday driving, IVIS design considerations risk being misaligned with actual user behavior, which may consequently lead to lower user acceptance of in-vehicle technologies (Stiegemeier et al., 2022).

From a **legislative perspective**, IVISs are commonly evaluated using standardized simulator scenarios and static acceptance criteria, including glance-based thresholds proposed by organizations such as NHTSA or JAMA (Japan Automobile Manufacturers Association (JAMA), 2004; National Highway Traffic Safety Administration (NHTSA), 2013). While these metrics are partly derived from on-road studies (Green, 1999; Klauer et al., 2006), they have been criticized for neglecting individual differences (Gonçalves et al., 2025), the dynamic nature of attentional resources (Shen et al., 2025), and the diversity of real-world driving contexts (Kujala et al., 2014; Tivesten and Dozza, 2015). Empirical evidence on how context shapes driver interaction behavior can support the development of more ecologically valid, context-sensitive evaluation methods that complement existing procedures.

To address the limited empirical evidence on driver engagement with IVISs in realistic scenarios, the current work aims to close this gap through the analysis of large-scale naturalistic data. Specifically, to better understand how drivers use IVISs in everyday driving, we analyze anonymized real-world interaction data collected from customer vehicles worldwide, with users' opt-in consent. We leverage interaction and driving-related sensor data of the german car manufacturer Mercedes Benz to derive usage information independently of any study-specific tasks or experimental manipulation, thereby reflecting naturalistic interaction and driving behavior. First, we characterize when, how often, and through which modalities drivers interact with their car in real-world driving across different global regions. Second, we examine how driving context relates to interaction behavior. Here we focus on touch interactions as they pose a high visual-manual distraction risk compared to the other input modalities (Ebel et al., 2023b; Zhong et al., 2024). We investigate how touch interaction timing, duration, and input structure change with contextual conditions.

In summary, our research addresses the following questions:

RQ1: what characterizes drivers' interactions with the IVIS while driving across different regions of the world?
- **RQ1.1:** how often do drivers interact within a trip?
- **RQ1.2:** what modalities do drivers choose to interact?
- **RQ1.3:** when do drivers interact during a trip?

RQ2: how does the driving context influence touch interaction while driving?
- **RQ2.1:** which context factors influence drivers' decision to interact?
- **RQ2.2:** which factors influence the duration and the number of inputs of an interaction sequence?

By answering these research questions, our work aims to strengthen the empirical basis on which researchers design their studies, manufacturers make product decisions, and legislators suggest regulations.

2. Related work

Ongoing trends toward larger displays and fewer physical controls in IVISs (DeGuzman et al., 2024) increase the potential for driver distraction. As a result, driver-system interaction has become an important focus of research. In the following section, we outline existing work investigating how the driving context shapes IVIS interaction behavior and discuss its role in transportation research. Finally, we summarize recent developments toward adaptive, context-88 sensitive in-vehicle systems

2.1. The influence of the driving context on secondary task engagement

Various studies have investigated how drivers adapt their interaction behavior to changes in the driving context. Vehicle speed is cited as a factor in a naturalistic driving study (N = 20) by Seaman et al. (2022), which observed drivers' NDRTs engagement over the period of one month. The results indicate that drivers reduce interaction frequency with increasing speed. Moreover, the effect size depends on the type of the NDRT: visual-manual tasks show stronger speed-related variation than voice-dominant tasks. These findings complement insights showing that drivers tend to reduce their speed and increase headway to reduce driving-induced workload when performing distracting activities (Singh and Kathuria, 2021).

Cuentas-Hernandez et al. (2023) further show that traffic density shapes engagement in NDRT, with higher levels in low-density traffic compared to high-density conditions. They also observe more frequent NDRT engagement on right curves compared to left curves and when driving uphill compared to downhill. These results are derived from an analysis of the naturalistic driving dataset SHRP2 (Campbell, 2012), collected over 3 years from over 3,000 drivers across multiple U.S. sites. A large-scale roadside observation study by Kidd et al. (2016) (16,556 observed vehicles) similarly reveals that drivers are most likely to engage while stopping at a red light and least likely in roundabouts. Another naturalistic driving study (N = 17, 4 weeks) conducted by Perez et al. (2015) shows that drivers perform longer interactions in stationary or slow-moving traffic, arguing that these conditions are perceived as safer. Interestingly, they also show that interactions occur more frequently when other traffic is present, which may indicate a perceived safety benefit when following another vehicle. In line with these observations, Tivesten and Dozza (2015) analyze video recordings of 1,432 car trips and find that drivers are more likely to initiate visual-manual tasks on their phone when stationary than at high speeds. Drivers adjust the timing of engagement based on lead-vehicle behavior, even though such behavior has little effect on whether a task is initiated at all. Christoph et al. (2019) use naturalistic driving data (N = 33, 3 years) and demonstrate that road type and situational complexity strongly influence secondary task engagement with mobile phones. Their results indicate that, relative to overall driving time, drivers spend less time engaging in visual-manual tasks on rural roads than on highways. In line with results of Ismaeel (2021) (N = 280, 21 month) they further find that during complex maneuvers such as turning at an intersection or changing the lane, engagements become less frequent.

Both simulator and naturalistic studies consistently show that driving automation and assistance systems substantially increases the likelihood of NDRT engagement (Reagan et al., 2025; Wandtner et al., 2018), with the extent of engagement closely tied to the drivers' trust in the automation system (Pan et al., 2023). This aligns with findings of Ebel et al. (2022, 2023a), who analyze naturalistic data from a test-vehicle fleet and report longer off-road glances during partially automated driving.

Moreover, literature presents partially contradictory findings on environmental influences like weather and lighting conditions. While drivers self-report that they adjust their secondary task engagement depending on weather conditions and during nighttime driving (Young and Lenné, 2010), naturalistic data studies paint a less clear picture. Ismaeel (2021) reports less frequent engagement under adverse weather conditions, whereas other naturalistic studies of Young et al. (2019) (186 trips) and Klauer et al. (2006) (N = 100, 12 month) find that drivers do not consistently consider environmental conditions such as weather or ambient light when deciding to engage in secondary tasks. The influence of such factors therefore remains unclear.

Research further indicates significant time-of-day differences. Specifically, Cuentas-Hernandez et al. (2023) and Kidd et al. (2016) report that drivers interact less in the morning compared to other times of the day.

Social aspects may also be associated with NDRT engagement. Findings from Christoph et al. (2019) and Kidd et al. (2016) show that drivers engage less in secondary tasks when a passenger is present. The latter also note that age plays a role, with older drivers showing the lowest rates of secondary engagements.

Taken together, prior work provides consistent evidence that driving context shapes both the likelihood and the characteristics of secondary task engagement. Literature identifies vehicle dynamics, traffic, and road infrastructure as key influencing factors, whereas the impact of environmental influences such as weather and lighting remains unclear. Social and demographic factors have also been suggested to affect driver behavior but have received comparatively limited research attention. Much of the existing literature relies on small naturalistic samples or simulator and interview studies. Moreover, many studies examine single contextual factors in isolation, thereby neglecting potential interaction effects. To our knowledge, comparable large-scale analyses of everyday interaction behavior based on production-vehicle data remain scarce.

2.2. Limitations of context representation in transportation research studies

The evidence presented in the previous section demonstrates that interaction behavior is shaped by driving context. This raises the question of how such findings are incorporated into the current transportation research literature. To investigate this, we reviewed two recent issues of *Transportation Research Part F: Traffic Psychology and Behaviour* (Volumes 114 and 115) and the proceedings of *AutomotiveUI'24* conference, focusing on reported limitations in behavioral analyses. Across these publications, many authors point to restricted test scenarios that fail to account for contextual differences, for example, omitting variation across road types (highway, rural, urban) (Asteriou et al., 2024; Illgner et al., 2024; Kontaxi et al., 2025), incomplete representations of traffic conditions (Asteriou et al., 2024; Kontaxi et al., 2025; Kuhlmann et al., 2025; Li et al., 2025; Puente Guillen et al., 2024), neglecting daytime variation (Ferriès et al., 2025; Klein et al., 2024; Li et al., 2025), limited coverage of weather (Asteriou et al., 2024; Ferriès et al., 2025; Klein et al., 2024; Li et al., 2025; Shi et al., 2025) or insufficient consideration of situational complexity (Kuhlmann et al., 2025; Li et al., 2025; Singh et al., 2025), road geometry (Puente Guillen et al., 2024; Shi et al., 2025; Singh et al., 2025), and speed (Kontaxi et al., 2025; Singh et al., 2025).

Overall, this non-systematic review suggests that many reported findings may be context-dependent, potentially biasing observed interaction patterns and limiting their generalizability to other settings. Given that human interaction behavior is strongly shaped by context (Schmidt et al., 1999), results obtained under narrowly defined or simplified study conditions may not reliably replicate across different driving contexts. Consequently, evaluations conducted under conditions that deviate from the complexity of real-world driving risk limited ecological validity and reduced applicability to naturalistic behavior (Zhai et al., 2018). In the broader discussions around the replication crisis in behavioral research (Gollwitzer and Schwabe, 2022; Locey, 2020), transportation research could benefit from a more comprehensive understanding of what factors shape drivers' behavior in everyday driving (Franchi et al., 2024).

While it is neither feasible nor desirable to account for all context factors, particularly in controlled experiments, empirical insights into when and how drivers naturally interact with IVISs could help to inform study design and support more ecologically valid and robust behavioral findings.

2.3. The role of context in adaptive IVIS design

Understanding how driving context shapes driver interaction is not only essential for valid behavioral analysis, but also for the design of adaptive IVIS. Adaptive User Interfaces (AUIs) are increasingly proposed to improve user experience and safety (Hartmann, 2009; Rittger et al., 2022), and recent work reflects a growing interest in such systems (Graefe et al., 2021; Rittger et al., 2020; Walter, 2019). However, existing approaches primarily rely on predicting internal driver states, such as affect (Braun, 2020; Nasoz et al., 2010) or cognitive load and attention (Gomaa et al., 2022; Neßelrath, 2013; Wen et al., 2024), which are inherently difficult to infer reliably in real-world settings. In contrast, driving context factors such as vehicle dynamics, road type, traffic, or environmental conditions are directly observable through vehicle sensors. Yet only few approaches explicitly leverage such contextual information for adaptation, for example by adapting interaction to acceleration patterns (Kim et al., 2018) or by integrating broader environmental and vehicle-related conditions (Khan and Khusro, 2020a; Wiedner et al., 2024). Grounding adaptation strategies in observable context factors could enable better adaptive behavior and reduce the risk of arbitrary or unexpected system responses (Graefe et al., 2021; Höök, 1998; Stiegemeier et al., 2022).

2.4. Limitations of previous research and our contribution

Existing research on context factors for NDRT engagement faces several limitations. Many studies are based on relatively small datasets with sparse data or rely on simulator experiments and interviews that are prone to bias as they do not reflect real-world scenarios. Many investigations focus on mobile phone use which may differ from stationary, large screen IVIS engagement. Moreover, previous research often consider a limited set of variables describing the driving environment and neglect potential interaction effects. Findings are sometimes inconsistent, such as for the weather influence. In addition, prior work has largely examined whether engagement occurs at all, offering little insight into the nature of engagement once initiated (e.g., interaction duration).

3. Methods

This chapter describes how we retrieve, process, and analyze driving and interaction data logged in customer vehicles.

3.1. Data collection

All data are collected over-the-air from modern Mercedes-Benz vehicles. The dataset was collected during four distinct one-week periods in March, June, September and December 2024, to minimize weekday and seasonal biases. All data are collected from recent mid-range and luxury vehicles that are comparable in their dimensions and interior design concept. Data are collected only after the driver has given opt-in consent. All data is anonymized according to the manufacturer's data protection regulations, ensuring that no personal data, interaction semantics or location information is collected. The share of cars with combustion or hybrid engines is 69.3 %, while the share of fully electric ones is 30.7 %. All vehicles included in this analysis are equipped with SAE Level 2 driving assistance systems, providing combined longitudinal and lateral assistance (On-Road Automated Driving (ORAD) Committee, 2021). They are further equipped with a center-stack touchscreen with a fast response OLED display with screen sizes ranging from 11.9 in. (1,624 x 1,728 pixel) to 17.7 in. (3,088 × 1,728 pixel). Examples of the vehicle interior, display configurations, and the vehicle manufacturer's physical controls are shown in Fig. 1.

All IVISs operate on the same version of the manufacturer's proprietary in-vehicle software platform. The system is organized around a central home screen (see Fig. 1), from which users can access a range of applications, including vehicle configuration functions (e.g., climate control), as well as infotainment features such as radio, telephone, and navigation. Users can customize the system to access various functions directly from the home screen via so-called *"tiles"* (see Fig. 1). In addition to direct interactions on the touchscreen, drivers can also control IVIS functions through voice or physical buttons. The voice interface can be activated either hands-free via a wake word or by pressing a dedicated button. In addition, steering wheel controls allow drivers to interact without taking their hands off the wheel, including buttons for menu navigation (arrow keys, "OK," "Home," and "Back"), call handling (answer/end), volume adjustment, voice control activation, and access to customizable favorites (see Fig. 1).

All data used in this work are collected from the vehicle's internal bus. Interaction data are recorded as events, capturing timestamps and the modality used (touch, speech, or physical buttons). Vehicle sensor data include continuously sampled dynamics (e.g., speed, longitudinal and lateral acceleration), as well as event-based information about the driving environment (e.g., rain, daylight, lane count) and the state of the automation system. It should be noted that the interaction logs do not contain semantic information about the purpose of the interaction. Therefore, the analysis focuses on temporal and contextual relationships rather than task-specific behavior. A more detailed overview of the available signal basis is provided in the Appendix in Table A.4.

To answer our research questions, we derive two datasets at different levels of abstraction. These datasets are constructed from the same underlying raw signals but differ in their level of aggregation and included variables.

The **trip dataset** contains aggregated statistics for each trip, including the total number of interaction sequences and the distribution of interaction modalities (touch, speech, and physical buttons). This dataset is used to analyze when interactions occur during driving and how modality preferences vary across global regions (RQ1).



Fig. 1. The figure illustrates the smallest and largest display configurations, an example of the user interface with a tile-based home screen, and a detailed view of the steering wheel controls for IVIS interaction (M. B. Group, 2021, 2022).

The **touch sequence dataset** consists of touch interaction sequences and includes the absolute sequence duration as well as the number of touch interactions per sequence alongside several variables that describe the driving context. This dataset is designed to investigate whether contextual factors affect the likelihood of initiating touch interactions (RQ2.1) or the characteristics of the interaction sequence itself (RQ2.2).

3.2. Preprocessing and data aggregation

To create the datasets, we start by deriving interaction sequences and aggregate associated single interactions into interaction sequences. We then aggregate these interaction sequences on trip-level to build the trip dataset.

3.2.1. Aggregating interactions on sequence level

Due to the naturalistic setting, drivers did not perform predefined tasks. Accordingly, the start and end of an interaction sequence need to be approximated. For this, we define interaction sequences by grouping temporally related inputs. Following the method proposed by Ebel et al. (2022), we define an interaction sequence as a series of one or more inputs with no more than 10 seconds between two inputs. If this 10 seconds interval is exceeded, the event at t_i marks the endpoint of interaction sequence I_k, and the subsequent event at t_{i+1} marks the start of a new interaction sequence I_{k+1}.

To answer RQ2, we augment all touch interaction sequences with contextual information derived from the vehicles' sensor signals, which are either event-based (e.g., automation status) or continuously sampled (e.g., speed). To determine the context state at the onset of a sequence, we use the closest valid signal before the start of the interaction sequence. If a context signal's status changes within a sequence, we use the status that is present for the majority of the sequence duration. This approach ensures that the assigned context reflects the dominant driving condition during the interaction sequence and mitigates the influence of short-term fluctuations in the context signals. The overview in Fig. 2 shows an example of how a touch interaction sequence, including contextual factors, could be composed (lower frame). To examine whether a context factor influences the likelihood of initiating touch interactions (RQ2.1), we expand the touch sequence dataset to compare these interaction sequences with non-interaction sequences. We sample an equal number of non-interaction periods from the trip pool and match the duration distribution to that of the interaction sequences to control for sequence length effects.

3.2.2. Aggregating interaction sequences on trip level

After defining interaction sequences, we derive the trip dataset (RQ1) by aggregating touch, speech, and physical button interaction sequences. Each trip is treated as a single observation summarizing the driver's IVIS interaction behavior over the entire trip duration. Interaction intensity is captured by counting the number of interaction sequences of each modality. We additionally extract timestamps for all observed sequences within a trip to examine where in the trip timeline they occur. Fig. 2 schematically outlines the aggregation of interaction sequences on the trip-level based on an example (upper frame). Alongside these interaction metrics, we determine the country of the trip to account for regional differences.

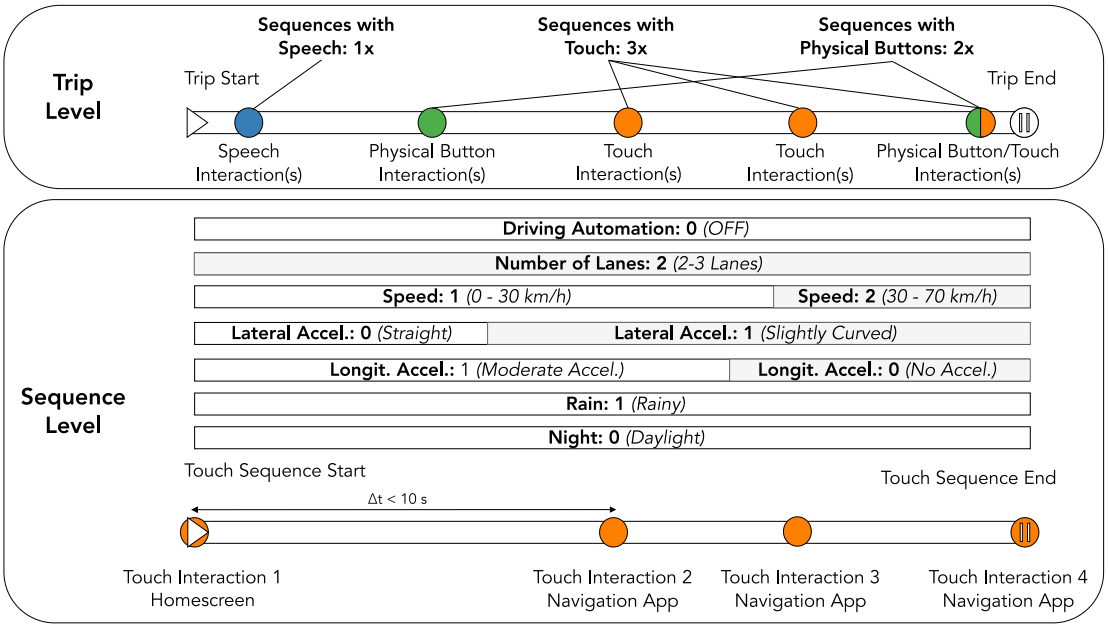


Fig. 2. Schematic representation of data aggregation on trip- (upper) and sequence-level (lower).

3.3. Data filtering and processing

To ensure that interactions can be reliably attributed to the driver and not a passenger, we filter both datasets for trips where no passenger is present.

From the **trip dataset**, we exclude very short trips (<5 minutes), as these may correspond to vehicle repositioning or brief standstill operations (e.g., starting the engine for climate control or closing a window), which do not represent driving episodes and therefore could bias our analysis. We also exclude very long trips (>5 hours), as they are not representative for everyday driving in private cars (Li et al., 2019) and could result from logging errors.

From the **touch sequence dataset**, we discard sequences where the vehicle is at standstill to filter for interactions while driving. Touch sequences with exceptionally high duration above the 99th percentile are filtered out, as they may result from erroneous logging or atypical use cases, similar to the procedure of Ebel et al. (2022). We delete records with missing context values due to signal unavailability. While this strict filtering reduces the overall sample size, it avoids value imputation and does not compromise the explanatory power given the large amount of available data. The complete filtering steps, including the number of observations after each step, are illustrated in Fig. A.11.

3.4. Statistical analysis

To answer RQ1, we analyze interaction frequency, timing, and modality use, and test for regional differences. For RQ2, we focus on touch interactions and fit two mixed-effects models to examine effects of contextual factors on touch interaction behavior. A significance threshold of $\alpha = 0.05$ is used throughout.

3.4.1. Comparative analysis

We compare interaction frequency (number of interactions per trip minute) and modality preferences across different global regions (RQ1). To test statistical significance of regional differences, we use *Python* (v3.11.8) and the *scipy.stats* module (v1.15.2). Because the Shapiro-Wilk test shows significant deviations from normality for all groups, we test group differences with the Mann-Whitney *U* test. Median percentage differences and 95 % confidence intervals are estimated via bootstrapping.

3.4.2. Mixed-effects modeling

We apply mixed-effects regression models to analyze the relationship between driving context and drivers' interaction behavior.

Dependent variables. To answer RQ2.1 we define a binary variable describing whether or not the driver interacted during this sequence. For RQ2.2, we use two measures to describe interaction style: the number of touch inputs per interaction and the absolute interaction duration in seconds. These complementary metrics capture both the temporal extent of an interaction sequence and its input frequency.

Table 1
Overview of all dependent and independent variables on interaction level, used to analyze the influence of driving context.

Variable	Levels
Dependent Variables	
Touch Inputs per Interaction	discrete (-)
Interaction Duration	continuous (s)
Independent Variables	
Daylight	bright, dark
Rain	no rain, rain
Speed	0–30, 30–70, 70–100, >100 (km/h)
Lateral Acceleration	0–0.2, 0.2–0.5, >0.5 (m/s^2)
Longitudinal Acceleration	0–0.2, 0.2–0.5, >0.5 (m/s^2)
Road Type	1 lane, 2–3 lanes, ≥4 lanes
Driving Automation Status	active, inactive
Mileage	discrete (100 km increments)

Independent variables. We include contextual variables that capture key environmental and vehicle states discussed as relevant for driving demands in Section 2. The variables listed in Table 1 represent external conditions (daylight, rain), driving dynamics (speed, lateral and longitudinal acceleration), road types (number of lanes), driving assistance (automation status), and mileage.

Mileage is used as a proxy for vehicle usage duration. We restrict the sample to vehicles below 150,000 km to remain within typical first-ownership operating ranges and to reduce the influence of used-car drivers. This approximation is supported by average annual driving distances of about 20,000 km (Federal Highway Administration, 2020) and an average ownership duration of 8.7 years for Mercedes vehicles in the U.S. (iSeeCars.com, 2024).

Models. We conduct the driving context analysis in *R Statistical Software* (v4.4.3). Multilevel models are fitted using the *lme4* package (v1.1.31) (Bates et al., 2015). We obtain p-values and R^2 values via the *lmerTest* (v3.1.3) (Kuznetsova et al., 2017) and the *performance* (v0.15.0) (Lüdecke et al., 2021) package. Pairwise post-hoc tests and estimated marginal means (with Tukey's correction for multiple comparisons) are computed with the *emmeans* (v1.8.2) package (Lenth, 2025).

We employ mixed-effects regression models to account for the hierarchical structure of the data, with interaction sequences nested within trips and trips nested within countries. This approach captures both trip-level dependencies and country-specific variation in driving and interaction behavior. The final models were determined through a multi-stage selection process. First, we compare standard, fixed-effect regression models with mixed-effects models and evaluate model fit using R^2. Second, we examine whether adding interaction terms further improves model performance based on ANOVA tests and comparisons of AIC and BIC. Third, we apply likelihood-ratio tests using the *drop1* function to assess whether removing individual predictors improves model fit. No predictor meets this criterion and all predictors are therefore retained in the final models. Detailed model comparisons are provided in Tables A.5 and A.6.

To address RQ2.1, we fit a generalized mixed-effects model with a logistic link to model interaction initiation. For RQ2.2, interaction duration is modeled using a linear mixed-effects model with a log-transformed response to account for right skew, and touch inputs per interaction sequence are modeled using a negative binomial mixed-effects model to account for overdispersion.

4. Results

This section presents the results of our analyses. We first describe the dataset and characterize general interaction behavior and regional differences (RQ1). We then focus on touch interactions and examine how driving context influences touch interaction behavior using mixed-effects modeling (RQ2).

4.1. Dataset

The trip dataset comprises 669,493 trips collected across 79 countries, with most trips recorded in Germany (194,160), the United States (172,735), South Korea (161,254), and Japan (60, 552). For regional analyses, trips are grouped into the broader global regions of Europe (298,670), East and Southeast Asia (236,771), North America (117,521), and South and Central Asia (6,680). Due to the small number of recorded trips in Africa as well as Central and South America (1,417 in total), these regions are excluded from regional comparisons.

The touch sequence dataset comprises 450,825 sequences from 94,266 trips. Of these, 314,851 originate from Europe, 43,996 from East and Southeast Asia, 15,959 from North America, 2,252 from Oceania, and 619 from Central and South Asia, 1,607 sequences stem from Africa and Central/South America, and for 71,564 sequences no valid country information is available. For the analysis of touch interaction initiation (RQ2.1), we augment the touch sequence dataset with matched non-interaction sequences. After distribution matching and removing records with missing values, the final dataset comprises 256,889 interaction sequences and an equal number of non-interaction sequences (513,778 in total).

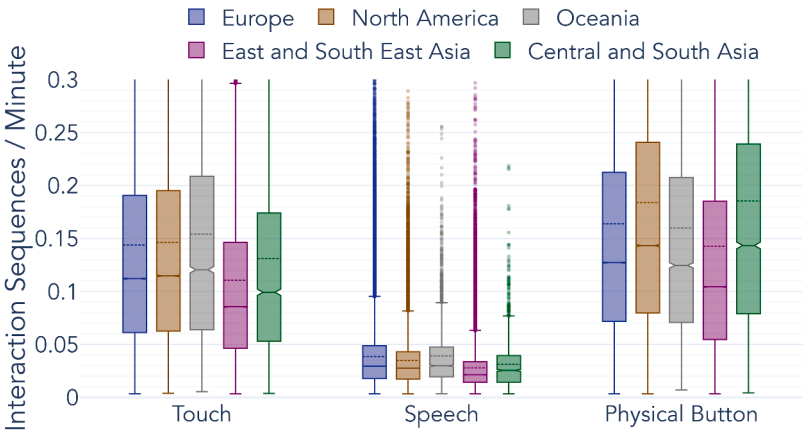


Fig. 3. The box plots show the relative interaction frequency (interactions per trip minute) for IVIS interactions involving touch, speech, and physical button inputs across global regions.

4.2. Characterizing drivers' IVIS interaction

We begin with reporting interaction frequency, modality use and temporal distribution within trips, including regional comparisons.

*4.2.1. **RQ1.1:** how often do drivers interact within a trip?*

Our results show that drivers interact in 98.0 % of all trips with the IVIS. Of these interactions physical button interactions are most common, occurring in 94.6 % of trips, followed by touch interactions in 71.8 % and speech interactions in 39.0 % of trips. Drivers interact with the IVIS on average every 5 minutes (Mean = 0.23 interactions/min, SD = 0.17, Median = 0.20, IQR = 0.20), although a substantial number of outliers exhibit higher interaction rates.

Drivers most frequently interact via physical buttons, with one interaction approximately every 6.5 minutes (Mean = 0.15 interactions/min, SD = 0.14). Drivers use touch interactions less frequently, engaging with touch roughly every 10 minutes (Mean = 0.10 interactions/min, SD = 0.11), while drivers rarely rely on speech, using it on average only once every 100 minutes (Mean = 0.01 interactions/min, SD = 0.03). A substantial number of trips include no touch or speech interactions at all. Among trips with at least one touch or speech interaction, touch occurs approximately every 7.5 minutes and speech about every 30 minutes.

Fig. 3 also shows significant regional differences in interaction frequency. To avoid distortions due to zero inflation, only trips with at least one IVIS interaction sequence are shown. Countries in Europe, North America, Central and South Asia, and Oceania exhibit significantly higher interaction rates across all modalities than East and Southeast Asian regions (e.g., East and Southeast Asia compared to Europe: 17.9 % [17.4 %; 18.4 %] fewer physical button, 23.6 % [24.1 %; 23.1 %] fewer touch, and 27.6 % [27.1 %; 28.2 %] fewer speech interactions per minute, with $p < .001$ for all modalities). Drivers in Oceania use touch interactions more frequently than drivers in all other regions, followed by North America and Europe ($p < .001$ for all pairwise comparisons). Speech interaction frequency is highest in Oceania, followed by Europe and North America, with all pairwise differences between regions being significant ($p < .05$). Physical button interactions occur most frequently in Central and South Asia as well as North America, with no significant difference between these two regions ($p = .69$). Both however show significantly higher physical button interaction frequency than all other regions (e.g., North America 12.6 % [11.7 %; 13.4 %] more physical button interactions than Europe, with $p < .001$).

*4.2.2. **RQ1.2:** what modalities do drivers choose to interact?*

More than half of all interactions with the IVIS involve physical buttons, with 54.3 % consisting solely of physical button inputs, as visualized in Fig. 4. A more detailed analysis shows that 88 % of all physical button inputs were performed using buttons integrated into the steering wheel. Touch inputs are ranked second, accounting for 42.2 % of all interactions, of which 34.0 % were exclusively touch-based. 5.5 % of all recorded interactions sequences include speech inputs, with 1.3 % representing speech-only sequences and 2.2 % speech-physical-button combinations. Among multimodal interaction sequences, sequences that contain both physical button and touch inputs are the most common combination (6.2 %). Overall, 10.4 % of all interaction sequences are multimodal, while 89.6 % are single-mode sequences.

Fig. 5 further shows how the distribution of interaction modalities differs across global regions. While interaction sequences involving physical buttons dominate across all markets, regional differences emerge in the relative adoption of modalities.

In Europe, 59.6 % of all interaction sequences contain physical button input, 46.7 % involve touch input, and 6.6 % include speech input. A comparable pattern is observed in Oceania (60.6 % physical button, 45.3 % touch, 5.4 % speech), while North America shows a stronger dominance of physical button interactions (65.4 % physical button, 40.6 % touch, 3.8 % speech). Asian regions exhibit even higher proportions of physical-button-based interaction sequences. In South and Central Asia, 72.9 % of all sequences contain physical

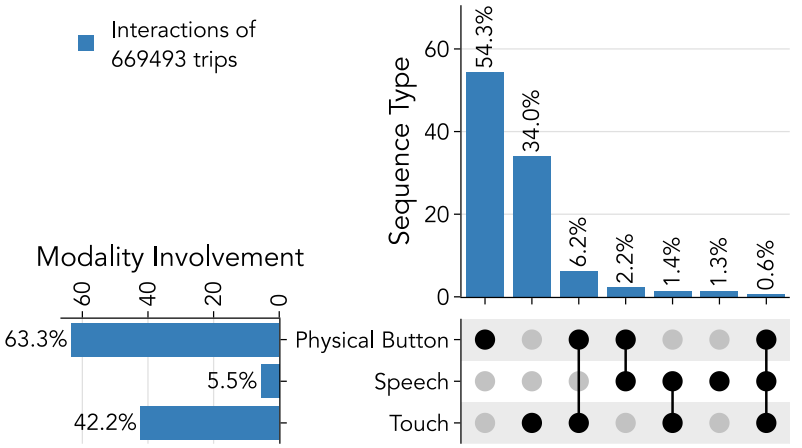


Fig. 4. The bar plots show the percentage of interactions involving the respective modality combinations on the y-axis, while the x-axis presents the percentage of interactions that contain at least one input of the respective modality.

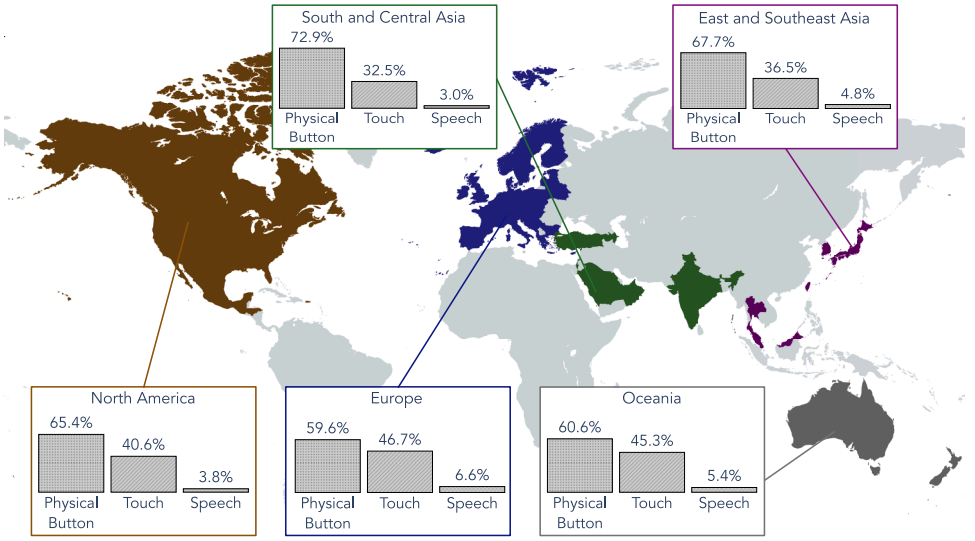


Fig. 5. The world map shows bar plots of the percentage of all interaction sequences within each region that include the respective modality. Because multimodal sequences contribute to multiple modalities, percentages can exceed 100 %. Colors indicate the countries included in each region.

button input, while touch and speech account for 32.5 % and 3.0 %, respectively. Similarly, in East and Southeast Asia, 67.7 % of sequences contain physical button interactions, followed by 36.5 % touch and 4.8 % speech input.

Overall, in both Asian regions more than two thirds of all interaction sequences contain physical button inputs, indicating a stronger dominance of physical controls compared to Europe and Oceania, where touch and physical button interaction shares are more balanced. Speech input remains a marginally used input modality across all regions, with its relative share being highest in Europe. We further test regional group differences of modality shares on trip-level using Mann-Whitney U tests, and find that all pairwise regional differences are statistically significant ($p < .001$).

*4.2.3. **RQ1.3:** when do drivers interact during a trip?*

To answer RQ1.3, we analyze how interactions are distributed across trips. Fig. 6 shows that drivers tend to perform most of their interactions at the beginning of a trip, as indicated by a peak in density near the start of the trip. This behavior is most pronounced for speech interactions. The peak in speech usage is followed by a steep drop in occurrence for the rest of the trip. While touch and button interactions show a similar profile the drop in density is not as pronounced. These tendencies can also be observed in the shifts between box plots and the amplitude of the density curves. Interaction frequency further declines as the trip progresses.

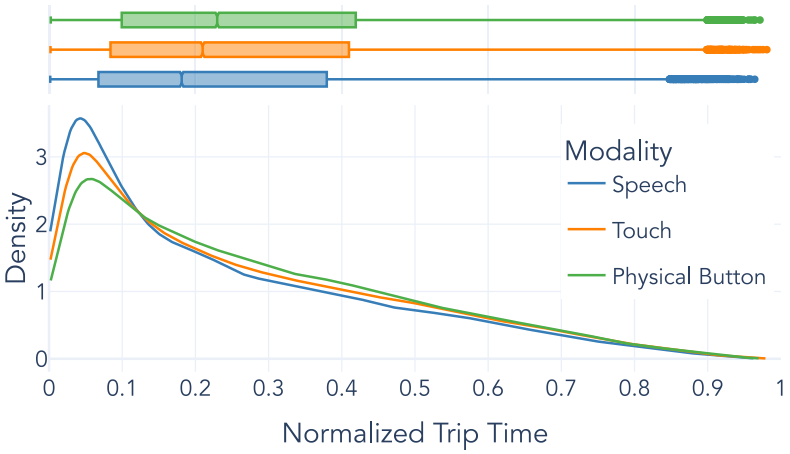


Fig. 6. The figure shows kernel density estimates of interactions over normalized trip time (0 = trip start, 1 = trip end) for the modalities speech, touch, and physical button. Boxplots of interaction occurrence over normalized trip time are shown above the density plots. The kernel density estimates are unitless due to the normalization of trip time on the x-axis.

Fig. 6 also shows that drivers interact less frequently in the second half of the trip: Drivers perform approximately 85 % of all speech interactions and more than 83 % of all touch and physical button interactions in the first half of their trips. Only about 3 % of all interactions occur in the last quarter of a trip.

4.3. *How context affects touchscreen interactions*

Given the distraction potential of touchscreen interactions (Ebel et al., 2023b), we extend our analysis to examine how driving context shapes touchscreen interaction behavior. Specifically, we investigate the influence of vehicle dynamics, road type, and environmental factors to gain a more fine-grained understanding of when and under which contexts drivers choose to engage in touch-based IVIS interactions.

4.3.1. ***RQ2.1:*** *which context factors influence drivers' decision to interact?*

Table 2 reports the fixed-effect estimates of the mixed-effects logistic regression model and the corresponding Odds Ratios (ORs), summarizing how driving context variables are associated with drivers' likelihood of initiating a touchscreen interaction. An overview of all pairwise contrasts in ORs is provided in Tables A.7 and A.8. Our results indicate that various context factors are associated with the likelihood of initiating an interaction. For each predictor, at least one level differs significantly from the baseline condition (0–30 km/h, daytime, no rain, lateral and longitudinal acceleration of 0–0.2 m/s^2, one lane, driving automation inactive, and a mileage of 33,744 km).

Drivers are more likely to interact with the IVIS during when driving automation (i.e., active cruise control and lane centering assistant) is active as shown by an increase of interaction odds by 31 %.

In contrast, driving in darkness was associated with significantly lower interaction odds (OR = 0.35), indicating a decrease in interaction engagement.

Our modeling results further suggest a speed-dependent effect of rainfall. At the reference speed of 0–30 km/h, rain increases the odds of an interaction (OR = 1.64). This effect is attenuated by the interaction terms, resulting in adjusted ORs of 1.44 for 30–70 km/h, 1.27 for 70–100 km/h, and no significant changes for speeds above 100 km/h. Thus, rainfall significantly increase interaction odds, with a more pronounced effect at lower speeds that diminishes as speed increases.

Drivers' interaction behavior changes with speed and road type, which can be seen in Fig. 7a and b. Fig. 7a shows that on single-lane roads, speeds above 30 km/h are associated with significantly higher interaction odds compared to 0–30 km/h (OR = 2.15, 2.01, and 1.92 for 30–70, 70–100, and >100 km/h vs. 0–30 km/h). However, between speed categories above 30 km/h, the ORs do not change significantly on one lane roads. In contrast, on multi-lane roads, drivers tend to interact progressively less when driving faster (2–3 lanes: OR = 0.87, 0.84, and 0.71 for 30–70, 70–100, and >100 km/h vs. 0–30 km/h), with the effect being strongest on roads with four or more lanes (OR = 0.75, 0.70, and 0.69 for 30–70, 70–100, and >100 km/h vs. 0–30 km/h).

Fig. 7b shows that, at speeds below 30 km/h, the interaction odds significantly increases on roads with multiple lanes compared to single-lane roads (OR = 3.01 for 2–3 lanes and 3.76 for 4+ lanes vs. 1 lane). The same applies for roads with 4+ lanes compared to roads with 2–3 lanes (OR = 1.25). This effect is smaller for vehicle speeds between 30 and 70 km/h (OR = 1.85 and 2.15 for 2–3 lanes and 4+ lanes vs. 1 lane). At speeds above 70 km/h, however, our model indicates no significant changes of odds between different road infrastructures.

Table 2
This table presents fixed-effect log-odds estimates with standard error from the mixed-effects logistic regression model predicting interaction initiation. ORs versus the reference level are based on contrasts of estimated marginal means (Tukey-adjusted p-values) and reported with 95 % CIs. For interactions, ORs compare contrasts under fixed speed categories (Complete OR tables: Tables A.7 and A.8). Significance levels are presented as: * $p < .05$, ** $p < .01$, *** $p < .001$.

Predictor	Estimate (log-odds)	SE	OR (vs. Baseline)	95 %CI
Driving Automation				
active	0.27***	0.02	1.31***	[1.27, 1.36]
Daylight				
darkness	−1.05***	0.02	0.35***	[0.33, 0.37]
Acceleration				
lateral 0.2–0.5 m/s^2	−0.08***	0.01	0.92***	[0.90, 0.95]
lateral > 0.5 m/s^2	−0.43***	0.02	0.65***	[0.61, 0.69]
longitudinal 0.2–0.5 m/s^2	−0.02	0.01	0.98	[0.96, 1.01]
longitudinal > 0.5 m/s^2	−0.65***	0.03	0.52***	[0.49, 0.56]
Weather				
rain	0.49***	0.04	1.34***	[1.29, 1.40]
Speed				
30–70 km/h	0.83***	0.02	1.08*	[1.00, 1.16]
70–100 km/h	0.82***	0.03	0.97	[0.90, 1.05]
100 + km/h	0.86***	0.07	0.86***	[0.78, 0.94]
Road Type				
2–3 lanes	1.10***	0.02	1.36***	[1.30, 1.44]
4 + lanes	1.32***	0.04	1.56***	[1.46, 1.67]
Speed × Rain				
30–70 km/h × rain	−0.13*	0.05	1.44***	[1.30, 1.60]
70–100 km/h × rain	−0.25***	0.05	1.27***	[1.13, 1.42]
100 + km/h × rain	−0.41***	0.05	1.09	[0.99, 1.19]
Speed × Road Type				
30–70 km/h × 2–3 lanes	−0.96***	0.03	1.15***	[1.06, 1.24]
30–70 km/h × 4 + lanes	-1.11***	0.05	1.24***	[1.12, 1.38]
70–100 km/h × 2–3 lanes	−1.00***	0.04	1.10	[1.00, 1.22]
70–100 km/h × 4 + lanes	−1.18***	0.06	1.16	[1.00, 1.34]
100 + km/h × 2–3 lanes	−1.20***	0.07	0.91	[0.73, 1.13]
100 + km/h × 4 + lanes	−1.23***	0.08	1.10	[0.87, 1.39]
Usage Duration				
Mileage	−0.94***	0.02	0.39*** (+1 SD)	[0.37, 0.41]

Together, these findings indicate that driving faster than 30 km/h increases interaction odds on single-lane roads, whereas it decreases them on multi-lane roads. On the contrary, multi-lane roads elevate interaction odds at low speeds (0–30 km/h) but exert little to no influence once speeds exceed 30 km/h.

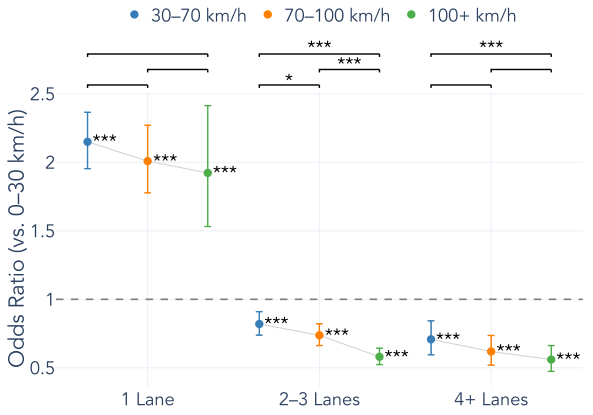
Moreover, drivers tend to interact less frequently during longitudinal and lateral acceleration, as shown in Fig. 7c. When lateral acceleration acts on the driver (e.g., induced by driving in a curve or roundabout), interaction odds decrease from 0–0.2 m/s^2 to 0.2–0.5 m/s^2 (OR = 0.92) and even stronger from 0.2–0.5 m/s^2 to 0.5 + m/s^2 (OR = 0.70). For longitudinal acceleration in driving direction, interaction odds do not decrease significantly with moderate accelerations from 0–0.2,m/s^2 to 0.2–0.5,m/s^2, but strongly from 0–0.2,m/s^2 to 0.5 + ,m/s^2 (OR = 0.52).

Another interesting finding can be observed in Fig. 7d, showing that the higher the mileage of the car the less likely the drivers are to interact. Increasing mileage from baseline (mean = 34470.81 km) by 50000 km corresponds to a significant reduction of 75 % in the odds of an interaction.

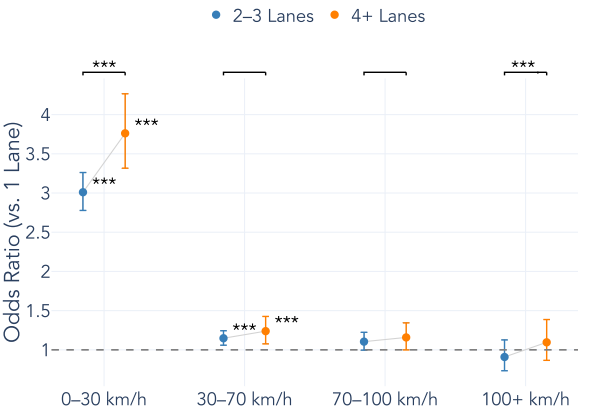
The model's random intercepts reveal that a considerable proportion of variance is attributable to differences across trips (SD = 4.13) and, to a lesser extent, across countries (SD = 0.14), reflecting heterogeneity inherent in naturalistic driving data. Nevertheless, the contextual predictors exhibit statistically significant and directionally consistent effects on drivers' likelihood of initiating an interaction.

*4.3.2. **RQ2.2:** which factors influence the duration and the number of inputs of an interaction sequence?*

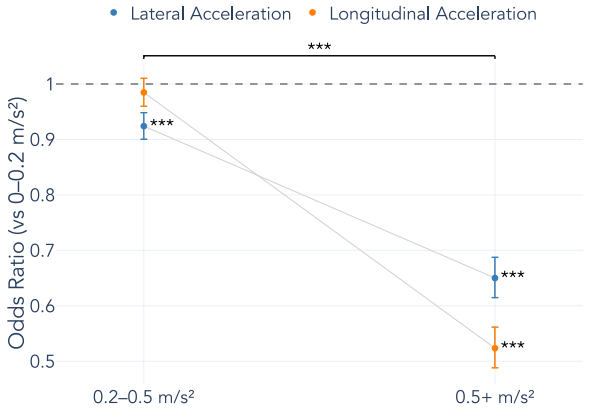
Beyond investigating in which situation drivers are more or less likely to initiate interactions with center-stack touchscreens, we also analyze how the driving context affects interaction duration and the number of inputs per interaction. This provides complementary insight into how driving context shapes not only the decision to interact, but also the way interactions are carried out once initiated. As shown in Table 3, several driving context variables significantly affect drivers' touchscreen interactions. Percentage



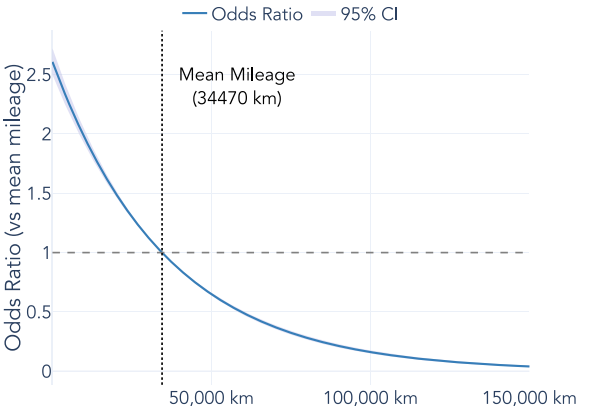
(a) ORs over speed categories across different road types (baseline: 0–30 km/h)



(b) ORs over road types across different speed categories (baseline: 1 lane)



(c) ORs over longitudinal and lateral acceleration (baseline: (0–0.2 m/s^2)



(d) OR over mileage (baseline: 33,447 km)

Fig. 7. OR plots for different context variables including 95 % CI. Dots above the dotted line represent increased odds of an interaction compared to baseline, dots below decreased odds of an interaction compared to baseline. The brackets with stars above the plots represent the significance levels of the OR of the connected variable values in relation to each other.

changes in interaction sequence duration and number of inputs are derived from estimated marginal means and are presented in the Appendix in Fig. A.12.

Our modeling results show that during driving in darkness, interaction sequences are longer with both interaction duration (+6.4 %) and number of inputs (+6.7 %) increasing at a similar rate. The results also indicate that drivers adapt their interaction style to the type of road. Touch interaction sequences are 2.7 %–3.0 % shorter on multi-lane roads compared to single-lane roads. The box plots in Fig. 8a demonstrate this pattern, with lower median interaction durations on multi-lane roads. In contrast, the number of inputs per interaction sequence shows an opposing trend, which leads to an increased input rate on multi-lane roads, that can be observed in Fig. 8b.

When driving faster than 30 km/h, drivers substantially reduce both interaction duration and the number of touch inputs. Our model suggests that drivers shorten the interaction duration when transitioning from low speeds (0–30 km/h) to medium speeds (30–70 km/h) by 20.5 %, which is also reflected in the box plots in Fig. 8c. Similarly, drivers decrease the number of touch inputs per interaction sequence by 22.3 % between 0–30 km/h and 30–70 km/h. At higher speeds, the model indicates smaller changes, with a 5.3 % decrease from 30–70 km/h to 70–100 km/h and a further 3.4 % decrease when transitioning from 70–100 km/h to speeds above 100 km/h. These effects are also evident in the Empirical Cumulative Distribution Function (ECDF) plot shown in Fig. 8d. The curve for the 0–30 km/h category (blue line) exhibits a noticeably shallower increase than the other speed categories (orange, green and pink lines), indicating that interaction sequences with more inputs are more likely at these lower speeds. The differences between the higher-speed categories are smaller but remain evident.

Our results further suggest an interaction effect between vehicle speed and driving automation. According to our models, driving automation affects interaction characteristics only at higher speeds. At speeds below 70 km/h, active driving assistance does not

Table 3
The table reports the estimates and standard errors of the linear mixed-effects model with log-transformed outcome variable predicting interaction duration as well as estimates and standard errors of the negative binomial generalized linear mixed-effects model predicting the number of touch inputs per interaction. Significance levels are presented as: * $p < .05$, ** $p < .01$, *** $p < .001$.

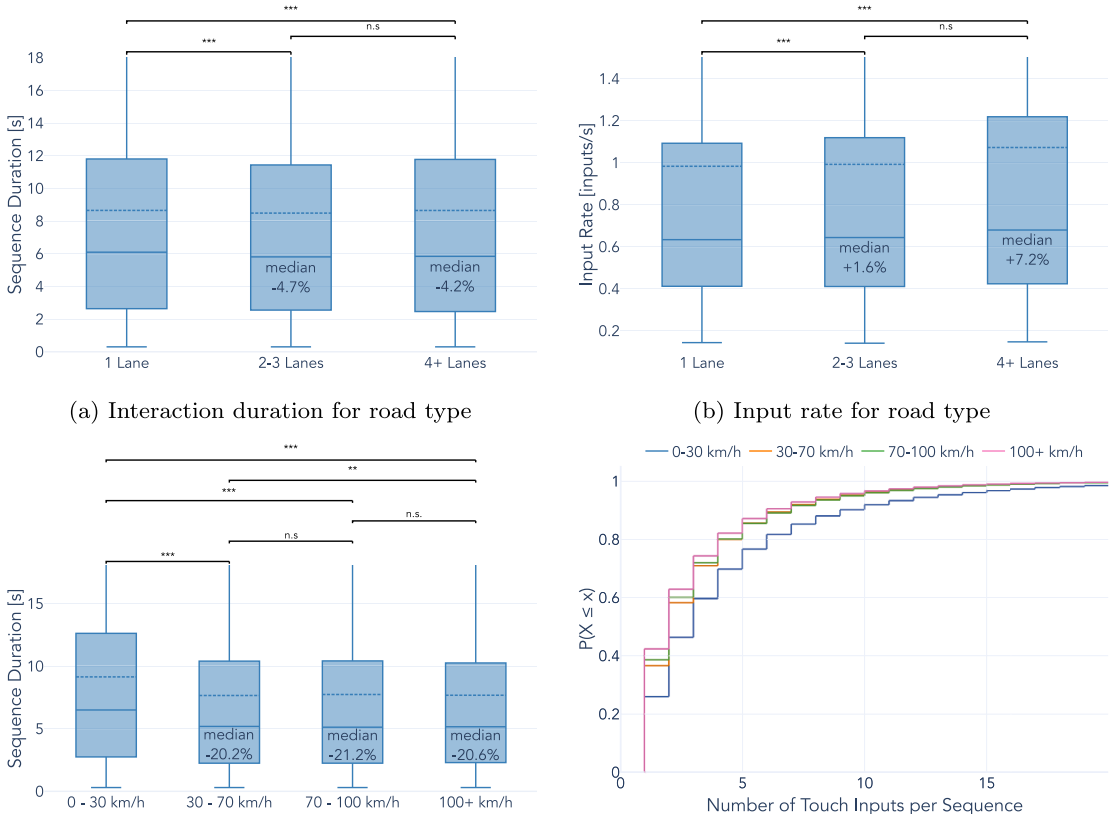
	Interaction Duration		Number of Touch Inputs	
Predictor	Estimate	SE	Estimate	SE
Intercept				
	8.880***	0.010	1.473***	0.026
Weather				
rain	0.324***	0.010	0.331***	0.007
Daylight				
darkness	0.062***	0.006	0.065***	0.004
Speed				
30–70 km/h	−0.193***	0.006	−0.226***	0.004
70–100 km/h	−0.246***	0.008	−0.315***	0.005
100 + km/h	−0.257***	0.008	−0.360***	0.005
Acceleration				
lateral 0.2–0.5 m/s^2	−0.212***	0.004	−0.172***	0.003
lateral >0.5 m/s^2	−0.520***	0.010	−0.439***	0.006
longitudinal 0.2–0.5 m/s^2	−0.122***	0.004	−0.061***	0.003
longitudinal >0.5 m/s^2	−0.252***	0.012	−0.230***	0.008
Road Type				
2–3 lanes	−0.031***	0.005	−0.005	0.003
4 + lanes	−0.028***	0.008	0.028***	0.005
Driving Automation				
active	−0.054***	0.012	−0.059***	0.008
Speed × Rain				
30–70 km/h × rain	−0.087***	0.014	−0.048***	0.010
70–100 km/h × rain	−0.097***	0.015	−0.074***	0.010
100 + km/h × rain	−0.098***	0.014	−0.069***	0.010
Driving Automation × Speed				
30–70 km/h × active	0.015	0.016	−0.004	0.010
70–100 km/h× active	0.090***	0.015	0.090***	0.010
100 + km/h × active	0.093***	0.014	0.106***	0.010
Usage Duration				
Mileage	−0.034***	0.002	0.007***	0.002
Random effects (SD)	trip = 0.303, country = 0.045		trip = 0.307, country = 0.170	

lead to significant differences in interaction duration and number of inputs compared to manual driving. However, at higher speeds (≥ 70 km/h), active driving automation corresponds to longer interactions, with similar increases in duration (+3.7 % to +4.0 %) and number of inputs (+3.2 % to +4.8 %). As shown in Fig. 9a, this trend is recognizable in the distributions of interaction duration under automated versus manual driving. Fig. 9b illustrates this trend for number of inputs, using an ECDF plot. The difference in the number of inputs in manual (dotted lines) versus automated driving (solid line) only becomes evident at higher speeds. While the cumulative density curves for activated and deactivated driver assistance systems remain almost identical at 30–70 km/h, there is a clear gap at highway speeds above 100 km/h, indicating that drivers tend to have higher input counts with automated driving than with manual driving.

Considering weather conditions, our modeling results indicate that rain is associated with both longer interaction durations and a higher number of inputs compared to dry conditions. These effects interact with driving speed. The increase in interaction duration is strongest at speeds below $30, \mathrm{km/h}$ (+38.3 %) and less pronounced at speeds above $30, \mathrm{km/h}$ (+25.4 − 26.8 %). A similar, but weaker, pattern is observed for the number of inputs, which increase by $39.2, \%$ at speeds below $30\, km/h$ and by $29.3 - 32.7, \%$ at higher speeds during rainy conditions. The stronger weather effects in low-speed contexts are also visible when looking at the data distribution in Fig. 9c.

Importantly, although the number of inputs increases during rainy conditions, interaction duration increases more strongly, resulting in significantly lower input rates under rainy conditions. This pattern is supported by Fig. 9d and highlights that changes in interaction behavior may only become apparent when interaction duration and input count are considered jointly.

Accounting for the effect of driving dynamics on interaction behavior, our modeling results show that for moderate lateral acceleration, drivers shorten their touch interactions by 19.1 % and perform 15.8 % fewer touch inputs. Strong lateral acceleration further



(a) Interaction duration for road type

(b) Input rate for road type

(c) Interaction duration for speed

(d) Number of inputs per sequence for speed

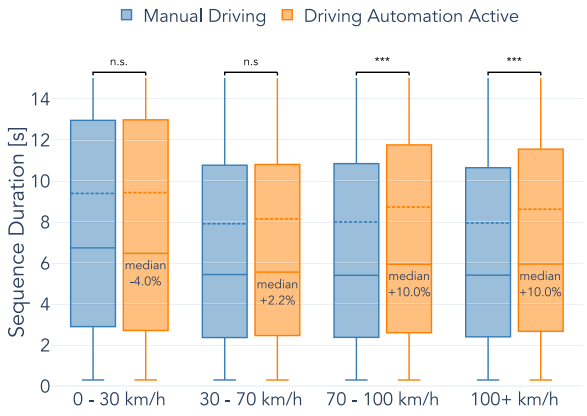
Fig. 8. The figure presents box plots that compare interaction duration and input rate as well as an ECDF plot comparing the number of inputs per interaction for the context variables speed and road type. The brackets with stars above the box plots represent the significance levels of the group differences of the connected variable values in relation to each other.

amplifies these effects, resulting in decreases of 40.5 % in duration and 35.5 % in inputs, compared interacting with no acceleration. Longitudinal acceleration exhibits a similar but slightly weaker pattern. Moderate levels of longitudinal acceleration lead to drivers reducing interaction duration by 11.5 % and inputs by 5.9 %, while strong longitudinal acceleration lead to a decrease in interaction duration by 22.3 % and a decrease in number of inputs by 20.6 %. The box plots in Fig. 10a support this trend. Fig. 10b shows that input rates increase for higher speeds. This indicates that interaction duration decreases more strongly than the number of inputs, resulting in faster successive inputs under higher acceleration.

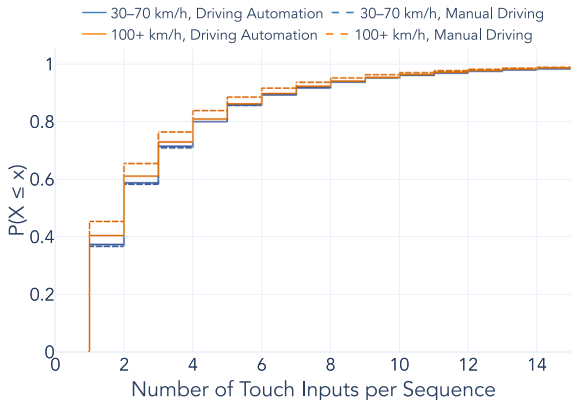
We finally analyze the effect of car mileage, used as a proxy for how accustomed drivers might be to the IVIS, on interaction behavior. Based on the average mileage in the dataset (33,323 km), an increase in mileage of one standard deviation (33,380 km) corresponds to a 3.30 % decrease in sequence duration and a 0.75 % increase in the number of inputs. This pattern is also reflected in the violin plots in Fig. 10c, where median sequence duration decreases by about 1.5 seconds, from 6.47 seconds for drivers with 0–5,000 km to 4.97 seconds for drivers with more than 100,000 km. In contrast, the number of inputs remains largely constant and even shows a slight increase with growing mileage. This suggests that drivers' input rates increase over time, as reflected in the input-rate curve in Fig. 10d. Moreover, a steeper increase in input rate is observed within the first 10,000–15,000 km of vehicle usage.

5. Discussion

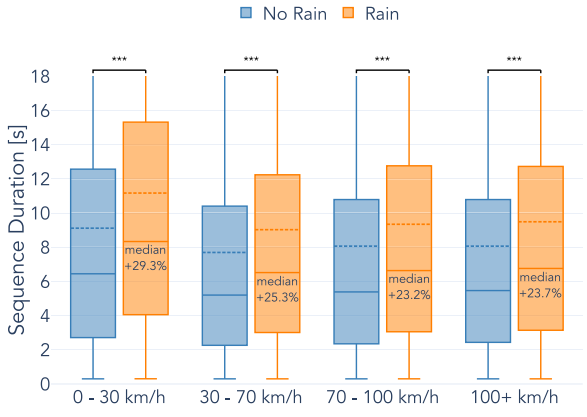
Our results show that the driver engages approximately every 5 minutes with the IVIS, spending a considerable amount of driving time on non-driving-related secondary tasks. This aligns with findings from previous studies (Dingus et al., 2016; Lansdown, 2012; Metz et al., 2014; Young et al., 2019). But how do people interact with these systems in real world-driving conditions? Which contextual aspects of real-world driving influence their interaction behavior? In the following we discuss our findings and address their implications for IVIS design and regulations.



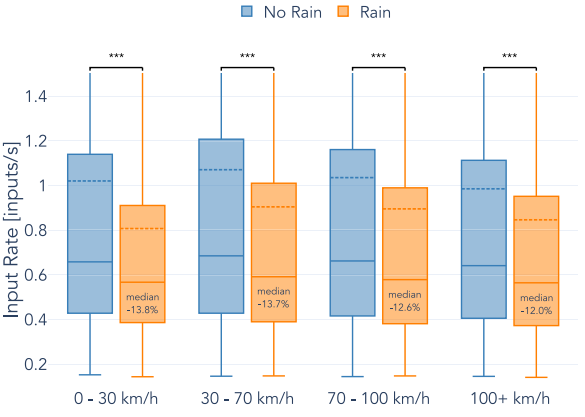
(a) Interaction sequence duration for driving automation across different speed categories



(b) Number of inputs for driving automation (30–70 km/h vs. 100+ km/h)



(c) Interaction sequence duration for speed x rain



(d) Input rate for speed x rain

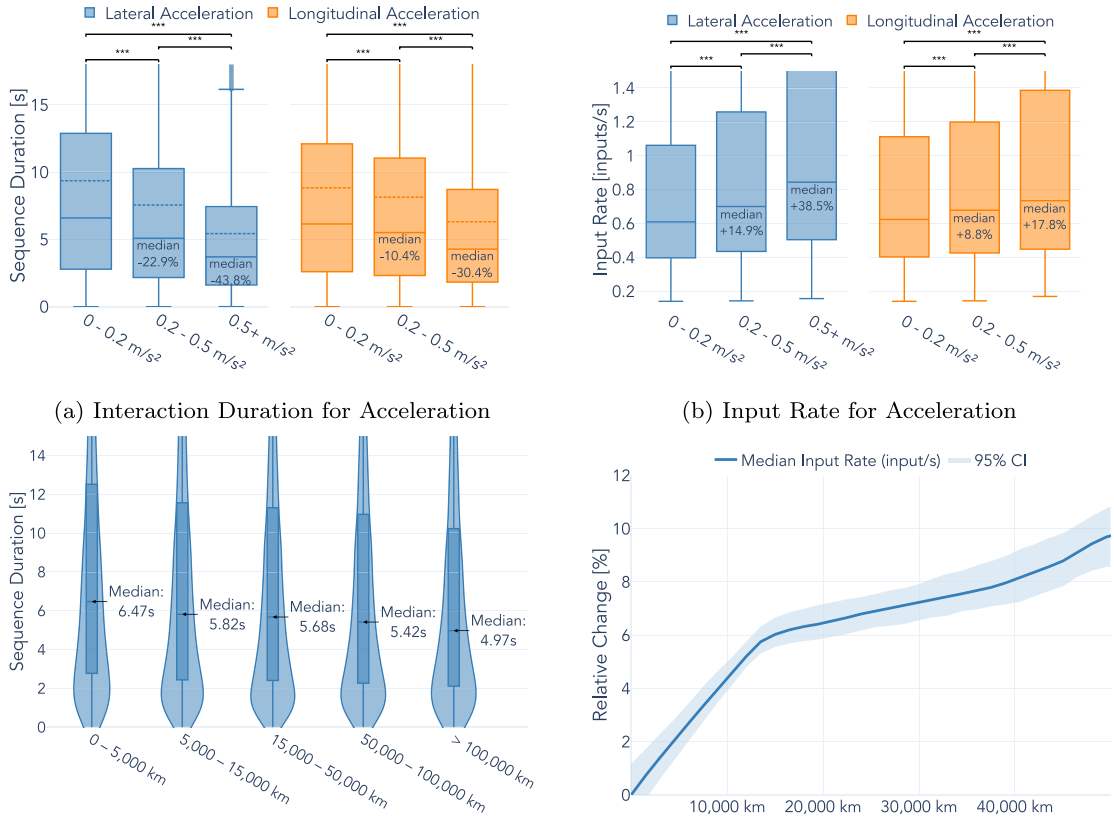
Fig. 9. The figure presents box plots and one ECDF plot that compare interaction duration, input rates and number of touch inputs per sequence for speed categories grouped after driving automation status and rain. The brackets with stars above the box plots represent the significance levels of the group differences of the connected variable values in relation to each other.

5.1. Physical controls remain the dominant modality in human-vehicle interaction

Our results indicate that physical button inputs, particularly steering-wheel buttons, constitute the dominant interaction modality while driving. Despite the widespread availability of touchscreen functionality, drivers continue to interact through physical button controls, with 63 % of all inputs containing at least one physical button input. While controlled experiments suggest that touch input can be faster (Ba h et al., 2008), prior work also indicates that tactile controls support reliable interaction, as fixed locations facilitates haptic memory (Masseno et al., 2024) and may reduce visual demand, for instance through shorter but more frequent glances compared to direct touch input (Ng et al., 2017). Further, our observations are consistent with the results of Large et al. (2016), who report that drivers prefer steering-wheel controls and rotary knobs when given a choice. This is supported by Ma et al. (2022), who find that knobs and steering wheel buttons are considered as more suitable for basic tasks. Together, these findings, along with our results, point toward drivers' reliance on physical buttons in real-world IVIS interaction, despite the ongoing shift toward larger touchscreens and fewer haptic controls (DeGuzman et al., 2024). However, physical and touch inputs do not necessarily cover the same functional scope, limiting direct comparability. Nevertheless, the strong reliance on physical inputs in everyday driving raises the question of whether drivers may prefer them for a broader range of functions, including those increasingly shifted to touchscreens. This highlights the need for further empirical investigation of modality preferences beyond current implementations.

5.2. Drivers rarely use speech interfaces

Drivers interact less often via speech compared to touch or physical buttons input, with speech present in 5.5 % of all interaction sequences and exclusively used in only 1.3 % of all sequences. This aligns with prior findings that voice-based systems are often



(a) Interaction Duration for Acceleration

(b) Input Rate for Acceleration

(c) Interaction Duration Mileage

(d) Input Rate Mileage

Fig. 10. The figure presents box plots and a violin plot that compare interaction duration and input rates for acceleration categories as well as mileage status. The brackets with stars above the box plots represent the significance levels of the group differences of the connected variable values in relation to each other. A line plot represents the percentual change of input rate over mileage.

underutilized in practice (Stiegemeier et al., 2022), even though auditory–speech tasks are associated with lower distraction than visual–manual tasks (Zhang et al., 2023; Zhong et al., 2024), and could therefore support safer interaction. Proposed explanations include limited system robustness, privacy concerns, insufficient anthropomorphism, and mismatches between system behavior and user's demands (Khandeparker et al., 2025; Liu et al., 2023; Sogemeier et al., 2024).

5.3. *Modality choice and interaction frequency differs across regions*

Pronounced regional differences across global markets emerge in both interaction frequency and modality use. Drivers in Europe, North America and Oceania show 13–40 % higher rates of touch interaction and a more balanced distribution between touch and physical button inputs than Asian regions. In Asia, drivers even more frequently interact via physical buttons and further show lower overall interaction rates. Notably, our data do not include data from China, and thus a major automotive market is not represented. Such variation likely reflects a combination of factors, including cultural preferences and language differences. However, the present data do not allow disentangling these influences, and the observed differences should therefore be interpreted as descriptive rather than causal. Nevertheless these findings support the notion that a simple transfer of *"western-style"* IVIS designs to Asian markets may be problematic (Young et al., 2012).

5.4. *Interactions demands outweigh workload regulation*

Previous research has established that the timing of secondary task engagement is shaped by driving workload and drivers' self-regulation strategies. Drivers are known to adapt interaction timing to momentary demands and to postpone interactions in situations they perceive as more demanding (Christoph et al., 2019; Ebel et al., 2023a; Metz et al., 2014; Tivesten and Dozza, 2015). While this perspective emphasizes continuous context-dependent regulation, our results show that drivers are much more likely to interact at the beginning of the trip, with frequencies declining substantially as the trip progresses. This pattern is particularly pronounced for speech interactions and suggests that a substantial share of IVIS engagement occurs during initial setup activities, such as entering a

destination or selecting media. Touch and physical button interactions show a similar pattern but persist more steadily throughout the trip, indicating their use for ongoing adjustments. Taken together, these findings could indicate that situational interaction demands have a stronger influence on interaction timing than previously emphasized. This resonates with everyday experiences such as starting to drive while fumbling with the navigation system because one is already running late. In such moments, urgency may outweigh self-regulatory strategies aimed at postponing interaction. Future research should more closely examine how this tension between immediate task goals and perceived driving demands shapes interaction decisions.

5.5. Driving automation only affects interaction behavior during high-speed driving

We show that partially automated driving is associated with an increased likelihood of interaction, suggesting that drivers tend to engage more with the IVISs when certain aspects of vehicle control are automated. This finding aligns with previous research showing increased NDRT engagement and higher distraction risk during partially automated driving compared to manual driving (Reagan et al., 2025; Wandtner et al., 2018). At the same time, our results show that drivers perform longer interactions that involve a greater number of inputs during partially automated driving sequences. Similar patterns are reported by Ebel et al. (2022), who find longer glances toward the display when adaptive cruise control and lane-keeping assistance are active. Our analysis extends these findings by showing that drivers tend to interact longer and perform more touch inputs only at speeds above 70 km/h. This suggests that automation may expand drivers' perceived interaction opportunities primarily in higher-speed driving contexts by freeing resources otherwise devoted to vehicle control. Taken together with the findings of Pan et al. (2023), who identify that higher trust in automation leads to higher NDRT engagement, and Liu et al. (2024), who show that drivers are less likely to look away from the NDRT at higher speeds during partially automated driving, our results support the hypothesis that the effects of partially automated driving on IVIS engagement are most relevant in high-speed driving environments. This may be related to lower confidence in the systems in low-speed environments or higher supervisory demands in more complex urban driving contexts.

5.6. Weather and lighting influence interaction behavior rather than interaction initiation

Our results indicate that adverse weather and lighting conditions (rain and darkness) are associated with longer interactions and a higher number of touch inputs. What might initially appear counterintuitive could be explained by drivers allocating more attention to the road under such conditions and therefore spreading IVIS interaction over a longer time span, for example by interrupting interactions more often, proceeding more cautiously, or even producing more input errors. This hypothesis is further supported by our finding of a clear reduction in input rate during rain. Prior work likewise shows that in more critical driving situations a larger share of glance time is directed to the road (Metz et al., 2011). An alternative hypothesis is that drivers may perceive adverse environmental situations as less critical due to accompanying circumstances, such as slower traffic flow during rain or reduced traffic density at night (Jägerbrand and Sjöbergh, 2016; Zhang et al., 2019). Situations perceived as less demanding have been associated with increased NDRT engagement (Cuentas-Hernandez et al., 2023) and more glances towards center-stack touchscreens (Ebel et al., 2023a), which could translate into more time spent interacting with the IVIS. However, such interpretations involve interaction effects between environmental conditions and traffic that cannot be measured with our data. Future work should therefore examine these dependencies on accompanying factors more explicitly.

Importantly, our results suggest that some environmental effects are moderated by speed. At higher speeds, the influence of rain on interaction characteristics becomes weaker. Above 100 km/h, the effect is about half as large as at speeds below 30 km/h and around 5 % smaller than at speeds between 30 and 70 km/h. This suggests that drivers may evaluate environmental risks differently at highway speeds. For interaction initiation, the pattern is less consistent. While night-time driving slightly reduces interaction odds, rain increases them in our data. Prior naturalistic studies, however, report no clear effects of poor lighting or bad weather on whether drivers engage at all (Klauer et al., 2006; Young et al., 2019). This inconsistency is also reflected in the systematic review by Huemer et al. (2018), who find that only 23 % of observational studies report higher NDRT prevalence in good weather. Given the 1:1 sampling of interaction and non-interaction periods, effect sizes for interaction probability should be interpreted with caution, as only ORs can be reported. Our results suggest that environmental conditions mainly influence how drivers interact, while their impact on interaction initiation must be further investigated in a broader context of accompanying factors.

5.7. Increasing driving dynamics reduce engagement and shorten interactions

Driving dynamics, captured by speed as well as lateral and longitudinal acceleration, show strong associations with IVIS engagement. Higher speed and higher acceleration are linked to a lower likelihood of initiating interactions and to shorter touch sequences, suggesting that drivers reduce engagement when vehicle control demands increase. This pattern aligns with naturalistic observational studies reporting less NDRT engagement at higher speeds (Cuentas-Hernandez et al., 2023; Seaman et al., 2022). Adding on the findings of Seaman et al. (2022) who suggested a reciprocal exponential function for modeling the probability of engagement over speed, our model similarly proposes an exponential decrease in duration and number of inputs of interaction sequences. We further observe an interaction between speed and road infrastructure. On multilane roads, interaction initiation likelihood decreases consistently as speed increases. In contrast, on single-lane roads, drivers are less likely to initiate interactions at stop-and-go speeds (0–30 km/h) but more likely to interact at higher speeds. A plausible explanation is that inner-city driving on narrow roads, despite low speed, is perceived as demanding due to frequent changes in traffic flow and increased monitoring requirements, whereas higher-speed single-lane driving may often reflect more stable conditions (e.g., rural roads with steady flow) that provide more opportunity for interaction.

Acceleration patterns show similar effects. Increased lateral acceleration substantially reduces both interaction initiation and interaction complexity. The findings align with prior work indicating reduced secondary-task engagement during curved-road driving (Ebel et al., 2022, 2023a) and low prevalence of secondary tasks in situations with high maneuvering demands such as roundabouts (Kidd et al., 2016) or turning at intersections (Christoph et al., 2019; Ismaeel, 2021). Overall, this works provides further evidence that vehicle dynamics play a key role in drivers' interaction behavior, and that speed moderates the impact of other contextual factors, such as road infrastructure and environmental conditions.

Notably, contextual effects do not always affect interaction duration and input count similarly, showing that both measures should always be considered jointly. On multi-lane roads, interaction sequences are shorter but drivers execute inputs faster, resulting in a higher input rate. Under acceleration, this pattern becomes even more pronounced, with input rates increasing by up to 38.5 %. This suggests that drivers speed up their interactions in more dynamic situations, potentially to maintain attention on the road.

5.8. Long-term usage leads to less IVIS usage but more efficient interactions

Finally, our data show a strong effect of mileage on touchscreen interaction. The higher the mileage, the less likely drivers are to interact with the IVIS. The fact that the interaction odds decrease strongly with higher mileage could be interpreted as declining interest in the IVIS functionalities with greater vehicle usage. On the other hand, increased mileage is associated with shorter interaction durations and slightly higher input rates, suggesting that drivers become more efficient in executing interactions as familiarity with the IVIS increases. The steep changes observed during early mileage stages (first 12,000 km) point toward a learning effect, which stabilizes as experience accumulates.

5.9. Implications for design and regulation

Our findings provide suggestions for user-centered IVIS design, context-aware interface adaptation, and the formulation of driver distraction regulations.

First, we find that drivers more frequently interact with the vehicle via physical buttons than via touchscreen. Importantly, the functional scope of physical controls and touchscreens only partially overlaps for the vehicles we analyzed, as the button design supports primarily simple functions (e.g., volume adjustment, menu navigation or call handling). Nevertheless, the high frequency of physical inputs indicates that they remain the most frequent interaction modality while driving. From a design perspective, we therefore argue that physical buttons should remain central for frequently used and core functions, and that a stronger focus on physical inputs, despite the trend toward large touchscreens (DeGuzman et al., 2024), should be systematically evaluated. This aligns with recent regulatory developments of the European New Car Assessment Programme (Euro NCAP), which require physical controls for essential vehicle functions to achieve top safety ratings (European New Car Assessment Programme, 2024; European Transport Safety Council, 2024). We further suggest that button inputs could be integrated into combined input methods (e.g., confirming or declining suggestions from a speech dialog via steering wheel buttons), similar to multimodal input strategies suggested by others (Ma et al., 2022, 2025). Beyond this, we find regional differences in interaction patterns, suggesting that user behavior should not be considered universal across markets. Designers should therefore consider region-specific modality preferences and usage patterns when prioritizing modalities and defining default behaviors. Overall, our findings support that decisions on interaction modalities should be guided more strongly by empirical usage patterns and user behavior, rather than being driven by on current design trends or economic considerations (DeGuzman et al., 2024).

Second, our results show that the driving context systematically shapes not only whether drivers interact, but in particular how they interact. For example, drivers' interaction behavior seems to be sensible to vehicle dynamics, as they tend to perform shorter and less input-intensive touch sequences at higher speeds and stronger accelerations, whereas under adverse environmental conditions and during automated driving, they tend to engage in longer and more input-intensive interaction sequences. These patterns provide clear directions for adaptive interface design. Rather than relying on static layouts or binary constraints (e.g., enabling or disabling functions), interaction design could adopt context-sensitive strategies that dynamically adjust interaction cost and complexity to the current driving situation (e.g., highway vs. urban driving). While context-sensitive interfaces are not a new suggestion (Khan and Khusro, 2020b), our results provide real-world evidence that can guide design decisions. In high-demand contexts, this may involve increasing target sizes, simplifying interaction flows, reducing available options, or prioritizing low-demand modalities such as voice or button input. In contrast, low-demand situations may allow for richer interaction and increased functionality. Strong trip- and country-level variability emphasizes that adaptation should not rely on context alone but also account for individual differences and cultural factors that need to be further investigated. Observed mileage effects point to longitudinal behavioral changes, highlighting the need for systems to adapt to evolving user behavior over time. We further find a high density of interactions at the beginning of trips suggesting that drivers aim to complete setup-related interactions early. This indicates that IVIS should be designed to efficiently support such initial interactions, for example through simplified startup flows or pre-configured states.

Third, the results suggest that current regulatory approaches for assessing modern IVISs might be optimized. Current acceptance criteria for IVIS evaluation often rely on standardized test scenarios and static thresholds, which do not reflect the diversity of real-world driving contexts and are increasingly criticized in the literature (Gonçalves et al., 2025; Kujala et al., 2014; Shen et al., 2025; Tivesten and Dozza, 2015). Our results support the argument that interaction behavior cannot be adequately captured without considering contextual variability and that one-size-fits-all approaches are not differentiated enough. We show that factors like driving speed lead to intrinsic interaction behavior changes. It remains to be examined whether these behavioral adaptations match

context-dependent changes in risk, for instance at higher speeds. We find that speed, road infrastructure, automation, and environmental conditions significantly shape interaction behavior, suggesting that distraction-relevant benchmarks should better reflect situational demands. Such self-regulation in secondary task engagement under demanding driving conditions has been reported in prior work (Ebel et al., 2023a; Metz et al., 2011; Oviedo-Trespalacios et al., 2019; Tivesten and Dozza, 2015), yet is not sufficiently reflected in current regulations. On the one hand, context-sensitive benchmarks could give manufacturers more design freedom in driving contexts where distraction poses less of a safety risk and, on the other hand, increase safety in situations where there is a mismatch between self-regulation of interaction behavior and the objective risk of the situation. Large-scale naturalistic evidence can therefore support the development of more realistic test procedures and benchmarks that better align with actual driver behavior. For example, display glance thresholds (such as the established 2-second-rule) could be adapted relative to the minimum required level of attention in a given driving context, similar to proposed concepts of Kircher and Ahlstrom (Kircher and Ahlstrom, 2017). In high-demand situations such as dense urban traffic, where demand is elevated, stricter thresholds would apply, whereas in low-demand conditions (e.g., highway driving with cruise control), more permissive thresholds could be considered. Such context-sensitive evaluation frameworks could improve safety while preserving design flexibility.

5.10. Limitations

We present new insights on how the driving context influences interaction behavior. Our observations from naturalistic driving data go beyond what has been found in previous work by examining multiple factors and their interactions and analyzing a large-scale dataset of customer data. However, while contextual predictors consistently exhibit statistically significant effects, we also find that they explain only a limited proportion of the overall variance in interaction behavior. In our models the random effects for trip and country indicate a substantial variability in all models. This means that despite influence of context, IVIS interaction is largely driven by unobserved heterogeneity across trips and regional differences. Individual driver characteristics and demographic information are not available for our analysis and should be considered as important measures in future research. Because semantic information may compromise user privacy and is therefore not accessible within the dataset, a more detailed analysis of interaction intent could not be conducted. Nevertheless, a more fine-grained analysis of task semantics would be important for further contextualizing and interpreting the present results. Furthermore, due to the limitation of available sensor signals, we only cover some of the contextual factors that may have an influence on interaction behavior. For example, our dataset contains no information about traffic volume or flow, which according to prior work is a crucial to interaction behavior (Cuentas-Hernandez et al., 2023; Liu et al., 2024; Perez et al., 2015). It should be investigated wether traffic measures interact with the metrics used in our analysis and thus might contribute to a deeper understanding. A further limitation is that our analysis is based solely on interaction logs and does not include direct measures of visual attention. Since gaze data are not recorded in customer vehicles for data protection reasons, we cannot assess the actual visual distraction associated with IVIS use, which would be necessary for a more complete understanding of context-dependent behavior. Another limitation is that we only investigated Mercedes-Benz vehicles. This potentially biases the results toward a specific customer base and the functionality of the IVIS. More real-world data from other manufacturers would enrich our findings and could be used to assess how well our insight generalize.

6. Conclusion and future work

With this work we deliver large-scale naturalistic evidence on when and how drivers interact with the IVIS while driving. Using customer data from everyday driving, we collect drivers' interaction behavior and driving data to characterize interaction frequency, modality use, and temporal patterns across regions. We further investigate how drivers' adapt their touch interaction behavior in relation to the driving context.

Our findings show that IVISs interactions are frequent and context-sensitive. Physical buttons and touch inputs dominate across all regions, drivers mostly interact at the beginning of trips, and both interaction frequency and modality choice vary across regions. These results highlight the importance of grounding user-centered IVIS design in naturalistic usage patterns (Ebel et al., 2021), for instance considering physical controls for frequently used functions and tailoring interaction concepts to regional differences.

We find that interaction behavior is systematically associated with driving context. For instance, drivers reduce engagement under higher vehicle dynamics and adjust interaction characteristics (duration and input intensity) depending on environmental conditions and driving automation. Moreover, increasing mileage relates to less interaction activity. Overall, the results suggest that drivers respond to combinations of contextual factors rather than single variables in isolation. However, while driving context explains systematic patterns, individual driver characteristics and intentions contribute additional variability in interaction behavior and require further investigation.

Future work should link context-dependent interaction behavior to objective safety outcomes to assess how self-regulation aligns with objective risk. In addition, controlled studies are needed to disentangle the behavioral mechanisms behind the observed patterns and to inform effective context-aware and adaptive interface strategies. Moreover, future work should incorporate the semantic characteristics of interaction sequences for example by distinguishing between brief, low-effort interactions (e.g., adjusting the air conditioning) and more complex, attention-demanding tasks (e.g., entering a navigation destination). Investigating how interaction behavior and modality choice varies across different IVIS task types could provide a more nuanced understanding of the observed context effects.

CRediT authorship contribution statement

Jan Hilbert: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization; **Natalia Sevcenko:** Writing – review & editing, Conceptualization; **Patrick Ebel:** Writing – review & editing, Supervision, Conceptualization.

Data availability

The data underlying this study cannot be made publicly available because they contain proprietary and confidential information owned by Mercedes-Benz AG.

Declaration of using generative AI and AI-assisted tools

The authors used ChatGPT to improve language and readability in the manuscript. We reviewed and edited all suggested updates of the manuscript and take full responsibility for the content of the published article.

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Appendix A.

A.1. Signal basis

Table A.4
Overview of all available raw signals including signal update type and output values.

Signal	Type	Output
Touch Input Log	On Event	Timestamp
Hardkey Input Log	On Event	Timestamp
Speech Input Log	On Event	Timestamp
Daylight Sensor	On Change	Timestamp, Binary
Rain Sensor	On Change	Timestamp, Binary
Speed	Cyclic	Timestamp, Category
Lateral Acceleration	Cyclic	Timestamp, Category
Longitudinal Acceleration	Cyclic	Timestamp, Category
Lane Detection	On Change	Timestamp, Category
Driving Automation Status	On Change	Timestamp, Binary
Mileage	On Trip Start	Timestamp, Integer

A.2. Filter process

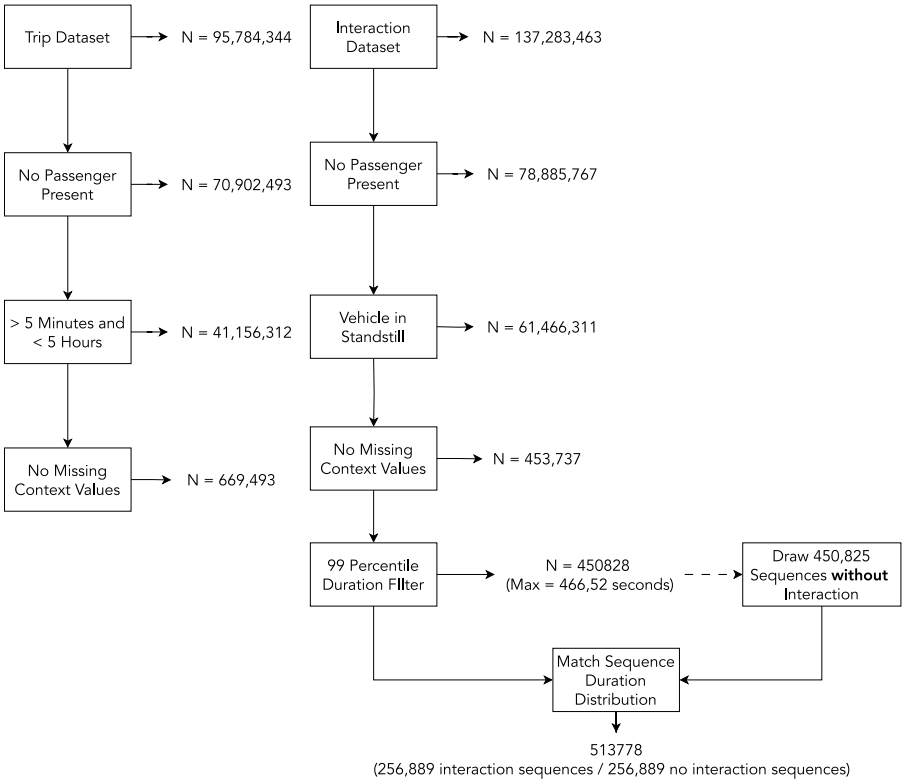


Fig. A.11. Schematic representation of the data filtering process from raw data to the final trip and interaction dataset.

A.3. Model selection process

Table A.5
Model selection process for estimating the likelihood to engage in an interaction. The mixed-effects logistic regression model with nested random intercepts outperform the simple generalized logistic model, as indicated by lower AIC/BIC values and higher explained variance. Adding interaction terms leads to another significant improvement of model fit (ANOVA: $\chi^2(9) = 1398.4$, $p < 0.001$) and results in the best-performing specifications.

Model Interaction Probability	AIC	BIC	R^2
Model 1: GLM	666926.8	667094.1	0.085
Model 2: GLMM (Country/Trip)	431005.6	431184.0	cond. 0.855, marg: 0.061
Model 3: GLMM (Country/Trip) + Interaction	429625.2	429903.9	cond. 0.849, marg: 0.064

Table A.6
Model selection process for sequence duration and touch inputs. Mixed-effects models with nested random intercepts outperform simple (generalized) linear models, as indicated by lower AIC/BIC values and higher explained variance. Adding interaction terms leads to another significant improvement of model fit (ANOVA: Interaction Duration: $\chi^2(6) = 130.3$, $p < 0.001$; Number of Inputs: $\chi^2(6) = 303.9$, $p < 0.001$) and results in the best-performing specifications.

Model	AIC	BIC	R^2
Sequence Duration			
Model 1: LM	816144.8	816303.0	0.032
Model 2: LMM (Country/Trip)	811267.3	816303.0	cond. 0.122, marg: 0.036
Model 3: LMM(Country/Trip) + Interaction	811190.4	811433.1	cond. 0.123, marg: 0.037
Number of Touch Inputs			
Model 1: GLM	2,018,077	2,018,242	0.102
Model 2: GLMM (Country/Trip)	1,979,842	1,980,029	cond. 0.259, marg: 0.062
Model 3: GLMM(Country/Trip) + Interaction	1,979,550	1,979,803	cond. 0.260, marg: 0.063

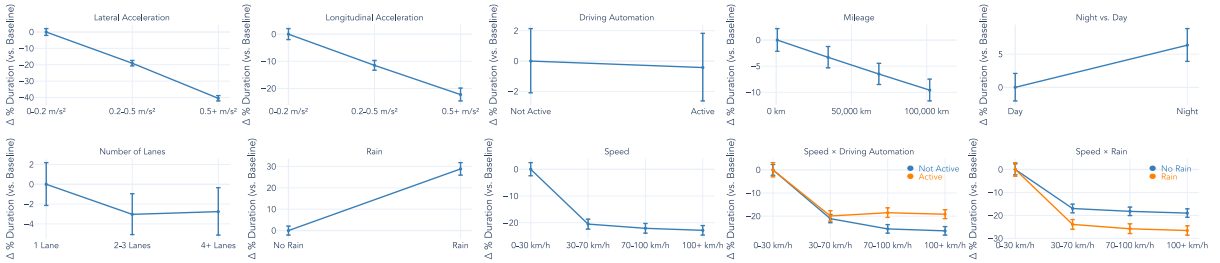
A.4. ORs and percent differences for mixed-effects regression models

Table A.7
This table presents population-averaged marginal ORs for main effects from the mixed-effects logistic regression model predicting interaction initiation. ORs are based on contrasts of estimated marginal means (Tukey-adjusted p-values) and reported with 95 % confidence intervals. Significance levels are presented as: * $p < .05$, ** $p < .01$, *** $p < .001$.

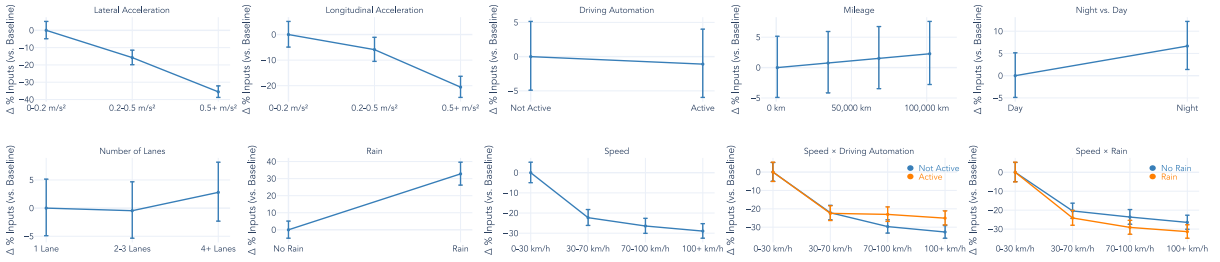
Contrast	OR	95 % CI
Driving automation		
active vs. inactive	1.31***	[1.27, 1.36]
Daylight		
dark vs. bright	0.35***	[0.33, 0.37]
Lateral acceleration		
0.2–0.5 m/s^2 vs. 0–0.2 m/s^2	0.92***	[0.90, 0.95]
> 0.5 m/s^2 vs. 0–0.2 m/s^2	0.65***	[0.61, 0.69]
> 0.5 m/s^2 vs. 0.2–0.5 m/s^2	0.70***	[0.67, 0.74]
Longitudinal Acceleration		
0.2–0.5 m/s^2 vs. 0–0.2 m/s^2	0.98	[0.96, 1.01]
> 0.5 m/s^2 vs. 0–0.2 m/s^2	0.52***	[0.49, 0.56]
> 0.5 m/s^2 vs. 0.2–0.5 m/s^2	0.53***	[0.50, 0.57]
Weather (Marginal Effects)		
rain vs. dry	1.34***	[1.29, 1.40]
Speed (Marginal Effects)		
30–70 vs. 0–30 km/h	1.08*	[1.00, 1.16]
70–100 vs. 0–30 km/h	0.97	[0.90, 1.05]
100+ vs. 0–30 km/h	0.86***	[0.78, 0.94]
70 - 100 vs. 30–70 km/h	0.90***	[0.84, 0.97]
100+ vs. 30–70 km/h	0.79***	[0.73, 0.87]
100+ vs. 70–100 km/h	0.88***	[0.81, 0.96]
Road Type (Marginal Effects)		
2–3 vs. 1 lane	1.36***	[1.30, 1.44]
4+ vs. 1 lane	1.56***	[1.46, 1.67]
4+ vs. 2–3 lanes	1.14***	[1.09, 1.20]
Mileage		
Mean + 1 SD	0.39***	[0.37, 0.41]

Table A.8
This table presents population-averaged marginal ORs for interaction effects from the mixed-effects logistic regression model predicting interaction initiation. ORs are simple-effects contrasts of estimated marginal means (Tukey-adjusted p-values) within each speed category and reported with 95 % confidence intervals. Significance levels are presented as: * $p < .05$, ** $p < .01$, *** $p < .001$.

Context	Contrast	OR	95 % CI
Rain × Speed			
0–30 km/h	rain vs. dry	1.64***	[1.45, 1.85]
30–70 km/h	rain vs. dry	1.44***	[1.30, 1.60]
70–100 km/h	rain vs. dry	1.27***	[1.13, 1.42]
100 + km/h	rain vs. dry	1.09	[0.99, 1.19]
Speed × Road Type			
0–30 km/h	2–3 vs. 1 lane	3.01***	[2.78, 3.26]
	4 + vs. 1 lane	3.76***	[3.32, 4.26]
	4 + vs. 2–3 lanes	1.25***	[1.10, 1.42]
30–70 km/h	2–3 vs. 1 lane	1.15***	[1.06, 1.24]
	4 + vs. 1 lane	1.24***	[1.12, 1.38]
	4 + vs. 2–3 lanes	1.08	[0.94, 1.24]
70–100 km/h	2–3 vs. 1 lane	1.10	[1.00, 1.22]
	4 + vs. 1 lane	1.16	[1.00, 1.34]
	4 + vs. 2–3 lanes	1.05	[0.92, 1.19]
100 + km/h	2–3 vs. 1 lane	0.91	[0.73, 1.13]
	4 + vs. 1 lane	1.10	[0.87, 1.39]
	4 + vs. 2–3 lanes	1.21***	[1.08, 1.35]



(a) Interaction sequence duration



(b) Number of inputs per interaction sequence

Fig. A.12. This figure shows the percent differences for estimated marginal means in interaction duration (a) and number of inputs per touch sequence (b) for all model coefficients.

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