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“Do I have it?”: How drivers shape their awareness of ADAS ownership

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ABSTRACT

Many drivers misjudge what their vehicle’s automation systems can actually do. This mismatch, known as mode confusion, can turn small misunderstandings into fatal consequences. Research has long examined drivers’ mental models and drivers’ confidence in engaging Advanced Driver Assistance Systems (ADAS), treating both as key contributors to mode confusion. Yet one crucial question remains largely unaddressed: do drivers know, correctly and confidently, which automation features are installed in their own vehicles? To address this question, we surveyed 1,487 U.S. vehicle owners whose manufacturers list Adaptive Cruise Control (ACC) and Lane Keeping Assistance (LKA) as standard equipment. Each respondent’s self-reported ownership awareness was compared with external model-trim data. Despite generally high ownership confidence, 17.1% incorrectly believed their vehicle lacked ACC and 29.4% believed it lacked LKA. Ownership awareness is uneven across ADAS: LKA is misjudged more often than ACC, even among drivers who are confident in their ownership judgments. Specifically, owning an older vehicle is associated with lower ownership accuracy and lower ownership confidence, while exposure to demanding trip contexts is more strongly related to lower ownership confidence than to lower ownership accuracy. Analyses of self-reported reasons using Holm-adjusted Fisher tests and association-rule mining reveal why ownership-awareness misalignment occurs. Misaligned ownership awareness commonly co-occurs with a lack of information and a lack of first-use experience, often coupled with an acceptance barrier that may reflect reluctance to engage initially with ADAS. In contrast, correct-and-confident ownership awareness co-occurs with prior ADAS use, clear in-vehicle feedback, and dealer explanation. Taken together, our findings suggest opportunities to help mitigate early mode confusion, including enhancing feedback and status visibility in in-vehicle interfaces and supporting guided first use through sales interactions or in-vehicle onboarding experiences, both of which warrant further testing.

1. Introduction

By regulating speed and lane position through Advanced Driver Assistance Systems (ADAS) such as Adaptive Cruise Control (ACC) and Lane Keeping Assistance (LKA), modern vehicle automation pushes driving toward greater safety and comfort (Varotto et al., 2022). Yet whether vehicle automation actually delivers these safety and comfort benefits depends on drivers’ understanding and correct use of automated driving capabilities and their operational limits (Calvert & Zgonnikov, 2025; Heikoop et al., 2019;

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Kidd et al., 2017; de Winter & Nordhoff, 2022). That understanding is increasingly challenged as vehicle automation grows more complex, exposing drivers to an ever-wider range of automated driving functions and interface designs (Carsten & Martens, 2019; Kim et al., 2024; Novakazi et al., 2021a,b). This expanding variety makes it increasingly difficult for drivers to maintain an accurate grasp of which vehicle automation functions their own vehicles provide and how these behave. Small gaps in this understanding can quickly escalate into hazardous situations, especially when drivers misjudge how their vehicle's automation will behave next. Such misjudgments can lead drivers into a state of *mode confusion*-misjudging their vehicle's active operational mode or, arguably worse, overlooking a mode entirely (Banks et al., 2018; Eom & Lee, 2022; Feldhütter et al., 2019; Wilson et al., 2020). Both experimental and real-world studies document instances of mode confusion (Kim, 2025), spanning situations where drivers repeatedly misinterpret automation alerts (Banks et al., 2018) to situations where drivers are unsure whether vehicle automation functions are engaged at all (Eom & Lee, 2015). In extreme cases, mode confusion has been associated with fatal crashes (NHTSA, 2024). Because mode confusion poses a serious safety risk, identifying how it can be mitigated has become increasingly critical. One intuitive approach is to reduce a vehicle's number of available automation modes (Boos et al., 2020; Feldhütter et al., 2019; Larsson et al., 2015; Lee & Eom, 2015; Novakazi et al., 2021b). Yet the wide variation in regulatory requirements and manufacturer design strategies renders strict limits impractical. Mode confusion therefore persists as a pressing threat to road safety and demands alternative mitigation strategies.

To mitigate mode confusion, it is crucial to understand how drivers form beliefs about what their vehicle's automation is doing and what it will do next (Wilson et al., 2020). Central to understanding mode confusion is the concept of *mode awareness*, defined as knowing which automation functions a vehicle includes and which of those functions are active at a given time (Kurpiers et al., 2020). Most research on mode awareness has focused primarily on the second part of this definition, implicitly assuming that drivers already know which automation functions their vehicles include. However, outside controlled experiments, this assumption breaks down: many drivers in real-world contexts misidentify which ADAS their vehicles are equipped with (Harms et al., 2020). The present study therefore returns to a more fundamental layer of mode awareness-ownership awareness-by examining whether drivers correctly recognize the presence of ACC and LKA in their vehicles. The distinction between correct and incorrect ownership awareness of ACC and LKA can have life-critical consequences. ACC provides temporary longitudinal control and LKA provides temporary lateral control-both functions directly relevant to road safety. When drivers misidentify whether ACC or LKA are present, they risk misjudging what their vehicle's automation will-or will not-do in a safety-critical moment.

If ownership awareness is a fundamental layer of mode awareness, the question becomes: how does it form? To address this, we draw on studies of drivers' mental models -internal representations of system behavior that guide predictions, even when incomplete (Norman, 1983). In driving contexts, mental models describe how and when a driver expects an automation function to act or refrain from acting (Beggiato & Krems, 2013). Existing work shows that accurate mental models can help drivers maintain safer headways and respond more quickly in certain situations (Gaspar et al., 2021), yet these benefits do not apply uniformly across different levels of vehicle automation (Kazi et al., 2007; Kim et al., 2024). Human-Machine Interfaces (HMIs), function naming, and training all influence how mental models form and, in turn, shape development of mode awareness. Although empirical work on HMI design reports mixed effects (Eom & Lee, 2022; Kim et al., 2025; Monsaingeon et al., 2023, 2021; Trösterer et al., 2024), a consistent finding is that poor interfaces can intensify mode confusion (Hogema et al., 2024; Monsaingeon et al., 2021; Tinga et al., 2023; Wilson et al., 2020). Clear, non-misleading function names and structured training for vehicle-automation use can therefore help steer drivers toward more accurate mental models and stronger mode awareness (Abraham et al., 2017; Feinauer et al., 2025; Teoh, 2020). In practice, however, dealership training-when offered at all-is typically brief (Boelhouwer et al., 2020a; Viktorová & Šucha, 2019). As a result, many drivers rely primarily on in-vehicle HMIs and personal experience to understand what their vehicle's automation can do-a process that may leave some drivers inaccurate in their ownership awareness of ADAS.

The preceding discussion suggests that ownership awareness can be inaccurate, but ownership accuracy alone does not capture the full picture. Even accurate ownership awareness is not enough to ensure safe engagement with vehicle automation if drivers lack confidence in what they know, or conversely, are overconfident in incorrect beliefs. Previous research on mental models of general ADAS knowledge suggests that confidence in that knowledge forms a second critical safety dimension (Blömacher et al., 2020). Excessive confidence can lead drivers to overstate their vehicles' automation capabilities (Mason et al., 2023), resulting in misuse or complacency (Carney et al., 2022; Gaspar et al., 2021; Parasuraman & Riley, 1997). Insufficient confidence, by contrast, can leave drivers unsure whether automation functions are active or even installed (DeGuzman & Donmez, 2021; Lubkowski et al., 2021). Both forms of miscalibrated confidence in vehicle automation functions raise safety risks. For instance, Lenneman et al. (2020) found that misinformed yet confident ADAS learners committed more lapses and errors in naturalistic driving, whereas uninformed learners-who typically reported low confidence-displayed elevated levels of risky driving behavior. Yet despite these concerns, previous studies addressing ADAS ownership awareness have examined either ownership accuracy or ownership confidence, rarely considered them jointly, and have not compared either against verified ownership data (DeGuzman & Donmez, 2021; Harms et al., 2020; Mohammad et al., 2026). As a result, it remains unclear *who* is most susceptible to *misaligned* ownership awareness-being wrong, unsure, or both-and *why* a driver's ownership awareness becomes misaligned in the first place.

To address this gap, the present study provides the first joint examination of correctness and confidence in drivers' ownership awareness of ACC and LKA. Building on Novakazi (2025)'s Driver-Vehicle-Context (D-V-C) framework, and extending earlier work that identifies subgroups expressing explicit uncertainty (e.g., lower annual driving distance, non-private ownership, younger age), we use external model-trim data to test ownership accuracy and confidence together. Specifically, this study addresses two questions: (1) Which driver, vehicle, and context factors are associated with being simultaneously correct and confident about whether a vehicle has ACC and LKA? and (2) Which self-reported reasons for ownership confidence or doubt are most strongly associated with ownership-awareness alignment or misalignment? To address these questions, the present study offers two main contributions: (i) a model of ownership awareness as a joint construct of ownership accuracy and confidence, compared with external model-trim availability data; and (ii) reason-pattern extraction to identify specific intervention opportunities for mitigating mode confusion. The remainder of this paper proceeds as follows. Section 2 describes the survey and modeling approach. Section 3 presents results on ownership accuracy, confidence, and stated reasons. Section 4 discusses key findings and future directions, and Section 5 concludes with recommendations for improving ADAS ownership awareness.

2. Methods

To identify which drivers are more susceptible to misaligned ownership awareness, we combine a cross-sectional survey with an external catalogue of ADAS equipment. Together, these data describe ownership awareness for ACC and LKA as a joint construct combining factual ownership *accuracy* and stated ownership *confidence*, and allow us to identify correlates of misalignment (cases where respondents are not both accurate and confident). The external catalogue lists factory-standard ADAS equipment by model and trim, providing a proxy for objective ADAS availability. The survey captures driver, vehicle, and trip-context covariates, along with respondents' stated reasons for their ownership confidence or doubt. Mixed-effects models relate the two dependent awareness variables (ownership accuracy and confidence) to independent variables drawn from Novakazi's Driver-Vehicle-Context (D-V-C) framework (Novakazi, 2025). Complementary over-representation tests and association-rule mining (ARM) then summarize how reasons co-occur, highlighting common patterns relevant for mode-confusion mitigation.

Outcomes and variables

Ownership awareness is represented by two dependent variables for each respondent-ADAS pair (ACC, LKA). First, *ownership accuracy* (accurate vs. inaccurate) is determined by comparing each respondent's ownership report with the external availability proxy (see Sampling frame). Second, *ownership confidence* is measured as the respondent's 1-5 Likert-scale confidence rating attached to that report. Because each respondent reports ownership awareness for both ACC and LKA, both ownership accuracy and confidence models include a respondent-level random intercept to account for within-person dependence.

Independent variables follow the D-V-C framework, enabling results to be mapped to priority driver-vehicle-context groups for mode-confusion mitigation

- **Driver** variables include age group, gender, license tenure, and frequency of using other vehicles.
- **Vehicle** variables include ADAS type (ACC/LKA), ownership type (own/lease), model year, and years using the vehicle.
- **Context** variables describe each respondent's "typical trip": continuous 0-100% sliders for highway, free-flow, and darkness exposure; a trip-distance measure; and the main trip purpose (commuting as reference).

To test whether the effect of "more time behind the wheel" depends on trip context, we include interactions between trip distance and each exposure percentage (% highway, % free-flow, % darkness). Item wording for trip-context variables follow prior work for clarity and comparability (Karlsson & Novakazi, 2023; Knoop, 2021; Ramos et al., 2020). Sliders are used to capture exposures as continuous rather than binned measures. Full details of the survey design are provided in Appendix A, Table A.5.

Sampling frame

Because no public, respondent-level dataset with verified ADAS configurations yet exists, establishing a verifiable ground truth for ownership accuracy is challenging. To address this, ownership responses are compared with an external model-trim catalogue listing factory-standard ADAS by model year (MY). Relative to study designs that rely solely on self-reported ADAS ownership, this approach offers a more reliable basis for assessing ownership accuracy, as prior work has shown that drivers sometimes report owning specific ADAS in ways that contradict their vehicle's specifications Harms et al. (2020). For the U.S. market, Consumer Reports; *Guide to Standard Advanced Safety Systems* provides detailed records of model-trim ADAS equipment (Consumer Reports, 2021; Sinclair, 2021). To ensure comparability and minimize ambiguity arising from optional packages or dealer-installed features, eligibility is restricted to U.S. MY 2021 and newer passenger-vehicle trims for which *both* ACC and LKA are standard equipment. This restriction reduces the risk of misclassification, since any respondent who reports not having these systems is inaccurate according to the catalogue. Although the resulting set of eligible vehicles is narrower, it still captures broad market coverage-137 models across 30 makes (Appendix B, Table B.6). Moreover, the sample includes 28 of the 30 eligible makes, with no single make comprising more than 19% of observations (Table 1), reducing concern that the catalogue-based approach is disproportionately influenced by make-specific discrepancies.

Survey instrument and procedure

The questionnaire (via Qualtrics) is structured according to the D-V-C framework, with sections corresponding to driver, vehicle, and context factors (Appendix A, Table A.5).

Screening. Screening items record driver's license tenure, vehicle ownership or lease, and make-model-year. Branching logic automatically terminates the survey if a respondent lacks a valid license, does not own or lease a vehicle, or reports a MY earlier than 2021. The survey also captures each respondent's length of vehicle ownership and frequency of using other vehicles.

Trip context. The trip-context block captures the distance of a respondent's typical trip (in miles) and the percentage of that trip spent on highways, in free-flow traffic, and in darkness using 0-100% sliders. From the original D-V-C framework, weather is omitted because a single "typical trip" cannot represent seasonal variability in the U.S. context. Respondents also select all applicable trip purposes and indicate one main purpose.

Ownership awareness. Next, ownership awareness is measured for ACC and LKA. Each ADAS is introduced separately, including a brief explanation that some manufacturers bundle the two systems (details in the online supplementary information) (DeGuzman & Donmez, 2021; McDonald et al., 2018). Respondents report ownership (Yes/No) and rate their ownership confidence on a 1-5

Likert scale (DeGuzman & Donmez, 2021). Conditional checklists then present select-all-that-apply stated reasons: *doubt* reasons if ownership confidence ≤ 3 (e.g., unclear feedback, confusing naming) and *confident* reasons if ownership confidence ≥ 4 (e.g., prior use, dealer explanation), drawing on prior work on how drivers learn about ADAS (Lubkowski et al., 2021; Viktorová & Šucha, 2019).

Demographics and recruitment. Finally, demographic items capture age group and gender using elements from recent mental-model research (Kim et al., 2024). Participants were recruited via Prolific, with platform prescreens for U.S. residence, a valid driver's license, and current vehicle ownership or lease. Screening questions within Qualtrics verified MY 2021+ eligibility and inclusion in the sampling frame before any ownership questions appeared. With electronic consent, data were collected between June 30 and July 2, 2025. Participation was voluntary and compensated at a fixed rate of 0.70 GBP. The study protocol is approved by the Delft University of Technology Human Research Ethics Committee.

Data preparation

To enforce the eligibility rules defined by the sampling frame, all raw responses are manually screened before analysis. Of 2,821 initial entries, 1,334 are excluded: 907 for lacking a valid driver's license or reporting a MY earlier than 2021, and 427 for owning a vehicle not listed in the eligible catalogue. All retained records are complete. The filtered sample consists of 1,487 respondents (52.7% of starters) with a median completion time of 189 seconds. To ensure stable mixed-effects estimation, demographic categories with fewer than 30 cases are omitted from the regression models. This affects three groups: respondents identifying as non-binary or 'prefer not to say' for gender ($n = 13$), respondents aged 75 or older ($n = 8$), and respondents with a driver's license tenure of less than one year ($n = 8$).

Given this final sample, adequacy for the mixed-effects logistic model is assessed using a common "10 events per variable" (EPV) heuristic (Peduzzi et al., 1996). Treating ≥10 EPV as a minimum, and assuming a conservative 10% ownership inaccuracy rate, a model with about 20 fixed-effect terms would require at least 200 ownership inaccuracy events. With 1,487 respondents contributing two ADAS ownership-accuracy observations each (2,974 total; ≈300 expected inaccuracy events), the sample comfortably exceeds this threshold, supporting stable mixed-effects estimation.

Statistical modeling

To isolate the effects of driver, vehicle, and context factors on ownership awareness, we model the two dependent outcomes-ownership *accuracy* and ownership *confidence*-using mixed-effects regression. This approach accounts for repeated responses per respondent and captures unobserved individual differences. Ownership *accuracy* (accurate vs. inaccurate) is estimated using a binomial logit model, while ownership *confidence* (1-5) is estimated using a linear mixed-effects model treating the Likert scale as approximately continuous in the main specification. Because each respondent provides data for both ACC and LKA, all mixed-effects regression models include a respondent-level random intercept to account for within-person clustering across ACC and LKA responses. Full model specifications, including the complete set of fixed effects, random-effects structure, link functions, optimizer settings, and reference categories, are reported in the Supplementary Information (Tables S1 and dummyTXdummy-(S4).

Fixed effects comprise the driver, vehicle, and context covariates (see Outcomes and variables), along with three distance-exposure interactions (% highway, % free-flow, % darkness) to test whether any distance effect depended on typical driving conditions. Several survey variables-age group, driver's license tenure, vehicle ownership tenure, car-sharing frequency, and model year-were originally recorded as ordered categories. In the regression models, these variables are therefore entered as integer-coded numeric predictors (1, 2, 3, etc.), assuming approximately equal spacing between adjacent categories. This specification preserves degrees of freedom and allows each variable to be summarized by a single per-unit slope rather than a set of dummy-category contrasts. For descriptive purposes, however, Table 2 reports these variables in their original categorical form. For interpretation, we report odds ratios for ownership accuracy and unstandardized coefficients for ownership confidence, each with corresponding statistical significance. Each mixed-effect model fit is summarized using marginal and conditional R^2, distinguishing explained variance from between-person heterogeneity. Multicollinearity among predictors is assessed via generalized variance inflation factors, and residual distributions are evaluated using binned residual plots for the logistic model and standard residual and QQ-plots for the linear model. Random-effects variance components and intraclass correlation coefficients are reported. Full diagnostics are provided in the Supplementary Information.

Because the confidence scale is ordinal and skewed toward higher values, we test the robustness of this specification with two complementary approaches: (i) a proportional-odds ordinal logit without random intercepts (population-level model), and (ii) a mixed-effects logistic model comparing high confidence (≥ 4) against doubt (≤ 3). Consistent signs and significance across all three models indicate that results are not artifacts of treating the Likert scale as continuous.

Reason analyses

To understand *why* and *how* ownership-awareness alignment or misalignment occurs, we treat the conditional reason lists as self-reported diagnostic clues. Each respondent's selected reasons-checked from either the *doubt* list (confidence ≤ 3) or the *confident* list (confidence ≥ 4)-serve as quantitative indicators of the reasoning behind their ownership-awareness answers. Since these checklists were presented in the survey according to the same ≤ 3 vs. ≥ 4 branching rule (see Survey instrument and procedure), the reason analyses necessarily use that same split. Alternative-threshold reason data do not exist, because each respondent was shown only one checklist based on their stated ownership confidence. Within this framework, we use a two-step analytic approach that addresses two complementary questions: which individual reasons distinguish ownership-awareness states, and which combinations of reasons tend to co-occur within those states. This combination strengthens inference by pairing error-controlled tests of single reasons with pattern detection for co-occurring explanations, yielding a more robust basis for interpretation and for identifying policy-relevant intervention opportunities.

Step 1: Testing individual diagnostic clues. Separately for ACC and LKA, we first examine whether certain reasons are reported disproportionately among respondents with accurate versus inaccurate ownership awareness. Holm-adjusted Fisher exact tests ($\alpha =$

Table 1
Vehicle make summary of participants' selected main vehicle in the survey sample (n = 1,487).

Vehicle make	Respondents	Group %	Vehicle make	Respondents	Group %	Vehicle make	Respondents	Group %
Toyota	273	18.4	Nissan	55	3.7	Lincoln	10	0.7
Honda	234	15.7	Audi	37	2.5	Volvo	10	0.7
Ford	140	9.4	Lexus	37	2.5	Infiniti	6	0.4
Hyundai	113	7.6	Mercedes	29	2.0	Genesis	4	0.3
Chevrolet	86	5.8	Jeep	21	1.4	Porsche	3	0.2
Tesla	79	5.3	Acura	17	1.1	Jaguar	2	0.1
Subaru	78	5.2	Chrysler	15	1.0	Land Rover	2	0.1
Kia	72	4.8	Buick	14	0.9	Polestar	1	0.1
Mazda	68	4.6	GMC	14	0.9	Lucid	0	0.0
BMW	56	3.8	Cadillac	11	0.7	Maserati	0	0.0

.05) identify reasons that are statistically over- or under-represented: comparing inaccurate vs. accurate ownership awareness within the doubt branch, and confident-accurate vs. confident-inaccurate ownership awareness within the confident branch. Fisher's exact test is chosen because it handles sparse, binary data without relying on large-sample assumptions, while Holm correction controls family-wise errors more efficiently than Bonferroni.

Step 2: Following co-occurring diagnostic clues. Next, we search for patterns in how reasons co-occur using association-rule mining (ARM). This method expresses frequent co-occurrences as simple if→then rules (e.g., "Feedback clear → Used it") (Law et al., 2011; Zhang et al., 2023). ARM is preferred over alternative approaches such as log-linear or latent-class models because it (i) handles sparse, high-dimensional checkbox data without strict distributional assumptions, (ii) produces directly interpretable rules for practitioners, and (iii) provides transparent diagnostics: *support* (how often a combination appears), *rule confidence* (its conditional probability), and *lift* (association strength compared with what would be expected under independence). In this analysis, association rules are the selected reason items, and outcomes correspond to one of four ownership-accuracy states (ACC-accurate, ACC-inaccurate, LKA-accurate, LKA-inaccurate). Following standard ARM practice (Han et al., 2012), we report only association rules meeting three thresholds-support ≥ .02 (≈30 respondents in this sample), rule confidence ≥ .50 (more likely than chance), and lift > 1 (positively associated). For accurate-versus-inaccurate contrasts, confident and doubt lists are analyzed separately. To prioritize insights, association rules are ranked by rule confidence, then support, then lift, and we report the top five co-occurring reason patterns for each ADAS ownership-accuracy state.

Software

All analyses are conducted using open-source software to ensure reproducibility. Mixed-effect models are fitted in `R` using the `lme4` package (`glmer`/`lmer`); the proportional-odds model uses the `ordinal` package. Association-rule mining (ARM) is implemented in Python with `mlxtend`, using the FP-growth algorithm, which efficiently extracts frequent patterns from sparse binary data compared with Apriori or Eclat.

3. Results

Ownership awareness of ACC and LKA varies not only between the two functions but also across drivers, vehicles, and trip contexts, reflecting underlying informational and experiential mechanisms. This section first summarizes the survey sample to establish the characteristics of the respondents represented in the findings. It then examines how ownership confidence aligns-or fails to align-with ownership accuracy across ADAS functions. Finally, it explores mechanisms underlying ownership-awareness misalignment-instances where drivers are not both correct and confident-based on respondents' stated reasons.

Descriptive statistics

The survey includes 1,487 valid respondents whose vehicles collectively represent 28 of the 30 eligible MY 2021 + makes (Table 1). As expected, the most commonly represented makes are Toyota (18.4%) and Honda (15.7%) (DeGuzman & Donmez, 2021). Most respondents are experienced drivers-91.8% have held a driver's license for more than five years-and 87.1% own rather than lease their vehicle. Gender is approximately balanced (51.2% male, 47.9% female), and ages concentrate in 25-44 years (56.7%), reflecting a demographic composition of the Prolific recruitment platform rather than the general population of newer-vehicle owners, who tend to skew older (Jordhamo, 2025). The implications of this age distribution for generalizability are discussed in Section 4.

Typical single trips are of moderate length (mean 42.3 km, SD 33.0 km) and include substantial highway and free-flow driving (means 42.9% and 48.9%; SDs 24.9% and 24.3%), with less exposure to darkness (mean 23.9%, SD 19.4%). Commuting is the most common main trip purpose (61.7%), suggesting that respondents mainly report regular, familiar travel conditions.

Most interestingly, ownership awareness of ACC and LKA differs between the two systems. Incorrect self-reported ownership is higher for LKA (29.4%) than for ACC (17.1%), while ownership confidence in LKA is slightly higher (77.5%) than in ACC (73.4% "very" or "fully" confident). These descriptive results already indicate that high ownership confidence does not necessarily coincide with accurate ownership awareness.

Associations with driver, vehicle, and trip-context variables

Table 2
Descriptive statistics of the survey sample (n = 1,487). Independent variables are grouped by Novakazi's Driver-Vehicle-Context (D-V-C) framework (Novakazi, 2025). Counts and percentages are shown for categorical variables; we report the mean, median, SD, min, and max for each continuous trip-context measure. Dependent variables are presented under ACC and LKA ownership awareness as claimed ownership (Yes/No) and response confidence (1-5).

Variable	n	%	Variable	n	%
Driver			**Context**		
Age			Trip purposes (all)		
Under 25	79	5.3	Commute	1297	87.2
25–34	433	29.1	Shop	1357	91.3
35–44	410	27.6	Leisure	1357	91.3
45–54	288	19.4	Drop-off/pick-up	1044	70.2
55–64	182	12.2	Other	36	2.4
65–74	87	5.9			
75+	8	0.5			
Gender			Typical trip purpose		
Male	761	51.2	Commute	917	61.7
Female	713	47.9	Shop	210	14.1
Non-binary/other	7	0.5	Leisure	231	15.5
Prefer not to say	6	0.4	Drop-off/pick-up	113	7.6
			Other	16	1.1
License tenure			Typical trip distance (km)		
<1 yr	8	0.5	Mean	42.3 (26.3 miles)	–
1–5 yrs	114	7.7	Median	32.2 (20 miles)	–
>5 yrs	1365	91.8	SD	33 (20.5 miles)	–
			Min	3.2 (2 miles)	–
			Max	160.9 (100 miles)	–
Car-sharing / rental			Typical trip free-flow (%)		
Never	485	32.6	Mean	48.9	–
Rarely	526	35.4	Median	50	–
Sometimes	400	26.9	SD	24.3	–
Often	58	3.9	Min	0	–
Always	18	1.2	Max	100	–
Vehicle					
Model year			Typical trip highway (%)		
2021	367	24.7	Mean	42.9	–
2022	474	31.9	Median	41	–
2023	298	20.0	SD	24.9	–
2024	232	15.6	Min	0	–
2025	116	7.8	Max	100	–
Ownership tenure			Typical trip darkness (%)		
<1 yr	249	16.7	Mean	23.9	–
1–2 yrs	467	31.4	Median	20	–
2–3 yrs	424	28.5	SD	19.4	–
3–4 yrs	233	15.7	Min	0	–
>4 yrs	114	7.7	Max	100	–
Ownership type					
Lease	192	12.9			
Own	1295	87.1			
ACC awareness			**LKA awareness**		
Claimed ownership			Claimed ownership		
No	254	17.1	No	437	29.4
Yes	1233	82.9	Yes	1050	70.6
Response confidence			Response confidence		
Not at all	32	2.2	Not at all	36	2.4
Slightly	107	7.2	Slightly	95	6.4
Moderately	256	17.2	Moderately	204	13.7
Very	402	27.0	Very	311	20.9
Fully	690	46.4	Fully	841	56.6

Ownership accuracy of ACC and LKA and ownership confidence in these systems vary with vehicle characteristics and trip context (Table 3). These associations indicate which respondent and usage characteristics coincide with more-or less-accurate and confident ownership awareness.

For *ownership accuracy*, the strongest associations are with ADAS type and vehicle model year. Respondents are less accurate about their ownership of LKA than of ACC (OR = 0.39, $p < .001$). Each additional model year step is associated with higher odds of correct ownership (OR = 1.65, $p < .001$). To illustrate that practical magnitude: the predicted accuracy of LKA ownership awareness rises from approximately 61% for MY 2021 to over 90% for MY 2025, a difference of nearly 30 percentage points (Fig. 1, panel b). For

Table 3
Mixed-effects models of ownership awareness organized by Novakazi's Driver-Vehicle-Context (D-V-C) framework (Novakazi, 2025). Ownership accuracy is estimated with a mixed-effects logistic regression; ownership confidence (1-5 Likert) with a mixed-effects linear regression. A respondent-level random intercept accounts for paired ACC/LKA responses. Reported values: Accuracy-odds ratios (OR) with p-values; Confidence-unstandardized coefficients with p-values. Significance codes: † p < .10, * p < .05, ** p < .01, *** p < .001. Marginal and conditional R^2 summarize explained variance.

		Accuracy			Confidence		
Level	Variable	OR (p)	OR 95% CI	SE	β (p)	95% CI	SE
	(Intercept)	0.83 (0.745)	[0.28, 2.49]	0.559	3.00*** (<0.001)	[2.58, 3.42]	0.214
D	age	1.06 (0.294)	[0.95, 1.18]	0.054	0.04† (0.066)	[-0.00, 0.08]	0.020
D	gender (female)	1.02 (0.901)	[0.79, 1.31]	0.129	-0.09† (0.073)	[-0.18, 0.01]	0.048
D	driver license tenure	1.37 (0.201)	[0.85, 2.21]	0.244	0.11 (0.239)	[-0.07, 0.30]	0.094
D	car sharing frequency	1.01 (0.921)	[0.87, 1.16]	0.073	0.02 (0.480)	[-0.03, 0.07]	0.027
V	function LKA	0.39*** (<0.001)	[0.32, 0.49]	0.110	0.14*** (<0.001)	[0.09, 0.20]	0.027
V	ownership type (own)	1.13 (0.534)	[0.77, 1.67]	0.198	0.03 (0.637)	[-0.11, 0.18]	0.073
V	model year	1.65*** (<0.001)	[1.44, 1.90]	0.071	0.16*** (<0.001)	[0.11, 0.21]	0.025
V	years using	1.06 (0.408)	[0.93, 1.21]	0.069	0.12*** (<0.001)	[0.07, 0.17]	0.026
C	purpose (shopping)	0.91 (0.627)	[0.62, 1.33]	0.193	0.05 (0.471)	[-0.09, 0.19]	0.072
C	purpose (leisure)	1.34 (0.114)	[0.93, 1.93]	0.186	0.08 (0.215)	[-0.05, 0.22]	0.068
C	purpose (drop-off/pick-up)	1.91* (0.014)	[1.14, 3.19]	0.262	0.13 (0.166)	[-0.05, 0.31]	0.091
C	purpose (other)	2.58 (0.212)	[0.58, 11.44]	0.760	0.16 (0.499)	[-0.30, 0.62]	0.237
C	distance	1.18* (0.050)	[1.00, 1.40]	0.086	-0.02 (0.562)	[-0.08, 0.04]	0.031
C	free flow (%)	1.05 (0.454)	[0.92, 1.20]	0.067	0.08*** (0.001)	[0.04, 0.13]	0.024
C	highway (%)	1.15† (0.065)	[0.99, 1.33]	0.075	0.06* (0.039)	[0.00, 0.11]	0.027
C	darkness (%)	0.88 (0.111)	[0.76, 1.03]	0.078	-0.09** (0.002)	[-0.15, -0.03]	0.030
C	distance:free flow (%)	1.03 (0.716)	[0.89, 1.18]	0.072	-0.01 (0.804)	[-0.06, 0.04]	0.025
C	distance:highway (%)	0.76*** (<0.001)	[0.66, 0.88]	0.074	-0.05† (0.066)	[-0.10, 0.00]	0.027
C	distance:darkness (%)	1.23*** (<0.001)	[1.09, 1.38]	0.060	0.03 (0.193)	[-0.01, 0.07]	0.021
	AIC	2943			8158		
	BIC	3068			8290		
	logLik	-1450.5 (df=21)			-4057.2 (df=22)		
	R^2_{marginal}	0.13			0.06		
	$R^2_{\text{conditional}}$	0.43			0.53		

ACC, ownership accuracy is consistently higher and follows a similar trend, increasing from approximately 80% (MY 2021) to 94% (MY 2025). This suggests that ownership awareness challenges are concentrated among owners of earlier model years.

Trip context also relates to ownership accuracy: longer typical trips correspond to higher odds of correct ownership (OR = 1.18, $p = .050$), though this association is weaker on highway-heavy trips (distance × highway: OR = 0.76, $p < .001$) and stronger with greater driving in darkness (distance × darkness: OR = 1.23, $p < .001$). Drivers whose main trip purpose is "drop-off/pick-up" show higher ownership accuracy than commuters (OR = 1.91, $p = .014$), possibly reflecting a subgroup of professional drivers. No driver-level variables reach significance, suggesting that ownership accuracy is not concentrated within specific demographic groups. The ownership accuracy mixed-effects model explains 13% of variance via fixed effects and 43% including random effects ($R^2_{\text{marginal}} = 0.13$, $R^2_{\text{conditional}} = 0.43$), indicating moderate explanatory power and notable between-person heterogeneity.

Associations with *ownership confidence* differ. Respondents report higher ownership confidence in LKA than in ACC ($\beta = 0.14$, $p < .001$), despite lower ownership accuracy for LKA.

Newer model years ($\beta = 0.12$, $p < .001$) and longer vehicle tenure ($\beta = 0.11$, $p < .001$) correspond to higher ownership confidence. Notably, LKA ownership confidence increases more steeply with model year than ACC ownership confidence even though LKA ownership accuracy remains lower across all model years (Fig. 1). This divergence between rising ownership confidence and persistently lower ownership accuracy for LKA highlights a growing over-confidence risk in owners of newer vehicles. Higher highway and free-flow shares are associated with higher ownership confidence ($\beta = 0.06$, $p = .038$; $\beta = 0.08$, $p = .001$) (Fig. 1, panels c, e). This effect suggests that familiar, low-workload driving environments may foster confidence about ADAS ownership - whether or not that confidence is justified. Conversely, age and gender show only weak associations ($p = .064$ and $p = .071$). The ownership confidence mixed-effects model explains 6% of variance via fixed effects and 53% including random effects ($R^2_{\text{marginal}} = 0.06$, $R^2_{\text{conditional}} = 0.53$), indicating substantial respondent-level variation beyond measured covariates as well. Alternative ordinal and binary specifications yield consistent signs and significance (see Supplementary Information).

Taken together, both ownership accuracy of ACC/LKA and ownership confidence in these systems are positively associated with owning newer and more familiar vehicles, while ownership confidence shows stronger links to trip-exposure conditions than ownership accuracy. Respondents tend to feel more certain-yet are less often correct-about owning LKA. These results motivate the next analysis, which examines how closely stated ownership confidence corresponds to observed ownership accuracy

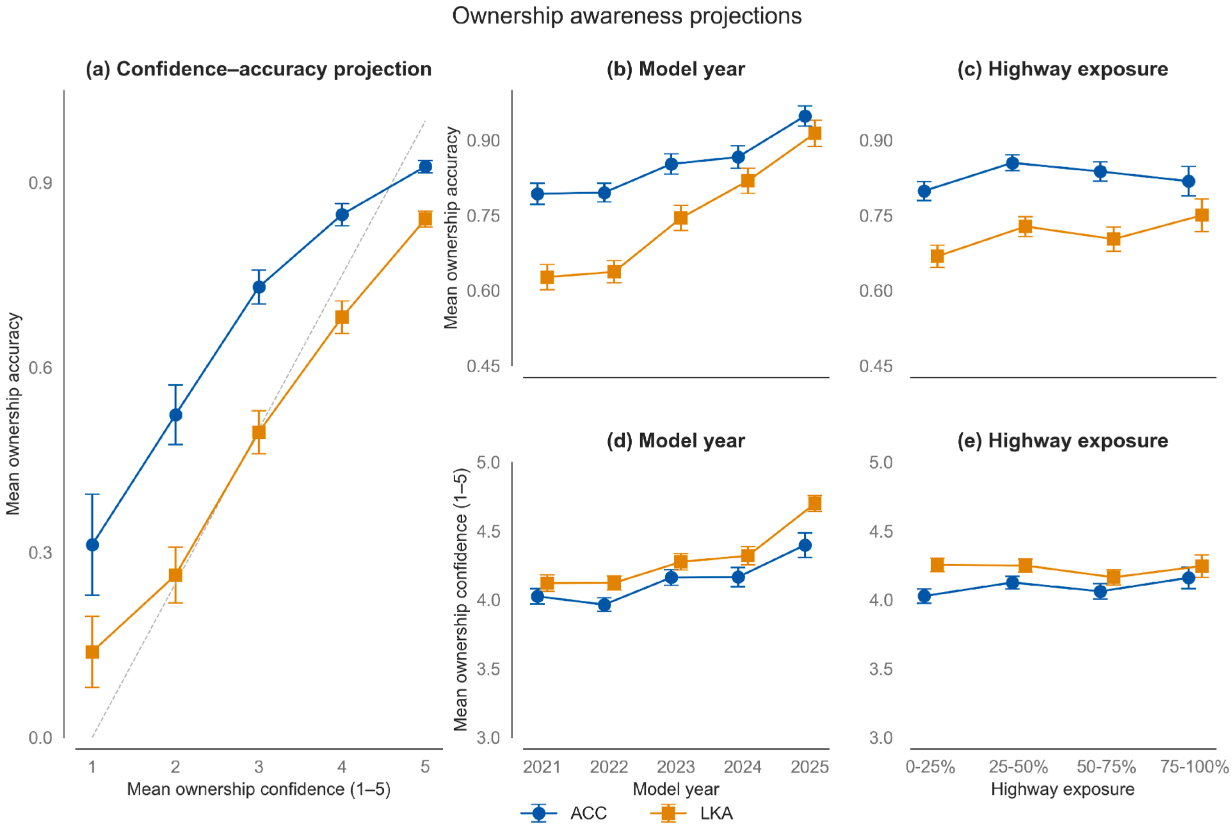

Fig. 1. Ownership awareness projections across ADAS function, model year, and highway exposure. Panel (a) projects mean ownership accuracy by stated ownership confidence (1-5) for ACC and LKA, with a 45° reference (dashed); panels (b-c) show mean ownership accuracy by model year and highway-exposure quartile; panels (d-e) show mean ownership confidence by model year and highway-exposure quartile. All panels separate ACC (circles) and LKA (squares). Points represent binned sample means; error bars denote ± 1 standard error.

Projection of ownership confidence to ownership accuracy

Ownership confidence corresponds to ownership accuracy in expected but not perfect ways. As shown in Fig. 1, mean ownership accuracy for both ACC and LKA increases consistently with stated ownership confidence, indicating that the confidence scale is informative about ownership awareness. However, the ownership confidence and ownership accuracy do not align exactly. At low ownership confidence (1-2), respondents are generally under-confident about owning ACC-their mean ownership accuracy exceeds their stated confidence. At high ownership confidence (4-5), mean ownership accuracy for both systems falls below the 45° reference line, indicating over-confidence, particularly for LKA. Across all ownership-confidence levels, ownership accuracy for ACC remains higher than for LKA, showing that self-assessments of ownership awareness are more reliable for ACC than for LKA. This relationship between ownership confidence and ownership accuracy provides context for interpreting respondents' stated reasons for ownership confidence and doubt.

Reasons for ownership confidence and doubt

The analysis of stated reasons (ownership confidence ≥ 4; ownership doubt ≤ 3) identifies which experiences and information sources coincide with aligned or misaligned ownership awareness. For each ADAS, respondents are grouped into four ownership-awareness states: Confident & Accurate, Confident & Inaccurate, Doubtful & Accurate, and Doubtful & Inaccurate. Differences between corresponding counter-states (Confident & Accurate vs. Confident & Inaccurate, and Doubtful & Accurate vs. Doubtful & Inaccurate) are examined through side-by-side over-representation tests (Fig. 2). The main findings for each ownership-awareness state are summarized below.

- **Confident & Accurate** (Panel A). The most common and over-represented reason is "I used it" (ACC 785; LKA 787), followed by "I understand," "Dealer explained," "Read manual," and "Feedback clear." These reasons indicate that accurate and confident ownership awareness is associated with hands-on use, clear system cues, and some form of instruction.
- **Confident & Inaccurate** (Panel B). "I used it" and "Dealer explained" are under-represented, while "I don't know" is over-represented. Respondents in this group exhibit confidence without direct experience or explanation, suggesting that assumption coincides with misplaced ownership confidence.

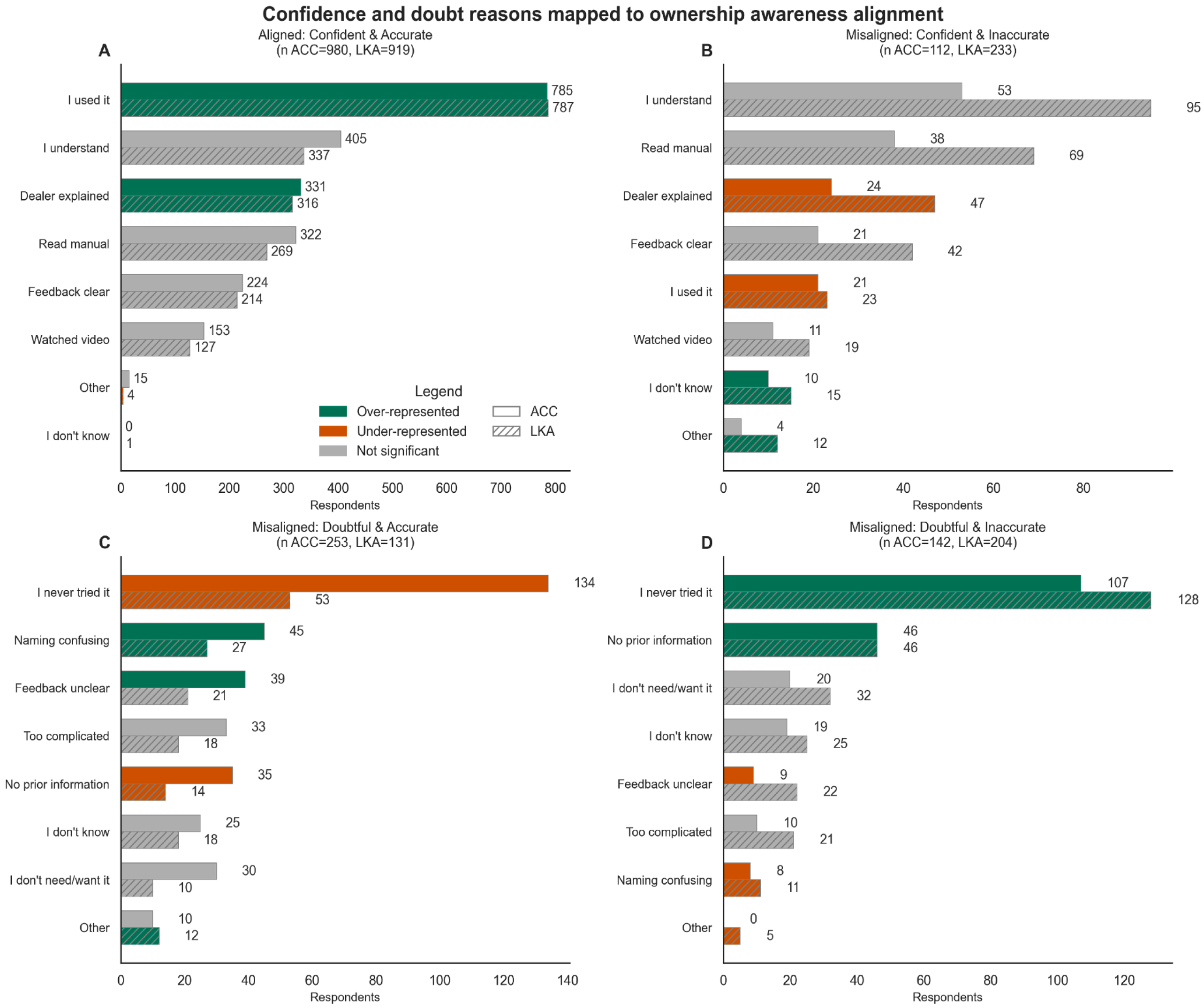

Fig. 2. Participants' stated reasons for ADAS ownership awareness are grouped by ownership *confidence-accuracy* state. Each panel corresponds to one state: Aligned - Confident & Accurate (A); Misaligned - Confident & Inaccurate (B), Doubtful & Accurate (C), and Doubtful & Inaccurate (D). The panel header reports the sample size (n). Within each panel, bars show raw counts (ACC = solid; LKA = hatched), while turquoise/orange overlays indicate relative prominence based on Holm-adjusted Fisher tests at $p < .05$ (turquoise = over-represented versus the matched counterpart state at the same confidence level; orange = under-represented; grey = not significant). A small bar can still be turquoise if that reason is disproportionately common in that state. Read panels as follows: in (A), turquoise on "I used it" marks hands-on use as characteristic of accurate confidence; in (B), orange on "Dealer explained" and "I used it" signals their relative absence among the confidently inaccurate; in (C), turquoise on "Naming confusing" (and, for ACC, "Feedback unclear") indicates label/status uncertainty despite being correct; in (D), turquoise on "I never tried it" and "No prior information" highlights coupled experience and information gaps where doubt and inaccuracy co-occur.

- **Doubtful & Accurate** (Panel C). "Naming confusing" and "Feedback unclear" are over-represented (the latter mainly for ACC), showing that even respondents with correct ownership awareness may remain uncertain when labels or feedback signals are ambiguous.
- **Doubtful & Inaccurate** (Panel D). "I never tried it" and "No prior information" are over-represented, indicating that limited experience and information gaps coincide with inaccurate and uncertain ownership awareness.

Together, these associations reveal two consistent mechanisms of misaligned ownership awareness: missing experience and missing information. The next analysis examines how these reasons co-occur, highlighting broader combinations of experience and information that underlie ownership-awareness misalignment.

Table 4
Top five single-antecedent → single-consequent reason rules within each ownership-accuracy state (Accurate ACC, Accurate LKA, Inaccurate ACC, and Inaccurate LKA ownership awareness), ranked by rule confidence. Rules are mined from confident reasons in accurate ownership awareness states and from doubt reasons in inaccurate ownership awareness states. Columns: Conf. (rule confidence) is the conditional frequency of the consequent given the antecedent; Sup. (support) is the joint prevalence of antecedent and consequent within that state; Lift is association strength compared with what would be expected under independence (> 1 indicates positive association). Only rules with support ≥ .02 and lift > 1 are reported; ties are broken by higher support, then lift.

Outcome	Rule (Reason 1 → Reason 2)	Conf.	Sup.	Lift
Accurate ACC ownership awareness (aligned)	ACC: I understand it → ACC: I used it	0.84	0.277	1.32
	ACC: Feedback is clear → ACC: I used it	0.83	0.152	1.31
	LKA: I used it → ACC: I used it	0.81	0.479	1.28
	LKA: Feedback is clear → ACC: I used it	0.80	0.147	1.26
	LKA: I understand it → ACC: I used it	0.78	0.233	1.23
Accurate LKA ownership awareness (aligned)	ACC: I used it → LKA: I used it	0.89	0.567	1.19
	LKA: Feedback is clear → LKA: I used it	0.86	0.176	1.15
	LKA: I understand it → LKA: I used it	0.85	0.274	1.14
	ACC: Feedback is clear → LKA: I used it	0.85	0.161	1.13
	ACC: I understand it → LKA: I used it	0.82	0.291	1.1
Inaccurate ACC ownership awareness (misaligned)	LKA: I never tried it → ACC: I never tried it	0.88	0.150	2.10
	ACC: I don't need/want it → ACC: I never tried it	0.70	0.055	1.66
	LKA: I received no prior info → ACC: I received no prior info	0.68	0.051	3.78
	ACC: I received no prior info → ACC: I never tried it	0.67	0.122	1.60
	LKA: I don't know → ACC: I never tried it	0.67	0.031	1.58
Inaccurate LKA ownership awareness (misaligned)	ACC: I don't need/want it → ACC: I never tried it	0.70	0.037	2.38
	ACC: I received no prior info → ACC: I never tried it	0.61	0.069	2.09
	LKA: I never tried it → ACC: I never tried it	0.52	0.153	1.79
	ACC: I never tried it → LKA: I never tried it	0.52	0.153	1.79
	LKA: I received no prior info → LKA: I never tried it	0.50	0.053	1.71

Co-occurring reasons from association-rule mining (ARM)

ARM identifies combinations of reasons that frequently co-occur within each ownership-awareness state. Table 4 summarizes the five strongest co-occurring reason pairs (i.e., rules) associated with accurate and inaccurate ownership awareness of both ACC and LKA.

In ownership-awareness states that are accurate, the most frequent co-occurrences link use and clarity-such as "Feedback clear → I used it" (ACC conf. = 0.83; LKA conf. = 0.86) and "I understand → I used it." Cross-ADAS relations are also present among the top five rules: "ACC used → LKA used" (conf. = 0.89) and "LKA used → ACC used" (conf. = 0.81), indicating that engagement with one ADAS commonly coincides with engagement with the other.

In ownership-awareness states that are inaccurate, co-occurrences center on missing information and non-use. "I never tried it" in one ADAS is frequently linked with "I never tried it" in the other (LKA → ACC conf. = 0.88; ACC → LKA conf. = 0.52), and "No prior information" tends to co-occur across ADAS (conf. = 0.68). The rule "I don't need/want it → I never tried it" (conf. = 0.70) further shows that stated disinterest often coincides with lack of experience.

Overall, these associations clarify mechanisms of ownership-awareness misalignment. Accurate ownership awareness coincides with clear feedback, understanding, and hands-on experience-sometimes spanning both ACC and LKA. In contrast, inaccurate ownership awareness coincides with combined information and experience gaps, often reinforced by disinterest in engaging with vehicle automation.

4. Discussion

This study examines drivers' ownership awareness of Adaptive Cruise Control (ACC) and Lane Keeping Assistance (LKA) as a joint construct that combines ownership accuracy and ownership confidence. By linking survey responses to an external catalogue of ADAS equipment, we identify which type of driver, vehicle, and trip-context factors are associated with accurate and confident ownership awareness (Fig. 3), and analyze the reasons drivers give for their confidence or doubt. Together, the results describe where ownership awareness aligns, where it misaligns, and how those differences can inform strategies to mitigate mode confusion.

Main findings

Three main findings emerge from the results: (1) ownership awareness differs systematically between ACC and LKA, (2) vehicle model year and trip context are associated with ownership accuracy and ownership confidence in distinct ways, and (3) alignment or misalignment in ownership awareness relates closely to the presence or absence of information and hands-on experience.

The first finding of this study is that, across the entire ownership-confidence scale, respondents are less accurate about whether their vehicle has LKA than about whether it has ACC. This difference persists at all ownership-confidence levels (Fig. 1) and is substantial in the mixed-effects model (Table 3, LKA vs. ACC OR = 0.39, $p < .001$). Even drivers with high ownership confidence are more often incorrect about owning LKA than ACC. This makes LKA ownership awareness a candidate priority for intervention. This finding aligns with prior work showing that drivers' uncertainty varies across ADAS (DeGuzman & Donmez, 2021; Huang

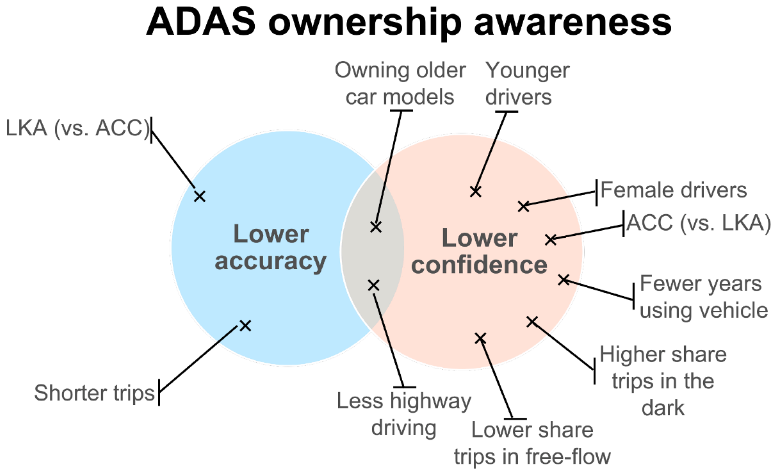

Fig. 3. Venn diagram summarizing factors from the mixed-effects models that are associated with *lower* ADAS ownership accuracy and *lower* ownership confidence, indicating groups more susceptible to misalignment (not both accurate and confident ownership awareness). Items follow from Novakazi's Driver-Vehicle-Context framework (Novakazi, 2025). Placement in the left or right region denotes an association with a single outcome; placement in the overlap denotes factors linked to both. Black crosses mark variables that are (marginally) significant in Table 3.

et al., 2023), and is consistent with the longer installation history of ACC. The longer market presence of ACC likely provides more consistent learning opportunities for drivers, whereas LKA remains newer, more heterogeneous, and more variable in its implementation.

The second finding is that owning a newer vehicle is associated with both higher ownership accuracy and higher ownership confidence. The practical magnitude of this effect is substantial: LKA ownership accuracy nearly doubles from MY 2021 to MY 2025 (Fig. 1, panel b), suggesting that plausible clearer ADAS standardization and more transparent feedback interfaces in more recent vehicles meaningfully improve ownership awareness. For practitioners, this implies that it is recommended that interventions focus primarily on owners of older vehicles. However, if our findings indeed represent an upper bound on ownership awareness relative to the broader population of vehicle owners, as discussed later in the limitations and future research section, then even owners of the newest vehicle models may benefit from improved ADAS-specific feedback designed to better calibrate owner's confidence to their actual ADAS ownership.

Trip context, by contrast, relates more strongly to ownership confidence than to ownership accuracy. Drivers who report typically higher shares of free-flow and highway driving tend to feel more confident, whereas more driving in darkness relates to lower ownership confidence. These conditions can help explain the observed over-confidence shown in Fig. 1: familiar, low-workload environments foster certainty in engagement with ADAS (Orlovska et al., 2020; Reagan et al., 2017), even when that certainty does not align with correct beliefs about what ADAS a vehicle has. Longer typical trip distances are associated with higher ownership accuracy overall, but the association weakens as highway share increases and strengthens with greater darkness exposure. This suggests that more time behind the wheel benefits ownership awareness mainly when ADAS feedback is less salient, such as in urban or low-visibility situations. Demographic variables show only weak associations with ownership confidence, indicating that ownership-awareness challenges likely cut across gender and age groups. The substantial residual variance in both mixed-effects models suggests that unmeasured factors-such as prior automation experience or technology affinity-may also contribute to ownership awareness (Beggiato & Krems, 2013; Greenwood et al., 2022).

The third finding from this study is that drivers with *aligned* ownership awareness-being both accurate and confident-most often report clear feedback, system understanding, and prior use of either ACC or LKA. Experience with one ADAS frequently coincides with experience of the other, suggesting that ownership awareness transfers across functions. In contrast, *misaligned* ownership awareness-being inaccurate or uncertain-is characterized by the co-occurrence of "never tried," "no prior information," and occasionally "I do not need or want it." These responses reveal an information deficit, a first-use gap, and an acceptance barrier that together maintain early ownership-awareness misalignment. This interpretation aligns with prior dealership and ADAS learning studies showing limited training and a reliance on self-learning or trial and error (Lubkowski et al., 2021; Viktorová & Šucha, 2019). In summary, ownership-awareness alignment depends on two key resources-information and experience-both of which are often missing.

Implications for mode-confusion mitigation

The results of this paper suggest three potential opportunities for early mode-confusion mitigation: improving HMI feedback, strengthening information at the point of sale, and supporting safe first use of ADAS through in-vehicle onboarding. These opportunities follow directly from the two main deficits identified-missing information and missing first-use experience-and are further discussed below.

The first opportunity involves prioritizing clear indication of LKA availability status in in-vehicle HMIs, as ownership accuracy is consistently lower for LKA than for ACC. Based on the observed associations, drivers need clearer signals about whether LKA is installed and when it is active. Reasons associated with aligned ownership awareness of LKA-such as “feedback is clear” and “I understand it”-frequently co-occur with “I used it,” implying that HMI cues support both system use and ownership confidence. It is therefore recommended that HMIs display standardized icons for “available,” “active,” and “unavailable,” offer a one-tap status page confirming whether LKA is present on the vehicle, and include a short, built-in demonstration of activation and limits (Boelhouwer et al., 2020b). Such cues would help confusion-prone drivers move from inaccurate ownership awareness toward accurate ownership awareness.

The second opportunity focuses on using points of sale to bridge information gaps and encourage initial use of ACC or LKA.“Dealer explained” and “I used it” are under-represented reasons among confident-but-inaccurate respondents, while “no prior information” and “never tried” dominate among respondents who doubt their ownership of ACC and LKA. A short, standardized delivery script could bridge both information and experience gaps (Boelhouwer et al., 2020a; Lubkowski et al., 2021; Nandavar et al., 2023). Sales staff can verify ADAS presence using the vehicle’s status page, demonstrate activation once, and briefly describe two boundary conditions (for example, highway-only operation). Even one guided interaction can have compounding benefits, as experience with either ACC or LKA is strongly associated with familiarity with the other.

Lastly, and most importantly, the third opportunity concerns supporting drivers’ initial use of ACC and LKA in contexts outside of dealership environments. Drivers of second-hand, rental, or shared vehicles often miss initial instruction entirely, yet these fleets increasingly include ACC and LKA. Because “never tried” and “no prior information” coincide with inaccurate or uncertain ownership awareness, vehicles may benefit from an automatic onboarding prompt when first detecting eligible conditions. A short, skippable demonstration or “try later” reminder could encourage safe first use even without dealer involvement. Experimental studies show that such onboarding improves comprehension of and engagement with vehicle automation (Boelhouwer et al., 2020b; Feinauer et al., 2023). The present results further indicate where onboarding matters most: respondents with higher ownership confidence typically drive in free-flow and highway conditions, whereas those who drive more often in darkness report lower ownership confidence. Therefore, onboarding prompts may be most effective during low-workload, daylight segments, and HMIs could reinforce ADAS availability status at night where ownership confidence is lower. Together, these three opportunities, if confirmed through further testing, offer practical directions for promoting more accurate and confident engagement with ADAS-a critical prerequisite to mitigate mode confusion.

Limitations and future research

While this study offers valuable insights from survey data analyses to identify early opportunities for mode confusion mitigation, several limitations warrant consideration. Our analysis of ownership awareness relies on Consumer Reports’ model-trim catalogue as an approximation of objective ADAS availability, restricting the sample to U.S. MY 2021 + trims on which ACC and LKA are standard (Consumer Reports, 2021; Sinclair, 2021). Although this study design reduces ambiguity relative to self-report alone, it cannot verify the absence of ACC and LKA for vehicles outside this sampling frame. Consequently, overstated ADAS ownership (i.e., cases in which respondents believe a system is installed when it is not) cannot be identified for other vehicle types (Harms et al., 2020). More fundamentally, while the catalogue represents the best available external reference for assessing ownership accuracy in this study, it is neither a scientifically curated dataset nor an individually verified record of each respondent’s vehicle configuration. The results should therefore be interpreted as evidence of likely ownership inaccuracy relative to a strong external benchmark, rather than as conclusive proof of each vehicle’s actual equipment. Even so, this strategy provides a more credible basis for evaluating ownership awareness than designs that depend exclusively on self-reported ADAS availability. Future research could strengthen this approach by combining survey responses with VIN-level build data or manufacturer-verified equipment records, enabling more definitive validation of ADAS ownership and more comprehensive detection of both under- and overreporting.

Beyond the vehicle eligibility criteria, the characteristics of the recruitment platform and sample composition warrant consideration. Participants were recruited through Prolific, an opt-in online survey platform. Respondents in such panels self-select into participation and may differ from the broader driving population in ways relevant to this study. In particular, online-panel participants may exhibit greater comfort with digital environments and stronger technology acceptance (Boas et al., 2020), which could elevate baseline awareness of and confidence in ADAS ownership relative to the general population. Furthermore, because newer vehicles are more expensive, owners of MY 2021 + vehicles are not demographically representative of all vehicle owners. Public market data indicate that recent new-vehicle acquisition in the U.S. is concentrated among older adults while younger adults aged 18-34 represent less than 10% (Jordhamo, 2025). Our sample, on the contrary, consists of 34.4% of respondents aged 44 years or younger (Table 2), likely overrepresenting younger newer-vehicle owners relative to the actual buyer population in the U.S.. Although Prolific draws from a nationwide U.S. panel, state-level location data were not collected; because data collection spanned multiple days, we consider the risk of strong geographic concentration low. Taken together, these characteristics mean that the observed levels of ownership awareness may represent an upper bound compared to the broader population of vehicle owners. The findings are therefore most directly generalizable to online-survey-willing owners of newer U.S. vehicles with standard ACC and LKA, rather than to all vehicle owners. Replication of our findings in more diverse samples (e.g., older vehicles, non-U.S. markets, and offline recruitment channels) remains an important direction for future work.

Measurement choices also shape the limits of interpreting the findings of this study. Residual diagnostics for both mixed-effects models (see Supplementary Information) indicate some deviations from model assumptions, likely reflecting unmeasured individual-level factors or non-linear relations. Ownership confidence is measured on a 1-5 Likert scale and modeled as continuous; two checks-a proportional-odds ordinal model and a binary mixed-logit for “high confidence” (≥ 4)-produce consistent signs and significance, which supports the main specification. Even so, the skew toward high values of ownership confidence may imply a ceiling effect.

We also measure exposure to trip conditions as a single "typical trip." This snapshot conveniently summarizes routine conditions but does not capture within-person variation across days, routes, or seasons, meaning some contextual dynamics may be missed. In addition to trip-context covariates, explanatory "reason" items are collected via check-all-that-apply lists shown conditionally on ownership confidence. This format efficiently surfaces broad patterns, yet it can under-represent nuance and is sensitive to item wording; the conditional display also means reasons were not shown uniformly across all respondents. Because our survey is cross-sectional, all reported relationships are associative rather than causal. Finally, substantial between-person variance in the mixed-effects models further suggests unmeasured heterogeneity-such as technology affinity or prior automation experience-that future work should measure explicitly (Beggiato & Krems, 2013; Greenwood et al., 2022). Future research could also use nonlinear methods, such as generalized additive mixed models, to test for threshold or plateau effects in key predictors.

Despite these limitations, converging evidence from three complementary analyses supports the main claims. The mixed-effects models identify where ownership awareness is weakest-particularly for LKA and for older vehicle models. The ownership-confidence-accuracy projection clarifies that high ownership confidence does not guarantee ownership accuracy, especially for LKA. The reason analyses then show that missing information and lack of first use underlie this misalignment. Together, these analyses triangulate the same message: improving in-vehicle feedback, addressing information gaps, and encouraging early experience can strengthen ownership awareness and, in turn, reduce early instances of mode confusion.

Future work can build on these findings in four ways:

1. Linking survey responses to verified vehicle model factory build records or dealer data to assess both underestimation (unawareness of present features) and overestimation (belief in absent features).
2. Extending sampling beyond the U.S. and into second-hand, rental, and car-sharing contexts to examine how sales channels, regional naming conventions, and fleet recency shape ownership awareness where information is scarce.
3. Incorporating measures of individual differences-such as prior automation exposure, trust, and technology affinity-and following participants longitudinally to observe how information and first use consolidate into aligned ownership awareness.
4. Evaluating in-vehicle onboarding concepts through prototyping, user studies, and field trials, identifying which prompt timing and delivery methods are most acceptable and, most importantly, effective in supporting ownership awareness.

Together, these extensions could clarify how ownership awareness develops and, in turn, how mode-confusion mitigation practices can sustain accurate and confident engagement with vehicle automation.

5. Conclusion

This paper examines which factors within Novakazi's Driver-Vehicle-Context framework contribute to ownership awareness of vehicle automation functions-an early layer of mode awareness that is essential for mitigating mode confusion. Among 1,487 U.S. vehicle owners, 17.1% and 29.4% incorrectly report not having ACC and LKA, respectively, despite generally high confidence in their ownership judgments. Ownership awareness is uneven across systems: ownership accuracy is lower for LKA than for ACC, and owners of older model-year vehicles are more susceptible to misalignment, that is, not being both correct and confident. Analysis of self-stated reasons reveals two main mechanisms underlying this misalignment: a lack of information and a lack of first use, often coupled with an acceptance barrier that may reflect reluctance to engage with ADAS at the outset.

Building on these findings-*while subject to further validation*-several opportunities emerge for mitigating mode confusion at an early stage by addressing the observed information and experience gaps:

- Improving HMIs by standardizing LKA icons and increasing the visibility of information on LKA presence and status.
- Targeting ownership-awareness interventions toward users of older vehicles.
- Upon vehicle delivery, verifying the presence of ACC and LKA and providing a brief first-use demonstration.
- In settings without salesperson support, triggering short, personalized onboarding through HMIs.
- Timing first-use prompts to coincide with low-workload driving segments, such as free-flow highway conditions.
- Guiding drivers at least once in the use of ACC or LKA, as experience with one function may facilitate adoption of the other.

Taken together, these opportunities address the core deficits underlying ownership-awareness misalignment-information and first-use experience-and, if confirmed through further testing, offer practical directions for promoting more accurate and confident engagement with ADAS. Beyond these applied implications, this study makes three contributions. Conceptually, it operationalizes ownership awareness as a measurable joint construct comprising ownership accuracy and ownership confidence, thereby moving beyond studies that have examined these dimensions in isolation. Empirically, it links this construct to Novakazi's Driver-Vehicle-Context framework and compares self-reported ownership with an external model-trim catalogue-an approach that provides a more reliable basis for assessing ownership accuracy than self-report-only designs, while acknowledging its limitation to detecting underestimation of ADAS ownership. Methodologically, it combines mixed-effects modeling with a two-step reason analysis-Holm-corrected over-representation tests to identify which individual reasons distinguish ownership-awareness states, and association-rule mining to reveal how those reasons co-occur-thereby yielding insights into the mechanisms underlying ownership-awareness misalignment that are both statistically supported and practically interpretable. Together, these contributions support the design of early mode-confusion mitigation practices and, ultimately, safer driver-vehicle automation interaction.

CRediT authorship contribution statement

Samir H.A. Mohammad: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization; **Soyeon Kim:** Writing – review & editing, Supervision, Methodology, Conceptualization; **Simeon C. Calvert:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Conceptualization; **Marjan P. Hagenzieker:** Writing – review & editing, Supervision, Resources, Methodology, Conceptualization.

Data availability

All the data and code produced in this study, as well as the printed version of the online survey information are available at https://osf.io/4ce73.

Appendix A. Survey design

Table A.5
Topic and source for of survey item.

Item	Item ID	Block	Source
Driver's license	Q1.1	A	Kim et al. (2024)
Ownership / Lease	Q1.2	A	DeGuzman and Donmez (2021)
Vehicle make selection	Q1.3	A	Self-developed
Vehicle model selection	Q1.4-Q1.32	A	Self-developed
Model year entry	Q2.1	A	Self-developed
Ownership duration	Q2.2	A	DeGuzman and Donmez (2021)
Car-share frequency	Q2.3	A	Self-developed
Trip purpose	Q3.1	B	Adapted from Ramos et al. (2020)
Trip distance	Q3.2	B	Self-developed
Free-flow share in typical trip	Q3.3	B	Adapted from Knoop (2021)
Highway/interstate share in typical trip	Q3.4	B	Adapted from DeGuzman and Donmez (2021)
Darkness share in typical trip	Q3.5	B	Adapted from Karlsson and Novakazi (2023)
Trip purpose typical trip	Q3.6	B	Adapted from Ramos et al. (2020)
ACC/LKA ownership	Q4.1, Q4.5	C	Adapted from DeGuzman and Donmez (2021)
Response confidence	Q4.2, Q4.6	C	Adapted from DeGuzman and Donmez (2021)
Reasons selection for doubt	Q4.3, Q4.7	C	Adapted from Lubkowski et al. (2021), Viktorová and Šucha (2019)
Reasons selection for confidence	Q4.4, Q4.8	C	Adapted from Lubkowski et al. (2021), Viktorová and Šucha (2019)
Demographics	Q5.1, Q5.2	D	Kim et al. (2024)

Appendix B. Eligible models

Table B.6
Eligible 2021 and newer vehicle models with ACC and LKA factory standard on all trims adapted from Sinclair (2021).

Make						
Acura	ILX	RDX	TLX			
Audi	A4	A5	A6	A7	A8	Q3
Audi (cont.)	Q5	Q7	Q8	E-Tron		
BMW	2 Series	2 Series Gran Coupe	4 Series	5 Series	7 Series	8 Series
Buick	Encore GX	Envision				
Cadillac	XT5	XT6				
Chevrolet	Equinox	TrailBlazer				
Chrysler	Pacifica					
Ford	Bronco Sport	Escape	Edge	Expedition	Explorer	Fusion
Ford (cont.)	Mach-E	Transit				
Genesis	G70	G80	G90	GV80		
GMC	Terrain					
Honda	Accord	Civic	Clarity	CR-V	Odyssey	Passport
Honda (cont.)	Insight	Pilot	Ridgeline			
Hyundai	Elantra	Ioniq	Kona	Kona EV	Nexo	Palisade
Hyundai (cont.)	Santa Fe	Sonata	Tucson	Venue	Veloster	
Infiniti	QX80					
Jaguar	E-Pace	F-Pace	F-Type	I-Pace	XF	
Jeep	Cherokee					
Kia	Forte	K5	Sportage	Telluride		
Land Rover	Defender	Discovery	Discovery Sport	Range Rover	Range Rover Evoque	Range Rover Sport
Land Rover (cont.)	Range Rover Velar					
Lexus	ES	GX	IS	LC	LS	NX
Lexus (cont.)	RC	RX	RXL	UX		
Lincoln	Aviator	Corsair	Navigator	Nautilus		
Lucid	Air					
Maserati	Quattroporte					
Mazda	3	6	CX-5	CX-9	CX-30	
Mercedes	G-Class	S-Class				
Nissan	Armada	Leaf	Murano	Rogue Sport		
Polestar	1	2				
Porsche	Taycan					
Subaru	Ascent	Forester	Legacy	Outback		
Tesla	Model 3	Model S	Model X	Model Y		
Toyota	Avalon	C-HR	Camry	Corolla	Corolla Hatchback	Highlander
Toyota (cont.)	Mirai	Prius	Prius Prime	RAV4	RAV4 Prime	Sienna
Toyota (cont.)	Supra	Venza				
Volvo	ID4	S60	S90	V90	V60	XC40
Volvo (cont.)	XC60	XC90				

References

Abraham, H., Seppelt, B., Mehler, B., & Reimer, B. (2017). What's in a name: Vehicle technology branding & consumer expectations for automation. In *Proceedings of the 9th international conference on automotive user interfaces and interactive vehicular applications* (pp. 226–234).

Banks, V. A., Eriksson, A., O'Donoghue, J., & Stanton, N. A. (2018). Is partially automated driving a bad idea? observations from an on-road study. *Applied ergonomics*, *68*, 138–145.

Beggiato, M., & Krems, J. F. (2013). The evolution of mental model, trust and acceptance of adaptive cruise control in relation to initial information. *Transportation research part F: traffic psychology and behaviour*, *18*, 47–57.

Blömacher, K., Nöcker, G., & Huff, M. (2020). The evolution of mental models in relation to initial information while driving automated. *Transportation research part F: traffic psychology and behaviour*, *68*, 198–217.

Boas, T. C., Christenson, D. P., & Glick, D. M. (2020). Recruiting large online samples in the united states and india: Facebook, mechanical turk, and qualtrics. *Political science research and methods*, *8*(2), 232–250.

Boelhouwer, A., Van den Beukel, A. P., Van der Voort, M. C., Hottentot, C., De Wit, R. Q., & Martens, M. H. (2020a). How are car buyers and car sellers currently informed about ADAS? an investigation among drivers and car sellers in the netherlands. *Transportation Research Interdisciplinary Perspectives*, *4*, 100103.

Boelhouwer, A., van den Beukel, A. P., van der Voort, M. C., Verwey, W. B., & Martens, M. H. (2020b). Supporting drivers of partially automated cars through an adaptive digital in-car tutor. *Information (Switzerland)*, *11*(4), 185.

Boos, A., Feldhütter, A., Schwiebacher, J., & Bengler, K. (2020). Mode errors and intentional violations in visual monitoring of level 2 driving automation. In *2020 IEEE 23rd international conference on intelligent transportation systems (ITSC)* (pp. 1–7). IEEE.

Calvert, S. C., & Zgonnikov, A. (2025). A lack of meaningful human control for automated vehicles: Pressing issues for deployment and regulation. *Frontiers in Future Transportation*, *6*, 1534157.

Carney, C., Gaspar, J. G., & Horrey, W. J. (2022). Longer-term exposure vs training: Their effect on drivers' mental models of ADAS technology. *Transportation research part F: traffic psychology and behaviour*, *91*, 329–345.

Carsten, O., & Martens, M. H. (2019). How can humans understand their automated cars? HMI principles, problems and solutions. *Cognition, Technology & Work*, *21*(1), 3–20.

Consumer Reports (2021). Understanding the Current State of Vehicle Automation. Technical Report Consumer Reports. Corrected edition. https://advocacy.consumerreports.org/wp-content/uploads/2021/11/CR-Understanding-Vehicle-Automation-Nov-2021-corrected.pdf.

DeGuzman, C. A., & Donmez, B. (2021). Knowledge of and trust in advanced driver assistance systems. *Accident Analysis & Prevention*, *156*, 106121.

Eom, H., & Lee, S. H. (2015). Human-automation interaction design for adaptive cruise control systems of ground vehicles. *Sensors*, *15*(6), 13916–13944.

Eom, H., & Lee, S. H. (2022). Mode confusion of human–machine interfaces for automated vehicles. *Journal of Computational Design and Engineering*, *9*(5), 1995–2009.

Feinauer, S., Groh, I., & Petzoldt, T. (2025). The impact of a priori information on drivers' mental models, attitudes, and behavior in interaction with partial and conditional driving automation. *International Journal of Human–Computer Interaction*, *41*(7), 3828–3840.

Feinauer, S., Voskort, S., Groh, I., & Petzoldt, T. (2023). First encounters with the automated vehicle: Development and evaluation of a tutorial concept to support users of partial and conditional driving automation. *Transportation research part F: traffic psychology and behaviour*, *97*, 1–16.

Feldhütter, A., Härtwig, N., Kurpiers, C., Hernandez, J. M., & Bengler, K. (2019). Effect on mode awareness when changing from conditionally to partially automated driving. In *Proceedings of the 20th congress of the international ergonomics association (IEA 2018) volume VI: Transport ergonomics and human factors (TEHF), aerospace human factors and ergonomics 20* (pp. 314–324). Springer.

Gaspar, J. G., Carney, C., Shull, E., & Horrey, W. J. (2021). Mapping drivers' mental models of adaptive cruise control to performance. *Transportation research part F: traffic psychology and behaviour*, *81*, 622–638.

Greenwood, P. M., Lenneman, J. K., & Baldwin, C. L. (2022). Advanced driver assistance systems (ADAS): Demographics, preferred sources of information, and accuracy of ADAS knowledge. *Transportation research part F: traffic psychology and behaviour*, *86*, 131–150.

Han, J., Kamber, M., & Pei, J. (2012). Mining frequent patterns, associations, and correlations. https://doi.org/10.1016/b978-0-12-381479-1.00006-x

Harms, I. M., Bingen, L., & Steffens, J. (2020). Addressing the awareness gap: A combined survey and vehicle registration analysis to assess car owners' usage of ADAS in fleets. *Transportation Research Part A: Policy and Practice*, *134*, 65–77.

Heikoop, D. D., Hagenzieker, M., Mecacci, G., Calvert, S., Santoni De Sio, F., & van Arem, B. (2019). Human behaviour with automated driving systems: a quantitative framework for meaningful human control. *Theoretical issues in ergonomics science*, *20*(6), 711–730.

Hogema, J., Post, R., Verstegen, R., & Souman, J. L., et al. (2024). Automated Driving System HMIs: "Clear and Unambiguous"? In *Proceedings of the 16th International Conference on Automotive User Interfaces and Interactive Vehicular Applications* (pp. 184–193). Stanford CA USA: ACM. https://doi.org/10.1145/3640792.3675728

Huang, C., He, D., Wen, X., & Yan, S. (2023). Beyond adaptive cruise control and lane centering control: drivers' mental model of and trust in emerging ADAS technologies. *Frontiers in Psychology*, *14*, 1236062.

Jordhamo, J. (2025). The vanishing young car buyer: New vehicle registrations drop for 18–34-year-olds. https://www.spglobal.com/automotive-insights/en/blogs/2025/06/new-vehicle-registrations-drop-for-18-34-year-olds. S&P Global Automotive Insights, accessed 2026-03-19.

Karlsson, M., & Novakazi, F. (2023). Drivers' usage of driving automation systems in different contexts: A survey in china, germany, spain and USA. *IET Intelligent Transport Systems*, *17*(10), 2004–2019.

Kazi, T. A., Stanton, N. A., Walker, G. H., & Young, M. S. (2007). Designer driving: drivers' conceptual models and level of trust in adaptive cruise control. *International journal of vehicle design*, *45*(3), 339–360.

Kidd, D. G., Cicchino, J. B., Reagan, I. J., & Kerfoot, L. B. (2017). Driver trust in five driver assistance technologies following real-world use in four production vehicles. *Traffic injury prevention*, *18*(sup1), S44–S50.

Kim, S. (2025). Toward a typology of mode awareness in automated vehicles: A multi-dimensional framework. *Available at SSRN 5473339*, .

Kim, S., Nordhoff, S., van Egmond, R., & Happee, R. (2025). The impact of visual user interfaces on drivers' understanding of driving control mode and hands-on steering wheel requirement in level 2 automated vehicles. *Transportation Research Part F: Traffic Psychology and Behaviour*, *109*, 255–271.

Kim, S., Novakazi, F., van Grondelle, E., van Egmond, R., & Happee, R. (2024). Who is performing the driving tasks after interventions? investigating drivers' understanding of mode transition logic in automated vehicles. *Applied Ergonomics*, *121*, 104369.

Knoop, V. L. (2021). Traffic Flow Theory: An Introduction with Exercises. TU Delft OPEN Publishing.

Kurpiers, C., Biebl, B., Mejia Hernandez, J., & Raisch, F. (2020). Mode awareness and automated driving-what is it and how can it be measured? *Information*, *11*(5), 277.

Larsson, P., Johansson, E., Söderman, M., & Thompson, D. (2015). Interaction design for communicating system state and capabilities during automated highway driving. *Procedia Manufacturing*, *3*, 2784–2791.

Law, R., Rong, J., Vu, H. Q., Li, G., & Lee, H. A. (2011). Identifying changes and trends in hong kong outbound tourism. *Tourism Management*, *32*(5), 1106–1114.

Lee, S. H., & Eom, H. (2015). Design of driver-vehicle interface to reduce mode confusion for adaptive cruise control systems. In *Adjunct proceedings of the 7th international conference on automotive user interfaces and interactive vehicular applications* (pp. 67–71).

Lenneman, J., Mangus, L., Jenness, J., & Petraglia, E. (2020). Delineating clusters of learners for driver assistance technologies. In *International conference on human-computer interaction* (pp. 601–610). Springer.

Lubkowski, S. D., Lewis, B. A., Gawron, V. J., Gaydos, T. L., Campbell, K. C., Kirkpatrick, S. A., Reagan, I. J., & Cicchino, J. B. (2021). Driver trust in and training for advanced driver assistance systems in real-world driving. *Transportation research part F: traffic psychology and behaviour*, *81*, 540–556.

Mason, J., Carney, C., Gaspar, J. G., Kim, W., Romo, A., & Horrey, W. J. (2023). Mapping comprehension of ADAS across different road users, .

McDonald, A., Carney, C., & McGehee, D. V. (2018). Vehicle owners' experiences with and reactions to advanced driver assistance systems, .

Mohammad, S. H. A., Calvert, S. C., & Hagenzieker, M. P. (2026). "i don't know if i use it": a conceptual model of driver's mental model of vehicle automation. *Transportation Research Procedia*, *95*, 345–352. https://doi.org/10.1016/j.trpro.2026.02.044

Monsaingeon, N., Caroux, L., Langlois, S., & Lemercier, C. (2023). Multimodal interface and reliability displays: Effect on attention, mode awareness, and trust in partially automated vehicles. *Frontiers in Psychology*, *14*, 1107847.

Monsaingeon, N., Caroux, L., Mouginé, A., Langlois, S., & Lemercier, C. (2021). Impact of interface design on drivers' behavior in partially automated cars: An on-road study. *Transportation research part F: traffic psychology and behaviour*, *81*, 508–521.

Nandavar, S., Kaye, S.-A., Senserrick, T., & Oviedo-Trespalacios, O. (2023). Exploring the factors influencing acquisition and learning experiences of cars fitted with advanced driver assistance systems (ADAS). *Transportation research part F: traffic psychology and behaviour*, *94*, 341–352.

NHTSA (2024). Information Request ID RQ24009. Information Request Letter (Recall Query) RQ24-009. U.S. Department of Transportation, National Highway Traffic Safety Administration 1200 New Jersey Avenue SE, Washington, DC 20590. Document ID: INIM-RQ24009-12199. https://static.nhtsa.gov/odi/inv/2024/INIM-RQ24009-12199.pdf.

Norman, D. A. (1983). Some observations on mental models. In *Mental models* (pp. 15–22). Psychology Press.

Novakazi, F. (2025). Perception's role for mental model formation in automated driving: Insights from four studies. *Journal of Cognitive Engineering and Decision Making*, (p. 15553434251334409).

Novakazi, F., Johansson, M., Erhardsson, G., & Lidander, L. (2021a). Who's in charge? the influence of perceived control on responsibility and mode awareness in driving automation. *it-Information Technology*, *63*(2), 77–85.

Novakazi, F., Johansson, M., Strömberg, H., & Karlsson, M. (2021b). Levels of what? investigating drivers' understanding of different levels of automation in vehicles. *Journal of cognitive engineering and decision making*, *15*(2-3), 116–132.

Orlovska, J., Novakazi, F., Lars-Ola, B., Karlsson, M., Wickman, C., & Söderberg, R. (2020). Effects of the driving context on the usage of automated driver assistance systems (ADAS)-naturalistic driving study for ADAS evaluation. *Transportation research interdisciplinary perspectives*, *4*, 100093.

Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. *Human factors*, *39*(2), 230–253.

Peduzzi, P., Concato, J., Kemper, E., Holford, T. R., & Feinstein, A. R. (1996). A simulation study of the number of events per variable in logistic regression analysis. *Journal of clinical epidemiology*, *49*(12), 1373–1379.

Ramos, É. M. S., Bergstad, C. J., & Nässén, J. (2020). Understanding daily car use: Driving habits, motives, attitudes, and norms across trip purposes. *Transportation research part F: traffic psychology and behaviour*, *68*, 306–315.

Reagan, I. J., Kidd, D. G., & Cicchino, J. B. (2017). Driver acceptance of adaptive cruise control and active lane keeping in five production vehicles. In *Proceedings of the human factors and ergonomics society annual meeting* (pp. 1949–1953). SAGE Publications Sage CA: Los Angeles, CA (*vol. 61*).

Sinclair, S. (2021). Guide to cars with advanced safety systems. Article updated 14 May 2021. https://www.consumerreports.org/cars/car-safety/cars-with-advanced-safety-systems-a7292621135/.

Teoh, E. R. (2020). What's in a name? drivers' perceptions of the use of five SAE level 2 driving automation systems. *Journal of safety research*, *72*, 145–151.

Tinga, A. M., van Zeumeren, I. M., Christoph, M., van Grondelle, E., Cleij, D., Aldea, A., & van Nes, N. (2023). Development and evaluation of a human machine interface to support mode awareness in different automated driving modes. *Transportation research part F: traffic psychology and behaviour*, *92*, 238–254.

Trösterer, S., Marx, C., Ebinger, N., Mirnig, A., Jakus, G., Sodnik, J., Lezamiz, J. S., Sekadakis, M., & Moertl, P. (2024). An integrated display of fluid human systems interactions. In *Shaping automated driving to achieve societal mobility needs: A human-systems integration approach* (pp. 33–58). Springer.

Varotto, S. F., Mons, C., Hogema, J. H., Christoph, M., van Nes, N., & Martens, M. H. (2022). Do adaptive cruise control and lane keeping systems make the longitudinal vehicle control safer? insights into speeding and time gaps shorter than one second from a naturalistic driving study with SAE level 2 automation. *Transportation research part C: emerging technologies*, *141*, 103756.

Viktorová, L., & Šucha, M. (2019). Learning about advanced driver assistance systems–the case of ACC and FCW in a sample of czech drivers. *Transportation research part F: traffic psychology and behaviour*, *65*, 576–583.

Wilson, K. M., Yang, S., Roady, T., Kuo, J., & Lenné, M. G. (2020). Driver trust & mode confusion in an on-road study of level-2 automated vehicle technology. *Safety Science*, *130*, 104845.

de Winter, J., & Nordhoff, S. (2022). Acceptance of conditionally automated cars: Just one factor? *Transportation research interdisciplinary perspectives*, *15*, 100645.

Zhang, J., Feng, T., Timmermans, H. J. P., & Lin, Z. (2023). Association rules and prediction of transportation mode choice: Application to national travel survey data. *Transportation Research Part C: Emerging Technologies*, *150*, 104086.