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“I don’t know if I use it”: a conceptual model of driver’s mental model of vehicle automation

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Abstract

Drivers often misjudge the capabilities of Advanced Driver Assistance Systems (ADAS), compromising safety. Guided by a Context–Vehicle–Driver (C-V-D) framework drawn from 22 empirical studies, this study analyzed a secondary survey of 838 drivers to identify predictors of self-reported “ADAS unawareness” (“I don’t know if I use it”). Analysis of the representation ratio (RR) showed that drivers with a low annual driving distance (< 5000 km), lack of private car ownership, and young age (18–29 years) were consistently overrepresented among unaware users (RR ≥ 1.2), while car sharing frequency and license tenure were not. Unawareness was highest for Adaptive Cruise Control (ACC) among the three ADAS examined. These results support a hierarchical account in which contextual factors outweigh vehicle and driver-level influences. The C-V-D model yields testable hypotheses for road type, traffic density, and interface design that merit evaluation in larger-sample studies. Addressing the priority groups identified here can help designers, dealers, and educators reduce mode confusion and promote safe ADAS adoption.

Keywords: ADAS; Mental model; Mode confusion; Conceptual framework

1. Introduction

Modern passenger vehicles routinely integrate Advanced Driver Assistance Systems (ADAS), for example, Adaptive Cruise Control (ACC) and Lane Keeping Assistance (LKA), which can automate discrete subtasks of the driving task. By reducing workload and smoothing traffic flow, ADAS promise substantial gains in safety and comfort (**?**)) (Milakis et al., 2017). However, real-world benefits materialize only if drivers adopt and use the systems appropriately (Nordhoff et al., 2023).

Driver behavior adapts to automation according to the driver’s mental model of ADAS (Rudin-Brown & Noy, 2002). A mental model is an internal representation of what automation can and cannot do (Norman, 1983). When

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well calibrated, it supports appropriate trust and avoids both disuse and misuse (Parasuraman & Riley, 1997). Surveys and naturalistic driving studies reveal that many drivers either overlook available assistance functions or overestimate their abilities, resulting in mode confusion at critical moments (Harms et al. 2020; Carney et al., 2022).

Most prior work examines isolated determinants of mental model formation: human–machine interface (HMI) design (Seppelt & Lee, 2019; Eom & Lee, 2022); system framing and nomenclature (Abraham et al., 2017; Teoh, 2020); or driver characteristics such as age, automation knowledge, and personality (Beggiatio & Krems, 2013; McDonough & Tefft, 2023). Contextual influences (e.g., traffic conditions and road type) receive considerably less attention (Jamson et al., 2013; Nees et al., 2020), leaving the relative weight of context, vehicle, and driver factors unclear. The Context–Vehicle–Driver (C-V-D) framework of Novakazi et al. (2021) proposes that these three levels interact hierarchically: the driving context constrains vehicle capabilities, which in turn shape drivers' mental models, control strategies and attentional demand.

This paper aims at two objectives. First, it refines the C-V-D framework into a conceptual model that links contextual, vehicular, and driver variables based on the literature to ADAS unawareness. Second, it tests that model by analyzing the survey of 838 drivers reported by Kim et al. (2024). Self-reported uncertainty—responses of "I don't know if I use it"—serves as an indicator of unawareness. Identifying the conditions under which unawareness is more likely to arise can inform interface designers, dealers, and educators looking to improve mental model calibration and foster the safe uptake of ADAS.

2. Literature review

This section synthesizes the theoretical frameworks and empirical findings that explain how drivers form mental models of vehicle automation.

2.1. Theoretical foundations

Early work by Rudin–Brown and Noy (2002) casts the process as a closed feedback loop: personality and initial trust shape the mental model, the model guides behavior, and observed system performance updates trust. Cotter et al. (2008) retain this logic but embed it in a triad of 'driver, system, situation', highlighting that mental representations adapt continuously to situational demands (i.e. opportunities for changes in behavior).

A limitation of these early accounts is their narrow view of "situation". The driver–vehicle–road taxonomy of Stanton and Salmon (2009) and the Joint Conceptual Theoretical Framework (JCTF) (Wege et al., 2014) widen the focus to infrastructure and other road users, showing that breakdowns can originate anywhere in the driving environment.

Novakazi et al. (2021) further refine these components into the dynamic Context–Vehicle–Driver (C-V-D) hierarchy: context heavily shapes driver interpretation, interacts with vehicle cues, and ultimately influences driver states such as trust, thus closing the loop by updating the mental model. The framework therefore predicts that contextual factors dominate when mental models are poorly calibrated.

2.2. Empirical evidence

Guided by the C-V-D framework, a Google Scholar query (`‘‘ADAS’’ AND ‘‘mental model’’ AND (usage OR trust OR acceptance)`) plus snowballing identified 22 studies that link specific variables to the formation of mental models (Table 1).

Context. Road type and traffic density modulate ADAS engagement: free-flow highways encourage activation, whereas congested or unfamiliar roads discourage it (Reagan et al., 2017; Orlovska et al., 2020; Halama et al., 2023; Karlsson & Novakazi, 2023). Longer trips and the use of shared cars also foster the exploration of automation (Orlovska et al., 2020; Huang et al., 2023; Karlsson & Novakazi, 2023; Pongratz et al., 2025).

Vehicle. Clear, multimodal HMIs strengthen mental models (Seppelt & Lee, 2019; Nees et al., 2020; Eom & Lee, 2022). Branding and feature naming set expectations and trust levels (Abraham et al., 2017; Kidd et al., 2017; Harms et al., 2020; Huang et al., 2023).

Driver. Age, license tenure and prior automation exposure correlate positively with mental model formation (Jennes et al., 2008; Greenwood et al., 2022; Hungund et al., 2024; Feinauer et al., 2025; Pongratz et al., 2025). The evidence for gender and personality traits (e.g., Big Five) is mixed (Zhang et al., 2022; Öztürk et al., 2024; Nordhoff & Lehtonen, 2025).

In sum, theory and isolated empirical studies endorse a multilevel account, but leave the relative weight of each layer, especially context, unresolved. These gaps motivate the focus of the present study on ADAS unawareness within the C-V-D framework.

Table 1. Likelihood effect on mental model of driving automation based on literature. The variables correspond to either level, C: Context, V: Vehicle, or D: Driver.

Level	Variable	Effect	Summary	Refs
C	Road type	Likely	More use on highways	Reagan et al. (2017); Halama et al. (2023); Karlsson & Novakazi (2023)
C	Weather conditions	Unlikely	Some refrain usage in poor weather, overall minimal impact	Orlovska et al. (2020); Karlsson & Novakazi (2023)
C	Traffic density	Likely	More comfortable to engage with automation in free-flow	Reagan et al. (2017); Orlovska et al. (2020); Karlsson & Novakazi (2023)
C	Social norms	Unlikely	Role unclear of cross-national differences	Orlovska et al. (2020); Louw et al. (2021); Karlsson & Novakazi (2023); Öztürk et al. (2024)
C	Trip duration	Likely	More use on long drives	Orlovska et al. (2020); Huang et al. (2023); Karlsson & Novakazi (2023); Pongratz et al. (2025)
C	Car-ownership	Likely	Car-sharers have higher driving automation knowledge	Pongratz et al. (2025)
C	Trip purpose	-	-	-
V	Human-machine interface	Likely	Clear and multimodal displays better mental model	Seppelt & Lee, (2019); Nees et al. (2020); Eom & Lee (2022)
V	ADAS/ADS type	Likely	Naming/brand differences, ease of use	Abraham et al. (2017); Kidd et al. (2017); Harms et al. (2020); Huang et al. (2023)
D	Gender	Unlikely	More linked towards acceptance instead of mental model	Son et al. (2015); Louw et al. (2021); Greenwood et al. (2022); Huang et al. (2023)
D	Age	Likely	Older drivers read more often manuals	Jennes et al. (2008); Greenwood et al. (2022); Zhang et al. (2022); Pongratz et al. (2025)
D	Driving experience	Likely	Years licensed correlates with stronger mental models	Huang et al. (2023)
D	ADAS/ADS experience	Likely	Training/exposure improves mental model	; Hungund et al. (2024); Feinauer et al. (2025)
D	Sensation seeking	-	-	-
D	Locus of control	-	-	-
D	Big Five trait	Unlikely	Most findings leans towards no effect	Zhang et al. (2022); Huang et al. (2023); Öztürk et al. (2024); Nordhoff & Lehtonen (2025)
D	Driving style	Likely	Planning affects system use	Huang et al. (2023)
D	Attitude towards technology	Likely	Tech affinity fosters better mental model	Kraus et al. (2021); Greenwood et al. (2022)

3. Methods

This study re-analyzed a survey to examine how context, vehicle and driver factors predict *ADAS unawareness* as self-reports of “I don’t know if I use it” for ACC, LKA or Lane Departure Warning (LDW).

3.1. Data source and variable mapping

The data originate from Kim et al. (2024), an online questionnaire of N=838 licensed drivers. Their survey aimed to evaluate the mental model of drivers with respect to *who is in control* (driver versus car) during various mode transitions in automated driving systems. The first two sections included demographics and driving and automation knowledge questions, including personal ADAS usage (ACC, LKA, LDW) with “Yes,” “No,” or “I don’t know if I use it.”

Each of these section’s items was mapped to the C-V-D hierarchy:
Context– annual distance (proxy for trip duration), car ownership, car-sharing frequency, trip purpose,
Vehicle– ADAS feature (ACC, LKA, LDW),
Driver– age, gender, license tenure, automation knowledge.

Variables absent from the survey but highlighted in previous work (road type, traffic density, HMI design, driving style, attitude to technology) could not be evaluated.

No missing values were reported. Residence was excluded because its highly skewed distribution prohibited valid group comparisons. Although misreporting of actual feature availability is possible (Harms et al., 2020), the focus on explicit *uncertainty* limits this risk.

3.2. Data analysis

The analysis linked the prevalence of *ADAS unawareness* with variables of the C-V-D framework through three steps. First, a baseline was established by counting “I don’t know if I use it” responses for each ADAS feature: LDW, ACC, LKA. Second, the relative weight of each explanatory factor was analyzed with the *representation ratio* (RR), obtained by dividing the share of a category in the unaware subgroup by its share in the complete sample; values greater than one denote overrepresentation and values below one denote underrepresentation. Categories representing fewer than ten percent of participants were excluded to avoid drawing conclusions from very small subgroups. In the final stage, the variables were classified according to the strength of the effect: an RR outside the 0.80 to 1.20 interval for the three ADAS features indicated a *strong* association, the same pattern for two features a *medium* association, and for a single feature a *weak* association. These strength labels were mapped onto the C-V-D model to identify whether contextual, vehicular, or driver-level influences dominated ADAS unawareness.

4. Results

The analysis quantifies how often drivers report ADAS unawareness and identifies the C-V-D factors most closely associated with that uncertainty.

Among the 838 respondents, “I don’t know if I use it” occurs more often for ACC (n = 54, 6.4%), followed by LKA (n = 31, 3.7%) and LDW (n = 22, 2.6%) (Table 2).

The low annual driving distance group (< 5000 km) is consistently overrepresented (RR_{LDW} = 2.45, RR_{ACC} = 1.63, RR_{LKA} = 2.01), as is the absence of private car ownership (RR 1.73–2.93). Younger drivers (18–29 years) are also overrepresented (RR 1.37–1.74). In contrast, gender has a weak effect (female RR_{LKA} = 1.46; other features ≈ 1.0), and license tenure below one year stands out only for LDW (RR = 4.76). Low self-rated automation knowledge shows a modest elevation for ACC and LKA (RR 1.24–1.30).

Unawareness often clusters: 70% and 59% of respondents unsure about respectively LKA and LDW were also unsure about at least one other feature.

Table 3 summarizes the magnitudes of the effects. Two contextual variables (driving distance and car ownership), one driver variable (age) and the vehicle variable *feature* (ACC) meet the *strong* criterion; trip purpose, automation knowledge, gender and license tenure fall in the medium to weak range. The context variables exert the strongest and most consistent influence on ADAS unawareness.

5. Discussion

5.1. Conceptual model of ADAS unawareness

This paper tests whether contextual, vehicle-specific and driver-specific variables, arranged in a Context–Vehicle–Driver (C-V-D) hierarchy, predict *ADAS unawareness*. The analysis reveals three main patterns.

First, contextual conditions are the strongest differentiator. Drivers who travel fewer than 5000 km per year or who do not own a passenger car are more than twice as likely to respond, “I don’t know if I use it.” Limited exposure reduces opportunities for trial-and-error learning, a mechanism consistent with previous work showing that ADAS uptake increases with travel time and use of the highway (Orlovska et al., 2020; Karlsson & Novakazi, 2023; Pongratz et al., 2025).

Second, at the vehicle level, ACC provokes the most uncertainty. The proportion of respondents who are not sure about ACC is roughly double that of LDW or LKA. Frequent rebranding terms such as “Smart Cruise” or “Intelligent Cruise”, and its similarity to conventional cruise control likely blur user expectations (Abraham et al., 2017).

Third, the age of the driver also matters. Respondents aged 18 to 29 years are overrepresented in every unaware subgroup, while gender differences are small and license tenure shows no consistent effect. Technology affinity, often linked to younger age, does not guarantee well-calibrated mental models; hands-on experience and reading manuals remain essential (Jennes et al., 2008; Hungund et al., 2024).

Figure 1 places these validated predictors, together with factors based on the literature but not tested, in a layered C-V-D framework. The model suggests that ADAS awareness peaks when drivers undertake long, uncongested highway

Table 2. Combined Frequency Tables: LDW, ACC, and LKA confusion. GP = group proportion, RR = representation ratio

	LDW				ACC				LKA			
Variable	Count	%	GP(%)	RR	Count	%	GP(%)	RR	Count	%	GP(%)	RR
Gender												
Female	11	50.00	2.70	1.03	30	53.57	7.35	1.10	22	70.97	5.39	1.46
Male	10	45.45	2.38	0.91	24	42.86	5.71	0.86	9	29.03	2.14	0.58
Prefer not to say	1	4.55	16.67	6.35	2	3.57	33.33	4.99	0	0.00	0.00	0.00
Prefer to self-describe	0	0.00	0.00	0.00	0	0.00	0.00	0.00	0	0.00	0.00	0.00
Age												
18–29	12	54.55	4.58	1.74	24	42.86	9.16	1.37	15	48.39	5.73	1.55
30–39	8	36.36	2.85	1.08	17	30.36	6.05	0.91	11	35.48	3.91	1.06
40–49	1	4.55	0.71	0.27	6	10.71	4.26	0.64	4	12.90	2.84	0.77
50–59	1	4.55	1.28	0.49	3	5.36	3.85	0.58	1	3.23	1.28	0.35
60–69	0	0.00	0.00	0.00	3	5.36	5.36	0.80	0	0.00	0.00	0.00
Over 69	0	0.00	0.00	0.00	3	5.36	15.00	2.24	0	0.00	0.00	0.00
Driving license												
<1 year	1	4.55	12.50	4.76	1	1.79	12.50	1.87	0	0.00	0.00	0.00
1–5 years	7	31.82	7.61	2.90	6	10.71	6.52	0.98	4	12.90	4.35	1.18
>5 years	14	63.64	1.90	0.72	49	87.50	6.64	0.99	27	87.10	3.66	0.99
Automation knowledge												
None	2	9.09	2.41	0.92	5	8.93	6.02	0.90	4	12.90	4.82	1.30
Little	12	54.55	2.70	1.03	37	66.07	8.31	1.24	19	61.29	4.27	1.15
Moderate	7	31.82	2.79	1.06	13	23.21	5.18	0.78	8	25.81	3.19	0.86
A lot	1	4.55	2.63	1.00	1	1.79	2.63	0.39	0	0.00	0.00	0.00
Extremely well	0	0.00	0.00	0.00	0	0.00	0.00	0.00	0	0.00	0.00	0.00
Driver type												
Private	19	86.36	2.75	1.05	48	85.71	6.95	1.04	27	87.10	3.91	1.06
Professional	2	9.09	11.76	4.48	2	3.57	11.76	1.76	1	3.23	5.88	1.59
Both	1	4.55	0.77	0.29	6	10.71	4.62	0.69	3	9.68	2.31	0.62
Driving distance												
<5000 km	13	59.09	6.44	2.45	22	39.29	10.89	1.63	15	48.39	7.43	2.01
5000–10000 km	4	18.18	1.56	0.60	16	28.57	6.25	0.94	8	25.81	3.12	0.84
10000–15000 km	2	9.09	1.16	0.44	9	16.07	5.20	0.78	2	6.45	1.16	0.31
15000–20000 km	2	9.09	1.71	0.65	8	14.29	6.84	1.02	5	16.13	4.27	1.16
20000–50000 km	1	4.55	1.22	0.46	1	1.79	1.22	0.18	1	3.23	1.22	0.33
50000+ km	0	0.00	0.00	0.00	0	0.00	0.00	0.00	0	0.00	0.00	0.00
Own car												
Yes	14	63.64	1.91	0.73	44	78.57	5.99	0.90	22	70.97	3.00	0.81
No	8	36.36	7.69	2.93	12	21.43	11.54	1.73	9	29.03	8.65	2.34
Car-sharing often												
Never	12	54.55	1.94	0.74	42	75.00	6.81	1.02	18	58.06	2.92	0.79
Few times per year	8	36.36	4.32	1.65	10	17.86	5.41	0.81	10	32.26	5.41	1.46
Few times per month	2	9.09	6.90	2.63	4	7.14	13.79	2.06	3	9.68	10.34	2.80
LDW experience												
Yes	–	–	–	–	32	57.14	7.86	1.18	16	51.61	3.93	1.06
No	–	–	–	–	20	35.71	4.89	0.73	6	19.35	1.47	0.40
I don't know	22	100	–	–	4	7.14	18.18	2.72	9	29.03	40.91	11.06
ACC experience												
Yes	12	54.55	2.76	1.05	–	–	–	–	14	45.16	3.22	0.87
No	6	27.27	1.73	0.66	–	–	–	–	4	12.90	1.15	0.31
I don't know	4	18.18	7.14	2.72	56	100	–	–	13	41.94	23.21	6.28
LKA experience												
Yes	5	22.73	1.76	0.67	16	28.57	5.63	0.84	–	–	–	–
No	8	36.36	1.53	1.05	27	48.21	5.16	0.77	–	–	–	–
I don't know	9	40.91	29.03	11.06	13	23.21	41.94	6.28	31	100	–	–

trips in personally owned vehicles—conditions that maximize the window of learning opportunities (Cotter et al., 2008).

5.2. Limitations and practical implications

The study measures only *conscious* uncertainty; respondents who misremember ADAS usage remain invisible to this analysis. Because the data are cross-sectional, the actual formation of mental models over time cannot be traced, and several potentially relevant variables, such as road type, traffic density, human–machine-interface layout, and personality, were unavailable. The results therefore remain descriptive and should be generalized with caution.

Even within these limits, the findings suggest actionable steps. Dealerships and rental agencies can provide short, context-rich demonstrations aimed at drivers with a low annual driving distance or without vehicle ownership. Design-

Table 3. Strength of selected variables' effect on mental model of driving automation based representation ratio analysis on the dataset from Kim et al. (2024).

Level	Variable	Effect strength	Overrepresented confusion group
C	Driving distance (trip duration)	Strong	< 5000 km
C	Car-ownership	Strong	Non-owners
C	Trip purpose	Inconclusive	Professional drivers
V	ADAS/ADS type	Strong	ACC
D	Gender	Weak	Females
D	Age	Strong	18-29
D	Driving experience	Weak	< 1 year
D	ADAS/ADS experience	Medium	None and Little

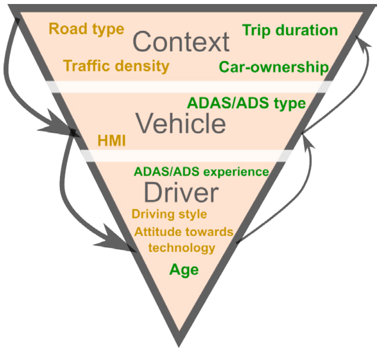

Fig. 1. Conceptual model of drivers' mental models of vehicle automation. Green variables are validated with the dataset of Kim et al. (2024); beige variables are untested but likely according to the literature. Font size reflects expected effect strength.

ers could support these efforts with adaptive onboard tutorials that surface only for novice or first-time users (Forster et al., 2019; Hartwich et al., 2021), thus tightening the calibration of the mental model where it is weakest.

6. Conclusion

Contextual exposure, especially trip duration and car ownership, emerges as the strongest predictor of ADAS unawareness, followed by driver age and the individual ADAS feature. These findings validate the C-V-D hierarchy and identify user groups for whom targeted training, labeling, and interface design are most likely to be beneficial in mitigating ADAS unawareness.

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