ASSESSING DRIVERS' MENTAL MODEL OF ADVANCED DRIVER ASSISTANCE SYSTEMS USING SIGNAL DETECTION THEORY

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Previous studies evaluated drivers' knowledge of advanced driver assistance systems (ADAS) using different kinds of percent-correctness-based mental model scores (MMS), which makes cross-study comparisons difficult. To resolve this issue, our study explored the use of sensitivity (i.e., d-prime (*d'*)) and response bias (i.e., criterion location (*c*)) in signal detection theory (SDT) as a measure of drivers' ADAS mental models. Based on the data collected from a survey among 287 ADAS users, regression models were fitted, and it was found that *d'* and *c* accounted for a large variance when estimating drivers' ADAS mental models as measured by MMSs (adjusted $R^2 > 0.8$). Further, predictors of MMSs were also predictors of *d'* and *c*, but d' and c include additional information that was not covered in MMSs. These findings support the usage of *d'* and *c* as standard metrics for assessing drivers' ADAS mental models in future research.

INTRODUCTION

With the rapid development of technologies, advanced driver assistance systems (ADAS) have become increasingly prevalent worldwide over the past decade, with a prior motivation for improving driving safety (Banks & Stanton, 2016). However, the misuse or overuse of ADAS has led to a large number of accidents in the past few years (National Highway Traffic Safety Administration, 2022) and drivers' inappropriate mental models of ADAS (i.e., driver knowledge of the functions and limitations of ADAS) were identified as one of the reasons leading to misuse or overuse of the ADAS (Dickie & Boyle, 2009; Rossi et al., 2020). Therefore, a number of studies have been conducted to understand drivers' ADAS mental models and explored how to help drivers construct appropriate mental models of ADAS.

To assess drivers' mental models of ADAS, surveys have been widely used in previous studies, in which questions were designed to evaluate drivers' knowledge of ADAS functions and limitations. For example, DeGuzman and Donmez (2021) used an online survey to evaluate drivers' understanding of adaptive cruise control (ACC) and lane-keeping assistant (LKA) with 51 questions, in which participants were asked to judge whether the statement regarding the functions and limitations of ACC/LKA was true or false. Similarly, Larsson (2012) assessed ADAS users' understanding of the system based on their "yes or no" answers to statements regarding ADAS functions and limitations. Participants' ADAS mental models were scored based on the percent correctness of participants' answers.

However, with the increasing complexity of the ADAS functions, simple binary responses (i.e., true or false) may not fully account for drivers' uncertainty about and confidence in ADAS functions and limitations. To overcome this limitation, some studies further scrutinized drivers' confidence in their answers regarding ADAS functions and limitations. A straightforward way to do so is to collect users' confidence in their answers in addition to the "yes or no" answers and then calculate the weighted score (i.e., the sum of confidence multiplied by correctness). For example, in addition to the binary response of yes or no regarding the statements about ADAS functions and limitations, previous studies asked drivers to indicate their confidence in each response (Carney et al., 2022; DeGuzman & Donmez, 2021a; Gaspar et al., 2021). However, the additional questions regarding confidence would double the length of the questionnaire. Thus, as an alternative solution, the Likert scale, was also adopted in some studies to account for participants' uncertainty in their responses. For example, Beggiato and Krems (2013) assessed drivers' knowledge about ACC using 35 questions, in which drivers answered questions using a Likert scale ranging from 1 ("totally disagree") to 6 ("totally agree"). Being different from the weighted score, when using the Likert scale in the questionnaire, drivers' ADAS knowledge levels were calculated as the absolute difference between actual responses and correct answers.

However, regardless of how the ADAS mental model was assessed, previous research mainly relied on scores derived from the percent-correctness of answers, which may not capture participants' bias towards ADAS (e.g., some participants may be more conservative to say yes to ADAS functions due to low trust in the system). Further, in different studies, the number of questions with yes as the correct answer may differ, making comparisons of percent correctness unfair (Wickens et al., 2021). Considering that drivers' judgment of whether the function/limitation exists or not can be modeled as a signal detection process, the two metrics from signal detection theory (SDT) may resolve these two issues and provide more insights into drivers' understanding of ADAS (Stanislaw & Todorov, 1999).

Thus, in our study, using the data from a survey study targeting towards ADAS mental model of ADAS users in China, we explored the use of sensitivity (i.e., *d'*) and criterion location (i.e., *c*, reflecting respondents' response bias) in SDT to assess drivers' ADAS mental models. To further explore if d-prime and *c* can provide additional information on top of percent correctness, we compared the influential factors of

percent correctness, d-prime, and *c*. Finally, to account for the uncertainty states of the responses when confidence-related responses were adopted, the Fuzzy SDT method (Parasuraman et al., 2000) was used and the results were compared with traditional SDT.

METHOD

Instrument

An online survey was designed to collect the data used in this study, which consisted of two parts: (1) demographic information and driving/vehicle-related information; (2) and the assessment of drivers' mental model of ADAS.

Table 1 summarizes the questions in the first part of the survey, extracted variables, and the distribution of the variables. To assess drivers' mental model of ADAS, we included 49 statements about the functions and limitations of ADAS based on a review of previous relevant studies (Beggiato et al., 2015; Beggiato & Krems, 2013; DeGuzman & Donmez, 2021a, 2021b; McDonald et al., 2018) and a review of user manuals from vehicle manufacturers. To facilitate participants' understanding of the situations in statements, we provided photos or videos from real-world scenarios along with some statements (23 out of 49). Similar to Beggiato and Krems (2013), participants were asked to rate their level of agreement with each statement, ranging from 1 ("*strongly disagree*") to 6 ("*strongly agree*"). Participants were informed that ratings below or equal to 3 indicate the intention to disagree while ratings above or equal to 4 indicate the intention to agree. Among all 49 statements, 34 of them described ADAS functions or limitations that indeed existed in the real world and can be treated as a signal in SDT; while 15 of them described functions/limitations that did not exist in the real world and can be treated as noise in SDT.

Table 1. Questions in the first part of the survey, extracted variables, and the distribution of the variables

Description	Variable[Type]	Distributions
The age of the participant.	Age[C]	M = 29.9 (SD: 6.1) years old Min: 20, Max: 58
The gender of the participant	Gender[N]	• Male (n=262) • Female (n=25)
The highest education level of the participant.	Education[N]	• Professional college or less (n=86) • Bachelor or above (n=201)
The working status of the participant.	Working status[N]	• Self-employed (n=115) • Full-time work (n=153) • Others (n=19)
The marriage status of the participant.	Marriage status[N]	• Married (n=173) • Not married (n=114)
The brand of the vehicle that the participant owned.	Vehicle brand[N]	• Tesla (n=141) • Others (n=146)
The duration of possession of the current vehicle.	Possession period[N]	• Within 1 year (n=95) • Over 1 year (n=192)
For many years since participants obtained their first driver's license.	Years of licensure[C]	M = 7.4 (SD: 4.4) Min: 1, Max: 28
Participants' self-reported driving frequency in the past year.	Driving frequency[N]	• Almost every day (n=148) • Several times per week (n=107) • Several times per month or less (n=32)
Participants' self-reported weekly average driving distance in the past year.	Weekly driving distance[N]	• < 99 km (n=122) • 100 - 299 km (n=106) • > 300 km (n=59)
Participants' self-reported experience of ADAS.	ADAS experience[N]	• < 1 month (n=23) • 1 - 6 months (n=127) • 6 - 12 months (n=85) • > 12 months (n=52)
Participants' self-reported frequency of using ADAS.	ADAS frequency[N]	• Almost every day (n=50) • Several times per week (n=138) • Several times per month (n = 79) • Several times per year or less (n=20)
Participants' self-reported familiarity with ADAS (average of three items, each ranging from 1 "very difficult" to 10 "very easy")(Chen & Donmez, 2016)	ADAS familiarity[C]	M = 8.2 (SD: 1.3) Min: 4.3, Max: 10

Note: C represents the continuous variable; N represents the nominal variable. M stands for mean and SD stands for standard deviation.

Participants

Participants were recruited through online advertisements in vehicle forums and interest groups of car owners on social media in mainland China. To be eligible for this study, participants had to be the owner of a vehicle with Level-2 ADAS and had experience using it. To control for the large variation in ADAS functions, this survey targeted towards

users of Level-2 ADAS that has functions similar to AutoPilot in Tesla, i.e., the vehicle can enter and exist highways following navigation and change lanes to pass slow vehicles automatically in addition to traditional ACC/LKA functions.

Unreliable and low-quality responses were filtered out through one attention check question and survey completion time. Responses with mismatching information (e.g., brand and vehicle type mismatch) were excluded after manual review. Finally, 287 valid responses were kept for analyses. Respondents of the valid survey sample were compensated with 10 RMB. This study was approved by the Human and Artefacts Research Ethics Committee in the Hong Kong University of Science and Technology (HREP-2022-0117).

Variable Extraction

Mental model scores (MMS). To evaluate participants' mental model of ADAS, percent-correctness-based MMS were calculated based on participants' responses to 49 statements about ADAS functions and limitations. For each statement, the perfect response was defined as 1 ("strongly disagree") if the statement is wrong and 6 ("strongly agree") if the statement is correct. Then, to simulate binary responses and confidence-based responses, we calculated two types of MMSs:

Binarized-MMS (bMMS): Following previous studies counting the number of correct responses, the bMMS for each participant was calculated as follows:

$$bMMS = \left(\sum_{i=1}^{49} I(binarize(R_i), P_i)\right)\frac{100}{49} \quad (1)$$

Where, $binarize(x) = \begin{cases} 1 & when\ x \leq 3 \\ 6 & when\ x \geq 4 \end{cases}$ and $I(m,n) = \begin{cases} 1 & when\ m = n \\ 0 & when\ m \neq n \end{cases}$. R_i is the actual response from the participant for the i^{th} statement; P_i is the perfect answer to the i^{th} statement (i.e., either 1 or 6). Thus, the bMMS indeed measures participants' mental model of ADAS using the percent correctness with participants' uncertainty of their responses omitted.

Continuous-MMS (cMMS): To account for participants' confidence in their responses, and inspired by the Manhattan distance, the cMMS for each participant was calculated as follows:

$$cMMS = \left(\sum_{i=1}^{49} \frac{5 - |R_i - P_i|}{5}\right)\frac{100}{49} \quad (2)$$

Where, R_i is the actual response from the participant for the i^{th} statement; P_i is the perfect answer to the i^{th} statement. Thus, being an integer within [0, 5], $|R_i - P_i|$ is the distance between the participant's response and the perfect answer.

Sensitivity and response bias. To evaluate participants' ability to identify the capabilities of ADAS, and their inclination towards believing the existence of ADAS function/limitation, *d'* and *c* in SDT were selected as the measures of sensitivity and bias. Similarly, to account for the binary responses and confidence-based responses, in this study, we calculated d-prime and *c* in two ways.

Traditional SDT-based sensitivity (*tra-d'*) and criterion location (*tra-c*): Traditionally, SDT was used to deal with binary responses. As has been clearly stated in the questionnaire, the responses can be binarized into "tends to disagree" (ratings $\leqslant 3$) and "tends to agree" (ratings $\geqslant 4$). Thus, the states of the participants' responses can be categorized as hit, miss, false alarm, and correct rejection based on the definitions in SDT. Then, the calculation of *d'* and *c* was performed using the *psycho* package in R 3.6.3 (R Core Development Team, 2019).

Fuzzy SDT-based sensitivity (*fuzzy-d'*) and criterion location (*fuzzy-c*):To handle the non-binary responses in Likert scale when assessing drivers' knowledge of ADAS, fuzzy SDT (Parasuraman et al., 2000) was adopted. The Fuzzy SDT enabled the analysis of fuzzy signals based on signal detection theory without arbitrarily binarizing the original responses. In Fuzzy SDT, the four states of the world (i.e., hit, miss, false alarm, and correct rejection) were calculated as follows:

$$Hit = \min(r, s) \quad (3)$$
$$Miss = \max(s - r, 0) \quad (4)$$
$$False\ Alarm = \max(r - s, 0) \quad (5)$$
$$Correct\ Rejection = \min(1 - s, 1 - r) \quad (6)$$

where, $r = \frac{5 - |R_i - P_i|}{5}$, which stands for the probability of response (i.e., the confidence of saying "yes"), while s represents the probability of a signal (which was 0 when the signal was absent and 5 when the signal was present). Then, the *fuzzy-d'* and *fuzzy-c* were calculated in the same way as *tra-d'* and *tra-c* in the traditional SDT.

Statistical Analysis

Overall, the analyses in this study include two parts. First, linear regression models (MMS Models) were fitted to explore how much of MMSs can be explained by the combination of *d'* and *c*. Specifically, four models were built with bMMS and cMMS as dependent variables and two sets of *d'* and *c* as independent variables. It should be noted that possible interaction terms between *d'* and *c* were also considered in the initial full models. The adjusted R-squared (adj-R^2) was used as the metric to evaluate the capability of *d'* and *c* in explaining the MMSs.

Then, to further understand the feasibility of using *d'* and *c* to explore the factors associated with participants' mental models, we fitted mixed models with MMSs, *d'*, and *c* as dependent variables and all other factors (i.e., demographic factors and driving/vehicle-related factors) as independent variables (Factor Models). A backward stepwise selection method based on Bayesian Information Criterion (BIC) was used for model selection.

All the models were built with SAS OnDemand for Academics, and all the data pre-processing and visualization were performed using R 3.6.3.

RESULTS

MMS Models: Capability of *d'* and *c* in estimating MMS

Table 2 summarizes the statistical results of MMS Models. In all four models, *d'* and *c* were found to be significant predictors of MMSs. Further, it seems that the

capability of *d'* and *c* in predicting MMS was associated with how the MMS, *d'* and *c* was calculated. Specifically, *d'* and *c* from traditional SDT (i.e., dealing with binary responses) had better performance in predicting bMMS (*adj-R^2*: model 1 > model 2); while *d'* and *c* from fuzzy SDT (i.e., dealing with non-binary responses) had better performance in predicting cMMS (*adj-R^2*: model 4 > model 3).

Figure 1 further illustrates the marginal effects of the interaction effects between *d'* and *c* in the two best-fit models (i.e., model 1 and model 4). Generally, with the increase of *c*, the marginal effect of *d'* on explaining MMS increases (Figure 1A and 1C). While with the increase of *d'*, the marginal effect of *c* would decrease (Figure 1B and 1D).

Table 2. Statistical results of four MMS Models

Model: DVs	***IVs***	***Estimate (SE)***	***t value***	***p-value***
Model 1:	Intercept	56.84 (0.33)	171.18	<.0001
bMMS	*tra-d'*	12.43 (0.64)	19.47	<.0001
	tra-c	-7.38 (0.33)	-22.38	< .0001
adj-R^2 = 0.84	*tra-d'* * *tra-c*	4.22 (0.71)	5.96	< .0001
Model 2:	Intercept	57.49 (0.64)	89.53	< .0001
bMMS	*fuzzy-d'*	24.24 (2.13)	11.41	< .0001
	fuzzy-c	-9.26 (0.81)	-11.47	< .0001
adj-R^2 = 0.49	*fuzzy-d'** *fuzzy-c*	15.26 (2.59)	5.89	< .0001
Model 3:	Intercept	55.30 (0.46)	119.81	< .0001
cMMS	*tra-d'*	6.67 (0.89)	7.52	< .0001
	tra-c	-4.42 (0.46)	-9.63	< .0001
adj-R^2 = 0.50	*tra-d'* * *tra-c*	1.25 (0.98)	1.28	.2
Model 4:	Intercept	51.91 (0.15)	343.26	< .0001
cMMS	*fuzzy-d'*	22.72 (0.50)	45.41	< .0001
	fuzzy-c	-10.43 (0.19)	-54.91	< .0001
adj-R^2 = 0.95	*fuzzy-d'** *fuzzy-c*	11.98 (0.61)	19.63	< .0001

Note: In this table and the following tables, DVs stands for dependent variables; IVs stands for independent variables; SE stands for standard error.

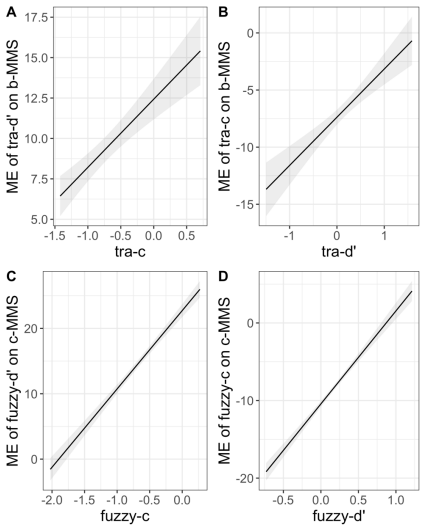

Figure 1. The marginal effects (ME) of the interaction effects between *d'* and *c* by in Model 1 (A & B) and Model 4 (C & D). In this figure and the following figures, the shadow represents a 95% confidence interval (CI) of the estimated effect.

Factor Models: Factors associated with d', c, and MMS

Table 3 summarizes the type 3 fixed effects for six Factor Models. It was found that factors associated with MMSs (e.g., ADAS familiarity for bMMS) were also associated with corresponding *d'* and *c*. At the same time, *d'* and *c* were associated with additional factors that were not associated with corresponding MMSs (e.g., possession period for *tra-d'* and ADAS experience for *tra-c*).

Table 3. Type 3 tests of fixed effects for six Factor Models

DVs	***IVs***	***F-value***	***p-value***
fuzzy-d'	Vehicle brand	F (1, 280) = 5.67	.02
	Possession period	F (1, 280) = 21.54	< .0001
	ADAS frequency	F (3, 280) = 3.88	.01
	ADAS familiarity	F (1, 280) = 6.63	.01
fuzzy-c	ADAS frequency	F (3, 282) = 3.78	.01
	ADAS familiarity	F (1, 282) = 82.73	< .0001
cMMS	Possession period	F (1, 281) = 8.43	.004
	ADAS frequency	F (3, 281) = 3.33	.02
	ADAS familiarity	F (1, 281) = 68.36	< .0001
tra-d'	Possession period	F (1, 285) = 8.76	.003
tra-c	ADAS experience	F (3, 282) = 3.61	.01
	ADAS familiarity	F (1, 282) = 8.10	.005
bMMS	ADAS familiarity	F (1, 285) = 6.74	.01

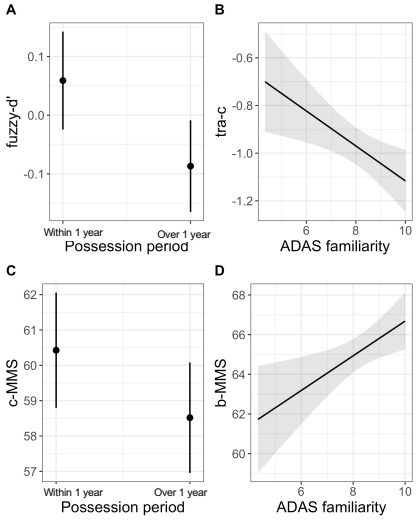

Figure 2. Predicted values of *fuzzy-d'* (A) and cMMS (C) by possession period; Predicted values of *tra-c* (B) and bMMS (D) by ADAS familiarity

In general, the trends of influence observed in *c* models and *d* models were consistent with the trends observed in the MMS models. For example, as shown in Figure 2, it was found that the influence of possession period on *fuzzy-d'* is in line with its influence on cMMS, where drivers exhibited higher *fuzzy-d'* and higher MMS when the possession period was within 1 year compared to that when the possession period was over 1 year. Besides, higher ADAS familiarity was associated with a lower *tra-c* value but higher bMMS – the lower *tra-c*, on the other hand, was negatively associated with bMMS according to MMS Models (Model-1). The influence of other variables was also consistent in both MMS models

and *d'* and *c* models, but due to space limits, were not visualized in the paper.

DISCUSSIONS

Based on the data collected from an online survey among 287 ADAS users in China, this study explored the potential of using sensitivity and response bias to assess drivers' ADAS mental models. The fitted linear models show that *d'* and *c* can be effective alternatives to MMS. Further, it was found that the association between *d'*, *c,* and MMS depended on how MMS and *d'* & *c* were calculated. Specifically, d' & c derived from traditional SDT exhibited better performance in predicting MMS calculated based on binary responses (i.e., bMMS); whereas when respondents' confidence in their answers were considered (i.e., cMMS), *d'* & *c* from fuzzy SDT were better choice. This might because traditional SDT was not able to capture the uncertainty in the process of making a choice and thus was not a good match to cMMS. On the other hand, the fuzzy SDT considered the uncertainty in the responses, while the calculation of bMMS abandoned such information, which also led to a mismatch between them. However, it should be noted that we were not able to judge which calculation method is a better evaluation of drivers' ADAS mental models. To do so, we need to further investigate how cMMS, bMMS, *d',* and *c* are associated with other explicit metrics (e.g., driving safety), which is beyond the scope of this paper but can be a future research direction.

In terms of the relationship between *d'* & *c* and MMS, for the two better-fitted models (Model 1 and Model 4), significant interaction effects between *d'* and *c* were observed. In both models, it was found that the increase of *c* led to an increase of the marginal effect of *d'* on MMS, which means that when the respondents were more conservative, the sensitivity would have a larger influence on MMS. Further, with the increase of *d'*, the marginal effect of *c* on MMS would increase, indicating that the response bias would have less effect on MMS when the respondents had higher sensitivity. The variation of the influence of *d'* as a result of *c* can be attributed to the imbalanced number of questions with "signal" and "noise only" in our survey (i.e., signal-noise ratio was around 2.3:1). The *d'* reflects respondents' capability to differentiate signals out of the noise and thus can be considered as an unbiased estimation of drivers' knowledge of the ADAS. However, knowledge is not equal to subjective understanding (as measured by MMS); the latter can be affected by respondents' bias towards the system, especially when the cases of signal and noise are not balanced, which is the case in the real world. Thus, we argue that MMS can measure drivers' subjective understanding of the system but may not be an objective measure of their mental model. As discussed above, we cannot comment on which metrics are better, unless we can connect the metrics with real-world driving safety measures.

To further investigate if *d'* and *c* can be alternatives to MMS, we explored factors associated with *d'*, *c*, and MMSs. It was found that all significant predictors of MMS were also predictors of *d'* and *c*. Further, *d'* and *c* were associated with additional factors that were not associated with corresponding MMSs. This finding indicates that *d'* and *c* might be feasible or even better alternatives if the research is targeted towards influential factors of drivers' mental models of ADAS. However, it should be noted that we only explored a few demographic and vehicle/driving-related factors. To further illustrate the relationships between MMS, *d'*, *c,* and signal-noise ratio, a more thorough investigation is needed.

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