1 **WHY DO THEY TRUST IT? DETERMINANTS OF THE INITIAL TRUST IN**

2 **AUTOMATED DRIVING**

3
4 **J. B. Manchon^{1,2}, Romane Beaufort³, Mercedes Bueno¹, and Jordan Navarro^{2,4}**

5 ¹ VEDECOM Institute, Versailles, France

6 ² Laboratoire d'Etude des Mécanismes Cognitifs (EA 3082), University Lyon 2, Bron, France

7 ³ IDUP, Paris, France

8 ⁴ Institut Universitaire de France, Paris, France

9
10 Correspondence address: J. B. Manchon, Institut VEDECOM, 23 bis Allée des
11 Marronniers, 78000 Versailles, France; e-mail: jb.manchon@vedecom.fr.

12
13 **Word count:** 4102

14 **HIGHLIGHTS**

- 15 • Trust in automated driving should be assessed with specific questionnaires, rather
16 than general ones.
- 17 • Initial trust in automated driving can be modelled using socio-demographics variables
18 alongside several constructs extracted from trust theoretical models.
- 19 • Younger people and women seem to trust less automated driving compared to other
20 drivers.
- 21 • Perceived reputation of automation, proneness to delegate tasks, attitude and
22 expectation of performance are linked with a higher level of trust in automated driving.
- 23 • Initial trust in automated driving scores can be predicted from the aforementioned
24 constructs.

ABSTRACT

Because driving automation is quickly increasing, humans' relation to automated driving evolves accordingly. Trust in automated driving has been shown to strongly correlate with drivers' acceptance of such systems. Nonetheless, there is currently a lack of specific questionnaires to assess drivers' level of trust in Highly Automated Driving (HAD). Moreover, little is known about which factors determine trust before any interaction with HAD systems. Theoretical trust in automation models propose several factors to explain how trust builds before and during interactions with automation. Using 844 answers collected through an online survey, this paper aims to propose a new scale designed to evaluate initial trust in automated driving. Moreover, we also measure other factors linked to drivers' initial level of trust in HAD by operationalizing the trust components proposed by Hoff and Bashir (2015)'s theoretical trust model. In order to better describe what determines trust in HAD, a linear model based on the collected data is proposed. The model not only weights the factors determining trust but is also able to predict the level of trust considering these factors.

Keywords: trust in automation, trust building, automated driving, prediction, linear model

1. INTRODUCTION

The increasing number of low-level automated vehicles on road are changing the way we drive. Tomorrow, Highly Automated Driving (HAD) will deeply modify the relationships between drivers and their automated vehicles (Navarro, 2019).

HAD is defined here as a technology that allows the driver to entirely disengage from the driving task when the HAD system is situated within its operational design domain (level 4, SAE, 2016) or when it does not have an operational design domain anymore (level 5, SAE, 2016). Nevertheless, for the HAD massive adoption to happen, drivers shall accept to engage in cooperation with such automations. Trust in Automation (TiA) has proved itself to be one of the most predictive factors influencing technology adoption (Kaur & Rampersad, 2018; Zhang et al., 2019) and use (Dzindolet et al., 2003; Lee & See, 2004; Rice, 2009).

Built on previous research and an extensive literature review, Hoff and Bashir (2015) proposed a general model of factors underlying and empowering TiA. This model proposes a three-layer structure (based on Marsh & Dibben, 2003) to describe TiA. The first layer, *dispositional trust*, focuses on individual factors such as age, gender, culture, and personality traits. It is described as a static layer which evolve slowly during an individual's life and has a relatively weak influence on TiA. The second layer, *situational trust*, designates environmental factors influencing the relation between an operator and the automation. It is composed of two parts corresponding to external and internal variabilities. External factors are related to, e.g., the type of automation, the complexity of the task, the workload, while internal factors refer to the operator's expertise, attentional capacities, mood, and self-confidence. This layer is supposed to evolve faster depending

on the aforementioned factors and have a stronger impact on TiA before the interaction with a particular automation. The third layer, *learned trust*, is divided in two sublayers: the *initial learned trust* and the *dynamic learned trust*. The initial learned trust leans on the operator's pre-existing knowledge about the automation, e.g., the attitudes and expectations, or the past experiences with similar automations. On the other hand, the dynamic learned trust focuses on factors related to the current operator's experience with a particular automation, during use. It includes several factors related to the automation performance and its design.

Because it brings a valuable synthesis of its topic, this model has been widely used during the past years and has proved itself to be a strong theoretical frame in the automated driving context (e.g., Ekman et al., 2018; Hergeth et al., 2016; Kraus, Scholz, Messner, et al., 2020; Manchon et al., 2022; Molnar et al., 2018; Walker et al., 2019). Hoff and Bashir's model describes and organizes the factors linked with trust and has been shown to fit for studying TiAD at several steps of the interaction between the driver and the HAD system (see Manchon et al., 2020 for a review). Nevertheless, this relation of trust has common points with the general TiA theory, but also some major particularities that justify the development of another, more specific concept: Trust in Automated Driving (TiAD). The safety critical nature of the driving task is especially consequential because it involves directly the driver and passengers' lives, as well as other people's lives on road. For example, if one uses a HAD system for two years without any incident, a dramatic drop of TiAD can be expected if the automation suddenly fails to prevent a collision with a cyclist. Contrarily, if one is uncomfortable with a HAD system's way to manage speed and steering control, a strong increase in TiAD may be expected if the automation achieves

88 to prevent a collision with the cyclist. The danger is therefore even more perceptible than
89 it is for other type of dangerous interactions with automation (e.g., powerplant
90 supervision). Because the driving environment is highly variable and likely to evolve
91 drastically in a few seconds, TiAD is prone to a dynamic evolution, including periodical
92 recalibrations within short periods of time. Moreover, the wide range of drivers' individual
93 differences (such as age, abilities, driving experience and driving style, expectations, level
94 of knowledge and understanding) lead to a heterogenous panel of automated driving
95 systems' potential users. This diversity of profiles must therefore be assessed in order to
96 better understand how TiAD builds. Furthermore, no current vehicle is equipped with HAD
97 systems (level 4 or 5, SAE, 2016). The factors related to previous experience and current
98 automation's performance therefore appear irrelevant. On the contrary, factors related to
99 drivers' mental representation of HAD (such as reputation, beliefs, knowledge) seems to
100 be determinant in this context. In the same manner Trust in Robots needed a specific
101 scale to assess more precisely its related factors (Schaefer, 2013), a scale integrating
102 specific factors related to Trust in Automated Driving seemed necessary to investigate
103 this construct. The combination of the aforementioned particularities makes TiAD a
104 specific construct to be assessed with a specific scale.

105 Nonetheless, few studies focused on the determinants underlying drivers' TiAD before
106 interaction with HAD. In an online survey, Kraus et al. (2019) showed that some
107 personality traits had a strong influence on participants' *a priori* information processing
108 regarding a level 3 (SAE, 2016) automated vehicle. They were able to show respondents'
109 initial TiAD was strongly influenced by the brand reputation and the level of expected
110 reliability of the level 3 driving automation. Ayoub et al. (2021) developed a predictive

model to understand what determines dispositional and initial learned trust. Their online survey included factors such as knowledge, experience, risk and benefit perceptions, and feelings about HAD systems. This model showed a strong effect of the expected risks and benefits, alongside with excitement, knowledge about HAD and eagerness to adopt new technologies. These two models bring valuable information about what determines drivers' initial level of TiAD, but many potential factors related to individuals and automations' characteristics have not been explored yet. To fill this gap, the present contribution proposes to investigate Hoff and Bashir (2015)'s factors linked with dispositional and initial learned trust to better understand their influence on the initial level of TiAD in the population.

The goals of this paper are therefore (a) to propose a new scale designed to assess trust in the specific context of driving automation and (b) to participate to fill the gap in the understanding of the initial level of TiAD, by assessing the numerous factors related to individuals (i.e., dispositional trust and initial learned trust, Hoff & Bashir, 2015), and proposing a model integrating the respective weights of these factors.

2. METHOD

Participants and procedure

The questionnaire was sent by email and several social media during summer 2020 to a large panel of people. The only criterion was to speak French, for participants to be able to understand the questions. Participants' socio-demographics data are reported in Table 2 and the procedure is displayed in Figure 1.

Figure 1. Data collection procedure. The left part represents the trust factors from Hoff and Bashir (2015). The center part presents the questionnaires that were used for the data collection. The right part displays the targeted outputs.

In the first part of the present contribution, a new 10-item TiAD scale was developed and assessed to inquire its internal validity and reliability. A total of 844 participants answered this 10-item TiAD scale, which was the first step of the overall questionnaire (Figure 1). In the second part of the contribution, the answers of 738 participants who had completed the full questionnaire were kept modelling the determinants of TiAD using the 10-item scale and the several other scales (Figure 1).

Trust scale

The present trust scale was created to measure the initial level of TiAD, in contrast with the dynamic level of TiAD that appears during the interactions between the driver and the HAD system. A careful literature review (Manchon et al., 2020) led to selecting 10 items inquiring trust and adapting them to the HAD context. Items were selected to minimize redundancy across dimensions. Items one, four and ten question general feelings about perceived safety and trust, that are central in the driving context and create the need for a dedicated scale. The seven other items are indirect measures of trust (i.e., comparison with manual driving, complex situation management, weather-related attitude, engagement in non-driving-related activities, boredom-related attitude, and tiredness-related attitude). These items explore participant's expectations and mental models about HAD, which lean on participants beliefs and knowledge about HAD, but also past experiences (with, e.g., advanced driving assistance systems if they have ever used one) and on overall HAD systems' reputation. The investigated questionnaire has been used in past experiments (Manchon et al., 2021, 2022) and has shown a strong correlation with objective trust measure (e.g., gaze behaviour, engagement in non-driving-related activities, Manchon et al., 2020). Items are shown in Table 1 and participants' demographic data are displayed in Table 2.

Each item response ranged from 1 to 6, and the total trust score was obtained by adding each item's value, reversing item 3 (Table 1). Trust scores were then converted in percentage by subtracting 10 from this total sum to make it range from 0 to 50. They were then transformed using the rule of three (i.e., dividing them by their theoretical maximum, 50, and multiplying them by their targeted maximum, 100). The formula, using s_i for the

total trust score and s_n for each item's value was $s_t = (s_1 + s_2 + (7 - s_3) + s_4 + s_5 + s_6 + s_7 + s_8 + s_9 + s_{10} - 10) \div 50 \times 100$. The scores used in further analysis were therefore linear conversions of the simple total sums, to ease readers' assessments of values by providing percentages.

Table 1. Trust in Automated Driving measurement scale

	Questions	Sources
1	I would feel safe in an automated vehicle.	O'Cass and Carlson (2012)
2	The automated driving system provides me with more safety compared to manual driving.	Payre et al. (2016)
3*	I would rather keep manual control of my vehicle than delegate it to the automated driving system on every occasion.	Payre et al. (2016)
4	I would trust automated driving system decisions.	O'Cass and Carlson (2012)
5	I would trust automated driving system capacities to manage complex driving situations.	Egea and González (2011)
6	If the weather conditions were bad (e.g., fog, glare, rain), I would delegate the driving task to the automated driving system.	Payre (2015)
7	Rather than monitoring the driving environment, I could focus on other activities confidently.	Egea and González (2011)
8	If driving was boring for me, I would rather delegate it to the automated driving system than do it myself.	Payre et al. (2016)
9	I would delegate the driving to the automated driving system if I were tired.	Payre et al. (2016)
10	How much do you trust automated driving systems?	Lee and Moray (1994)

*item was inverted for scoring

Table 2. Participant's socio-demographics data for the trust scale validation.

	n			Frequency (%)		
Total	844			100%		
Female	448			53.10%		
	Min	1st Q	Med	Mean	3rd Q	Max
Age (years)	16	29	40	40.47	51	93
Driver's licence since (years)	0	10	21	21.89	32	73
Driving frequency						
	Every day or almost	412		48.82%		
	Several times a week	170		20.14%		
	Several times a month	92		10.90%		
	Less often	93		11.02%		
	No driving licence	77		9.12%		
Kilometres driven by year						
	Less than 5,000 km	208		24.64%		
	Between 5,000 and 10,000 km	214		25.36%		
	Between 10,000 and 20,000 km	214		25.36%		
	Between 20,000 and 50,000 km	131		15.52%		
Education						
	None	4		0.47%		
	GCSE	6		0.71%		
	BTEC National Diploma	30		3.55%		
	A-levels	138		16.35%		
	HND or Two years degree	202		23.93%		
	Bachelor's degree or Three years degree	96		11.37%		
	Bachelor's with Honours degree or Four years degree	70		8.29%		
	Master's degree or Five years degree	244		28.91%		
	PhD or Eight years degree	54		6.40%		
Socio-economic Classification						
	Higher grade occupations	360		42.65%		
	Intermediate occupations	53		6.28%		
	Employees	285		33.77%		
	Students	109		12.91%		
	Retired people	37		4.38%		

Other constructs and other scales

In order to investigate the determinants of TiAD, other scales were used to measure related constructs, following the Hoff and Bashir (2015)'s model. Whenever it was possible, well-accepted and well-standardized scales were used. In several cases, proxy variables were used to approach some Hoff and Bashir (2015)'s factors. For example, because of a lack of funding, culture could not be assessed with multi-language questionnaire broadcasted in several countries. Culture was therefore inquired through socio-professional category, level of diploma, marital status, and parenthood. The complete inventory of constructs is listed in Table 3.

Table 3. Measured constructs and related scales.

Measured constructs		Number of items	Scale type	Reference
Hoff and Bashir (2015)'s dispositional trust				
Age		1		
Gender		1		
Culture				
	Socio-Professional Category	1	Custom	Desrosières and Thévenot (2002)
	Diploma	1	Custom	New item
	Marital status	1	Custom	New item
	Parenthood	1	Custom	New item
Personality Traits				
	Technophilia questionnaire	4	7-point Likert type	Agarwal and Prasad (1998)
	Propensity to trust technology questionnaire	6	7-point Likert type	Schneider et al. (2017)
Big Five Inventory (French reduced adaptation)		45		
	Extraversion	8	5-point Likert type	Plaisant et al. (2010)
	Agreeableness	10		
	Conscientiousness	9		
	Neuroticism	8		
	Openness	10		
Smart Tools Proneness Questionnaire (STP-Q)		27		
	Smart tools performances and efficiency	12	7-point Likert	Navarro et al. (submitted)
	Social acceptance and smart tools personal	8		

	suitability		type	
	Proneness to delegate tasks	7		
Hoff and Bashir (2015)'s initial learned trust				
Unified Theory of Acceptance and Use of Technology (UTAUT)		12		
	Attitude	4	6-point Likert type	Adapted from Venkatesh et al. (2003)
	Expectation of performance	4		
	Expectation of utility	4		
Perceived reputation of automated driving systems		4		
	General reputation of HAD systems	1	6-point Likert type	New scale
	Reputation of HAD systems designers (capabilities)	1		
	Reputation of cars manufacturers selling HAD systems (reliability)	1		
	Reputation of institutional actors promoting HAD system (general interest of public policies)	1		
Previous experiences with automated driving systems		3		
	As a driver in a personal car	1	Custom	New scale
	As a passenger in a personal car	1	Custom	New scale
	As a passenger in an automated shuffle or another public transport automated vehicle	1	Custom	New scale
Self-evaluated understanding and knowledges about automated driving systems		1	Custom	New scale
Driving experience				
	Number of years since the obtention of a driving licence	1		
	Driving frequency	1	Custom	

Data analysis

In the next section, the 844 scores from the trust scale have been examined through exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) in order to investigate the structure and properties of the proposed trust scale. Then, 738 complete answers have been used to yield a linear model integrating the principal determinants of TiAD, considering the other constructs linked to trust by Hoff and Bashir (2015). This linear model has then been analysed to weight the relative influence of each construct on the participants' level of TiAD. To do so, each construct have been scored in accordance with

authors recommendations, then rescaled to range from 0 to 100. This conversion was done to ease interpretations. To construct the linear model, data were standardized.

3. RESULTS

Trust scale validation

The properties of the trust in automated driving scale were analysed using *R* 3.6.1 (R Core Team, 2017), the *psych* (Revelle, 2020) and the *lavaan* packages (Rosseel, 2012).

Figure 2. Correlation matrix of the scales' items. All correlations are significant at $p < 0.001$ using Benjamini & Hochberg (1995)'s correction for multiple comparisons.

Homogeneity and internal consistency were good (Cronbach's $\alpha = .94$, McDonald's $\omega_h = .78$, and $\omega_t = .96$). The correlation matrix of each item's score is displayed in Figure 2. It shows all items are strongly related.

Data were appropriate for a factor analysis, according to the measure of sampling adequacy ($KMO = 0.95$). Furthermore, the Bartlett's test of sphericity confirmed the number of significant correlations was sufficient for a factor analysis ($X^2(45) = 6725.04$, $p < .001$). The use of a single factor structure for the 10-item scale was supported by 11 out of the 23 (47.83%) methods used to determine the optimal number of factors (i.e., t , p , Optimal coordinates, Acceleration factor, Parallel analysis, Kaiser criterion, SE Scree, R^2 , VSS complexity 1, Velicer's MAP, and RMSEA). Following Revelle (2020)'s proposed procedure, exploratory factor analysis (EFA) was then applied to investigate the scale's factor structure. A maximum likelihood factor analysis using varimax rotation was used to study this single factor (i.e., trust), following Costello and Osborne (2005)'s recommendations. The EFA showed that a one-dimensional factor accounted for 62.92% of the total variance of the data. EFA loadings are displayed in Table 4. A confirmatory factor analysis (CFA) was then produced to confirm the EFA results. Seventy percent of the data were used for the CFA training and the remaining thirty percent for testing. The following model was yielded: $X^2 = 125.1$, $df = 35$, $p < .001$, AGFI = .86 (good: $\geq .85$), CFI = .95 (good: $\geq .85$), TLI = .92 (good: $\geq .80$), RMSEA = .10 (acceptable: $\leq .10$, CI low = .08; CI high = 0.12) and SRMR = .04 (good: $\leq .05$). Details for each item are given in Table 4. The path weight corresponding to this CFA are displayed in Figure 3. Considering the aforementioned indicators, the model seemed good according to Brown (2015)'s recommendations. The scale can therefore be confidently used in further analyses.

Table 4. Loadings for the EFA and CFA related to the TiAD measurement scale

Items	EFA			CFA			
	Loadings	Complexity	Uniqueness	Estimate	Standard Error	z-value	p
Q1	0.91	1.00	0.18	1.000			
Q2	0.83	1.00	0.31	0.977	0.047	20.654	<0.001
Q3	0.73	1.00	0.47	0.897	0.063	14.154	<0.001
Q4	0.85	1.00	0.27	0.871	0.044	19.870	<0.001
Q5	0.77	1.00	0.41	0.831	0.050	16.476	<0.001
Q6	0.68	1.00	0.54	0.844	0.066	12.835	<0.001
Q7	0.73	1.00	0.47	0.833	0.060	13.853	<0.001
Q8	0.76	1.00	0.43	0.853	0.060	14.322	<0.001
Q9	0.74	1.00	0.46	0.800	0.058	13.824	<0.001
Q10	0.91	1.00	0.17	0.913	0.038	24.193	<0.001

Figure 3. Path weights calculated from the CFA.

214 Linear model construction

215 The linear model describing trust through several related constructs was created using R
 216 3.6.1 (R Core Team, 2017). The correlation matrix of the variables and constructs is

217 displayed in Figure 4. This matrix shows that numerous variables are related all together,
218 confirming the need for a model that untangle these complex relations.

219 The construction of the models led to drop variables that were showing strong collinearity
220 and were therefore redundant (e.g., age and number of years since the obtention of a
221 driving licence). Several other variables appeared to have no specific effect (i.e., all things
222 being equal, technophilia was mostly explained by attitude and added no more
223 information) and were removed from the model to increase its performance and ease the
224 interpretations. This iterative process was repeated, and temporary models were
225 compared to select the best one. The final model is presented in Table 5.

Figure 4. Correlation matrix of the variables and constructs. All displayed correlations are significant at $p < 0.05$ using Benjamini & Hochberg (1995)'s correction for multiple comparisons.

Considering factors linked with the dispositional TiAD, the model exhibited an increase in TiAD when age grown (ten years increase TiAD by 1 point, all things equal otherwise), alongside an effect of the gender, where female trusted less HAD systems than male (4.6 points less, all things equal otherwise). Higher education also seemed to have a positive effect on TiAD, which was not significant (each supplemental year increase TiAD by 0.5 points, all things equal otherwise). Regarding personality traits, the proneness to delegate tasks from the STP-Q showed a positive effect on TiAD, making TiAD increase of 0.16

233 points for each declared point. One dimension from the Big Five (i.e., conscientiousness)
 234 showed a very small negative effect on TiAD.

235 Considering factors linked with initial learned TiAD, the model showed a negative effect
 236 of the driving frequency that increased when participants drove more frequently,
 237 compared to participants that drove less frequently. Two constructs from the UTAUT
 238 (Venkatesh et al., 2003) had a significative influence on TiAD: 1 point of attitude made
 239 TiAD increase of 0.4 points, while 1 point of expectation of performances made TiAD
 240 increase of 0.3 points. Perceived HAD systems' reputation also had a positive effect,
 241 making TiAD increase by 0.2 points for each declared point.

Table 5. Final linear model including variables and constructs linked to TiAD.

Adjusted R² = .74, F = 176.9, DF = 12 & 725.

Variables and constructs	Estimate	p
(Intercept)	4.404	.
Factors linked with dispositional TiAD		
Age (in years)	0.109	*
Female	-4.588	***
Higher education (in years)	0.503	.
STP (Proneness to delegate tasks)	0.099	***
Big Five		
Conscientiousness	-0.049	*
Factors linked with initial learned TiAD		
Driving frequency		
Every day	-5.230	***
Every week	-2.945	.
Less than every week	Reference	
UTAUT		
Attitude	0.441	***
Expectation of performance	0.262	***
Perceived reputation	0.167	***

Linear model predictions

The previously presented model can also be used to make predictions, considering all the variables that were included. To test the predictive performances of this model, it was compared to a random TiAD score assignment, and three other models. One integrates only socio-demographic data (i.e., age, gender, diploma, socio-professional category, marital status, parenthood, number of years since the obtention of the driving licence, driving frequency); one integrates all the variables related to dispositional trust; and one integrates all the variables related to initial learned trust. The deviation between observed and predicted TiAD scores from the random assignment and the four models are presented in Figure 5.

Figure 5. Boxplots of the deviation between observed and predicted TiAD scores from three models. Random: min = -5.10, Q1 = -0.98, med = 0.01, mean = -0.01, Q3 = 0.96, max = 4.96. Socio-demographic: min = -2.25, Q1 = -0.7, med = 0.01, mean = 0.00, Q3 = 0.73, max = 2.14. Final model: min = -1.87, Q1 = -0.30, med = 0.03, mean = 0.00, Q3 = 0.35, max = 1.63.

The results show that using only socio-demographic data to predict TiAD strongly reduces the number of outliers, compared to a random assignment. The random model has an average deviation of 34.3 points of TiAD score, compared to observed data. Comparatively, the socio-demographic model has an average deviation of 25.8 points, which is 8.5 points less. The prediction effectively improves with the dispositional model, which has an average deviation of 20.9 points of TiAD score (4.9 points less), compared to observed data. The initial learned model is better, with an average deviation of 12.3 points of TiAD score (8.6 points less) and a lower number of outliers. The previously constructed model is the best one, with an average deviation of 12.2 points of TiAD score. This final model has therefore an average deviation of 22.1 points less than the random model, 13.6 points less than the socio-demographic model, 8.7 points less than the dispositional model, and 0.1 points less than the initial learned model. These results indicate the proposed model brings valuable information, compared with simple socio-demographic data or variables related to the dispositional trust. They also indicate the variables related to the initial learned trust are determinant and may have a good prediction capability even considered alone.

4. DISCUSSION

The present paper had two main goals : (a) to propose a new specific scale to measure the initial level of TiAD; and (b) to use this scale in a large-scale online survey aiming to assess several factors linked with TiAD. The resulting answers were used to construct a linear model indicating what constructs were the most influential on trust. The model was then used to predict trust using different information.

Initial level of TiAD assessment

A previous literature review (Manchon et al., 2020) initiated a conceptual differentiation regarding the nature of TiAD, compared to the TiA theory that was developed during the last decades. The present contribution aims to extend this theoretical work, proposing a new scale specifically designed to assess TiAD, contrary to the very often used Jian et al. (2000)'s scale that inquires the general TiA. Previous experiments showed this scale was able to measure variation in trust before and after drivers had a simulated experience with a HAD system. Moreover, the results complied with other measures linked with trust, such as visual strategies and engagement in non-driving related activities (Manchon et al., 2021, 2022). These results were consistent with the literature (e.g., Hartwich et al., 2018; Hergeth et al., 2017; Körber et al., 2018; Kraus, Scholz, Stiegemeier, et al., 2020), and led to further investigation about this scale's properties. The present results from the EFA and the CFA confirmed this new scale is relevant to assess TiAD. The numerous indicators of the resulting model exhibited the scale's properness to measure the single factor (i.e., trust) it was designed to evaluate. Future studies could compare results from this scale and Jian et al. (2000)'s scale to extend knowledge regarding its ability to assess TiAD.

Determinants of the dispositional TiAD

The construction of a linear model explaining which factors are the most relevant to explain TiAD provided valuable findings.

Regarding variables linked with Hoff and Bashir (2015)'s dispositional trust, increasing age showed a very small positive effect on initial TiAD. Previous papers reported elderly people were sometimes interested in HAD because it was a solution to their decreasing

driving skills (Körber et al., 2016; Shin et al., 2019), an explanation consistent with our results. In the same manner, the model indicates females have lower level of initial TiAD, compared to male. This effect of the gender is usually absent in experiments, and this finding raises a few questions. It might exist a gender effect in the overall population, as indicated by Ayoub et al. (2021)'s model, that fades away in experimental sessions because some females that distrust HAD are not interested in participating in this kind of experiments. This finding should be examined thoroughly before even being considered.

Personality traits such as the proneness to delegate tasks showed a positive effect on TiAD, which is consistent with the construct (Navarro et al., submitted). Agreeableness, which include a trust subfactor, is usually positively correlated with trust in other human. The negative link between agreeableness and TiAD in the present model is therefore surprising. Additional studies are needed to better understand how general trust differ from TiAD (i.e., how trusting a machine differ from trusting a human), and what other factors are overwhelming the effect of this personality trait. Without surprise, conscientiousness had a negative impact on TiAD. This is consistent with Ayoub et al. (2021)'s model, where participants who feel in control during manual driving show a lower level of TiAD.

Determinants of the initial learned TiAD

Regarding the variables linked with Hoff and Bashir (2015)'s initial learned trust, it seems that experience with manual driving (i.e., driving frequency) had a strong impact on trust. Daily commuters showed a lower level of TiAD, compared to people that drive few times a week, and these weekly drivers also had a lower level of TiAD than casual drivers. As reported by Ayoub et al. (2021), the number of years of driving also seemed to have a

negative impact on TiAD. It is possible that frequent drivers have developed a high level of confidence in their own driving skills and thus tend to trust driving automation less, in line with the seminal findings reported by Lee and Moray (1994).

Constructs from the UTAUT (Venkatesh et al., 2003) were highly correlated with TiAD. In particular, attitude was a powerful predictor of TiAD, alongside the expectation of performance. These two constructs were so self-explaining they hid the effects of other constructs that were less correlated, like technophilia or propensity to trust automation. This finding reinforces the idea that these questionnaires are very powerful to predict individuals' attitudes toward automation. Trust in automation might be, at least partly, included in individuals' assessments when completing these questionnaires. That being said, trust specific questionnaires are also valuable because trust remains a major influence of operator's reliance in complex and uncertain situations, such as driving, especially with very complex automation, like HAD systems (Lee & See, 2004).

Finally, participants' perceived reputation of HAD systems was a solid predictor of TiAD, confirming results from Kraus et al. (2019). Otherwise, Kraus et al. (2019) found that people with higher need for cognition relied more on given information about brand or reliability. Here, the openness factor from the Big Five, which is often associated with the need for cognition, did not seem to be a good predictor of TiAD all things equal otherwise. As the present contribution did not manipulate any information prior to the survey, this result is not surprising, but it raises questions about the influence of such personality traits on people's initial learned level of TiAD.

Limitations and perspectives

Culture is one of the several factors linked with dispositional trust. Nevertheless, the survey used in the present study was in French only. Future studies could investigate the topic in other language-speaking areas, to compare results and better understand the effect of culture on TiAD. Next, because HAD systems are currently not fully implemented, drivers' level of TiAD seems strongly influenced by their mental model of such automation. In this context, manufacturers' demonstrations, advertising, reports of accidents and other external stimuli are likely to have a major influence on this mental representation, and therefore on people's level of TiAD. It seems urgent to assess finely the impact of external data on drivers' level of trust and include this supplemental input in predictive models to extend their accuracy. Then, the presented model should be confronted with other data. For example, it may be valuable to test the model with level of trust computed with the Jian et al. (2000)'s scale, in order to confront the model with a general TiA measure. Finally, the present contribution did not assess the Hoff and Bashir (2015)'s situational trust layer. This seemed irrelevant to study drivers' initial level of trust at this point of HAD development, but this trust layer will have to be assessed in the future.

5. CONCLUSION

On top of the assessment of a TiAD specific scale to measure the initial level of trust in Automated Driving, the current contribution offered a modelling of the dispositional and initial learned levels of trust proposed by Hoff and Bashir (2015) within the automotive domain. A general synthesis of the model's findings is available in Figure 6. The model allows to propose a partial operationalization of the Hoff and Bashir (2015)'s model, adapted to the HAD context. The estimates predicted by the model are indicated for each

364 factor, allowing to better understand what TiAD is made of. It appears female and people
365 who drive frequently will tend to trust less HAD. People with higher education, who have
366 a positive attitude, expect performances will tend to trust HAD more. Elder people, people
367 who perceive HAD with a positive reputation, and people who are prone to delegate tasks
368 will also trust HAD more. Finally, conscientious people will likely trust HAD less.

Figure 6. Synthesis of the findings from the linear model. Factors from Hoff and Bashir (2015) are indicated in *italic*. Estimates calculated by the linear model are indicated near each arrow.

ACKNOWLEDGMENTS

Funding: This study was supported by VEDECOM Institute, “Institute for Energy Transition” and part of the French governmental plan “Investment for the Future” (ANR-10-IEED-0009).

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

REFERENCES

- Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information Systems Research*, 9(2), 204–215. <https://doi.org/10.1287/isre.9.2.204>
- Ayoub, J., Yang, X. J., & Zhou, F. (2021). Modeling dispositional and initial learned trust in automated vehicles with predictability and explainability. *Transportation Research Part F: Traffic Psychology and Behaviour*, 77, 102–116. <https://doi.org/10.1016/j.trf.2020.12.015>
- Benjamini, Y., & Hochberg, Y. (1995). Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing. *Journal of the Royal Statistical Society: Series B (Methodological)*, 57(1), 289–300. <https://doi.org/10.1111/j.2517-6161.1995.tb02031.x>
- Brown, T. A. (2015). *Confirmatory factor analysis for applied research*, 2nd ed (pp. xvii, 462). The Guilford Press.
- Carlson, J., & O'Cass, A. (2012). An empirical assessment of consumers' evaluations of web site service quality: Conceptualizing and testing a formative model. *Journal of Services Marketing*, 26(6), 419–434. <https://doi.org/10.1108/08876041211257909>
- Costello, A. B., & Osborne, J. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research, and Evaluation*, Vol. 10., Article 7. <https://doi.org/10.7275/JYJ1-4868>
- Desrosières, A., & Thévenot, L. (2002). *Les catégories socioprofessionnelles: Vol. 5e éd.* La Découverte; Cairn.info. <https://www.cairn.info/les-categories-socioprofessionnelles--9782707138569.htm>

397 Dzindolet, M. T., Peterson, S. A., Pomranky, R. A., Pierce, L. G., & Beck, H. P. (2003). The role of
398 trust in automation reliance. *International Journal of Human-Computer Studies*, 58(6),
399 697–718. [https://doi.org/10.1016/S1071-5819\(03\)00038-7](https://doi.org/10.1016/S1071-5819(03)00038-7)

400 Egea, J. M. O., & González, M. V. R. (2011). Explaining physicians' acceptance of EHCR systems:
401 An extension of TAM with trust and risk factors. *Computers in Human Behavior*, 27(1),
402 319–332. <https://doi.org/10.1016/j.chb.2010.08.010>

403 Ekman, F., Johansson, M., & Sochor, J. (2018). Creating appropriate trust in automated vehicle
404 systems: A framework for HMI design. *IEEE Transactions on Human-Machine Systems*,
405 48(1), 95–101. <https://doi.org/10.1109/THMS.2017.2776209>

406 Hartwich, F., Witzlack, C., Beggiato, M., & Krems, J. F. (2018). The first impression counts – A
407 combined driving simulator and test track study on the development of trust and
408 acceptance of highly automated driving. *Transportation Research Part F: Traffic
409 Psychology and Behaviour*. <https://doi.org/10.1016/j.trf.2018.05.012>

410 Hergeth, S., Lorenz, L., & Krems, J. F. (2017). Prior familiarization with takeover requests affects
411 drivers' takeover performance and automation trust. *Human Factors*, 59(3), 457–470.
412 <https://doi.org/10.1177/0018720816678714>

413 Hergeth, S., Lorenz, L., & Vilimek, R. (2016). Keep your scanners peeled: Gaze behavior as a
414 measure of automation trust during highly automated driving. *Human Factors*, 3(58), 509–
415 519. <https://doi.org/10.1177/0018720815625744>

416 Hoff, K. A., & Bashir, M. (2015). Trust in automation: Integrating empirical evidence on factors that
417 influence trust. *Human Factors*, 57(3), 407–434.
418 <https://doi.org/10.1177/0018720814547570>

419 Kaur, K., & Rampersad, G. (2018). Trust in driverless cars: Investigating key factors influencing
 420 the adoption of driverless cars. *Journal of Engineering and Technology Management*, 48,
 421 87–96. <https://doi.org/10.1016/j.jengtecman.2018.04.006>

422 Körber, M., Gold, C., Lechner, D., & Bengler, K. (2016). The influence of age on the take-over of
 423 vehicle control in highly automated driving. *Transportation Research Part F: Traffic*
 424 *Psychology and Behaviour*, 39, 19–32. <https://doi.org/10.1016/j.trf.2016.03.002>

425 Körber, M., Prasch, L., & Bengler, K. (2018). Why do I have to drive now? Post hoc explanations
 426 of takeover requests. *Human Factors*, 3(60), 305–323.

427 Kraus, J., Forster, Y., Hergeth, S., & Baumann, M. (2019). Two routes to trust calibration: Effects
 428 of reliability and brand information on Trust in Automation. *International Journal of Mobile*
 429 *Human Computer Interaction*, 11(3), 17.

430 Kraus, J., Scholz, D., Messner, E.-M., Messner, M., & Baumann, M. (2020). Scared to trust? –
 431 Predicting trust in highly automated driving by depressiveness, negative self-evaluations
 432 and state anxiety. *Frontiers in Psychology*, 10. <https://doi.org/10.3389/fpsyg.2019.02917>

433 Kraus, J., Scholz, D., Stiegemeier, D., & Baumann, M. (2020). The more you know: Trust
 434 dynamics and calibration in highly automated driving and the effects of take-overs, system
 435 malfunction, and system transparency. *Human Factors: The Journal of the Human Factors*
 436 *and Ergonomics Society*, 62(5), 718–736. <https://doi.org/10.1177/0018720819853686>

437 Lee, J. D., & Moray, N. (1994). Trust, self-confidence, and operators' adaptation to automation.
 438 *International Journal of Human-Computer Studies*, 40(1), 153–184.
 439 <https://doi.org/10.1006/ijhc.1994.1007>

440 Lee, J. D., & See, K. (2004). Trust in automation: Designing for appropriate reliance. *Human*
 441 *Factors*, 46(1), 50–80. https://doi.org/10.1518/hfes.46.1.50_30392

442 Manchon, J. B., Bueno, M., & Navarro, J. (2020). From manual to automated driving: How does
 443 trust evolve? *Theoretical Issues in Ergonomics Science*, 1–27.
 444 <https://doi.org/10.1080/1463922X.2020.1830450>

445 Manchon, J. B., Bueno, M., & Navarro, J. (2021). Calibration of Trust in Automated Driving: A
 446 matter of initial level of trust and automated driving style? *Human Factors*, (accepted).

447 Manchon, J. B., Bueno, M., & Navarro, J. (2022). How the initial level of trust in automated driving
 448 impact drivers' behavior and early trust construction. *Transportation Research Part F:*
 449 *Traffic Psychology and Behaviour*, (accepted).

450 Marsh, S., & Dibben, M. R. (2003). The role of trust in information science and technology. *Annual*
 451 *Review of Information Science and Technology*, 37(1), 465–498.
 452 <https://doi.org/10.1002/aris.1440370111>

453 Molnar, L. J., Ryan, L. H., Pradhan, A. K., Eby, D. W., St. Louis, R. M., & Zakrajsek, J. S. (2018).
 454 Understanding trust and acceptance of automated vehicles: An exploratory simulator
 455 study of transfer of control between automated and manual driving. *Transportation*
 456 *Research Part F: Traffic Psychology and Behaviour*, 58, 319–328.
 457 <https://doi.org/10.1016/j.trf.2018.06.004>

458 Navarro, J. (2019). A state of science on highly automated driving. *Theoretical Issues in*
 459 *Ergonomics Science*, 20(3), 366–396. <https://doi.org/10.1080/1463922X.2018.1439544>

460 Payre, W. (2015). *Conduite complètement automatisée: Acceptabilité, confiance et apprentissage*
 461 *de la reprise de contrôle manuel* [Unpublished psychology thesis, Université Paris 8].
 462 <https://www.theses.fr/2015PA080115>

463 Payre, W., Cestac, J., & Delhomme, P. (2016). Fully automated driving: Impact of trust and
 464 practice on manual control recovery. *Human Factors*, 58(2), 229–241.
 465 <https://doi.org/10.1177/0018720815612319>

466 Plaisant, O., Courtois, R., Réveillère, C., Mendelsohn, G., & John, O. P. (2010). *Validation par*
467 *analyse factorielle du Big Five Inventory français (BFI-Fr). Analyse convergente avec le*
468 *NEO-PI-R*. 168(2), 97–106.

469 R Core Team. (2017). *R: A Language and Environment for Statistical Computing*. R Foundation
470 for Statistical Computing. <https://www.R-project.org/>

471 Revelle, W. (2020). *psych: Procedures for personality and psychological research* (R package
472 version 2.0.8) [Computer software]. North-western University, Evanston.

473 Rice, S. (2009). Examining single-and multiple-process theories of trust in automation. *The*
474 *Journal of General Psychology*, 136(3), 303–322.

475 Rosseel, Y. (2012). lavaan: An R Package for Structural Equation Modeling. *Journal of Statistical*
476 *Software*, 48(2). <https://doi.org/10.18637/jss.v048.i02>

477 SAE International. (2016). *Taxonomy and Definitions for Terms Related to Driving Automation*
478 *Systems for On-Road Motor Vehicles*. https://doi.org/10.4271/J3016_201609

479 Schneider, T., Jessup, S., Stokes, C., Rivers, S., Lohani, M., & McCoy, M. (2017). *The influence*
480 *of trust propensity on behavioral trust*. Poster session presented at the meeting of
481 Association for Psychological Society, Boston.

482 Shin, K. J., Tada, N., & Managi, S. (2019). Consumer demand for fully automated driving
483 technology. *Economic Analysis and Policy*, 61, 16–28.
484 <https://doi.org/10.1016/j.eap.2018.10.002>

485 Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information
486 Technology: Toward a Unified View. *MIS Quarterly*, 27(3), 425.
487 <https://doi.org/10.2307/30036540>

488 Walker, F., Wang, J., Martens, M. H., & Verwey, W. B. (2019). Gaze behaviour and electrodermal
489 activity: Objective measures of drivers' trust in automated vehicles. *Transportation*
490 *Research Part F: Traffic Psychology and Behaviour*, 64, 401–412.
491 <https://doi.org/10.1016/j.trf.2019.05.021>

492 Zhang, T., Tao, D., Qu, X., Zhang, X., Lin, R., & Zhang, W. (2019). The roles of initial trust and
493 perceived risk in public's acceptance of automated vehicles. *Transportation Research Part*
494 *C: Emerging Technologies*, 98, 207–220. <https://doi.org/10.1016/j.trc.2018.11.018>

495