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Disposition towards automated driving scale (DADS): Development and psychometric properties of a brief self-report measure to assess subject's disposition towards automated driving

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A R T I C L E I N F O

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A B S T R A C T

Positive disposition and trust in automated vehicle systems is a fundamental requisite for using, buying and taking full advantage of automated vehicles (AVs). The present study aims at developing a short, but psychometrically sound, measures of AVs acceptance that could be administered to both large samples and during experimental sessions. To this aim, in a preliminary study, we developed the Disposition towards Automated Driving Scale (DADS), an 11-item self-report measure. To test the psychometric properties of the DADS, 590 adult participants were administered the Disposition towards Automated Driving Scale (DADS). The DADS showed adequate factor structure and internal consistency. Additionally, the DADS showed negative and significant associations with theoretically relevant constructs, including subject's interest in car driving (Spearman $r = -0.11$, $p < 0.01$), Driver Behavior Questionnaire Aggressive Violations scale scores (Spearman $r = -0.13$, $p < 0.0125$), and Big Five Inventory Neuroticism scale scores (Spearman $r = -0.14$, $p < 0.01$). To test the practical utility of the DADS in an experimental context, an independent sample of 55 participants completed the DADS during an experimental automated driving study using a dynamic driving simulator. Notably, the DADS scores were provided with adequate reliability also in this context and showed positive and significant associations with the involvement experienced during the automated driving experimental session (Spearman $r = 0.32$, $p < 0.05$), and the subjective experience of realism (Spearman $r = 0.37$, $p < 0.01$). As a whole, the use of the DADS may contribute to understanding AVs acceptance across different populations and contexts, while paving the way for future studies on the barriers that still hinder the acceptance of AVs.

1. Introduction

The rapid advancement of Automated Driving (AD) technologies will radically transform transportation on our roads and highways (e.g., Tan, Zhao, & Yang, 2022; Tan et al., 2024). AD technology is typically described in terms of the level of automation and the amount of assistance required by the driver. Specifically, the Society of Automotive Engineers (SAE International, 2018) defines six

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levels of driving automation: 0 (no driving automation), 1 (driver assistance), 2 (partial driver automation), 3 (conditional driver automation), 4 (high driving automation) and 5 (fully driving automation). Automated vehicles (AVs) will be able to perform all aspects of driving without human control of the vehicle (SAE International, 2014), allowing people to work, socialize, relax and be involved in other activities while they are travelling, even if they are physically or visually impaired (e.g., Smith & Anderson, 2017). Moreover, AVs are expected to be safer and more energy efficient than current automobiles and reduce traffic congestion and insurance rates.

Positive disposition and trust in automated vehicle systems is a fundamental requisite for using, buying and taking full advantage of AVs (e.g., Yu, Bao, Zhang, Sullivan, & Flannagan, 2021). Indeed, the possibility to completely change our transportation system moving from traditional vehicles to AD will largely depend upon the positive disposition of the potential users towards AD/AV (e.g., Panagiotopoulos & Dimitrakopoulos, 2018; Xu et al., 2018a). Because there are considerable reservations about AD, understanding the individual's intentions and attitudes toward automated driving is crucial for this technological innovation to be successful (e.g., Xu et al., 2018a).

1.1. Assessing the acceptance towards AD: Available evidence and possible limitations

Numerous studies examined the acceptance towards AD across different countries (e.g., Kyriakidis, Happee, & De Winter, 2015; Tennant et al., 2019), and populations (e.g., professional drivers, lay drivers, etc. – see, for instance, Gruchmann, Grenzfurtner, & Salzmann, 2024). However, extant literature suggested that one of the major difficulties in examining AVs acceptance is related to the dearth of measures with sound and empirically evaluated psychometric properties, which are also fast and easy to administer (e.g., Tan et al., 2024). Specifically, Tan et al. (2024) suggested that development of measures for the timely study of AVs did not permit careful psychometric testing (e.g., Sanbonmatsu, Strayer, Yu, Biondi, & Cooper, 2018). Indeed, the large majority of empirical investigations relied on interviews or surveys designed *ad hoc* for the purposes of each study (e.g., Xu et al., 2018a). While being based on a tailored approach to the assessment of acceptance towards AD, this method choice may result in difficulties in comparing results across different studies and underdeveloped psychometric properties of the measures (e.g., Tan et al., 2024; Xu et al., 2018b).

Additionally, surveys used to assess disposition towards AVs are often long and time consuming (e.g., Tennant et al., 2019) making it difficult to use them in driving experimental session where assessing disposition towards AVs is only one assessment in a much larger protocol, and time may have a great impact on costs associated with experimental sessions. Against this background, the availability of short, but psychometrically sound, measures of AVs acceptance that could be administered to both large samples and during experimental sessions (e.g., during driving simulation experiments), may represent a useful addition to the extant literature allowing to gain a deeper understanding of AD acceptance.

1.2. Relevant aspects of the acceptance towards AVs

Available models, like the Technology Acceptance Model (TAM; Davis, 1989), offer theoretical frameworks to understand the acceptance towards AVs (e.g., Guo, Burke, & Griggs, 2025). According to the TAM, two main constructs are considered crucial to explain technology acceptance: perceived usefulness and ease of use. Indeed, perceived ease of use is posited to influence the attitude because it enhances the perceived sense of efficacy and personal control with regard to the ability to carry out actions needed to use AVs (Davis, 1989). Notably, previous empirical evidence suggested that additional aspects may impact the willingness to use AVs. In her *meta*-analysis of 72 studies from 54 articles (N = 32,540), Adnan (2024) showed that previous investigations showed that perceived safety is crucial for widespread adoption of AVs (e.g., Prasetio, & Nurliyana, 2023). Indeed, driving is a safety–critical activity, and entrusting safety to the automated system has been recognized as a crucial aspect in AVs adoption (see also, Xu et al., 2018b; Zhang et al., 2022). Moreover, a literature review on automated driving and acceptance (Gkartzonikas & Gkritza, 2019) suggested that specific acceptance factors such as trust, driving pleasure (e.g., Hohenberger, Spörrle, & Welpe, 2016), or safety may be useful to understand the acceptance of automated driving. The willingness to share roads with AVs represents another important aspect of disposition towards AD. Indeed, before the process of shifting from traditional mobility to AD will be completed, both AV and traditional vehicles will share the same roads (e.g., Nair & Bhat, 2021). This scenario will pose to human drivers the major challenge of sharing streets and infrastructures with other vehicles that are operated by other human beings or by computer systems. Because the SAE expected that AVs market penetration worldwide will reach 5 % by 2028 and 12 % by 2030, and other studies suggested that the automated fleet will be in the range of 50 %–75 % between 2035 and 2045 (e.g., Bierstedt et al., 2014), the willingness to sharing roads with AVs represents an important aspect of the disposition towards AD (Nair & Bhat, 2021).

1.3. Assessing AVs acceptance: Preliminary study

Against this background, to appropriately map AVs disposition construct, we carried out a preliminary investigation relying on an integrative empirical approach in order to: (a) overcome the psychometric limitations of previous measures used to assess the willingness to use AVs (e.g., Guo, Burke, & Griggs, 2025; Sanbonmatsu et al., 2018; Tan et al., 2024); and (b) develop a short measure that could be used across a wide range of contexts (e.g., large population studies, driving simulation experiments). Accordingly, we carefully evaluated the content of measures used in previous investigations of AVs acceptance, considering the results of available *meta*-analytic studies on this topic (e.g., Adnan, 2024; Zhang et al., 2022). Then, to map acceptance towards AVs, an initial item pool of 31 items assessing disposition towards AVs were written using the approach for item construction described in Clark and Watson (1995; 2019). In particular, we considered the following areas to assess the disposition towards AVs: (a) perception of AVs safety (5 items); (b) need for control while driving (7 items); (c) ease of use (7 items); (d) driving pleasure (6 items); and (e) sharing roads with AVs and traditional vehicles (6 items). For each dimension, at least two reverse-scored (i.e., items for which a high score indicates the opposite of the construct being assessed) were considered to disrupt undesirable response sets such as acquiescence (Nunnally, 1978), and to avoid careless responding due to loss of attention. Indeed, although it is known that the inclusion of both positively and negatively worded items leads to method effects (e.g., Marsh, 1996), reverse-scored items may prevent respondents from engaging in response sets in which they respond based on general feelings rather than attend to the actual item content (Barnette, 2000; Podsakoff et al., 2003; see also, Kam & Meyer, 2015). One hundred and forty community-dwelling participants were asked to complete all the 31 items. Eleven items were selected for the final version of the scale on the basis of main criteria (a) item-total correlation coefficients, and (b) avoiding explicitly redundant items based on correlation coefficients larger than 0.90 (Nunnally & Bernstein, 1994). At the end of this initial item evaluation process, 11 items were selected to assess driver's disposition towards AVs based on both item-total correlation values and exploratory factor analysis (EFA) results. In this preliminary investigation, EFA was used to identify the underlying latent dimensions and to use them as the basis for scale creation (e.g., Clark & Watson, 1995; 2019; Simms & Watson, 2007). At least one item for each of the areas considered during the item writing phase of the study was retained; five reverse-scored items were included. The item writing, initial test, and item selection process is summarized in Fig. 1. This process resulted in the development of the Disposition towards Automated Driving Scale (DADS).

1.4. The present study

Based on these premises, we designed the present study with two major purposes. Firstly, we aimed at extensively testing the psychometric properties of the DADS among community participants who were not involved in any study or experimental session on AVs/AD. Specifically, we were interested in assessing the reliability, factor validity, external validity of a set of items designed to capture different features of the disposition towards AVs. Secondly, to evaluate the actual relevance and practical utility of the newly developed measure, we carried out an experimental study using the dynamic driving simulator at the DriSMi Laboratory of Politecnico di Milano, Milan, Italy (DriSMi, 2024). The availability of the DADS will pave the way for conducting independent studies on the acceptability of AVs, allowing for comparisons across different contexts, countries, etc. relying on a sound psychometric measure for the assessment of the disposition towards AVs.

Hypotheses. In the present study, we extensively assessed the dimensionality of the newly developed measure in order to establish if the disposition towards AVs could be considered as a unidimensional or multidimensional construct. Indeed, although previous studies usually considered different aspects of the disposition towards AVs (e.g., Madigan, Louw, Wilbrink, Schieben, & Merat, 2017), recent data suggested the usefulness of general acceptance factor (e.g., de Winter & Nordhoff, 2022; Nordhoff, de Winter, Kyriakidis, van Arem, & Happee, 2018). Thus, empirical investigations focused on the dimensionality of the disposition towards AVs may prove useful

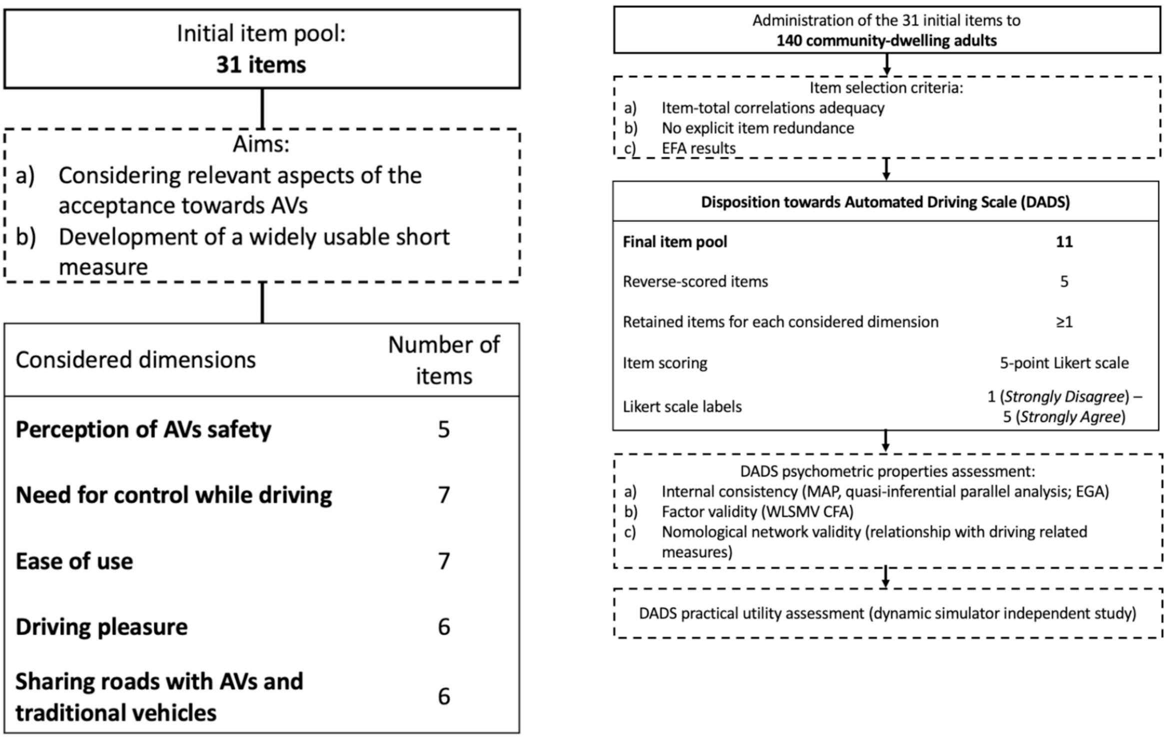

Fig. 1. Summary of the disposition towards automated driving scale item writing, initial test, and item selection process.

(e.g., de Winter & Nordhoff, 2022). Indeed, if this construct is multidimensional, different aspects should be targeted in order to affect potential users' willingness to adopt these vehicles. Based on previous investigations, we hypothesized that the DADS would show an essentially unidimensional factor structure (H1).

Additionally, we assessed the nomological network validity of the newly developed measure by evaluating its associations with selected driving-related variables (H2), aberrant driving behaviors (H3), and personality traits (H4). Indeed, previous investigations showed that the degree of acceptance of ADs is quite mixed, being dependent on both demographic characteristics (e.g., male participants are usually more likely to use AVs and have more positive attitudes compared to female participants; e.g., Classen et al., 2023; Kyriakidis et al., 2015; Qu, Xu, Ge, Sun, & Zhang, 2019), and individual differences. For instance, experiencing a wide range of negative emotions (i.e., high neuroticism; John & Srivastava, 1999) was found to have a negative impact on trust in automation (e.g., Qu et al., 2021; Skippon et al., 2016). Fig. 2 summarizes the hypothesized factor structure of the DADS scale (upper panel), and the relationships considered to assess the nomological network of the DADS (lower panel).

Finally, we administered the newly developed measure to an independent sample of participants who took part in a cable driven driving simulator study on SAE Level 4 automated vehicles (AVs) in order to evaluate the usefulness of the self-report measure in capturing relevant driving variables in an applied context. To this aim, we considered the subjective sense of presence (i.e., participant's experience) during a Level 4 driving simulation session. Indeed, sense of presence can be defined as the subjective experience of being in a real driving condition even though the person is not physically present in that environment (Witmer & Singer, 1998), and consists of three main components: (a) spatial presence, (b) involvement (i.e., the feelings of being included and acting within a specific environment), and (c) experienced realism. Based on previous studies (e.g., Cheli et al., 2022) on the associations between the sense of presence and positive emotions during driving simulation sessions using the same cable driven driving simulator that was relied on in the present investigation (i.e., DiM400), we hypothesized that higher scores on the DADS would be associated with higher scores on involvement (H5) and experienced realism (H6) measures (i.e., measures of appreciation of the Level 4 driving simulation session). Fig. 3 displays the hypothesized relationships.

2. Materials and method

2.1. Participants

2.1.1. Main sample

The sample was composed of 590 Italian community-dwelling adult participants; to be included in the sample, participants had to have been in possession of a car driver's license. Two hundred ninety-five (50.0 %) participants were female, and 295 (50.0 %) participants were male; participants' mean age was 36.83 years (SD = 15.80 years; age range: 18 years – 80 years). The main participant demographic characteristics are summarized in Table 1.

2.1.2. Driving simulation experimental sample

Participants were 55 University students (65.5 % male, n = 36), who had no previous experience with the dynamic driving

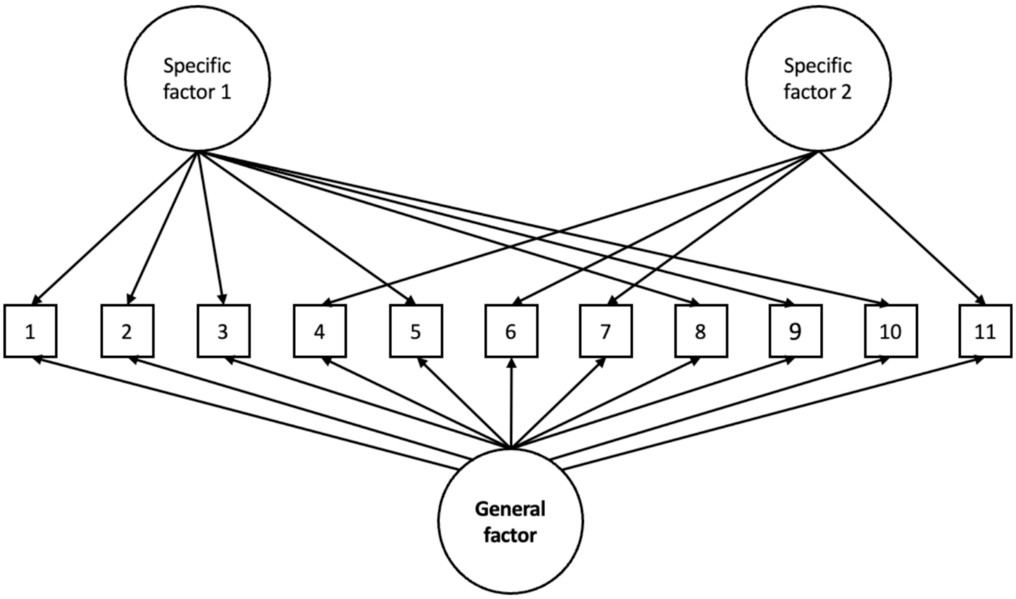

Fig. 2. Hypothesized factor structure of the disposition towards automated driving scale (H1). Nomological network validity of the disposition towards automated driving scale.

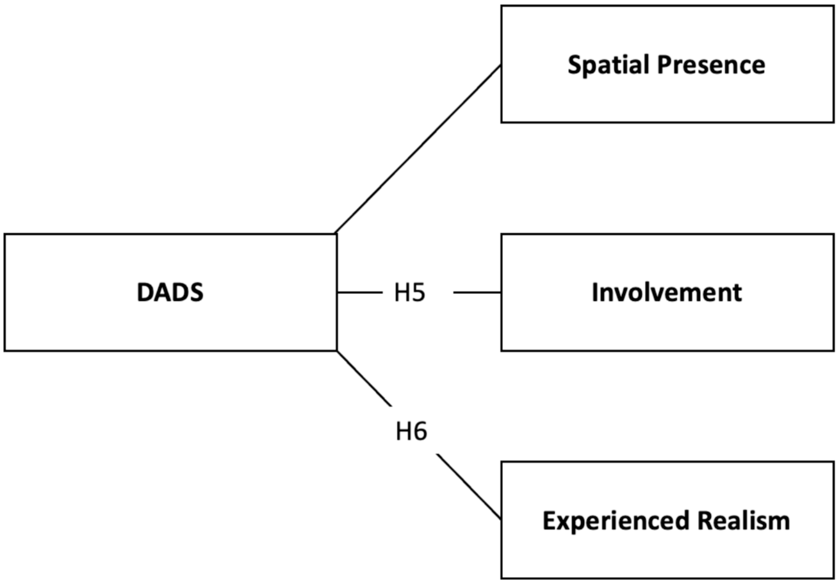

Fig. 3. Driving simulation experiment: constructs considered and specific hypotheses.

simulator and Level 4 driving. All participants had normal or corrected-to-normal vision. Age ranges from 19 to 29 years, with a mean age of 23.90 years, *SD* = 2.08 years. Driving license years vary from 41 to 15 (*M* = 5.66, *SD* = 2.50). All subjects were briefed on the take-over modalities and the safety rules. A technician attended the simulation in the passenger seat, handling the onboard sensors' initialization and verifying their correct functioning during the test.

2.2. Procedures

All participants completed the study online using Online Surveys Jisc, an online survey tool designed for academic research (https://www.onlinesurveys.ac.uk/); participants volunteered to take part in the study receiving no economic incentive or academic credit for their participation. To be included in the sample, participants had to document that they were of adult age (i.e., 18 years of age or older). Moreover, participants agreed to online written informed consent in which the study was extensively described. All procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and were performed in accordance with the 1964 Declaration of Helsinki and its later amendments.

2.2.1. Experimental study testbed procedures

Participants completed questionnaire assessing demographic characteristics and the DADS before starting the driving simulation session; after completing the pre-test assessment participants were given at least a 5 min. to familiarize with the driving simulator. The dynamic driving simulator installed at the DriSMi laboratory of Politecnico di Milano (DriSMI, 2024) was used for the Level 4 driving

Table 1
Demographic characteristics of participants (N = 590).

Demographic characteristics	*N* (%)
Education level	
Junior High School Degree	24 (3.9 %)
High School Degree	238 (40.3 %)
University Degree	290 (49.2 %)
Post-Graduate Degree	39 (6.6 %)
Civil Status	
Unmarried	329 (55.8 %)
Married	238 (40.3 %)
Divorced	17 (2.9 %)
Widow/-er	4 (0.7 %)
Refused to Report	2 (0.3 %)
Job	
Employed	555 (94.1 %)
Unemployed	13 (2.2 %)
Retired	19 (3.2 %)
Refused to Report	3 (0.5 %)

session study. The simulator features a two-stage motion system combining the low frequency in plane motion of a cable driven platform with the higher frequency spatial motion of a hexapod located on the platform (see Supplementary Fig. 1). Eight shakers are also present to provide very high frequency vibration. This arrangement allows for providing the driver with a realistic feedback of the motion of the vehicle. This feeling is enhanced by haptic feedback from active seat belts, brake pedal, and steering wheel. A five-speaker system reproducing noise sources inside and outside the vehicle and a 270° wide high-definition screen, on which real-world scenarios are projected, complete the simulation environment and guarantee realism during tests. A detailed description of the dynamic driving simulator is provided in the Supplementary Material. The driving scenario represented different environments. After completing the simulation session, participants were requested to fill in questionnaires assessing the L4 driving experience.

2.3. Measures

2.3.1. Disposition towards automated driving scale (DADS)

The DADS is an 11-item scale designed to assess driver's disposition towards AVs. The development of the measure, as well as is content is summarized in the Introduction section. Each DADS item was rated on a 5-point Likert scale ranging from *1* (*Strongly Disagree*) to *5* (*Strongly Agree*). Items were summed and averaged to yield the DADS total score, the higher the DADS total score, the higher the driver's positive disposition towards automated vehicles. The DADS scale is provided in the Supplementary Material.

2.4. Main sample measures

2.4.1. Driver behavior questionnaire (DBQ; Reason et al., 1990)

The DBQ is a widely used self-report measure developed to assess different types of self-reported aberrant driving behaviors. Although different versions and factor structures of the DBQ have been proposed, previous investigations supported the four-factor structure of the DBQ (e.g., Åberg & Rimmö, 1998), also for the Italian context (e.g., Smorti & Guarnieri, 2016; Spano et al., 2019). Specifically, the DBQ allows to assess Aggressive Violations (i.e., interpersonal aggressive component), Ordinary Violations (i.e., behaviors such as speeding or overtaking on the inside), Errors (i.e., behaviors such as not noticing pedestrians crossing or not checking mirrors), and Lapses (i.e., behaviors such as forgetting where one's car is parked or driving away in third gear). Previous *meta*-analyses showed that the DBQ represents a useful instrument to predict involvement in a road traffic collision (e.g., de Winter & Dodou 2010), and the preeminent role of errors and violations, in predicting self-reported accidents and recorded violations (e.g., De Winter, Dodou, & Stanton, 2015).

2.4.2. Big five Inventory (BFI; John & Srivastava, 1999)

The BFI consists of 44 items which are rated on a five-point Likert scale from 1 ("disagree a lot") to 5 ("agree a lot"). The BFI items are assigned to five scales measuring Extraversion (8 items), Agreeableness (9 items), Conscientiousness (9 items), Neuroticism (8 items), and Openness to experience (10 items). The BFI showed adequate psychometric properties also in its Italian translation (Fossati, Borroni, Marchione, & Maffei, 2011).

2.4.3. Driving variables

Participants were asked to report the number of years of driving experience, the self-reported number of car accidents, and to what degree they were interested in driving cars on a Likert-type scale ranging from *1* = "*Not interest at all*" o *5* = "*Highly interested*".

3. Driving simulation experimental sample

3.0.1. Presence questionnaire (PQ; Almallah et al., 2021)

The PQ consists of 13 items meant to assess the subjective sense of presence (i.e., participant's experience) during the Level 4 driving simulation session. The PQ items are assigned to three scales, Spatial Presence (i.e., sense of being physically present), Involvement (i.e., attention and involvement experienced during the driving experience), and Experienced Realism (i.e., subjective experience of realism). In the present experimental sample, Cronbach's alpha values for the Spatial Presence, Involvement, and Experienced Realism were 0.70, 0.72, and 0.71, respectively.

3.1. Data analysis

Spearman r coefficient was used to assess the relationships between continuous variables; polychoric correlation coefficient was computed to assess the associations between ordinal variables. Minimum average partial (MAP; Zwick & Velicer, 1986) and quasi-inferential parallel analysis (Buja & Eyuboglu, 1992) were used as traditional methods for dimensionality analysis. Parallel analysis requires that the eigenvalues of a correlation matrix of P random uncorrelated variables should be contrasted with those of the data set in question based on the same sample size (Zwick & Velicer, 1986). Quasi-inferential parallel analysis makes use of the full null distribution, using upper 5 % or 1 % null quantiles instead of means, which may reduce some liberal tendencies of parallel analysis (e.g., extraction of minor components; Buja & Eyuboglu, 1992). Following Buja and Eyuboglu's (1992) suggestions, the determination of quantile-based p-values for DADS item correlation matrix eigenvalues was based on 1,000 independent correlation matrices that were obtained by random permutations of the original data. Monte Carlo studies have shown that parallel analysis is the most efficient method for recovering the correct number of factors (Zwick & Velicer, 1986).

As a further non redundant dimensionality analysis, we relied on exploratory graph analysis (EGA; Golino & Epskamp, 2017). EGA is a method for dimensionality assessment which produces a visual guide (i.e., network plot), that indicates the number of dimensions to retain. EGA combines the Gaussian graphical model (Lauritzen, 1996), with the Walktrap algorithm (Pons & Latapy, 2006) for community detection on weighted networks to assess the dimensionality. In EGA models, nodes (i.e., circles) represent variables and edges (i.e., lines) represent associations between the nodes. The EGA approach currently uses two network estimation methods (for a review, see Golino et al., 2020), namely, graphical least absolute shrinkage and selection operator (GLASSO; Friedman, Hastie, & Tibshirani, 2008) and triangulated maximally filtered graph (TMFG; Massara, Di Matteo, & Aste, 2016). In the present study, in line with the results of Golino and colleagues' (2021) simulation study, we relied on Von Neumann Entropy (EFI.vn) to compare the results of graphical least absolute shrinkage and selection operator EGA (EGA_{GLASSO}) and triangulated maximally filtered graph EGA (EGA_{TMFG}); specifically, we selected the model with the lowest TEFI.vn (Golino et al., 2021). Moreover, to estimate the stability of dimensions identified by EGA, we relied on Bootstrap EGA (bootEGA; Christensen & Golino, 2021a), which allows to evaluate the stability of EGA results across bootstrapped EGA results. In the present study, we relied on the non-parametric bootEGA procedure that is implemented by resampling with replacement from the empirical dataset; in particular, we relied on 1,000 bootstrap samples. Structural consistency, defined as the extent to which each empirically derived dimension has an identical variable composition recovered from the replicate bootstrap samples (Christensen, Golino, & Silvia, 2020); values of structural consistency and item stability greater than 0.75 were considered as indicators of sufficient stability (Christensen & Golino, 2021b).

The latent structure of DADS items was firstly evaluated by fitting a weighted least square mean-and-variance adjusted (WLSMV) confirmatory factor analysis of the DADS polychoric correlation matrix. A one-factor model of the DADS items, in which all items were expected to load on the same factor was estimated, as well as a multidimensional factor model based on dimensionality results. Following Hu and Bentler's (1999) suggestions and cut-off scores, we used several measures to identify model fit. Specifically, the model fit was evaluated using the χ^2 test, the comparative (CFI) and Tucker-Lewis (TLI) fit indices, and the standardized root mean square residual (SRMSR). Consistent with Hu and Bentler's (1999) indications, we used the following cut-off values to evaluate the model fit: a TLI/CFI of 0.90 and higher are indications of an adequate fit, while a TLI/CFI of 0.95 and higher are indications of a good fit. It has been suggested that a SRMSR lower than 0.08 indicates good fit (Hu & Bentler, 1999).

In recent years, the bifactor model (Holzinger & Swineford, 1937) has gained attention as an alternative for accommodating method effects (e.g., Rodriguez, Reise, & Haviland, 2016). A bifactor model represents a special case of the correlated-traits correlated-methods model, which is used to examine method effects (Bollen & Hoyle, 2012; Gu et al., 2015). In our study, we relied on bifactor modeling for evaluating the feasibility of the assumption of multidimensionality of the DADS items in the presence of inconclusive dimensionality analysis findings. Specifically, we formally assessed the possibility to reject a strict unidimensional model in favor of a bifactor model of the DADS items that explicitly models method effects (e.g., item wording). According to the bifactor modeling approach, a single latent factor of AVs acceptance is proposed to explain the majority of item covariation, whereas other grouping latent factors arising as a consequence of item covariation occurring due to the positive and negative wording of the items can also be modeled (e.g., Rodriguez et al., 2016). The bifactor modelling approach, therefore, has the advantage of being capable of distinguishing error variance and method variance among the observable indicators, allowing for a deeper investigation of the dimensionality of the DADS.

Because findings of multidimensionality do not guarantee that possible subscales can provide meaningful and reliable information about subdomains that is unique from the general construct, we estimated the percentage of variance in observed scores due to variance on a single common latent variable (i.e., the target construct). To this aim, we tested a WLSMV bifactor model of the DADS item polychoric correlation matrix. If model fit indices suggested inadequate fit for the CFA model, we fitted a WLSMV confirmatory bifactor model, with a DADS general factor, as well as specific factors condensing method variance. In our confirmatory bifactor models, specific factors were constrained to be orthogonal with respect to each other and the general factor. Then, we computed the proportion of total score variance that can be attributed to a single common factor (i.e., ω-hierarchical coefficient). Additionally, we estimated the reliability of subscale scores and the degree to which subscales provide reliable information that is unique from the general factor (Reise et al., 2013). The estimate of reliability for a subscale after controlling for the general factor is indexed by ω_h-specific coefficient (Reise et al., 2013). To assess if the DADS item confirmatory bifactor analysis results suggested that the measure was essentially unidimensional (i.e., the measure essentially measures one dimension, even when other dimensions are identified; Nandakumar & Ackerman, 2004), we calculated the explained common variance (i.e., the proportion of all common variance that is explained by the factor) of the general factor and the specific factors (Rodriguez et al., 2016). Rodriguez et al. (2016) indicated that when ECV value is greater than 0.70 the common variance can be regarded as essentially unidimensional. Rather, when general ECV values are greater than 0.60 and ω_h values for the general factor are greater than 0.70, the presence of some multidimensionality is not severe enough to disqualify the interpretation of the instrument as primarily unidimensional (Reise et al., 2013). Finally, the *H* index (Hancock & Mueller, 2001) and factor determinacy index (FD; Gorsuch, 1983) were computed to assess the construct replicability and the correlation between factor scores and factors for the general factor, as well as for the specific factors. *H* index values greater than 0.80 are indicative of well-defined latent variables (Gorsuch, 1983); rather, factor score estimates should be used only when FD values are greater than 0.90 (Gorsuch, 1983).

4. Results

4.1. Dimensionality analysis results

Table 2 summarizes the dimensionality analysis (i.e., quasi-inferential parallel analysis and MAP statistic) results of the DADS item polychoric correlation matrix. The polychoric correlations among the 11 DADS items are summarized in Table S1 in the Supplementary Materials. Although quasi-inferential parallel analysis suggested that two factors should be retained for further analyses, the MAP static values clearly supported the unidimensional model of the DADS items. EGA dimensionality results are summarized in Fig. 4. According to TEFI.vn fit index, the EGA_{TMFG} model was provided with better fit (i.e., lower TEFI.vn value = −6.29) than EGA_{GLASSO} model; as it can be observed in Fig. 4 (top panel), the EGA_{TMFG} model supported a two-dimensional latent structure of the 11 DADS items. However, EGA stability analyses of the DADS item based on 1,000 bootstrap replications of the original data showed that two latent dimensions were not stable, as suggested by values of structural consistency of 0.28 for dimension 1 and 0.73 for dimension 2. Similarly, low item stability coefficient values were observed for DADS item 1, item 2, and item 5 (see Fig. 4, bottom panel). These findings seemed to suggest that the two-dimensional structure identified by EGA_{TMFG} may be non-replicable because it may account for method issues (e.g., distributional artifacts, item wording).

4.2. Factor analysis results

Because dimensionality analysis results were inconclusive in supporting the dimensionality of the 11 DADS items, we formally tested the goodness-of-fit of three competing models of DADS item latent structure in WLSMV CFA of the item polychoric correlation matrix. Namely, we fitted the following models: a) a one-factor model of the DADS items, in which all items were expected to load on the same factor; b) a two correlated factor model based on EGA stability analysis results, in which DADS item 4, item 6, item 7, and item 11 were assigned to one factor, whereas the remaining DADS items were forced to load on the other factor; and c) a bifactor model with one general factor and two orthogonal specific factors, which were defined according to EGA stability analysis results (see Fig. 4, bottom), and were expected to condense only method variance. Because our bifactor model was not nested in our two correlated factor model, the difference in CFI values was used to assess improvement in model fit (Cheung & Rensvold, 2002). Goodness-of-fit statistic values of the three WLSMV CFA models of the DADS item latent structure are reported in Table 3. As it can be observed, goodness-of-fit statistic values suggested inadequate fit for the one-factor model of the DADS items; rather, both two correlated factors model and bifactor model of the DADS items showed adequate goodness-of-fit statistic values. Interestingly, the difference between the CFI value for the bifactor model and the CFI value for the two correlated factor model was as large as 0.026, suggesting that the bifactor model should be retained as the best fitting model. The bifactor model specifies that correlations among DADS items can be accounted for by: (a) a general factor representing shared variance among all the items (i.e., AVs acceptance); and (b) group factors accounting for shared variance among subsets of items over and above the general factor (e.g., item wording). Fig. 5 summarized the standardized factor loading values of the DADS items for the best fitting model (i.e., bifactor model).

4.3. Model-based reliability analysis results

The standardized factor loadings explained common variance, omega-hierarchical coefficient values, omega-hierarchical specific coefficient values, *H* coefficient values, and FD coefficient values for the general factor and specific (i.e., method) factor of our bifactor model of the 11 DADS items are summarized in Table 4. The explained common variance value greater than 0.70 and the omega-hierarchical coefficient value greater than 0.80 for the general factor in our WLSMV CFA bifactor model suggested that the presence of some multidimensionality was not severe enough to disqualify the interpretation of the DADS as primarily unidimensional (Reise et al., 2013).

DADS item descriptive statistics, item-total correlations corrected for part-whole overlap, mean inter-item correlation, and Cronbach's alpha value for the DADS total score are reported in Table 5. All item-total *r* values corrected for part-whole overlap were greater than 0.30, whereas both mean inter-item *r* and Cronbach's alpha coefficient values suggested adequate reliability for the DADS total score (Nunnally & Bernstein, 1994; Clark & Watson, 1995; 2019). According to Shapiro-Wilks test results, in our study the

Table 2
Disposition towards automated driving scale items: dimensionality analyses of the item polychoric correlation matrix (N = 590).

Eigenvalue Number			Random Eigenvalues Based on 1,000 Permutation of the Original Data	Minimum Average Partial Dimensionality	
	Real Data	Average Eigenvalue	Upper 95th Percentile	Number of Dimensions	Minimum Average Partial Statistic
1	5.43*	1.25	1.31	1	0.04*
2	1.30*	1.18	1.22	2	0.05
3	0.92	1.13	1.16	3	0.17
4	0.63	1.08	1.11	4	1.00
5	0.61	1.04	1.07	5	–-
6	0.54	1.00	1.03	6	–-
7	0.43	0.96	0.99	7	–-
8	0.38	0.91	0.94	8	–-
9	0.33	0.87	0.91	9	–-
10	0.23	0.83	0.87	10	–-
11	0.21	0.77	0.82	11	–-

Note. *: Number of factors that should be retained for further analyses; –-: Statistic not computed.

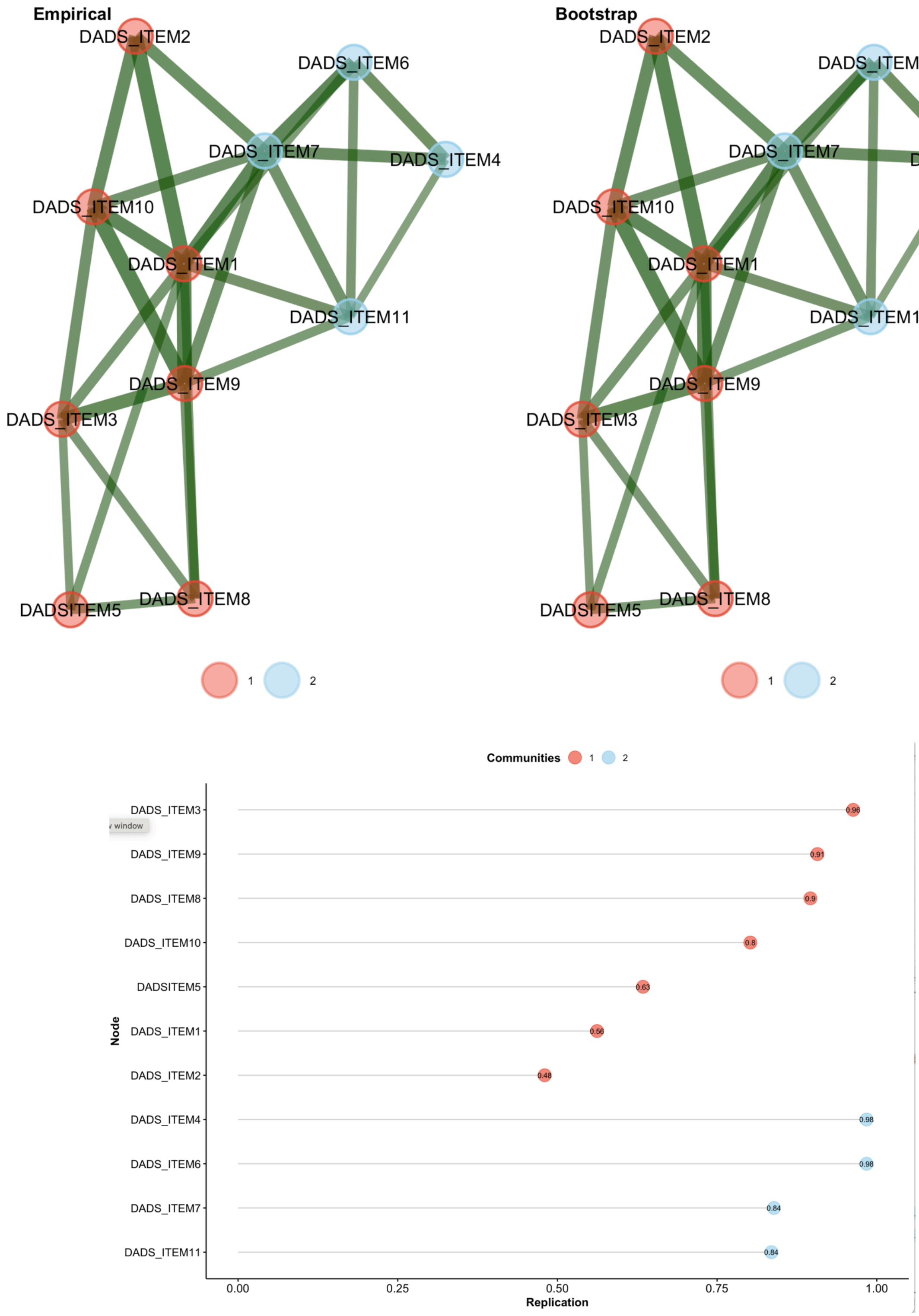

Fig. 4. Exploratory graph analysis dimensionality assessment of the disposition towards automated driving scale. Note. Triangulated maximally filtered graph (TMFG) best fitting model based on total entropy fit index is displayed on top on the left side, and TMFG best fitting model based on stability analyses (averaged over 1,000 bootstrap replications) is displayed on top on the right side. Item stability analysis results are displayed at the bottom of the figure.

Table 3
Weighted least square mean and variance adjusted confirmatory factor analyses of the disposition towards automated driving scale item polychoric correlation matrix: goodness-of-fit statistics (N = 590).

Models	χ^2 (*df*)	Comparative Fit Index	Tucker-Lewis Index	Standardized Root Mean Square Residual
One-factor model	749.546 (44)***	0.897	0.871	0.063
Two correlated factors model	374.893 (43)***	0.952	0.938	0.044
Bifactor model (one general factor and two orthogonal specific factors)	185.128 (33)***	0.978	0.963	0.030

Note. *** $p < 0.001$.

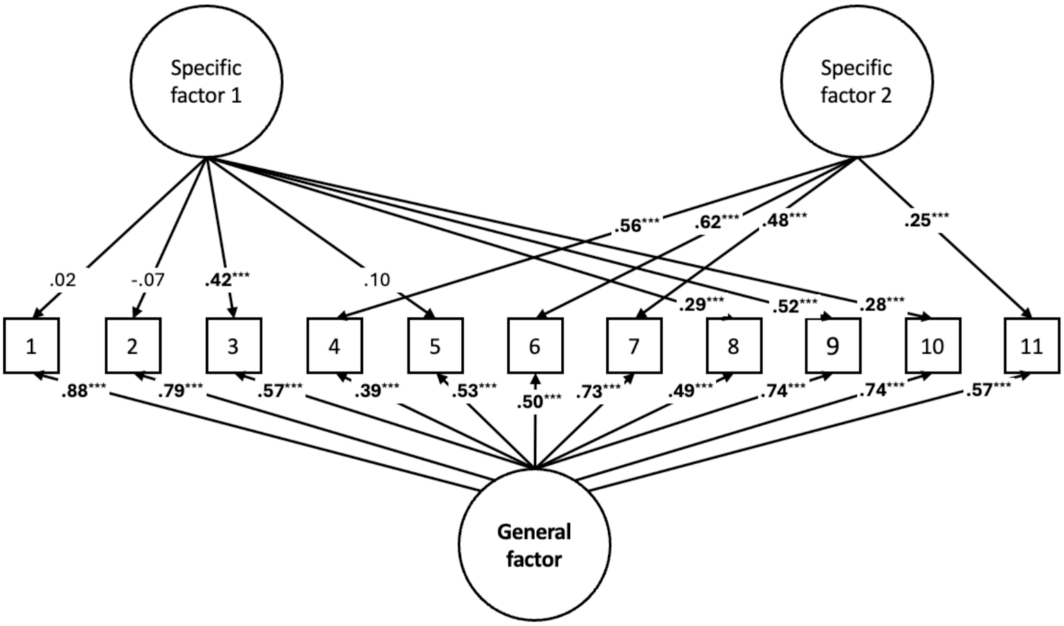

Fig. 5. Standardized factor loading values of the disposition towards automated driving items.

Table 4
Weighted least square mean and variance adjusted confirmatory factor analysis bifactor model of the 11 disposition towards automated driving scale items: standardized factor loadings explained common variance, omega-hierarchical coefficient values, omega-hierarchical specific coefficient values, H coefficient values, and factor determinacy coefficient values (N = 590*)*.

Disposition Towards Automated Driving Scale Items	General Factor	Specific Factor 1	Specific Factor 2
Item 1	0.88***	0.02	–-
Item 2 (Reverse scored item)	0.79***	−0.07	–-
Item 3 (Reverse scored item)	0.57***	0.42***	–-
Item 4	0.39***	–-	0.56***
Item 5 (Reverse scored item)	0.53***	0.10	–-
Item 6	0.50***	–-	0.62***
Item 7	0.73***	–-	0.48***
Item 8 (Reverse scored item)	0.49***	0.29***	–-
Item 9 (Reverse scored item)	0.74***	0.52***	–-
Item 10	0.74***	0.28***	–-
Item 11	0.57***	–-	0.25***
Explained common variance	0.740	0.100	0.159
Omega-hierarchical/specific coefficient	0.816	0.087	0.358
H coefficient	0.916	0.437	0.591
Factor determinacy coefficient	0.948	0.756	0.816

Note. –-: Parameter fixed at 0.00; *** $p < 0.001$.

distribution of the DADS total score seemed to deviate significantly, albeit slightly from the normal distribution, Shapiro-Wilks static = 0.995, $p < 0.05$.

4.4. Nomological network validity results

4.4.1. Driving-related variables

In our sample, the DADS total score showed a significant, albeit modest association with the one-item self-report measure of subject's interest in car driving (*Mdn* = 4.00, inter-quartile range = 3, 5; min. value = 1.00 (["no interest at all"], 5.00 ["highly interested]), Spearman $r = -0.11$, $p < 0.01$. Rather, in our sample no significant association has been observed between the DADS total score, and the self-reported number of years of driving experience ($M = 17.73$, *Mdn* = 11.00, $SD = 15.27$, Shapiro-Wilks statistic = 0.876, $p < 0.001$), Spearman $r = -0.04$, $p > 0.30$, and self-reported number of car accidents ($M = 0.22$, *Mdn* = 0.00, $SD = 0.97$, Shapiro-Wilks statistic = 0.197, $p < 0.001$), Spearman $r = 0.02$, $p > 0.60$.

4.4.2. Aberrant driving behaviors and personality traits

The descriptive statistics and reliability estimates (i.e., Cronbach's α coefficient) for the DBQ and BFI scale scores, as well as their bivariate associations (i.e., Spearman r values) with the DSDS total score are summarized in Table 6. In our sample, all DBQ scale scores were non-normally distributed, with Shapiro-Wilks statistic values ranging from 0.780 (DBQ Errors scale score) to 0.940 (DBQ Ordinary Violations scale score), all *ps* < 0.001. The four DBQ scale scores were non-trivially interrelated, with Spearman *r* values ranging from 0.20 (aggressive Violations scale scores and Lapses scale scores) to 0.58 (Errors scale scores and Lapses scale scores), all *ps* < 0.001.

Among our participants, BFI scale scores showed slight, albeit significant departures from the normal distribution, as it was indicated by Shapiro-Wilks statistic values ranging from 0.978 (BFI Conscientiousness scale score) to 0.994 (BFI Neuroticisms scale score), all *ps* < 0.05. Except for BFI Openness and BFI Neuroticism scale score, Spearman $r = -0.03$, $p > 0.40$, all other BFI scale scores were significantly inter-correlated, with Spearman *r* values ranging from -0.33, $p < 0.001$ (BFI Conscientiousness and BFI neuroticism sale scores) to 0.25, $p < 0.001$ (BFI Conscientiousness and BFI Agreeableness scale scores). A summary presentation of these findings is depicted in Fig. 6.

4.5. Experimental driving simulation validity results

In the experimental sample, the DADS total score showed adequate internal consistency (mean inter-item correlation = 0.25; Cronbach's $\alpha = 0.79$), as well as significant association with the SP Involvement scale (Spearman $r = 0.32$, $p < 0.05$), and SP Experiences Realism scale (Spearman $r = 0.37$, $p < 0.01$). Rather, no significant association with the SP Spatial presence scale was observed, Spearman $r = -0.13$, $p > 0.30$.

5. Discussion

To the best of our knowledge, the present study represents the first attempt at developing a short measure for assessing subject's disposition towards automated driving; specifically, our measure was designed independently from a specific study, and usable across different contexts. Although the relatively limited size of our sample suggests considering our findings as preliminary in nature, our results seemed to indicate that the DADS represents an easy-to-administer self-report questionnaire with adequate psychometric properties. Additionally, in our study, we were able to provide some evidence for the practical usefulness of the DADS in a Level 4

Table 5
Disposition towards automated driving scale items: descriptive statistics, item-total r coefficient values corrected for part whole overlap, scale descriptive statistics, mean inter-item correlation and Cronbach's alpha coefficient value (N = 590).

Disposition Towards Automated Driving Scale Items	*M*	*SD*	$r_{i\text{-}t}$
Item 1	2.54	1.21	0.73
Item 2 (Reverse scored item)	2.49	1.04	0.63
Item 3 (Reverse scored item)	2.19	0.95	0.53
Item 4	3.59	0.94	0.44
Item 5 (Reverse scored item)	2.63	0.98	0.47
Item 6	3.12	1.01	0.54
Item 7	3.22	0.99	0.72
Item 8 (Reverse scored item)	2.31	0.77	0.45
Item 9 (Reverse scored item)	2.29	0.99	0.67
Item 10	2.30	1.01	0.65
Item 11	3.05	1.04	0.54
DADS Total Score *M*	29.72		
DADS Total Score *SD*	7.32		
DADS Mean Inter-Item *r*	0.39		
DADS Cronbach's Alpha Coefficient Value	0.87		

Note. DADS: Disposition Towards Automated Driving Scale; $r_{i\text{-}t}$: Item-total *r* coefficient values corrected for part whole overlap.

Table 6
Descriptive statistics and reliability estimates (i.e., *Cronbach's α* Values) for the driver behavior questionnaire and big five inventory scale scores, as well as their bivariate associations (i.e., spearman r values) with the disposition towards automated driving scale total score (N = 590).

Aberrant Driving Behaviors and Personality Traits	Disposition towards Automated Driving Scale Total Score			
	M	*SD*	*α*	Spearman *r*
Driver Behavior Questionnaire				
Aggressive violations	0.96	0.95	0.71	−0.13*
Ordinary Violations	1.17	0.82	0.81	0.05
Errors	0.44	0.50	0.81	0.04
Lapses	0.90	0.63	0.74	−0.03
Big Five Inventory				
Openness to Experience	36.96	6.03	0.80	0.10
Conscientiousness	35.18	5.60	0.82	−0.10
Extraversion	25.76	5.78	0.83	0.00
Agreeableness	32.93	5.16	0.72	−0.03
Neuroticism	24.26	6.01	0.83	−0.14**

Note. In testing the associations between the Disposition towards Automated Driving Scale (DADS) total score and the Driver Behavior Questionnaire scale scores, we corrected the nominal significance level (i.e., p <.05) for Spearman r coefficient according to the Bonferroni procedure and set it at p <.0125. Similarly, the nominal significance level (i.e., p <.05) for the relationships (i.e., Spearman r coefficients) between the DADS total score and the five Big Five Inventory scale scores was corrected according to the Bonferroni procedure and set at p <.01.
* p <.0125
** p <.01

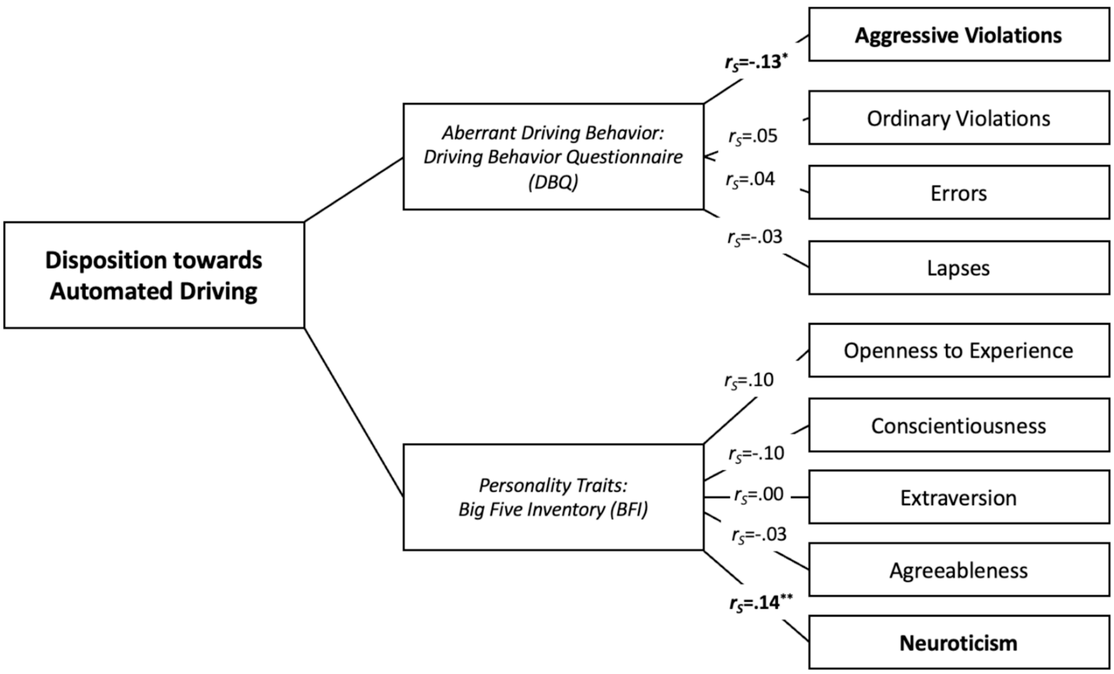

Fig. 6. Associations between the disposition towards automated driving scale tital scores and aberrant driving behavior and personality traits, respectively.

driving simulation session carried out using a cable-driven driving simulator. Thus, one of the advantages of developing the DADS was related to the possibility to reach a variety of potential AVs users, assessing their willingness to rely on AVs for their transportation needs in a very limited amount of time (e.g., Nastjuk et al., 2020).

5.1. Psychometric properties of the DADS

Our method choice to include five (45.5 %) reverse-scored items in developing the DADS aimed at improving subject's attention while completing the measure; however, it may have the potential for generating extra-factors condensing method variance, i.e., spurious co-occurrences among the items because of shared negative wording (DeMars, 2013). Moreover, it should be considered that also distribution artifacts related to item skewness and/or frequency may be responsible for method factors in item-level factor analyses (Nunnally & Bernstein, 1994). Thus, in our study it was not surprising to observe inconclusive findings in both EGA and traditional (i.e., quasi-inferential parallel analysis and MAP statistic) dimensionality analyses; indeed, quasi-inferential parallel analysis and EGA model based on 1,000 bootstrap replication suggested that two latent dimensions explained the correlations among the 11 DADS items, whereas MAP and EGA model based on TEFI.vn supported our one-factor model of the DADS items. Interestingly, it should be observed that in our quasi-inferential parallel analysis, we considered both the average and the upper 5 % quantile of the full null distribution of eigenvalues in order to decide the number of factors to be retained in factor analyses. Although relying on quasi-inferential parallel analysis proved to be useful in correcting the liberal tendency of Horn's parallel analysis (i.e., effective significance level of approximately 50 %), future studies may consider relying on a more stringent significance level (i.e., using a higher quantile; Buja & Eyuboglu, 1992).

To account for the differences observed in dimensionality analysis results, we tested three alternative models of the DADS item latent structure: a) a unidimensional (i.e., one-factor) model; b) a two correlated factor model, in which the item-to-factor assignment rule was based on the EGA model based on 1,000 bootstrap replications; and c) a bifactor model, in which all DADS items were expected to be influenced by the same general factor, while two orthogonal specific factors (based on the EGA model based on 1,000 bootstrap replications) were expected to condense only spurious method correlations. Although we observed sub-optimal fit static values for the one-factor model and adequate goodness-of-fit index values for the two correlated factor model of the DADS items, the difference in CFI values suggested to retain the bifactor model as the best fitting model of the DADS item latent structure. Interestingly, all DADS items showed significant, positive and substantial (i.e., greater than 0.30) standardized factor loading values on the general factor (H1). When we relied upon Reise and colleagues' (2013) approach to evaluate if both general factors and specific factors condensed reliable variance, both in terms of model-based reliability (i.e., omega-hierarchical/omega-hierarchical specific value $>$ 0.70) and factor determinacy (i.e., H coefficient value $>$ 0.80 and FD value $>$ 0.90), in our study only the DADS item general factor proved to be provided with both model-based scale and factor reliabilities. In addition, in our study we observed an omega-hierarchical coefficient value $>$ 0.80 and an ECV value $>$ 0.70 for the DADS item general factor; this finding seemed to suggest that the presence of some multidimensionality was not severe enough to disqualify the interpretation of the DADS as primarily unidimensional (Reise, Bonifay, & Haviland, 2013). This finding was consistent with the possible method artifacts introduced by reverse scored items (e.g., Marsh et al., 2010).

Consistent with standardized factor loading values on the general factor that were observed in our WLSMV CFA bifactor model, item-total correlations, corrected for part-whole overlap were substantial and positive, suggesting no validity problem with the 11 DADS items. Extending our data on model-based reliability estimates of the DADS item factor scale, our results suggested adequate reliability also for the DADS raw scores, both in terms of mean inter-item correlation, which laid in the $0.15 - 0.50$ range for internally consistent measures (Clark & Watson, 1995, 2019), and Cronbach's alpha coefficient value, which was well above the 0.70 cut-off that is usually reported in the literature for adequate reliability (Nunnally & Bernstein, 1994). As a whole, these data suggest that the DADS is likely to represent a structurally sound, reliable self-report instrument, purportedly assessing subject's disposition towards automated driving.

Interestingly, in our sample the DADS total score showed significant, albeit weak correlations with selected external variables indexing driving behavior and personality dimensions, respectively. In particular, a positive disposition towards automated driving seemed to be negatively related to the driver's tendency to engage in aggressive violations to traffic rules, e.g., disregard of the speed limit on residential roads, sounding horn to indicate annoyance to another road user, etc. Although the corresponding effect size was in the small-to-moderate range by conventional standards (Cohen, 1988), the theoretical relevance of this association should not be neglected, because aggressive violations, at least as they were operationalized in the DBQ, were shown to be associated with self-reported accidents and recorded vehicle speed in previous *meta*-analyses (e.g., De Winter et al., 2015). Interestingly, in our sample the DADS total score was not associated with the number of accidents; this finding is consistent with previous interview-based studies showing that safe driving is usually a positive predictor of the acceptance of automated vehicles. Moreover, in our study, the DADS total score was negatively and significantly, albeit weakly, with subject's pleasure in car driving, while showing no significant relationships with the number of self-reported car accidents, interest in driving, and the number of years of driving experience. On the one hand, these findings seem to suggest that the length of driving experience and the pleasure in car driving do not have a meaningful relationship with disposition towards automated driving, providing useful information regarding variables that could be omitted in order to improve potential users' interest in AVs. On the other hand, our results should be also considered in the light of some method considerations. Indeed, our self-report measure of interest in driving is a single item instrument and it might not capture the full complexity of an individual's attitude towards driving; thus, future studies on this topic are needed. As a whole, these data indicate that disposition towards automated driving, at least as it was operationalized in the DADS total score, showed meaningful relationships with selected driving behavior dimensions, while being largely dissociable from other constructs related to driving, at least as they were operationalized in our study.

Finally, subject's specific personality dimensions seemed to be significantly, albeit modestly related to their self-reported disposition towards automated driving, at least as it was operationalized in the DADS total score. Consistent with previous investigations (Devaraj, Easley, & Crant, 2008; Qu, Sun, & Ge, 2021) in our sample low scores on BFI Neuroticism scale were selectively and significantly, albeit modestly correlated with high levels of DADS total score. In other words, participants who were positively inclined towards automated driving (i.e., scoring high on the DADS total score) were more prone to be calm, not easily upset, and emotionally stable (i.e., scoring low on BFI Neuroticism scale). Although self-reported disposition towards automated driving was significantly associated with a selected personality profile, our data indicated that the effect size for this association was small enough to suggest substantial dissociability of the two constructs. Notably, the effect size for this association was consistent with previous investigations (e.g., Qu et al., 2021; Skippon et al., 2016), suggesting that different aspects seemed to play a small, albeit significant, role in AVs acceptance.

5.2. Practical utility of the newly developed measure

Despite their preliminary nature, the results of the Level 4 driving simulation session seemed to provide additional evidence for the practical usefulness of the DADS scale. Indeed, in our experimental sample, the DADS total score was significantly associated with measures of involvement in the Level 4 driving experience and subjective experience of realism during the driving simulation session. In other terms, the DADS scores were significantly associated with indicators of enjoyment of the Level 4 driving session, suggesting its potential practical usefulness in predicting the behaviors of drivers who had no previous experience with Level 4 driving. These findings provided initial evidence for the usefulness of the DADS in applied contexts and its usability for the prediction of real-life behaviors.

5.3. Limitations

Of course, our findings should be considered in the light of several limitations. Although we relied on a moderately large community-dwelling adult sample, it was composed of adults who volunteered to participate in the study. Thus, it represents a convenient study group rather than a sample representative of the Italian population. Moreover, participants were volunteers who received no incentive for taking part in the research. Future studies based on representative samples are needed.

In our research, we were interested in developing a short measure in order to provide interested readers with a quick and efficient self-report measure of acceptance towards AVs. However, reducing the scale to 11 items may have led to a loss of content richness and coverage. Thus, future studies should examine the validity of the DADS scores with respect to more comprehensive assessments of AVs acceptance. Indeed, in our study we were not able to administer a convergent validity measure for the DADS. Although previous studies relied on ad hoc interviews (e.g., Nastjuk et al., 2020), and surveys (e.g., Tan et al., 2022) to assess disposition towards AVs, no gold standard for assessing AV acceptance is currently available (e.g., Tan et al., 2022). In our study, we relied exclusively on self-report measures, with no possibility to rely on observations and/or interviews. Additionally, we relied on selected self-reported measures to assess the nomological network validity of the DADS, relying on one measure for each construct, with some driving-related variables being assessed by single item measures. Thus, further studies based on different methods of assessment are badly needed before accepting our findings.

Finally, although we relied on multiple psychometric approaches to test the dimensionality of the DADS items, we think that independent replications of our findings are needed. For instance, our dimensionality analyses provided inconsistent findings, with EGA suggesting retaining a two-dimensional structure which was not consistently replicated across bootstrap samples. Thus, future studies could focus on further examining the factor structure and reliability of the DADS items across different samples and contexts.

5.4. Conclusions

Even keeping these limitations in mind, we think that our study may provide a useful addition to the available literature providing researchers with a psychometrically sound, easy and brief measure of disposition towards AVs. In summary, in our main sample participants with positive dispositions towards automated driving, at least as they were operationalized in elevated DADS total scores, were not likely enjoying car driving, engaging in aggressive violations of traffic rules, and being easily upset, while manifesting emotional stability. When we expressed the average DADS total score that was observed in our sample as percent of maximum possible scores (POMP; Moeller, 2015), we obtained a value of 42.55 %. This finding was consistent with previous studies (e.g., Kyriakidis, Happee, & De Winter, 2015), providing further evidence for the validity of the DADS total score; moreover, it seemed to suggest the need for further improving individuals' dispositions towards automated driving for full acceptance of this major change in mobility system. Thus, the availability of short, easy-to-administer, self-report measures like the DADS may make it easy to carry out large sample surveys of disposition towards automated driving, particularly for monitoring opinion modifications after information campaigns.

Notwithstanding the preliminary nature of our Level 4 simulated driving session results, they provide additional evidence of the potential practical usefulness of the DADS across different contexts. Future studies may also examine the longitudinal invariance of the DADS in order to assess its usefulness for monitoring changes in the acceptance of AVs. To conclude, the possibility to rely upon the DADS may facilitate comparison across studies, while expanding available research and paving the way for future studies on the barriers that still hinder the acceptance of automated vehicles.

CRediT authorship contribution statement

Antonella Somma: Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Conceptualization. **Andrea Fossati:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Linda Boscaro:** Writing – review & editing, Investigation, Data curation. **Andrea Galbiati:** Writing – review & editing, Investigation, Data curation. **Maria Gabriella Signorini:** Writing – review & editing, Investigation, Funding acquisition. **Massimiliano Gobbi:** Writing – review & editing, Investigation, Funding acquisition, Conceptualization.

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Declaration of competing interest

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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trf.2025.04.017.

Data availability

Data will be made available on request.

References

Åberg, L., & Rimmö, P.-A. (1998). Dimensions of aberrant driver behaviour. *Ergonomics, 41*(1), 39–56. https://doi.org/10.1080/001401398187314

Adnan, N. (2024). Exploring the future: A meta-analysis of autonomous vehicle adoption and its impact on urban life and the healthcare sector. *Transportation Research Interdisciplinary Perspectives, 26*, 101110. https://doi.org/10.1016/j.trip.2024.101110

Almallah, M., Hussain, Q., Reinolsmann, N., & Alhajyaseen, W. K. M. (2021). Driving simulation sickness and the sense of presence: Correlation and contributing factors. *Transportation Research Part F: Traffic Psychology and Behaviour, 78*, 180–193. https://doi.org/10.1016/j.trf.2021.02.005

Barnette, J. J. (2000). Effects of stem and Likert response option reversals on survey internal consistency: If you feel the need, there is a better alternative to using those negatively worded stems. *Educational and Psychological Measurement, 60*(3), 361–370. https://doi.org/10.1177/00131640021970592

Bierstedt, J., Gooze, A., Gray, C., Peterman, J., Raykin, L., & Walters, J. (2014). *Effects of NextGeneration Vehicles on Travel Demand and Highway Capacity*. Fehr & Peers.

Bollen, K. A., & Hoyle, R. H. (2012). Latent variables in structural equation modeling. In R. H. Hoyle (Ed.), *Handbook of structural equation modeling* (pp. 56–67). The Guilford Press.

Buja, A., & Eyuboglu, N. (1992). Remarks on Parallel Analysis. *Multivariate behavioral research, 27*(4), 509–540. https://doi.org/10.1207/s15327906mbr2704_2

Cheli, F., Gobbi, M., Melzi, S., Previati, G., Somma, A., Del Linz, L., & Minen, D. (2022, July). Subjective/Objective Assessment of a Cable-Driven Simulator Immersivity and Realism. In *International Munich Chassis Symposium* (pp. 144-153). Berlin, Heidelberg: Springer Berlin Heidelberg.

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling, 9*(2), 233–255. https://doi.org/10.1207/S15328007SEM0902_5

Christensen, A. P., & Golino, H. (2021). Estimating the stability of psychological dimensions via bootstrap exploratory graph analysis: A Monte Carlo simulation and tutorial. *Psych, 3*(3), 479–500.

Christensen, A. P., Golino, H., & Silvia, P. J. (2020). A psychometric network perspective on the validity and validation of personality trait questionnaires. *European Journal of Personality, 34*(6), 1095–1108. https://doi.org/10.1002/per.2265

Clark, L., & Watson, D. (1995). Constructing validity Basic issues in objective scale development. *Psychological Assessment, 7*, 309–319. https://doi.org/10.1037/1040-3590.7.3.309

Clark, L. A., & Watson, D. (2019). Constructing validity: New developments in creating objective measuring instruments. *Psychological Assessment, 31*(12), 1412–1427. https://doi.org/10.1037/pas0000626

Classen, S., Sisiopiku, V., Mason, J., Yang, W., Hwangbo, S. W., McKinney, B., & Li, Y. (2023). Experience of drivers of all age groups in accepting autonomous vehicle technology. *Journal of Intelligent Transportation Systems, 28*, 1–17. https://doi.org/10.1080/15472450.2023.2197115

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.). Hillsdale: NJ Lawrence Erlbaum Associates, Publishers.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

de Winter, J. C., & Dodou, D. (2010). The Driver Behaviour Questionnaire as a predictor of accidents: A meta-analysis. *Journal of Safety Research, 41*(6), 463–470. https://doi.org/10.1016/j.jsr.2010.10.007

de Winter, J. C., Dodou, D., & Stanton, N. A. (2015). A quarter of a century of the DBQ: Some supplementary notes on its validity with regard to accidents. *Ergonomics, 58*(10), 1745–1769. https://doi.org/10.1080/00140139.2015.1030460

de Winter, J., & Nordhoff, S. (2022). Acceptance of conditionally automated cars: Just one factor? *Transportation Research Interdisciplinary Perspectives, 15*, Article 100645. https://doi.org/10.1016/j.trip.2022.100645

DeMars, C. E. (2013). A tutorial on interpreting bifactor model scores. *International Journal of Testing, 13*(4), 354–378. https://doi.org/10.1080/15305058.2013.799067

Devaraj, S., Easley, R. F., & Crant, J. M. (2008). How does personality matter? Relating the five-factor model to technology acceptance and use. *Information Systems Research, 19*(1), 93–105. https://doi.org/10.1287/isre.1070.0153

DriSMi. "Driving Simulator Politecnico di Milano. https://www.drismi.polimi.it/.

Fossati, A., Borroni, S., Marchione, D., & Maffei, C. (2011). The Big Five Inventory (BFI): Reliability and validity of its Italian translation in three independent nonclinical samples. *European Journal of Psychological Assessment, 27*(1), 50–58. https://doi.org/10.1027/1015-5759/a000043

Friedman, J., Hastie, T., & Tibshirani, R. (2008). Sparse inverse covariance estimation with the graphical lasso. *Biostatistics (Oxford, England), 9*(3), 432–441. https://doi.org/10.1093/biostatistics/kxm045

Gkartzonikas, C., & Gkritza, K. (2019). What have we learned? A review of stated preference and choice studies on autonomous vehicles. *Transportation Research Part C: Emerging Technologies, 98*, 323–337. https://doi.org/10.1016/j.trc.2018.12.003

Golino, H. F., & Epskamp, S. (2017). Exploratory graph analysis: A new approach for estimating the number of dimensions in psychological research. *PLoS ONE, 12*(6), Article e0174035. https://doi.org/10.1371/journal.pone.0174035

Golino, H., Moulder, R., Shi, D., Christensen, A. P., Garrido, L. E., Nieto, M. D., & Boker, S. M. (2021). Entropy fit indices: New fit measures for assessing the structure and dimensionality of multiple latent variables. *Multivariate Behavioral Research, 56*(6), 874–902. https://doi.org/10.1080/00273171.2020.1779642

Golino, H., Shi, D., Christensen, A. P., Garrido, L. E., Nieto, M. D., Sadana, R., Thiyagarajan, J. A., & Martinez-Molina, A. (2020). Investigating the performance of exploratory graph analysis and traditional techniques to identify the number of latent factors: A simulation and tutorial. *Psychological Methods, 25*(3), 292–320. https://doi.org/10.1037/met0000255

Gorsuch, R. (1983). *Factor analysis* (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates.

Gruchmann, T., Grenzfurtner, W., & Salzmann, A. (2024). From inside the cabin: Truck drivers' technology acceptance of driving assistance systems. *Logistics Research, 17*(1). https://doi.org/10.23773/2024_1

Gu, H., Wen, Z., & Fan, X. (2015). The impact of wording effect on reliability and validity of the Core Self-Evaluation Scale (CSES): A bi-factor perspective. *Personality and Individual Differences, 83*, 142–147. https://doi.org/10.1016/j.paid.2015.04.006

Guo, L., Burke, M. G., & Griggs, W. M. (2025). A new framework to predict and visualize technology acceptance: A case study of shared autonomous vehicles. *Technological Forecasting and Social Change, 212*, Article 123960.

Hancock, G. R., & Mueller, R. O. (2001). Rethinking Construct Reliability within Latent Variable Systems. In R. Cudeck, S. du Toit, & D. S?rbom (Eds.), *Structural Equation Modeling: Present und Future—A Festschrift in Honor of Karl Joreskog* (pp. 195–216). Lincolnwood, IL: Scientific Software International.

Hohenberger, C., Spörrle, M., & Welpe, I. M. (2016). How and why do men and women differ in their willingness to use automated cars? The influence of emotions across different age groups. *Transportation Research Part A: Policy and Practice, 94*, 374–385.

Holzinger, K. J., & Swineford, F. (1937). The bi-factor method. *Psychometrika, 2*, 41–54. https://doi.org/10.1007/BF02287965

Hu, L.-T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118

John, O. P., & Srivastava, S. (1999). The Big Five Trait taxonomy: History, measurement, and theoretical perspectives. In L. A. Pervin, & O. P. John (Eds.), *Handbook of personality: Theory and research* (2nd ed., pp. 102–138). Guilford Press.

Kam, C. C., & Meyer, J. P. (2015). Implications of Item Keying and Item Valence for the Investigation of Construct Dimensionality. *Multivariate Behavioral Research, 50*(4), 457–469. https://doi.org/10.1080/00273171.2015.1022640

Kyriakidis, M., Happee, R., & de Winter, J. C. F. (2015). Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. *Transportation Research Part F: Traffic Psychology and Behaviour, 32*, 127–140. https://doi.org/10.1016/j.trf.2015.04.014

Lauritzen, S. L. (1996). *Graphical Models*. Oxford University Press.

Madigan, R., Louw, T., Wilbrink, M., Schieben, A., & Merat, N. (2017). What influences the decision to use automated public transport? Using UTAUT to understand public acceptance of automated road transport systems. *Transportation Research Part F: Traffic Psychology and behaviour, 50*, 55–64. https://doi.org/10.1016/j.trf.2017.07.007

Marsh, H. W. (1996). Positive and negative global self-esteem: A substantively meaningful distinction or artifactors? *Journal of Personality and Social Psychology, 70*(4), 810–819. https://doi.org/10.1037/0022-3514.70.4.810

Marsh, H. W., Lüdtke, O., Muthén, B., Asparouhov, T., Morin, A. J. S., Trautwein, U., et al. (2010). A new look at the big five factor structure through exploratory structural equation modeling. *Psychological Assessment, 22*(3), 471–491. https://doi.org/10.1037/a0019227

Massara, G. P., Di Matteo, T., & Aste, T. (2016). Network filtering for big data: Triangulated maximally filtered graph. *Journal of Complex Networks, 5*, 161–178.

Moeller, J. (2015). A word on standardization in longitudinal studies: Don't. *Frontiers in psychology, 6*, 1389. https://doi.org/10.3389/fpsyg.2015.01389

Nair, G. S., & Bhat, C. R. (2021). Sharing the road with autonomousautomated vehicles: Perceived safety and regulatory preferences. *Transportation research part C: Emerging technologies, 122*, Article 102885. https://doi.org/10.1016/j.trc.2020.102885

Nandakumar, R., & Ackerman, T. (2004). Test modeling. In D. Kaplan (Ed.), *The Sage handbook of quantitative methodology for the social sciences* (pp. 93-105). Thousand Oaks, CA: Sage. doi: 10.4135/9781412986311.n5.

Nastjuk, I., Herrenkind, B., Marrone, M., Brendel, A. B., & Kolbe, L. M. (2020). What drives the acceptance of autonomousautomated driving? An investigation of acceptance factors from an end-user's perspective. *Technological Forecasting and Social Change, 161*, Article 120319. https://doi.org/10.1016/j.techfore.2020.120319

Nordhoff, S., De Winter, J., Kyriakidis, M., Van Arem, B., & Happee, R. (2018). Acceptance of Driverless Vehicles: Results from a Large Cross-National Questionnaire Study. *Journal of Advanced Transportation, 2018*(1), Article 5382192. https://doi.org/10.1155/2018/5382192

Nunnally, J. C. (1978). *Psychometric theory*. New York: McGraw-Hill.

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory*. New York: McGraw-Hill Inc.

Panagiotopoulos, I., & Dimitrakopoulos, G. (2018). An empirical investigation on consumers' intentions towards autonomous driving. *Transportation Research Part C: Emerging Technologies, 95*, 773–784. https://doi.org/10.1016/j.trc.2018.08.013

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Pons, P., & Latapy, M. (2006). Computing Communities in Large Networks Using Random Walks. *Journal of Graph Algorithms and Applications, 10*, 191–218.

Prasetio, E. A., & Nurliyana, C. (2023). Evaluating perceived safety of autonomous vehicle: The influence of privacy and cybersecurity to cognitive and emotional safety. *IATSS research, 47*(2), 160–170.

Qu, W., Sun, H., & Ge, Y. (2021). The effects of trait anxiety and the big five personality traits on self-driving car acceptance. *Transportation, 48*(5), 2663–2679. https://doi.org/10.1007/s11116-020-10143-7

Qu, W., Xu, J., Ge, Y., Sun, X., & Zhang, K. (2019). Development and validation of a questionnaire to assess public receptivity toward autonomousautomated vehicles and its relation with the traffic safety climate in China. *Accident; Analysis and Prevention, 128*, 78–86. https://doi.org/10.1016/j.aap.2019.04.006

Reason, J., Manstead, A., Stradling, S., Baxter, J., & Campbell, K. (1990). Errors and violations on the roads: A real distinction? *Ergonomics, 33*(10–11), 1315–1332. https://doi.org/10.1080/00140139008925335

Reise, S. P., Bonifay, W. E., & Haviland, M. G. (2013). Scoring and modeling psychological measures in the presence of multidimensionality. *Journal of personality assessment, 95*(2), 129–140. https://doi.org/10.1080/00223891.2012.725437

Reise, S. P., Scheines, R., Widaman, K. F., & Haviland, M. G. (2013). Multidimensionality and structural coefficient bias in structural equation modeling: A bifactor perspective. *Educational and Psychological Measurement, 73*(1), 5–26. https://doi.org/10.1177/0013164412449831

Rodriguez, A., Reise, S. P., & Haviland, M. G. (2016). Applying bifactor statistical indices in the evaluation of psychological measures. *Journal of Personality Assessment, 98*(3), 223–237. https://doi.org/10.1080/00223891.2015.1089249

SAE International (2014). *Automated driving levels of driving automation are defined in new SAE international standard J3016*.

SAE International. (2018). Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles. *SAE International, 4970*(724), 1–5.

Sanbonmatsu, D. M., Strayer, D. L., Yu, Z., Biondi, F., & Cooper, J. M. (2018). Cognitive underpinnings of beliefs and confidence in beliefs about fully automated vehicles. *Transportation research part F: traffic psychology and behaviour, 55*, 114–122.

Simms, L. J., & Watson, D. (2007). The construct validation approach to personality scale construction. In R. W. Robins, R. C. Fraley, & R. F. Krueger (Eds.), *Handbook of research methods in personality psychology* (pp. 240–258). The Guilford Press.

Skippon, S. M., Kinnear, N., Lloyd, L., & Stannard, J. (2016). How experience of use influences mass-market drivers' willingness to consider a battery electric vehicle: A randomised controlled trial. *Transportation Research Part A: Policy and Practice, 92*, 26–42. https://doi.org/10.1016/j.tra.2016.06.034

Smith, A., & Anderson, M. (2017). *Automation in Everyday Life*. Washington, DC: Pew Research Center.

Smorti, M., & Guarnieri, S. (2016). Exploring the factor structure and psychometric properties of the Manchester Driver Behavior Questionnaire (DBQ) in an Italian sample. *TPM. Testing, Psychometrics, Methodology*. *Applied Psychology, 23*(2), 185–202.

Spano, G., Caffò, A. O., Lopez, A., Mallia, L., Gormley, M., Innamorati, M., Lucidi, F., & Bosco, A. (2019). Validating Driver Behavior and Attitude Measure for Older Italian Drivers and Investigating Their Link to Rare Collision Events. *Frontiers in psychology, 10*, 368. https://doi.org/10.3389/fpsyg.2019.00368

Tan, H., Liu, J., Chen, C., Zhao, X., Yang, J., & Tang, C. (2024). Knowledge as a key determinant of public support for autonomousautomated vehicles. *Scientific Reports, 14*(1), 2156. https://doi.org/10.1038/s41598-024-52103-6

Tan, H., Zhao, X., & Yang, J. (2022). Exploring the influence of anxiety, pleasure and subjective knowledge on public acceptance of fully autonomous vehicles. *Computers in Human Behavior, 131*. https://doi.org/10.1016/j.chb.2022.107187

Tennant, C., Stares, S., & Howard, S. (2019). Public discomfort at the prospect of autonomousautomated vehicles: Building on previous surveys to measure attitudes in 11 countries. *Transportation Research Part F, 64*, 98–118. https://doi.org/10.1016/j.trf.2019.04.017 36

Tennant, C., Stares, S., & Howard, S. (2019). Public discomfort at the prospect of autonomous vehicles: Building on previous surveys to measure attitudes in 11 countries. *Transportation Research Part F: Traffic Psychology and Behaviour*, *64*, 98-118. doi: 10.1016/j.trf.2019.04.017.

Witmer, B. G., & Singer, M. J. (1998). Measuring presence in virtual environments: A presence questionnaire. *Presence: Teleoperators and Virtual Environments, 7*(3), 225–240. https://doi.org/10.1162/105474698565686

Xu, Z., Zhang, K., Min, H., Wang, Z., Zhao, X., & Liu, P. (2018). What drives people to accept automated vehicles? Findings from a field experiment. *Transportation Research Part C: Emerging Technologies, 95*, 320–334. https://doi.org/10.1016/j.trc.2018.07.024

Yu, B., Bao, S., Zhang, Y., Sullivan, J., & Flannagan, M. (2021). Measurement and prediction of driver trust in automated vehicle technologies: An application of hand position transition probability matrix. *Transportation Research Part C: Emerging Technologies, 124*, Article 102957. https://doi.org/10.1016/j.trc.2020.102957

Zhang, Q., Yang, X. J., & Robert, L. P., Jr (2022). Individual differences and expectations of automated vehicles. *International Journal of Human–Computer Interaction, 38*(9), 825–836.

Zwick, W. R., & Velicer, W. F. (1986). Comparison of five rules for determining the number of components to retain. *Psychological Bulletin, 99*(3), 432–442. https://doi.org/10.1037/0033-2909.99.3.432