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Measurement invariance of the driving inattention scale (ARDES) across 7 countries

Candida Castro [a,*], P. Pablo Doncel [a], Rubén D. Ledesma [b], Silvana A. Montes [b], D. Daniela Barragan [c], Oscar Oviedo-Trespalacios [d], Alessandra Bianchi [e], Natalia Kauer [e], Weina Qu [f], Jose-Luis Padilla [a]

[a] CIMCYC (Mind, Brain and Behaviour Research Centre), Faculty of Psychology, University of Granada, Spain
[b] IPSIBAT, Instituto de Psicología Básica, Aplicada y Tecnología, CONICET (National Scientific and Technical Research Council) and Universidad Nacional de Mar del Plata, Argentina
[c] George Mason University, USA
[d] Delft University of Technology, The Netherlands
[e] UFPR (Federal University of Parana), Brazil
[f] CAS Key Laboratory of Behavioural Science, Institute of Psychology, Chinese Academy of Sciences, Beijing, China

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ABSTRACT

The Attention-Related Driving Errors Scale (ARDES) is a self-report measure of individual differences in driving inattention. ARDES was originally developed in Spanish (Argentina), and later adapted to other countries and languages. Evidence supporting the reliability and validity of ARDES scores has been obtained in various different countries. However, no study has been conducted to specifically examine the measurement invariance of ARDES measures across countries, thus limiting their comparability. Can different language versions of ARDES provide comparable measures across countries with different traffic regulations and cultural norms? To what extent might cultural differences prevent researchers from making valid inferences based on ARDES measures? Using Alignment Analysis, the present study assessed the approximate invariance of ARDES measures in seven countries: Argentina ($n = 603$), Australia ($n = 378$), Brazil ($n = 220$), China ($n = 308$). Spain ($n = 310$), UK ($n = 298$), and USA ($n = 278$). The three-factor structure of ARDES scores (differentiating driving errors occurring at Navigation, Manoeuvring and Control levels) was used as the target theoretical model. A fixed alignment analysis was conducted to examine approximate measurement invariance. 12.3 % of the intercepts and 0.8 % of the item-factor loadings were identified as non-invariant, averaging 8.6 % of non-invariance. Despite substantial differences among the countries, sample recruitment or representativeness, study results support resorting to ARDES measures to make comparisons across the country samples. Thus, the range of cultures, laws and collision risk across these 7 countries provides a demanding assessment for a cultural-free inattention while-driving. The alignment analysis results suggest that ARDES measures reach near equivalence among the countries in the study. We hope this study will serve as a basis for future cross-cultural research on driving inattention using ARDES.

1. Introduction

Driver inattention and distraction are among the leading causes of road accidents and for this reason have received particular attention in road safety research (Beanland et al., 2013; Dingus et al., 2016; Klauer et al., 2006; NHTSA, 2020; Papantoniou et al., 2017; Oviedo-Trespalacios and Regan, 2021; Qin et al., 2019; Regan, Hallett and Gordon, 2011; UK Department for Transport, 2021).

Many aspects of this problem have been studied from different approaches and scientific disciplines, and changes in the sources of driving distraction have been explored (Kidd and Chaudhary, 2019). Among them, the interaction with technology and interference with driving from secondary tasks (e.g. use of mobile phones or the Advanced Drivers Assistance Systems, ADAS) have captured a significant part of

* Corresponding author at: CIMCYC (Mind, Brain and Behaviour Research Centre), Facultad de Psicología, Departamento de Psicología Experimental, Universidad de Granada, Campus Cartuja, s/n, Granada 18197, Spain.
E-mail address: candida@ugr.es (C. Castro).

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researchers' interest (see, for example, Caird et al., 2008; Li et al., 2020; Masello et al., 2023; Nguyen-Phuoc et al., 2020; Peng et al., 2023; Oviedo-Trespalacios et al., 2016; Young and Salmon, 2012; Zhou, Yu and Wang, 2016). Other issues, such as internal sources of distraction, individual differences and personality traits that might predispose the driver to inattention have, by contrast, been studied much less (Burdett et al., 2016; Steinberger et al., 2016; Vaezipour et al., 2022). This research seeks to contribute to cross-cultural research on driving inattention by testing the equivalence of a measure of driving inattention. To have equivalent measures of driving inattention will allow researchers on safe driving to make valid comparisons across countries. Specifically, we analyse the approximate measurement invariance of driving inattention in seven countries: Argentina, Australia, Brazil, China, Spain, UK and USA.

ARDES is a self-report instrument that evaluates individual differences in the propensity to make errors related to inattention while driving (Ledesma, et al., 2010; Ledesma et al., 2015). ARDES includes unintentional (involuntary) errors at the three levels of the driving task (Michon et al., 1985): a). Control/Operational level, b). Manoeuvring/Tactical level, and c.) Navigation/Strategic level. It is assumed that these errors, as measured by ARDES, reflect a trait-like variable that can be consistent across countries and cultures (See Table 1).

Without testing the cross-cultural equivalence of ARDES measures, it is not possible to make valid comparisons between countries in international studies of driving inattention. To research the equivalence of ARDES measures, differences in driving across the countries where ARDES was adapted should be considered. For example, according to the World Health Organisation (WHO (World Health Organization) (2018)) the estimated prepandemic road fatality rates (deaths per 100,000 population, year 2016) were China 18.2, Argentina 14, USA 12.4, Spain 4.1, U.K. 3.1, Brazil 19.2, and Australia 5.6, which suggests legal and social differences in traffic rules, road infrastructure, and driving habits and attitudes. Notably, these differences can be found even between areas with similar levels of road safety. For example, while the vehicle crash statistics of the UK and Spain are much more similar than with those of China, these countries still differ significantly in culture, road safety and vehicle rules. The most striking difference being the side of the road on which these countries drive (drive on the left or right). Thus, across all 7 countries we have a range of cultures, laws, and risk of collision that provides a demand for a cultural-free inattention-while-driving. See Table 2 for differences in legislation and road user behaviour by country as shown in a 2018 WHO brief report.

Table 1
ARDES 3-level structure (3 operational levels of the driving task proposed by Michon, 1985.

	Definition	Example of item
Control / Operational	Driving errors that occur at the operational control level, the lowest level driving task, which involves the execution of basic actions, such as steering, braking and handling other automobile controls	e.g., "*I unintentionally shift gears incorrectly or shift to the wrong gear*"
Manoeuvring / Tactical	Driving errors occur at the tactical manoeuvring level, which is the second-level driving task, involving actions such as keeping one's distance from surrounding traffic, changing lanes and crossing an intersection.	e.g., "*I fail to realise that the vehicle right in front of me has slowed down, and I have to brake abruptly to avoid a crash*"
Navigation / Strategic	Driving errors at the routing or navigation level. This is the top-level driving task and deals with processes such as route planning and maintenance	"*When driving somewhere, I make more turns than I have to*"

1.1. ARDES in different countries

The original ARDES was developed in Argentina, but later, adaptation and validation studies were carried out in other countries, including Spain (Roca et al., 2013), China (Qu et al., 2015), UK (Peña-Suarez et al., 2016), and USA (Barragan, Roberts and Baldwin, 2016). Table 3 summarises the psychometrics obtained in these studies. Overall, the results have brought evidence of reliability and validity that is in consonance with those of the original version of ARDES. It is promising that despite the significant differences in language, culture, traffic norms and driving habits of these countries, the psychometrics of the different ARDES versions converge.

We believe this bears out the idea that ARDES measures a construct that is highly dependent on drivers' individual characteristics (which are, to some extent, independent of contextual factors) and that equivalent measures of driving inattention can be obtained across countries.

Previous studies have provided validity evidence of ARDES measures in different countries. Ledesma et al., (2015) reported a 6-month test-retest correlation of $r = 0.79$ ($p < .01$). Correlations were also positive and high for the sub-scale scores generated at different moments in time (Navigation: $r = 0.74$, $p < .01$; Manoeuvring: $r = 0.73$, $p < .01$; Control: $r = 0.71$, $p < .01$). ARDES also correlated with measures of everyday inattention and with dissociative personality traits (Barragan, Roberts, and Baldwin, 2016; Ledesma et al., 2010). Distractibility ARDES scores were related to performance in a Hazard Prediction test (Castro et al., 2019) and ARDES was associated with differences in objective measures of attentional performance (López-Ramón et al., 2011; Montes et al., 2016).

ARDES appears to be an easy-to-use, reliable and valid self-report measure of driving inattention in different countries. However, no studies have been carried out to date on the measurement equivalence of ARDES measures, preventing researchers from making valid comparisons across countries. Moreover, most of the single-country validation studies propose a one-factor structure while the three-factor solution proposed by Ledesma, et al., (2015) has been supported in two studies (Barragan, Roberts and Baldwin, 2016; Castro et al., 2019). The three-factor structure showed the best fit in these two studies and proved to be more interesting from both the theoretical and applied points of view. For example, it was observed that different types of error could be associated differently with the driver's accident history (i.e., Manoeuvring errors appear to be linked to a greater risk, Ledesma et al., (2015). In addition, Castro et al., (2019) found that ARDES factors are associated differently with Hazard Prediction. Specifically, novice drivers who score highly in the Manoeuvring Errors ARDES factor also have lower scores in the Hazard Prediction test. That is, they are also less able to predict upcoming hazards on the road.

Despite adequate single-country ARDES psychometrics, there is no validity evidence to support cross-cultural comparisons across different countries. Well-established instruments used in road safety research and assessment, developed in western cultures, have faced important challenges in terms of validity and its psychometric properties when used in other cultures, e.g. the Manchester Driver Behaviour Questionnaire [DBQ] (Lajunen et al., 2004; Ang et al., 2019); the Behaviour of Young Novice Drivers Scale [BYNDS] (Oviedo-Trespalacios and Scott-Parker, 2017; Tosi et al., 2020), etc.

Evidence is needed that ARDES works in a similar way in different countries despite national differences (cultural, language, road safety rules, etc.). Specifically, research is needed to test that ARDES measures are equivalent across countries (i.e., its functioning is not dependent on socio-cultural variations, scale translations or other confounding variables).

Table 2
Legislation and road user behaviour by country. Colour code: Green (best practice), Yellow (intermedium practice), Red (worst practice), Adapted from WHO (2018), brief report.

Countries with:	Argentina	Australia	Brazil	China	EE.UU.	Spain	UK
Speed laws meeting best practice, 2017	Red	Green	Red	Green	Red	Green	Green
Drinking-and-driving laws meeting best practice, 2017	Yellow	Green	Green	Green	Yellow	Yellow	Yellow
Helmet laws meeting best practice, 2017	Green	Green	Green	Yellow	Red	Yellow	Green
Seat-belt laws meeting best practice, 2017	Green	Green	Green	Green	Yellow	Green	Green
Child restraint laws meeting best practice, 2017	Yellow	Yellow	Yellow	Red	Yellow	Green	Green
Applying UN (United Nations) vehicle safety standards, 2018	Yellow	Green	Yellow	Yellow	Yellow	Green	Green

1.2. *The present study*

The present study assessed measurement equivalence for ARDES scores in seven countries with different levels of road safety performance (Argentina, Spain, Brazil, UK, Australia, USA and China), using the three-factor structure proposed by Ledesma et al., (2015) as reference.

Initially, a multi-group confirmatory factor analysis (CFA) analytical approach was used. With multi-group CFA, equivalence between country versions is analysed by using increasingly restrictive conditions. First, "configural invariance" is proved if factor structure results are the same across countries. Second, "metric invariance" is proved if, in addition to factor structure equality, item loadings are equal across countries. Third, "scalar invariance" is proved if, added to the equality of factor structure and item loadings, item intercepts are equal across countries. If this last level of equivalence is achieved, comparisons between latent means across countries are supported. However, this approach can be problematic due to multiple possible violations of invariance assumptions, involving many model modifications that could lead to the wrong model (Asparouhov and Muthén, 2014). Byrne and van de Vijver (2010) pointed out three main problems of the CFA approach in large-scale studies: a) baseline models for each group can be different, b) multi-group models are prone to several problems related to translation, sample differences or different interpretations of the item content depending on the country's culture; and c) testing the equality of parameters by comparing two groups at a time is not practical when there are many groups. Several alternative methods have been proposed to overcome these limitations, such as Exploratory Structural Equation Modelling (ESEM; Asparouhov and Muthén, 2009), Bayesian Structural Equation Modelling (BSEM; Muthén and Asparouhov, 2012) or Alignment Analysis (Asparouhov and Muthén, 2014). All aim to a) relax classic multi-group CFA assumptions; and b) allow testing approximate measurement invariance, Given the number and diversity of countries involved in the study, Alignment Analysis was chosen as an alternative, as it has been used in other cross-cultural applications like van de Byrne and Vijver (2017). This analysis presents several advantages: a) it is a viable approach when analysing measurement invariance with many groups b) it allows us to determine which model parameters are approximately invariant and which are not, and c) it allows comparisons of latent factor means across groups. We hope this study will serve as a basis for future cross-cultural research on driving inattention.

2. Methods

2.1. *Participants*

Participants of the study belonged to different countries: Argentina, Spain, Brazil, UK, Australia, USA and China (See Table4). Sample socio-demographic characteristics along with initial and after-refinement sample sizes for each country are shown in Table 4. To remove aberrant response patterns that could have distorted further analysis, a data refinement process was carried out, consisting of (a) removing any cases with the same response to all items, (b) removing any cases with more than two response omissions; and (c) using data multiple imputation (Predictive mean matching; Landerman, et al., 1997) when a case had two or fewer missing values.

2.2. *Procedure*

Country research teams collected data using different ARDES administration modes. Table 5 summarises the characteristics of data collection procedures in each country. For example, Argentinian participants were recruited via non-probability sampling in Mar del Plata city, and they responded to the questionnaire using paper and pencil as the administration mode (a few participants completed the questionnaire online) (for more detailed information check Montes, Introzzi, Ledesma and López, 2016).

2.3. *Measures*

2.3.1. *Attention-related driving errors scale (ARDES)*

ARDES is a 19 item self-report scale designed to evaluate proneness to experiencing attentional lapses while driving. It is assumed that inattention varies between drivers but is relatively stable and independent of other factors. Drivers are asked to read each item and rate how frequently they experience the situation described in each item stem by using a 5-point Likert-response set, varying from 1 (never or almost never) to 5 (always or almost always). ARDES was originally developed by Ledesma et al., (2010), and validity evidence obtained from a sample of Argentinian drivers. Subsequently, the scale was adapted to the Spanish spoken in Spain by Roca et al., (2013), to UK English by Peña-Suarez et al., (2016), to USA English by Barragan et al., (2016) and to

Table 3
Summary of previous studies on ARDES.

Study	N	Reliability estimate Cronbach' α	Factors	Other validity evidence
Argentina (Ledesma et al., 2010)	614	0.86	One	ARDES discriminated between drivers who had reported road accidents and traffic offences and those who had not. Expected correlations with other theoretically-related variables were obtained (ARCES, (Attention-Related Cognitive Errors Scale) and DES (Dissociative Experiences Scale) and MAAS (Mindful Attention Awareness Scale)
China (Qu et al., 2015)	317	0.88	One	ARDES scores were positively correlated with both DDDI scores and number of accidents in the previous year. ARDES scores were strongly correlated with ARCES scores and negatively correlated with MAAS scores. ARDES scores varied with years of driving experience.
Spain (Roca et al., 2013).	320	0.88	One	Differences in ARDES-Spain scores were found between drivers who reported road accidents with material damage and those who did not.
UK (Peña-Suarez et al., 2016)	301	0.89	One	ARDES-UK scores were significantly different between drivers who reported road accidents with material damage and those who did not.
USA (Barragan Roberts and Baldwin, 2016)	296	0.89 Navigation = 0.89 Manoeuvring = 0.80 Control = 0.72	Three	Significant correlations between ARDES-US, CFQ (Cognitive Failures Questionnaire), ARCES and MAAS. Women, drivers who reported traffic offences within the previous 2 years and those with a lower level of education had a greater propensity to self-reported driver inattention as measured by ARDES-US.
Argentina (Ledesma, Montes, Poó and López-Ramón, 2015)	201	Navigation = 0.74 Manoeuvring = 0.75 Control = 0.68	Three	Significant correlations between ARDES subscale scores, DES and IDA (Index of Distracting Activities)
Spain (Castro et al., 2019)	95	Navigation = 0.67 Manoeuvring = 0.76 Control = 0.57	Three-factors	Significant correlations between Manoeuvring Errors and Hazard Prediction Scores

Table 4
Sample sizes and socio-demographic characteristics for each country.

	Initial size	Refinement Size	Age Mean (S.D.)	% Men	Driving experience Mean of Years (S.D.)
Argentina	614	603	36.85 (13.11)	51.8	16.44 (13.08)
Spain	320	310	39.75 (11.96)	61.9	18.60 (11.16)
Brazil	224	220	34.27 (14.19)	45.6	14.29 (12.80)
UK	301	298	52.97 (14.29)	48.5	32.56 (14.39)
Australia	406	378	30.36 (11.46)	35.2	11.83 (11.20)
USA	296	278	31.67 (14.00)	37.8	14.98 (13.93)
China	317	308	38.30 (10.11)	67.2	6.72 (5.40)
Total	2478	2395	37.57 (14.33)	49.9	16.30 (13.93)

Chinese by Qu et al., (2015). Currently, Australian and Brazilian adaptations are under development. Ledesma et al., (2015) proposed a three-factor structure for ARDES (Navigation, Manoeuvring and Control), which was also tested on an Argentinian sample, obtaining better fit indices than the unidimensional factor solution. In this solution, Item 18 was removed from the scale due to a low factor loading. The three-factor solution was subsequently evaluated in the US sample and was also found to have better fit indices than the one-factor structure (Barragan et al., 2016). Table 6 presents the UK English version of the items' contents for the three-factor structure.

2.4. Data analysis

First, a reliability and descriptive analysis was performed by calculating Cronbach's alpha coefficient, mean and standard deviation for each factor and for the total scale, using IBM SPSS Statistics (Version 25). Second, a Confirmatory Factor Analysis (CFA) was made for each country separately, using MPLUS Version 8.8 (Muthén and Muthén, 1998–2017). Third, a Multigroup Confirmatory Factorial Analysis (MGCFA) was made to test configural invariance, metric invariance and scalar invariance across countries, using R version 3. 6. 3. (R Core Team, 2020). Testing invariance is needed for making valid comparisons of ARDES scores across countries. Finally, to overcome traditional MGCFA

Table 5
Country and details of sample recruitment.

Country	Recruitment Through	Administration	Sample	Location
Argentina	Research Team Non-probability sampling	Paper and Pencil (Small sample online)	Argentinian drivers	Mar del Plata city
Brazil	Research TeamUFPR: Federal University of Parana, Curitiba (Brazil)	Paper and pencil Individual	Brazilian drivers	Public spaces (streets, squares, small markets…) in Curitiba
China	Research company	Interviewing individual drivers	Chinese drivers	
Australia	Research Team(QUT) Queensland University of Technology	Online questionnaire	Australian drivers	Using social media, local press releases, mailing lists and face-to-face dissemination. South East Queensland
UK	Research team(UGR) University of Granada	Paper and Pencil (Face-to-face)	British drivers	Granada-Jaén Airport and in the access lobby to the Alhambra, in Granada
USA	Research Team George Mason University, Fairfax, Virginia	On-line. Internet platform (Qualtrics online survey)	American drivers	
Spain	Research team(UGR) University of Granada	Tablet computer (Face-to-face)	Spanish drivers	Granada-Jaén Airport and Granada Train Station. Granada

Table 6
ARDES items' content for the UK translation.

FACTORS
Navigation Errors Factor
1. Heading towards a known place, becoming distracted, and then going several streets beyond it
4. Suddenly realising that I'm lost or that I've taken the wrong road on a familiar route
11. Forgetting for a brief moment where I'm driving to
12. Taking a roundabout route to arrive at a place I know how to get to
16. Leaving for one destination and suddenly realising I'm going somewhere else
Manoeuvring Errors Factor
3. Being distracted when reaching a junction, and as a result failing to see a car approaching the junction
5. When arriving at a junction, instead of looking in the direction the traffic is coming from, looking in the other direction
6. On arriving at a junction, not realising that a pedestrian is crossing the street
7. Not realising there is an object or a car behind me and hitting it unintentionally
8. Not realising that the vehicle in front has slowed down and having to brake sharply to avoid a collision
9. Another driver sounding their horn because I'm distracted and haven't noticed that the traffic lights have changed to green
13. Going through traffic lights when they've just turned red, not realising they had changed because I was blindly following the preceding traffic
17. Due to distraction, realising that I haven't even noticed the traffic lights
Control Errors Factor
2. Signalling a manoeuvre, but unintentionally making another one (for example, switching on the indicator to turn one way but instead turning the other)
10. Forgetting my lights are on full beam until another driver flashes their lights to warn me
14. Trying to drive off and realising I'm not in first gear
15. Intending to use one device, but using another instead (for example, meaning to switch on the windscreen wipers and instead switching on the lights)
19. Unintentionally crunching the gears or going into an unsuitable gear

limitations, a fixed (i.e. fixing to 0 the factor means of one of ARDES adaptation scores) Alignment Analysis (Asparouhov and Muthén, 2014) was conducted, using MPLUS Version 8.8 (Muthén and Muthén, 1998–2017). The 18 item three-factor structure proposed by Ledesma et al., (2015), which involves deleting item 18 in the original scale, was used for all the analyses.

As compliance with the multivariate normality distribution assumption was not met using Mardia's (1970) test results, Maximum Likelihood was discarded as an estimation method, and Weighted Least Squares Mean and Variance (WLSMV) was chosen as the ordinal estimation method for all the analyses. In addition, examining the frequency distribution of items, it can be seen that for most of the items and most of ARDES adaptations, Categories 1 and 2 have high choice percentages while for Categories 4 and 5 they are very low or even null in many cases (Annex 1). DiStefano, Shi and Morgan (2020) explored sparse data modelling in the CFA framework through a simulation study and found that in conditions with many items with sparse data and many low-frequency categories (as is the case in ARDES adaptations), collapsing categories results in better model outcomes for WLSMV estimators. Thus, ARDES items were collated in lower categories when higher categories had a frequency lower than 2 % (one of the two cut-off criteria defined for DiStefano et al., [2020]). Collapsing was carried out by giving every ARDES adaptation the same number of categories for a given item, so that ordinal factorial models could be estimated. The final number of categories for each item is shown in Annex 1. Subsequent CFA, MGCFA and Alignment analyses were run after applying this collapse strategy because of the aforementioned advantages of doing so when analysing sparse data.

3. Results

3.1. Reliability and descriptive analysis

Cronbach's Alpha coefficient value, mean and standard deviation for the three subscales and total scale, broken down by countries, are shown in Table 7. For ARDES Spain, USA and China, all alpha values show an acceptable or almost-acceptable value, i.e., higher than 0.70 (Cortina, 1993). For ARDES Argentina, Brazil and UK, the Control factor alpha value is below an acceptable value. In the case of ARDES Australia, the scale taken as a whole has a good reliability index, but the three subscales do not.

3.2. Multigroup confirmatory factor analysis (CFA)

In the first place, CFA models were estimated for each country separately, using Ledesma et al's (2015) three-factor structure. Results of goodness-of-fit indices were adequate in most cases: values lower than 0.08 for SRMR, values lower than 0.06 for RMSEA and values higher than 0.90 for TLI and CFI (Table 8). Only ARDES UK and Australia are slightly lower than 0.90 for TLI, whereas ARDES UK and China are slightly higher than 0.060 for RMSEA. In conclusion, it can be said that the three-factor structure is appropriate and has a good fit for every country.

The next step was to test configural, metric and scalar invariance via classic Multigroup Confirmatory Factor Analysis (CFA). Results are shown in Table 9. Goodness of fit values for configural invariance and metric invariance were adequate.

When exploring different levels of equivalence via invariance analysis, a value of χ^2 statistic is associated with each one. This value can be seen as an index of the "bad fit" of the equivalence model, implying a significant increment when adopting a stricter level of equivalence as evidence of its non-fulfilment. As we used WLSMV estimation, a scaled χ^2 (Satorra et al., 2000) instead of the usual one was used for invariance testing comparisons. Results of the invariance analysis (see Table 10) show that assuming metric invariance does not suppose a decrement of the configural invariance fit. This is not the case with scalar invariance, which supposes a significant decrement of the configural invariance fit. Thus, only metric invariance can be assured, not allowing latent means comparisons between countries.

3.3. Alignment analysis

Given the limitations of multi-group CFA (see the Introduction section), an alignment approach was used to allow approximate measurement invariance.

Fixed alignment optimisation was chosen because the a priori free optimisation recommended by Asparouhov and Muthén (2014) results in a poorly identified model, fixing ARDES UK factor means at 0 (based on free alignment results, this adaptation had the combination of factor means closest to 0 in absolute value, which is Asparouhov and Muthén's recommendation for fixation choice).

Non-invariance results for both item intercepts and loadings are shown in Table 11. Evidence of invariance was found for 17 out of 37 item intercepts and for 17 out of 18 of the item loadings (non-invariance loadings were found only for the Manoeuvring factor). 12.3 % of the intercepts and 0.8 % of the loadings were found to be non-invariant, resulting in 8.6 % total non-invariance. These values are below the 25 % cut-off point proposed by Asparouhov and Muthén (2014) for trustworthy alignment results.

A total of 5 items (3, 4, 11, 14, and 15) show complete invariance for intercepts and loadings across all ARDES adaptations. ARDES Argentina showed a higher number of non-invariance intercepts, adding up to a total of 10. Only one non-invariant loading was found for Item 17 in ARDES China ("Due to distraction, realising that I haven't even noticed the traffic lights"). This result is in consonance with the classic

Table 7
Alpha coefficients, Mean and S.D. for ARDES three factors and Total.

	Navigation Errors			Manoeuvring Errors			Control Errors			Total		
	α	Mean	SD	α	Mean	SD	α	Mean	SD	α	Mean	SD
Argentina	0.73	1.60	0.53	0.71	1.52	0.39	0.63	1.44	0.44	0.82	1.52	0.35
Spain	0.71	1.64	0.53	0.82	1.58	0.48	0.69	1.50	0.48	0.87	1.58	0.41
Brazil	0.70	1.86	0.63	0.68	1.64	0.44	0.58	1.58	0.49	0.82	1.69	0.41
UK	0.72	1.84	0.59	0.72	1.62	0.40	0.62	1.80	0.50	0.83	1.73	0.39
Australia	0.61	1.54	0.44	0.63	1.44	0.32	0.52	1.41	0.36	0.78	1.46	0.29
USA	0.71	1.73	0.52	0.78	1.60	0.44	0.70	1.51	0.47	0.87	1.61	0.41
China	0.68	1.88	0.58	0.81	1.77	0.52	0.70	1.72	0.54	0.88	1.79	0.48

Table 8
Individual CFAs' goodness of fit indices.

	χ^2	df	p-value	RMSEA (CI 90 %)	CFI	TLI	SRMR
Argentina	251.810	132	<0.001	0.039 (0.031–0.046)	0.956	0.949	0.053
Spain	200.882	132	0.0001	0.041 (0.029–0.052)	0.966	0.961	0.057
Brazil	172.891	132	0.0098	0.038 (0.019–0.052)	0.957	0.950	0.065
UK	277.603	132	<0.001	0.061 (0.051–0.071)	0.908	0.893	0.071
Australia	269.906	132	<0.001	0.053 (0.044–0.062)	0.909	0.895	0.071
USA	205.287	132	<0.001	0.045 (0.032–0.056)	0.968	0.963	0.059
China	310.534	132	<0.001	0.066 (0.057–0.076)	0.934	0.924	0.069

Table 9
Goodness of fit indices for levels of invariance.

Invariance level	χ^2 (df)	CFI	TLI	RMSEA (90 % CI)	SRMR
Configural	1680.550 (9 2 4)**	0.946	0.937	0.049 (0.045–0.053)	0.069
Metric	1698.516 (1014)**	0.951	0.948	0.044 (0.041–0.048)	0.078
Scalar	3063.429 (1110)**	0.860	0.865	0.072 (0.069–0.075)	0.075

** p <.001.

Table 10
Classic invariance analysis.

Invariance level	χ^2 (df)	$\Delta\chi^2$ (Δdf)	Δ χ^2 *p-value*
Configural	1342.2 (924)		
Metric	1718.4 1014	110.97 (90)	0.06621
Scalar	2989.5 1110	702.94 (96)	<0.001

invariance analysis results, where metric invariance could be kept but scalar invariance could not.

3.4. Fit information

For each parameter of the model, an R^2 is calculated. It represents "parameter variation across groups in the configural model, explained by variation in the factor mean and factor variance across groups" (Asparouhov and Muthén, 2014). It can also be interpreted as the degree of non-invariance that can be absorbed by factor means and variances variation. A value close to 1 implies a high degree of invariance, while a value close to 0 implies a low degree of invariance (See Table 12 and F. 1).

4. Discussion

Self-reports are very common in research on driving behaviours (Taubman—Ben-Ari et al., 2016). Simplicity and low cost are two of the main reasons why these methods are used so extensively. The use of questionnaire research is of vital importance in low- and middle-income countries where access to other road safety tools such as naturalistic and simulation studies is limited (Haghani et al., 2022). Whilst questionnaires are seen as less technologically sophisticated, it is important to highlight that they play an important role in supporting evidence-based road safety practice and policy development in areas that are over-represented in road trauma. The existence of certain limitations pertaining to self-reports is also recognised. Among these, one could mention response bias and the possible lack of equivalence between populations that are linguistically or culturally diverse (Ozkan et al., 2006). This last particularly affects the validity of self-reporting to generate results shared across populations, for example, those originating in different countries. In this study, the equivalence of one measure of inattention in driving (ARDES) that has been adapted and used in different languages and countries was studied. Our data included samples representing four languages (Spanish, Portuguese, English and Mandarin) and seven countries (Argentina, Australia, Brazil, China, Spain, UK and USA, which offers a basis). In addition, these countries present important differences in variables relating to road safety. The study's specific aims were to test approximate measurement invariance and identify sources of inequivalence for ARDES cross-cultural comparisons in the aforementioned countries. The factorial model proposed by Ledesma et al., (2015) was tested in each of the different countries. This model includes three factors that correspond to different levels of driving (Control, Manoeuvring and Navigation) where errors can occur. Model estimation problems related to sparse data were solved by collapsing item categories. Using classic invariance analysis, configural and metric invariance models obtained satisfactory fit indices. Therefore, ARDES proved suitable for testing driver inattention across geographic borders. Despite substantial differences among the

Table 11
ARDES: Non-invariance items across ARDES adaptations.

Non-invariance Item Intercepts	ARDES adaptations with non-invariance intercepts	ARDES adaptations with non-invariance loadings
Item 1 (1)	Spain	
Item 1 (2)	USA	
Item 1 (3)	Argentina	
Item 2 (1)	UK	
Item 2 (2)		
Item 3 (1)		
Item 3 (2)		
Item 4 (1)		
Item 4 (2)		
Item 5 (1)	Argentina	
Item 5 (2)	Argentina	
Item 6 (1)	Argentina, Brazil, China	
Item 6 (2)		
Item 7 (1)	Spain, China	
Item 7 (2)	Spain, China	
Item 8 (1)	Australia, USA, China	
Item 8 (2)		
Item 9 (1)	Argentina	
Item 9 (2)	UK	
Item 10 (1)	Brazil, UK	
Item 10 (2)		
Item 11 (1)		
Item 11 (2)		
Item 12 (1)	Argentina, UK	
Item 12 (2)	Argentina, Brazil, China	
Item 13 (1)	Argentina	
Item 13 (2)	Argentina, Brazil	
Item 14 (1)		
Item 14 (2)		
Item 15 (1)		
Item 15 (2)		
Item 16 (1)	USA	
Item 16 (2)		
Item 17 (1)	Brazil, Australia	China
Item 17 (2)		
Item 19 (1)	Argentina	
Item 19 (2)		

countries, the 'equivalence' of the measure can be assumed. Our results show that it is indeed reasonable to assume that equivalence despite differences between countries. This is probably due to the fact that ARDES measures a "trait-like" driver variable (Ledesma et al., 2010; Ledesma et al., 2015), which is relatively independent of contextual factors: a driver's proneness to inattention.

Thus, across these 7 countries we have a range of cultures, laws, and risk of collision, providing a demanding assessment for a cultural-free inattention-while-driving. The alignment analysis results suggest that ARDES measures reach near equivalence among the countries in the study. We hope this study will serve as a basis for future cross-cultural research on driving inattention using ARDES.

However, scalar invariance, which is needed to allow mean comparisons between different ARDES adaptations, was not reached. As previously mentioned, the problem with classic invariance analysis is that it is very strict and very difficult to achieve when there are so many comparison groups (countries in our case). With regard to the alignment analysis, the results show that non-invariance only exists in a very small percentage of the factorial loadings (0.8 %). In particular, only one item loading, specifically Item 17 loading for the Manoeuvring factor in ARDES China ("*Due to distraction, realising that I haven't even noticed the traffic lights*"), shows a significantly lower loading in this adaptation compared with the other countries' adaptations (except for ARDES Australia, where the loading difference is not significant).

To look for these invariance sources and try to understand their rationale should be the next step and a contribution of further research. There are wide cultural differences in the nature of driving in these different countries, including both the legal and social rules (i.e. fines and punishment) that govern acceptable and unacceptable driving

Table 12
R-square measures for each model parameter.

Items	Loadings			Intercepts	
	Navigation Loadings R^2	Manoeuvring Loadings R^2	Control Loadings R^2	Item intercepts	R^2
Navigation Errors Factor					
Item 1	0.287			**Item 1 (1)**	0
				Item 1 (2)	0.487
				Item 1 (3)	0
Item 4	0.080			**Item 4 (1)**	0.841
				Item 4 (2)	0.946
Item11	0.110			**Item 11 (1)**	0.570
				Item 11 (2)	0.968
Item 12	0			**Item 12 (1)**	0
				Item 12 (2)	0.318
Item 16	0.637			**Item 16 (1)**	0.639
				Item 16 (2)	0.814
Manoeuvring Errors Factor					
Item 3		0.041		**Item 3 (1)**	0.199
				Item 3 (2)	0.754
Item 5		0.592		**Item 5 (1)**	0.122
				Item 5 (2)	0
Item 6		0.508		**Item 6 (1)**	0.194
				Item 6 (2)	0.834
Item 7		0.433		**Item 7 (1)**	0.657
				Item 7 (2)	0.503
Item 8		0.370		**Item 8 (1)**	0
				Item 8 (2)	0.640
Item 9		0.432		**Item 9 (1)**	0.405
				Item 9 (2)	0.679
Item 13		0.680		**Item 13 (1)**	0
				Item 13 (2)	0.236
Item 17		0		**Item 17 (1)**	0
				Item 17 (2)	0.630
Control Errors Factor					
Item 2			0.534	**Item 2 (1)**	0.705
				Item 2 (2)	0.625
Item 10			0.365	**Item 10 (1)**	0.596
				Item 10 (2)	0.769
Item 14			0.184	**Item 14 (1)**	0.812
				Item 14 (2)	0.957
Item 15			0.558	**Item 15 (1)**	0.473
				Item 15 (2)	0.611
Item 19			0.505	**Item 19 (1)**	0.357
				Item 19 (2)	0.489

behaviours, which in turn influence the nature of distraction. For example, trying to hypothesise, in the case of the above mentioned item 17 among Chinese drivers: ("Due to distraction, realising that I haven't even noticed the traffic lights") shows a slightly significantly positive lower loading in this adaptation compared with the other countries' adaptations (i.e. 0.514 in China vs.0.640 in Australia to 0.785 in Brazil). This could be due to the different legislation norms of these countries regarding traffic light regulations. As of 2013, yellow lights turn to red for China's Traffic Signals. The country's Ministry of Public Security is attempting to improve Traffic Safety with the new law: Yellow lights are now considered functionally the same as red lights. After a double violation of the yellow-light norm the driver receives 12 demerit points (6+6) and his/her driver's license is suspended. The offending driver should retake road training at a driving school and pass an official driving exam.

5. Limitations and further research

Further research should take into account the methods used in the research. For example, sampling and recruitment were different in the participant countries. Even though ARDES measures reach approximate measurement invariance, we recognize that differences in methods can limit comparisons of the substantive results. Despite the potential problems associated with differences in sample recruitment and representativeness, the results provide a clear indication that ARDES is relatively free of cross-cultural differences, such as driving habits and hazardousness thresholds that appear culturally-biased. This test provides a cultural-free scale and offers a blueprint for future test development at a global level.

Specifically, a shortcoming of this study is that the samples are not equivalent in important variables (e.g. age, distribution) and were obtained by ad hoc procedures that differ according to the country. In addition, future studies could continue to provide further evidence of ARDES validity to measure proneness to attentional error by analysing its association with varying cognitive and psychological performance.

Although in convenience sampling it is relatively common for researchers to recruit subjects in unusual locations (e.g., foreign participants in airports, tourist attractions, hotels…), this practice may over bias the sample. Besides the evident dissimilarities in recruitment (e.g., internet-based invitations answered via an online questionnaire vs. face-to-face invitations responded via Computer Assisted Personal Interview (CAPI)) that were addressed previously, some respondent profiles seem dissimilar. For example, the sample in ARDES-UK does not represent young drivers and British tourists holding a driver's license have the same label as Chinese drivers approached by a specialised research company. This does not invalidate the research, however. If it did, every cross-sectional study could be considered flawed for a specific reason.

Another limitation arises from the method of analysis chosen. Collapsing categories was required to improve model estimations. This could have produced a loss of information in relation to the few participants who chose 4 ("Often") or 5 ("Always or almost always") in ARDES item categories. Nevertheless, it is worth reconsidering ARDES scale length and/or labels for future adaptations.

Despite the potential problems associated with differences in samples, recruitment methods and representativeness, the results provide a clear indication that ARDES is relatively free of cross-cultural differences, such as driving habits and hazardousness thresholds that appear culturally-biased. This test provides a cultural-free scale and offers a blueprint for future test development at a global level. ARDES could also be adapted to measure inattention of other traffic users. For example, ARDES-Motorcyclists version has also been recently validated with a Spanish motorcyclists' sample (Ledesma et al., 2023).

5.1. Conclusion

To summarise, the present study suggests that ARDES could be a reasonably equivalent instrument for measuring inattention in drivers of different cultures that could be used with a certain level of guarantee. The most relevant practical use of the study's results is the possibility to compare observed or latent ARDES factor scores between groups (i.e. countries) once scalar invariance is achieved via alignment analysis (Luong and Flake, 2021). ARDES may not be culturally sensitive, and consequently it is suitable for adoption in other countries. In effect, despite big differences among the countries analysed, the alignment results tend to show a relatively low percentage of non-invariance. ARDES may be useful to assess "fitness to drive", to analyse vigilance-related driving behaviour and thus help prevent traffic collisions. Additionally, we believe that ARDES could be a useful tool for research and assessment purposes (e.g., to detect risk groups with high inattention propensity). It could also be adapted to measure inattention of other traffic users. For example, ARDES-Motorcyclists version has also been recently validated with a Spanish motorcyclists' sample (Ledesma et al., 2023). This would also serve to develop interventions and preventive actions aimed at reducing the effects of inattention on road traffic accidents.

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.

Data availability

Data will be made available on request.

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