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## Decoding acceptance of driver monitoring systems: Evaluating alternative measurement models, cross-country variations, and behavioural intention

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### ABSTRACT

Driver monitoring systems (DMS) demonstrate significant potential for enhancing road safety. It is imperative to comprehend potential users' attitudes towards DMS to optimise their benefits and increase public acceptance. This study investigates potential users' acceptance of DMS in conditionally automated driving systems (SAE level 3) by evaluating alternative measurement models and assessing cross-country variations across nine countries (i.e., Germany, Spain, France, Japan, Poland, Sweden, the United Kingdom, the United States, and China). Utilising survey data from 9025 drivers, we compared the principal component analysis and the four models (a single-factor model, a six factors model, a two higher-order factors model, and a two lower-order factors model) via structural equation modelling. A model with two correlated factors, *General Acceptance* and *Concerns*, emerged as the optimal solution with high reliability across constructs. Significant cross-country differences in all constructs were found, although only 0.3% of the variance in behavioural intention was attributable to country-level differences. A linear mixed model demonstrated that the general acceptance factor positively related to behavioural intention, whereas concerns had a small but significant negative effect. The implications for research and practice suggest that while individual-level perceptions are paramount, country context also plays a role, albeit a modest one, in shaping users' willingness to adopt DMS technologies.

## 1. Introduction

### 1.1. User acceptance of driver monitoring systems

Driver Monitoring Systems (DMS) has emerged as a critical component in contemporary automotive safety. As these systems become increasingly prevalent in both private vehicles and commercial fleets, understanding user acceptance is of paramount importance. User acceptance may influence not only the initial adoption of DMS technologies but also their long-term utilisation and integration into traffic systems. In other words, the efficacy of DMS may be affected by how end users perceive their benefits (e.g., Coyne et al., 2024) and how they evaluate potential concerns such as privacy and system intrusiveness (e.g., Coyne et al., 2024;

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Guttman & Gesser-Edelsburg, 2011; Guttman & Lotan, 2011).

There is limited research on (potential) users' perspectives on driver monitoring systems (e.g., Chan, 2017; Chu et al., 2023; Coyne et al., 2024; Ehsani et al., 2024; Guttman & Gesser-Edelsburg, 2011; Guttman & Lotan, 2011; Jannusch et al., 2021; Presta et al., 2022; Smyth et al., 2021). Chan (2017) identified nine factors affecting users' acceptance of driver monitoring: "comparing benefits and costs, privacy, autonomy of driver, driver's ideals and morale, ownership of vehicle, trust, design of system, awareness of technology, and media and marketing". In a focus group study, Coyne et al. (2024) found that while there are generally positive attitudes toward DMS, participants expressed concerns regarding the reliability, security, and privacy of the system. Smyth et al. (2021) found that users' intention to use DMS increases with effort expectancy, performance expectancy, and social influence, whereas an inverse relationship was observed for anxiety. In another study, Ehsani et al. (2024) found that users' acceptance of DMS is influenced more by perceived benefits, insurance discounts, and rewards for safe driving and less so by privacy concerns and the cost of the system in the US. Users are also less likely to adopt DMS if they have greater data and privacy concerns (Chu et al., 2023). In this context, assessing acceptance extends beyond satisfaction metrics and serves as a critical determinant in the technology's widespread implementation and continuous refinement.

## 1.2. Dimensionality in technology acceptance

As outlined by Taherdoost (2018) and Lai (2017), various theories and models address technology acceptance, including the Theory of Planned Behaviour (TPB by Ajzen, 1991), the Technology Acceptance Model (TAM by Davis, 1989), and the Unified Theory of Acceptance and Use of Technology (UTAUT by Venkatesh et al., 2003). Each model significantly relates to behavioural intention (e.g., Al Haddad et al., 2024; Rahman et al., 2017). Furthermore, other studies (e.g., Ghazizadeh et al., 2012; He et al., 2025; Nordhoff et al., 2021; Xiao et al., 2024) have introduced additional variables into the models, thereby enhancing their predictive validity. For instance, a literature review conducted by Marangunić and Granić (2015) examined research utilising the TAM from 1986 to 2013 and identified several new constructs that have been incorporated into the TAM. The identification and future integration of these new constructs into the model have been recognised as a prospective area for further research.

A recent but central debate in the literature on technology acceptance concerns whether acceptance should be conceptualised as a unidimensional construct or a multidimensional construct. The unidimensional perspective posits that a single latent factor can encapsulate overall acceptance (e.g., Aasvik et al., 2024; de Winter & Nordhoff, 2022) and suggests that a general predisposition towards technology, such as automated vehicles, drives its adoption and continued utilisation. In this regard, a number of studies (e.g., Aasvik et al., 2024; Nees and Zhang, 2020; Nordhoff et al., 2021; de Winter & Nordhoff, 2022) have examined the dimensionality of factors related to acceptance and investigated the factorial structure of technology acceptance leading to a General Acceptance Factor (GAF). For instance, de Winter and Nordhoff (2022) found that a single acceptance factor explained 55 % of the variance in acceptance of conditionally automated vehicles. In support of a single GAF, Aasvik et al. (2024) incorporated multiple items from various constructs, including 18 items representing the Multi-Level Model of Automated Vehicle Acceptance (MAVA) constructs, three items pertaining to social preferences, three items related to discrimination, and an additional three items addressing a set of factors (climate targets transport, indifference toward bus, in target group) when explaining acceptance of shared fully automated vehicles. Following the principal component analysis, four factors (i.e., MAVA, interpersonal security, sociability, and attractivity features) were identified as best reflecting the factorial structure. The study concluded that a general latent GAF factor, as suggested by de Winter and Nordhoff (2022), may exist and predict the willingness to use with the largest effect size. Usefulness and trust may be two variables effectively measuring the GAF. Furthermore, it was found that social situations and vehicle design constituted separate latent factors. Although not tested as part of the study, the ability of usefulness and trust items to formulate the GAF factor, along with other factors being distinct from the GAF, may also indicate the presence of higher-order factors in explaining acceptance.

In support of the multidimensional nature of acceptance, Nordhoff et al. (2019) reviewed the studies in the literature on automated vehicle acceptance and proposed a multi-level multidimensional model where 28 factors were identified across micro and meso levels, addressing aspects ranging from personality to exposure to automated vehicles. For example, studies on the UTAUT (e.g., Blut et al., 2022; He et al., 2025; Madigan et al., 2017; Nordhoff et al., 2021) examined the relationships among various constructs (e.g., performance expectancy, social influence, facilitating conditions) and showed the validity and the benefits of a multidimensional approach.

In addition to the discussion on unidimensional and multidimensional aspects, Chu et al. (2023) conducted a study examining the acceptance of DMS through six factors: perceived usefulness, trust, behavioural intention, collection concerns, secondary use concerns, and perceived insecurity. The analysis indicated that perceived usefulness, trust, and behavioural intention were associated with a general acceptance factor, while collection concern, secondary use concern, and perceived insecurity were related to privacy concern. These two factors were identified as higher-order independent factors, with three lower-order factors loading onto each.

This discussion holds significant importance for both theoretical and practical reasons. Theoretically, it is crucial as it is closely linked to behavioural intention and can serve as a foundation for behavioural interventions. Additionally, the distinction between unidimensional and multidimensional models also varies in terms of the effort required for data collection and analysis. Compared to the unidimensional model, the multidimensional model allows for the recognition that different aspects may be more relevant in different contexts or for different groups. However, to the best of our knowledge, this central discussion has not been empirically tested in the context of DMS acceptance by comparing different models. In light of these findings, further research is needed to explore the nature of acceptance specifically for DMS.

### 1.3. Objectives of the study

Within the framework of the DMS technologies, the models of DMS acceptance has not yet been examined across different countries. As discussed by de Winter and Nordhoff (2022), the multidimensionality of constructs should be scrutinised in technology acceptance research. In this context, it is imperative to empirically test varying models based on data to provide further insights. Building on unidimensional and multidimensional discussion, it is possible that higher-order models could be proposed wherein first-order factors converge into a second-order latent construct representing global acceptance. This multifaceted perspective could facilitate a more nuanced analysis, acknowledging that drivers of acceptance may vary not only in magnitude but also in their relative impact on user behaviour. With respect to this, the study specifically aims to:

- (1) determine whether the acceptance of DMS in conditionally automated driving systems is best represented by a unidimensional model, a multidimensional model, or a higher-order structure that integrates multiple factors into higher-order constructs,
- (2) assess cross-country variability in identified factor(s), and
- (3) investigate how identified factor(s) relate to the intention to use DMS in conditionally automated driving systems.

## 2. Method

### 2.1. Survey design and data collection

In May 2024, as part of the Hi-Drive project (Horizon Europe: 101006664), an online survey was administered across nine countries to examine car drivers' attitudes toward automated driving systems and driver monitoring systems. On average, completing the survey took approximately eight minutes. This study followed the ethical guidelines established by the Finnish National Board on Research Integrity TENK ([https://tenk.fi/sites/default/files/2021-01/Ethical\\_review\\_in\\_human\\_sciences\\_2020.pdf](https://tenk.fi/sites/default/files/2021-01/Ethical_review_in_human_sciences_2020.pdf)), and informed consent was obtained from all participants before their involvement. The research ensured that participants' daily routines, physical health, and safety were not adversely affected. Participation was entirely voluntary, with individuals receiving compensation for their time.

Data collection was carried out by INNOLINK, a Finnish market research firm. The research team originally developed the survey in English, and INNOLINK subsequently translated it into the target languages. Each translation was independently verified by a separate researcher, fluent in both English and the respective language, who was not previously involved with the survey but possessed relevant expertise in the field. This cross-language verification process was performed for each language individually. Importantly, the company did not participate in either the design of the survey or in the analysis of its results. The sample for each country (Germany, Spain, France, Japan, Poland, Sweden, United Kingdom, United States, and China) was chosen to reflect a representative distribution of gender and age.

### 2.2. Participants

A total of 9025 drivers took part in the study. Table 1 shows the age and gender distribution of the sample.

### 2.3. Measurements

#### 2.3.1. Acceptance of DMS

To assess various constructs related to acceptance and willingness to use the DMS. Participants were given the following definition of DMS.

*“Driver Monitoring Systems (DMS) are coming to new cars. For example, from 2026, every new car in Europe is expected to be equipped with a DMS. The DMS monitors if a driver is capable or ready to resume control from an automated driving system in the case of a system failure, or when automated mode is no longer available. These systems use cameras and sensors to track drivers' gaze patterns and body posture, evaluating their alertness while automation is on, and their capability to resume control when requested. If there are concerns*

**Table 1**  
Age and gender distribution by country.

Country	n	Age				Gender			
		M	SD	Min.	Max.	Woman	Man	Other	Not reported
Germany	1001	48.38	16.42	18	85	500	500	1	0
Spain	1002	47.27	14.84	18	85	490	509	0	1
France	1002	48.20	17.13	18	82	514	487	0	1
Japan	1005	49.31	14.13	18	81	496	504	2	2
Poland	1003	46.02	15.15	18	82	494	504	2	2
Sweden	1002	47.96	16.92	18	85	520	476	2	4
United Kingdom	1002	46.97	17.04	18	85	493	506	2	1
United States	1004	45.49	16.49	18	85	505	493	5	1
China	1004	35.94	8.92	18	70	482	522	0	0

*about a driver's ability to resume control of the vehicle in the lead-up to a takeover request, the DMS will provide a visual or auditory warning to encourage the driver to more actively monitor the road. If the DMS identifies that a driver is unfit to resume control, the AV may have to take appropriate actions to minimize the driving risk for the driver and other road users e.g. by stopping at the side of the road."*

Participants were introduced to DMS as an integrated concept, which encompasses both assessing the driver's state and, when necessary, triggering vehicle actions to mitigate risk. Consequently, the acceptance ratings gathered in this study represent participants' perception on this combined system, rather than separating their attitudes toward monitoring and intervention. Items are developed based on the following lower-level constructs. The items and measurement structures are presented in [Section 3.1](#).

**Performance expectancy (PE):** Three items adapted from [Smyth et al. \(2021\)](#) were used to measure the performance expectancy of participants from DMS.

**Perceived ease of use (PEU):** The effort expectancy from the DMS was measured with four items adapted from [Ghazizadeh et al. \(2012\)](#).

**Trust (TRT):** Trust in DMS was measured with three items adapted from [Ghazizadeh et al. \(2012\)](#).

**Collection concerns (CC):** Three items were adapted from [Chu et al. \(2023\)](#) and [Smith et al. \(1996\)](#) to assess participants' concerns related to the information collected by DMS.

**Secondary use concerns (SU):** The SU for DMS focused on concerns related to the secondary use of the data and were measured with three items adapted from [Chu et al. \(2023\)](#) and [Smith et al. \(1996\)](#).

**Perceived insecurity (PI):** The PI regarding DMS was measured with three items adapted from [Chu et al. \(2023\)](#) and [Cichy et al. \(2021\)](#).

**Behavioural intention (BI):** The BI to use DMS was measured with three items from [Ghazizadeh et al. \(2012\)](#).

### 2.3.2. Socio-demographic information

As part of the demographic questions, participants' age, gender ([Table 1](#)) and place of residence ([Fig. 1](#)) were recorded.

### 2.4. Analysis

The analysis was conducted using Jamovi 2.6.26 ([Gallucci & Jentschke, 2021](#); [Jorgensen et al., 2019](#); [The Jamovi Project, 2024](#); [R Core Team, 2024](#); [Rosseel, 2019](#)) and IBM SPSS Amos v29. Due to the limited number of participants in gender categories other than male and female, the participants from "other" ( $n = 14$ ) and "not reported/prefer not to say" ( $n = 12$ ) categories have been excluded

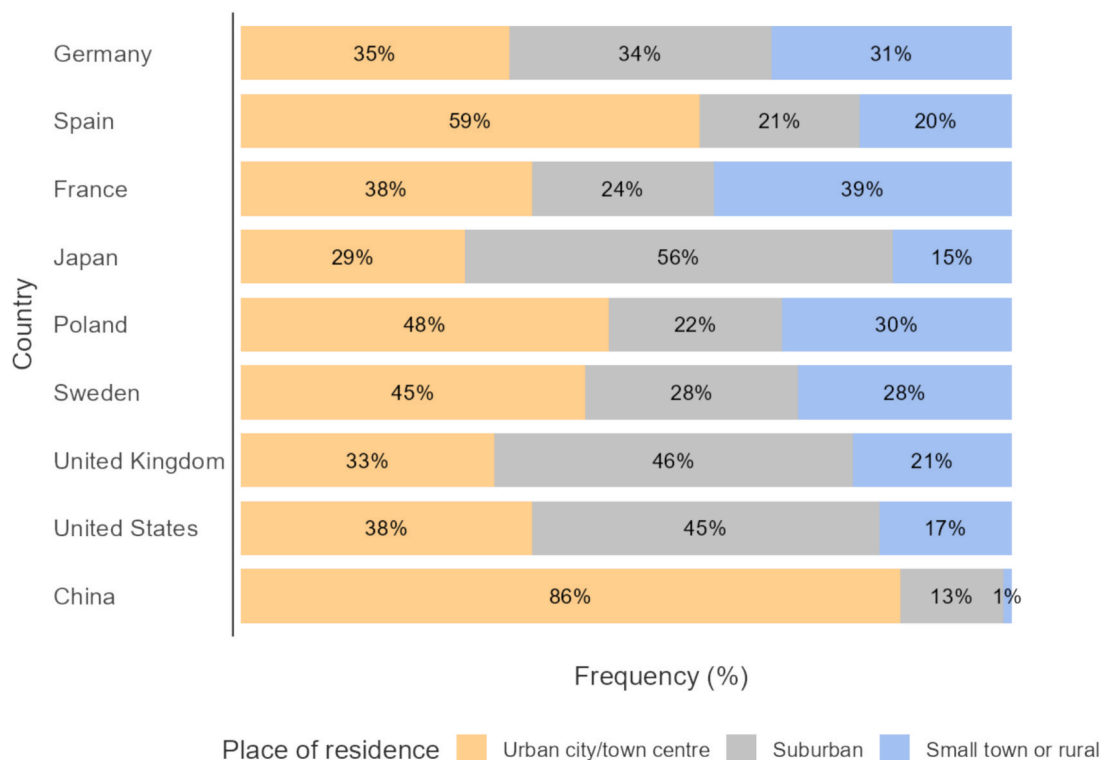


Fig. 1. Place of residence by country.

from further analysis. After presenting item-level descriptives for the pooled sample (and per country in [Appendix A](#)), the measurement models ([Section 3.1](#)) were tested through a principal component analysis (PCA) and a series of structural equation modelling (SEM) excluding behavioural intention. The data were randomly divided into two groups for both PCA ( $n = 4363$ ) and CFA ( $n = 4632$ ), ensuring balanced and sufficient sample sizes for both analyses. The KMO values for both samples were 0.957 and 0.956 showing that the two samples can be regarded as optimally equivalent for the purpose of the analysis ([Lorenzo-Seva, 2022](#)) and do not introduce a bias due to random splitting. For the SEM, the following four models were examined to explore the relationships between constructs based on the associations evaluated in previous studies focusing on acceptance (e.g., [Aasvik et al., 2024](#); [Chu et al., 2023](#); [de Winter &](#)

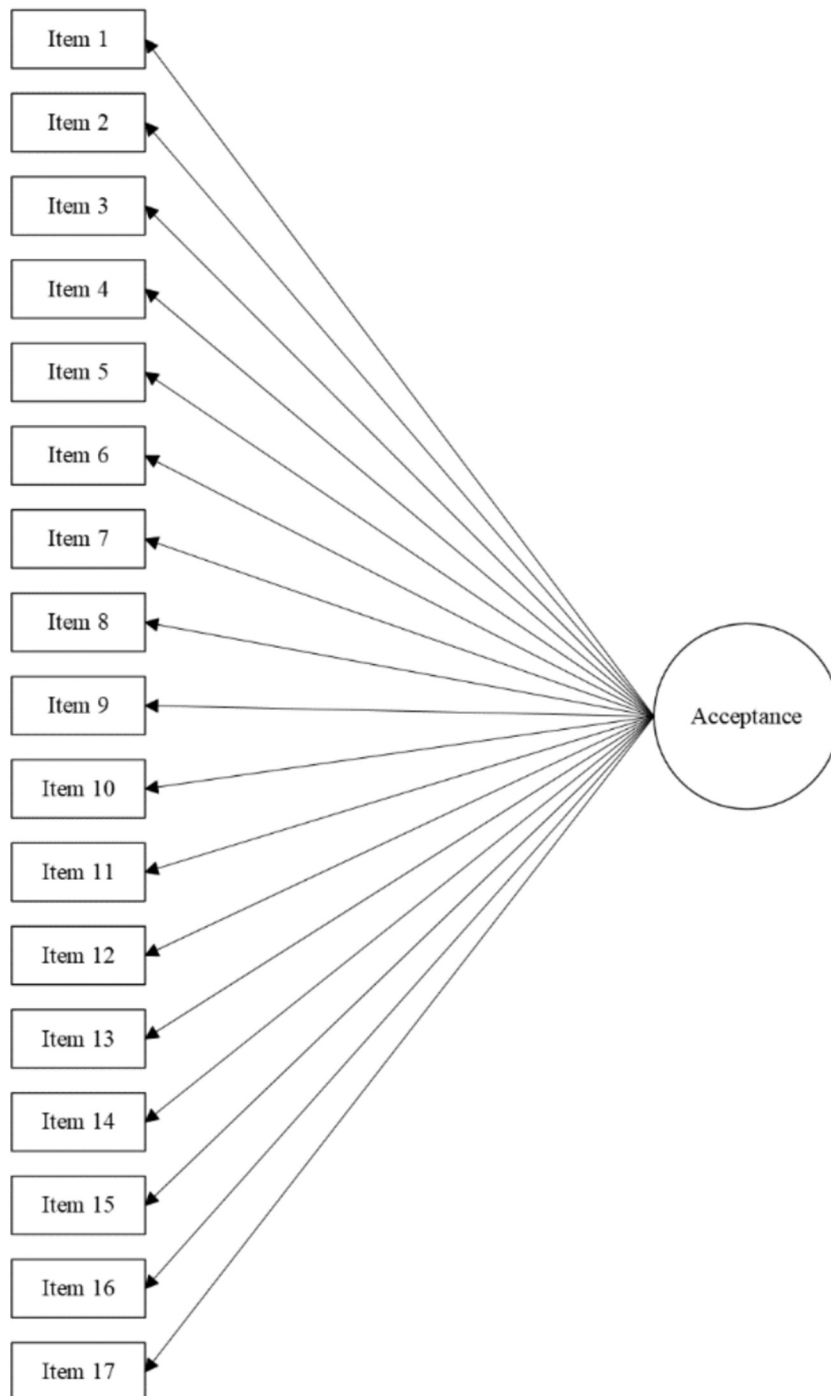


Fig. 2. Model with the single-factor.

Nordhoff, 2022):

**Model 1 – Model with a single-factor:** The model indicates that all factors converge into a single overarching factor termed “acceptance” without any underlying latent variables (Fig. 2, Appendix B1).

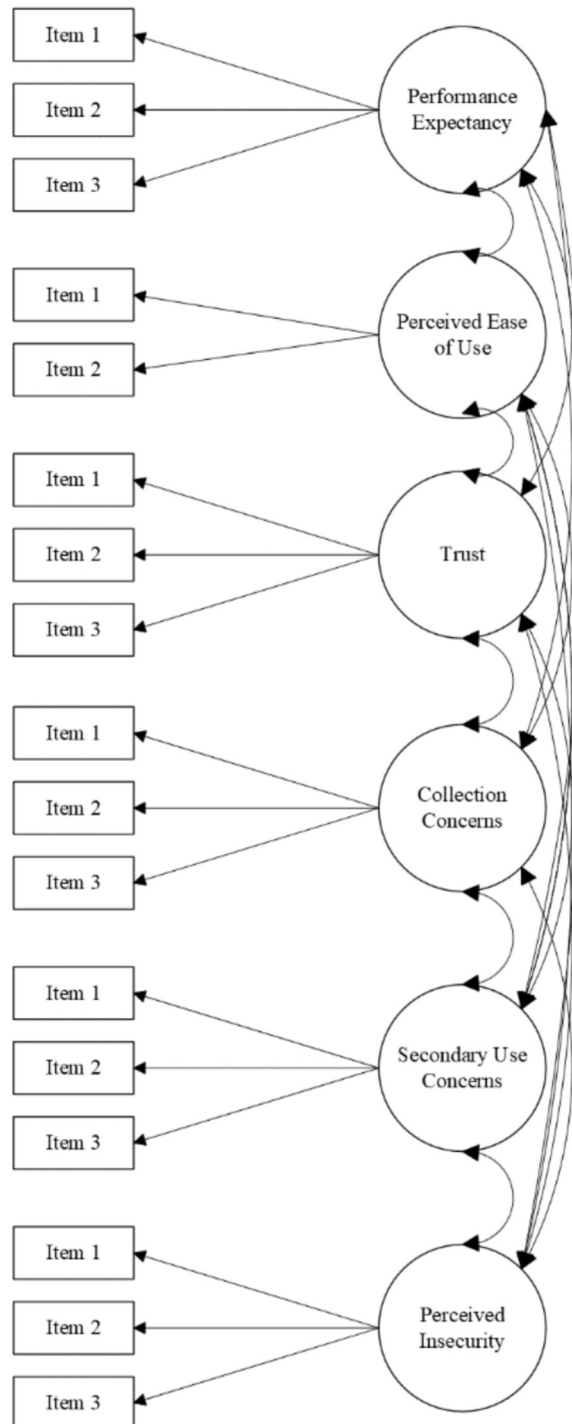


Fig. 3. Model with six oblique lower-order correlated factors.

**Model 2 – Model with six oblique lower-order factors:** This model examines the six factors (i.e., performance expectancy, perceived ease of use, trust, collection concerns, secondary use concerns, and perceived insecurity) separately and allows them to be correlated (Fig. 3, Appendix B2).

**Model 3 – Model with two higher-order factors:** Building upon previous models and previous study of Chu et al. (2023), Model 3 examines performance expectancy, perceived ease of use, and trust load into a higher-order “acceptance” factor, whilst collection concerns, secondary use concerns, and perceived insecurity loading into a higher-order “concern” factor. The model allows for correlations between Concern and Acceptance (Fig. 4, Appendix B3).

**Model 4 – Model with two lower-order factors:** In consideration of the positive correlations observed within acceptance factors (i.e., performance expectancy, perceived ease of use, and trust) and within concern-related constructs (i.e., collection concerns, secondary use concerns, and perceived insecurity), Model 4 examines the two lower-order factors model wherein items of performance expectancy, perceived ease of use, and trust load directly into the “acceptance” construct, while items of collection concerns, secondary use concerns, and perceived insecurity directly load into the “concerns” construct (Fig. 5, Appendix B4).

For each mode, the model fit was assessed through the comparative fit index (CFI,  $> 0.95$ ), the Tucker-Lewis Index (TLI,  $> 0.95$ ), the standardised root mean square residual (SRMR,  $< 0.08$ ), the root mean square error of approximation (RMSEA,  $< 0.06$ ) (Hu & Bentler, 1999; Schermelleh-Engel et al., 2003; Weston & Gore Jr., 2006). We have used the robust weighted least squares (WLSMV) estimator to estimate the CFA results. Missing values were handled with the pairwise deletion. While the results of PCA facilitate the investigation of dimensionality within the data, which the factor structure should reflect, the CFA enables the testing of different models based on prior literature.

After establishing the component structure (Section 3.1), measurement invariance, including configural, metric, and scalar invariance, was assessed (section 3.2). Configural invariance evaluated whether the overall factor structure remained consistent across the nine countries. Metric invariance assessed the consistency of factor loadings between countries, offering insights into how each item contributes to the latent constructs. Lastly, scalar invariance examined the consistency of item intercepts across different countries (Furr, 2021; Putnick & Bornstein, 2016). The goodness of fit indices obtained (CFI  $> 0.90$ , RMSEA  $< 0.08$ ) suggested a well-fitting model (Hu and Bentler, 1999). Chi-squared comparisons were omitted due to their sensitivity to large sample sizes (van de Schoot et al., 2012).

After factorial structure and measurement invariance testing, Pearson’s correlations between variables were reported in Section 3.3 for the pooled sample. In the subsequent section (Section 3.4), results examining country differences in acceptance, concerns, and behavioural intention were presented via a non-parametric (Kruskal-Wallis) one-way analyses of covariance (ANOVA).

Finally (Section 3.5), a separate mixed-effects model was applied to examine the relationship between age, gender, acceptance, concerns, and behavioural intention. Given the differences across countries, random intercepts for “country” and “age by country” were incorporated into the model to account for between-country variability. The model comprised fixed effects for gender (dummy coded), age, acceptance, concerns, acceptance by age interaction, and concerns by age interaction. Interaction terms for age were incorporated into the model to account for the interaction between age and acceptance, as demonstrated by de Winter and Nordhoff (2022). All covariates are centred on the mean. The interaction effects were visualised using the Johnson-Neyman technique.

### 3. Results

#### 3.1. Descriptives and model comparisons

The item-level descriptives are presented in Table 2.

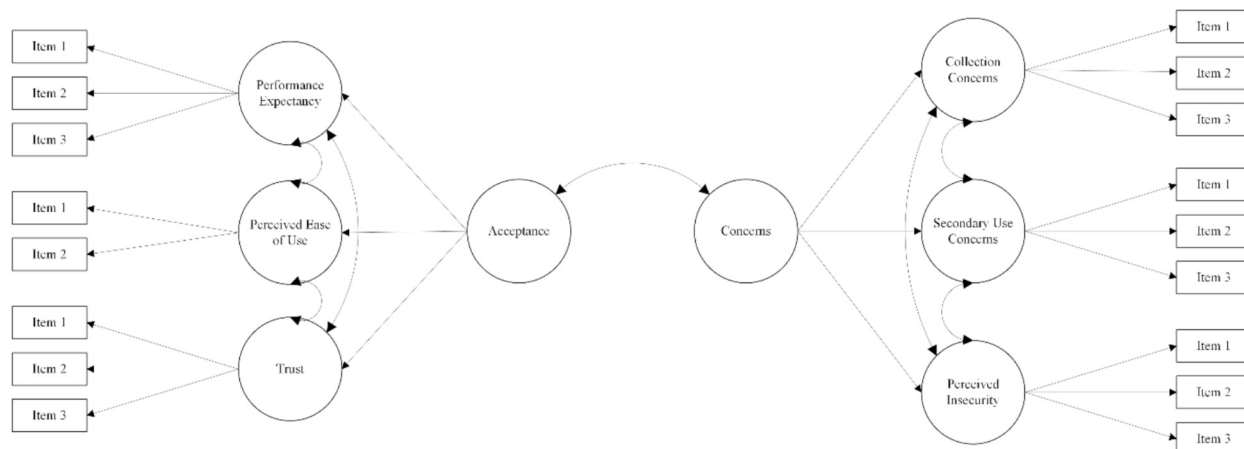


Fig. 4. Model with two higher-order factors.



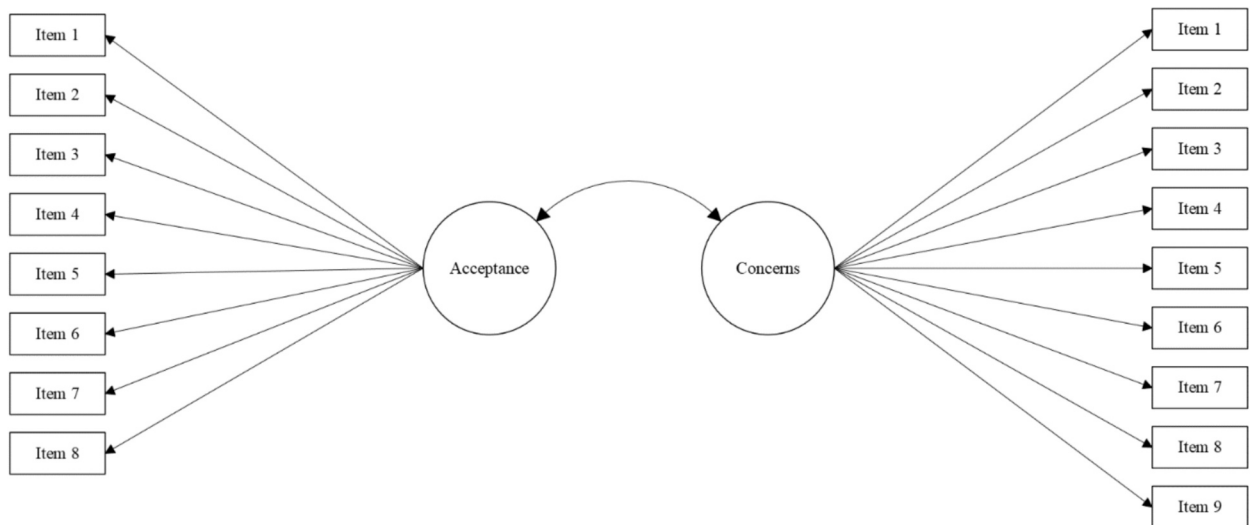


Fig. 5. Model with two lower-order factors.

**Table 2**  
Item-level descriptives.

	N	Missing	Mean	SD	Skewness		Kurtosis	
					Skewness	SE	Kurtosis	SE
PE1: I would find the DMS useful while driving	8980	15	3.303	1.075	−0.444	0.026	−0.241	0.052
PE2: Using the DMS would help me to re-take control of the vehicle safely when required	8976	19	3.347	1.019	−0.453	0.026	−0.024	0.052
PE3: I think that the DMS would reduce the risk of being involved in a traffic accident	8982	13	3.328	1.041	−0.412	0.026	−0.149	0.052
PEU1: I think the DMS will be easy to interact with	8971	24	3.232	0.988	−0.342	0.026	0.006	0.052
PEU2: I think the DMS will be easy to understand	8977	18	3.279	1.011	−0.360	0.026	−0.114	0.052
PEU3*: I think the DMS will be annoying	8973	22	2.947	1.087	−0.012	0.026	−0.517	0.052
PEU4*: I think the DMS will be distracting	8972	23	2.977	1.043	0.028	0.026	−0.405	0.052
TRT1: I will trust the information I receive from the DMS	8974	21	3.182	1.013	−0.353	0.026	−0.143	0.052
TRT2: I think I can rely on the DMS	8976	19	3.115	1.041	−0.323	0.026	−0.257	0.052
TRT3: I would feel more comfortable doing other things (e.g. looking at my phone) with the DMS on	8985	10	3.010	1.127	−0.210	0.026	−0.631	0.052
CC1: I am worried that the DMS is recording my facial image data in real time	8977	18	3.314	1.104	−0.293	0.026	−0.489	0.052
CC2: It bothers me that the DMS is recording my facial image data in real time	8981	14	3.312	1.125	−0.247	0.026	−0.581	0.052
CC3: I am concerned that the DMS is collecting too much personal information about me	8982	13	3.386	1.117	−0.323	0.026	−0.541	0.052
SU1: I am concerned that the manufacturer of the DMS will sell my facial image data to other companies e.g. insurers	8980	15	3.347	1.121	−0.296	0.026	−0.536	0.052
SU2: I am concerned that my facial image data will be used for other purposes while using the DMS	8978	17	3.378	1.117	−0.349	0.026	−0.498	0.052
SU3: I am concerned that the manufacturer of the DMS will share my facial image data with a third party without my authorisation	8975	20	3.374	1.121	−0.327	0.026	−0.527	0.052
PI1: I believe that hackers can easily break into the DMS and get my facial image data	8977	18	3.372	1.075	−0.281	0.026	−0.422	0.052
PI2: I am concerned that my facial data will be leaked	8981	14	3.374	1.129	−0.342	0.026	−0.554	0.052
PI3: I believe that using a DMS poses a real risk to the protection of personal information	8983	12	3.303	1.073	−0.228	0.026	−0.429	0.052
BI1: I would use a car that had a DMS	8977	18	3.169	1.115	−0.361	0.026	−0.425	0.052
BI2: I would be happy for the DMS to monitor my driving	8979	16	3.128	1.108	−0.318	0.026	−0.512	0.052
BI3: If I had a DMS, I would take its' advice	8980	15	3.320	1.002	−0.437	0.026	0.031	0.052

Note. Items with \* are reversed.

The PCA of the 19 items, utilising Promax rotation (Table 3), showed a two-factor structure based on the Scree plot, parallel analysis, and Eigenvalue scores. The results of Bartlett's Test of Sphericity were significant ( $\chi^2(171) = 46576.520, p < 0.001$ ), and the KMO measure of sampling adequacy was 0.957, indicating that the data is well-suited for factor analysis. Two factors achieved an Eigenvalue cut-off of 1.0, and parallel analysis also confirmed a two-factor solution. The inter-component correlation was modest



**Table 3**  
Component loadings and the Uniqueness values of the items.

	Component Concerns	Acceptance	Uniqueness
TRT1	−0.017	0.803	0.348
TRT2	−0.061	0.767	0.385
TRT3	0.026	0.678	0.548
PE1	0.020	0.836	0.308
PE2	0.085	0.802	0.384
PE3	0.056	0.788	0.399
PEU1	0.065	0.784	0.407
PEU2	0.049	0.757	0.444
PEU3*	−0.532	0.300	0.545
PEU4*	−0.488	0.158	0.698
CC1	0.815	0.015	0.342
CC2	0.783	−0.040	0.370
CC3	0.829	0.014	0.319
SU1	0.829	0.089	0.342
SU2	0.837	0.042	0.316
SU3	0.851	0.080	0.305
PI1	0.754	0.009	0.435
PI2	0.834	0.049	0.323
PI3	0.758	−0.002	0.425

Note. Items with \* are reversed.

negative (−0.255). The first factor, labelled as *concerns*, comprised nine concern-related elements, with an initial eigenvalue of 7.168. The second factor, termed *acceptance*, included the remaining elements from trust, performance expectancy, and perceived ease of use, with an initial eigenvalue of 4.188.

As for the CFA results with the second half of the sample, following initial model testing for Model 1 and Model 2 and the PCA results, the items (PEU3\*, PEU4\*) were excluded from the analysis due to low loading into the relevant constructs and high cross-loading for PCA and resulting in lower Average Variance Extracted (AVE) for PEU factor for CFA. The CFA models were subsequently re-analysed without the two items.

According to Table 4 (and detailed measurement solutions in Appendix B), the single-factor model demonstrated inadequate fit overall. Model 2 (six correlated factors) exhibited excellent fit with robust standardised factor loadings, near-ideal fit indices, and high factor reliabilities. Model 3 (the two higher-order factors model with Concerns and Acceptance) displayed good fit indices. However, this model presented negative variance and standardised loadings over 1. This resulted in the Heywood case (e.g., Kolenikov & Bollen, 2012; Wang et al., 2023), indicating an improper model solution (Appendix B). Model 4 (two correlated factors similar to the PCA results) exhibited excellent fit indices in comparison to Models 1 and 3 but not Model 2 (higher  $\chi^2$ ). In light of the strong positive correlations among the lower factor variables in Model 2 and the congruence of the CFA results with the PCA outcomes for Model 4, subsequent analyses were conducted using Model 4, employing two distinct constructs (Acceptance and Concerns).

### 3.2. Measurement invariance

In the pooled sample, the configural invariance for the two-factor model across nine countries was established with a satisfactory absolute fit ( $\chi^2(1062) = 2873.982$ ,  $p < 0.001$ , CFI = 0.979, TLI = 0.973, RMSEA = 0.014). The metric invariance model was upheld, demonstrating a good fit without substantial deterioration with the application of the equal constraints ( $\chi^2(1182) = 3177.210$ ,  $p < 0.001$ , CFI = 0.977, TLI = 0.973, RMSEA = 0.014). For the scalar invariance, China was selected as the reference model as the two-model structure had been previously established in China (Chu et al., 2023). The scalar invariance was achieved ( $\chi^2(1302) = 4351.791$ ,  $p < 0.001$ , CFI = 0.965, TLI = 0.963, RMSEA = 0.016) with a slight decline in model fit as expected. Despite the fact that  $\Delta$ CFI slightly exceeded 0.010, we determined that full invariance had been achieved, given the sensitivity of the indices to large sample sizes and the  $\Delta$ RMSEA being below 0.015 (Chen, 2007). The intercepts were approximately equivalent across countries, indicating that latent means can be compared across the nine countries.

**Table 4**  
Fit indices for the four models.

	df	$\chi^2$	CFI (robust)	TLI (robust)	SRMR (robust)	RMSEA (robust)
Model 1	119	32378.618	0.466	0.390	0.214	0.231
Model 2	104	524.221	0.994	0.992	0.012	0.027
Model 3	112	1179.591	0.990	0.988	0.022	0.032
Model 4	118	1557.782	0.985	0.982	0.024	0.039

### 3.3. Correlations

In total sample, Pearson's correlation coefficients (Table 5) indicated that age exhibited a positive correlation with concerns total score, collection concerns, secondary use concerns, and perceived insecurity whilst demonstrating a negative correlation with general acceptance score, performance expectancy, perceived ease of use, trust, and behavioural intention. Performance expectancy, perceived ease of use, trust, general acceptance score, and behavioural intention were all positively correlated with one another and negatively correlated with concerns total score, collection concerns, secondary use concerns, and perceived insecurity (which demonstrated positive correlations among themselves). The lower-level factors from Model 2 were included in the correlation table (Table 5) solely for descriptive purposes.

### 3.4. Cross-country comparison

Significant country differences were observed for acceptance ( $\chi^2(8) = 820.161, p < 0.001, \epsilon^2 = 0.091$ ), concerns ( $\chi^2(8) = 227.379, p < 0.001, \epsilon^2 = 0.025$ ), and behavioural intention ( $\chi^2(8) = 637.881, p < 0.001, \epsilon^2 = 0.071$ ) and all post hoc comparisons were presented in Appendix C. In terms of overall patterns (Table 6), China exhibited the highest scores in acceptance and behavioural intention, followed by Spain. Spain and Poland also demonstrated the highest values for concerns, whereas Sweden recorded the lowest values.

### 3.5. Factors related to behavioural intention

According to the mixed-effects model (Table 7, Marginal  $R^2 = 0.732$ , Conditional  $R^2 = 0.734$ , AIC = 11818.102, BIC = 11895.880, ICC = 0.003), acceptance were positively and concerns were negatively related to behavioural intention. Furthermore, there were significant interaction effects of age by acceptance and age by concerns ( $p = 0.003$ ).

For the majority of participants, age does not exhibit a discernible impact once acceptance and concerns are considered. The significant interaction effects ( $p < 0.003$ ), as revealed by Johnson–Neyman analyses of the fixed-effect coefficients (see Fig. 6 for acceptance and age interaction and Fig. 7 for concerns by age interaction) indicate that for low acceptance ( $\leq -0.84$  SD) or high concerns ( $\geq +0.98$  SD), age is negatively associated with behavioural intention. Conversely, for very high acceptance ( $\geq +1.93$  SD) or very low concerns ( $\leq -2.10$  SD), an increase in age is associated with a slight increase in behavioural intention.

**Table 5**  
Pearson's correlation matrix.

		1	2	3	4	5	6	7	8	9	10
1.Age	Pearson's r	—									
	df	—									
	p-value	—									
2.Performance expectancy	Pearson's r	-0.136	—								
	df	8696	—								
	p-value	<.001	—								
3.Perceived ease of use	Pearson's r	-0.127	0.63	—							
	df	8695	8986	—							
	p-value	<.001	<.001	—							
4.Trust	Pearson's r	-0.183	0.764	0.604	—						
	df	8696	8988	8987	—						
	p-value	<.001	<.001	<.001	—						
5.Collection concerns	Pearson's r	0.045	-0.145	-0.442	-0.208	—					
	df	8696	8988	8987	8989	—					
	p-value	<.001	<.001	<.001	<.001	—					
6.Secondary use concerns	Pearson's r	0.049	-0.088	-0.375	-0.169	0.813	—				
	df	8693	8985	8984	8985	8986	—				
	p-value	<.001	<.001	<.001	<.001	<.001	—				
7.Perceived insecurity	Pearson's r	0.073	-0.127	-0.424	-0.198	0.802	0.812	—			
	df	8694	8986	8985	8987	8987	8985	—			
	p-value	<.001	<.001	<.001	<.001	<.001	<.001	—			
8.Concerns	Pearson's r	0.059	-0.127	-0.442	-0.204	0.934	0.939	0.93	—		
	df	8697	8989	8988	8990	8991	8987	8988	—		
	p-value	<.001	<.001	<.001	<.001	<.001	<.001	<.001	—		
9.Acceptance	Pearson's r	-0.179	0.925	0.728	0.919	-0.182	-0.13	-0.167	-0.17	—	
	df	8697	8989	8989	8990	8990	8986	8988	8991	—	
	p-value	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	—	
10.Behavioural intention	Pearson's r	-0.165	0.799	0.641	0.793	-0.231	-0.174	-0.205	-0.217	0.853	—
	df	8695	8987	8986	8987	8988	8987	8986	8989	8988	—
	p-value	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	—
	Cronbach's alpha	—	0.82	0.74	0.77	0.83	0.86	0.79	0.93	0.90	0.82

**Table 6**

Descriptives of acceptance, concerns, and behavioural intention by country.

	Country	N	Mean	Median	SD	IQR
Acceptance	Germany	999	3.207	3.250	0.833	0.875
	Spain	999	3.380	3.375	0.763	0.875
	France	1001	3.009	3.000	0.842	0.875
	Japan	1000	3.051	3.000	0.579	0.500
	Poland	998	3.199	3.125	0.720	0.875
	Sweden	996	3.017	3.000	0.856	0.875
	United Kingdom	999	3.149	3.250	0.849	1.000
	United States	998	3.239	3.250	0.869	1.125
	China	1004	3.762	3.750	0.572	0.750
	Germany	1000	3.374	3.333	0.957	1.111
Concerns	Spain	999	3.509	3.556	0.887	1.056
	France	1001	3.266	3.111	0.980	1.222
	Japan	1000	3.193	3.056	0.700	0.667
	Poland	998	3.565	3.556	0.835	1.000
	Sweden	996	3.137	3.000	0.953	1.122
	United Kingdom	998	3.431	3.444	0.886	1.111
	United States	998	3.403	3.333	0.904	1.111
	China	1004	3.278	3.444	0.829	1.111
	Germany	1000	3.177	3.000	0.943	1.333
	Spain	999	3.361	3.333	0.869	1.000
Behavioural intention	France	1000	2.974	3.000	0.971	1.333
	Japan	999	3.039	3.000	0.675	0.667
	Poland	998	3.123	3.000	0.881	1.000
	Sweden	995	3.050	3.000	0.990	1.000
	United Kingdom	998	3.155	3.333	0.975	1.333
	United States	998	3.188	3.333	1.005	1.333
	China	1004	3.780	4.000	0.652	1.000

**Table 7**

Fixed effects parameter estimates.

95 % Confidence Intervals								
	Estimate	SE	Lower	Upper	F	df	t	p
Intercept	3.207	0.010	3.187	3.226		7.648	320.025	<.001
Gender (0: Man; 1: Woman)	0.007	0.010	-0.013	0.027	0.502	8636.987	0.708	0.479
Acceptance	0.950	0.007	0.937	0.964	19059.272	6582.985	138.055	<.001
Concerns	-0.071	0.006	-0.083	-0.059	142.926	8048.299	-11.955	<.001
Age	0.000	0.001	-0.002	0.001	0.321	7.700	-0.566	0.587
Acceptance by age	0.001	0.000	0.000	0.002	9.049	7277.825	3.008	0.003
Concerns by age	-0.001	0.000	-0.002	0.000	9.064	7988.660	-3.011	0.003

## 4. Discussion

In this study, our primary objective was to evaluate varying measurement models for users' acceptance of driver monitoring systems (DMS) in conditionally automated driving systems and to assess the extent to which these models capture the nature of user acceptance. Specifically, we compared a unidimensional model, a six-factor correlated model, a two-factor higher-order structure, and a two-factor correlated model to determine which best represents the underlying constructs of DMS acceptance. Additionally, we examined the impact of country-level differences on these constructs by conducting cross-country comparisons and incorporating a random intercept for the country in our analyses. Furthermore, we explored the relationship between the identified dimensions and potential users' behavioural intention to use DMS whilst accounting for key demographic factors (i.e., age and gender). This multifaceted approach was designed to provide a robust and nuanced understanding of DMS acceptance across diverse international contexts.

### 4.1. Discussion of the main findings

Regarding the first objective of the study, which compared different measurement models from the PCA and CFA results, the CFA results indicated that both six correlated factors and two correlated factors model demonstrated good model fit compared to the other models. The PCA results also supported the two-factor model. Consistent with previous research (Aasvik et al., 2024), the unidimensional approach incorporating one general factor for various constructs exhibited poor fit, so Model 1 was deemed unacceptable. Attempts to create a higher-order structure (Model 3 based on the study of Chu et al., 2023) encountered identification problems. The model displayed acceptable fit indices but yielded negative latent variance. Both the results of PCA and CFA indicated that concerns

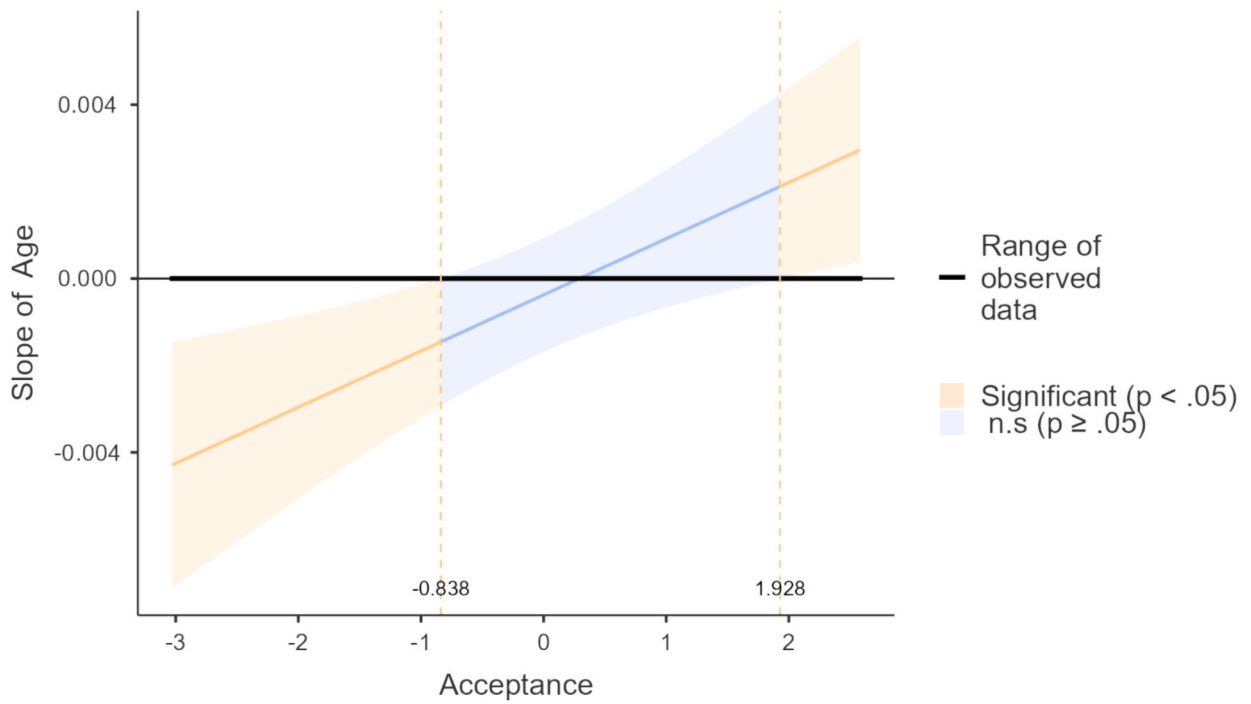


Fig. 6. Johnson-Neyman plot for the acceptance by age effect.

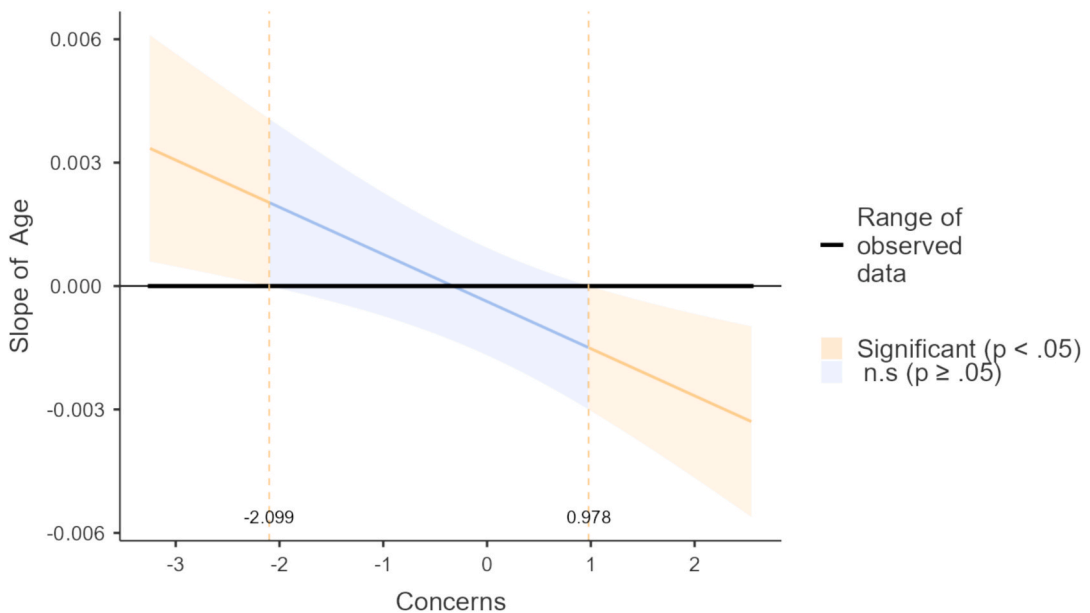


Fig. 7. Johnson-Neyman plot for the concerns by age effect.

and acceptance factors are distinct variables, supporting the findings of previous literature (Chu et al., 2023). In alignment with the general acceptance factor discussed by de Winter and Nordhoff (2022), the lower-order model (Model 4) demonstrated superior performance compared to the higher-order model (Model 3). The general acceptance factor comprised elements of trust, performance expectancy, and perceived ease of use.

Regarding the second objective, significant differences among all three constructs were identified for the country. The results indicated that respondents' evaluation of DMS was culturally embedded. Notwithstanding the identification of country differences through ANOVA, the intraclass correlation coefficient was also notably low (0.003), indicating that the majority of variance occurs at

the individual level on behavioural intention. This finding suggests that, despite statistical significance, the practical implications of country-specific factors on behavioural intention may be minimal. Thus, while country-level differences exist, tailoring interventions or communication strategies to specific cultural contexts may yield only marginal benefits. Nevertheless, for market deployment or policy-making purposes, it is prudent to consider these disparities.

Regarding the final objective, approximately 73.2 % of the variance in behavioural intention is accounted for by the fixed predictors (i.e., individual-level factors). General acceptance factor emerged as the most significant determinant of behavioural intention with other factors (concerns, age by acceptance interaction, and age by concerns interaction) contributing marginally to the model. This observation aligns with findings in the domain of shared automated vehicle acceptance, which highlight a modest yet significant impact of other constructs beyond general acceptance (Aasvik et al., 2024). In line with the previous studies (e.g., Ehsani et al., 2024; Smyth et al., 2021) addressing different constructs associated with the general acceptance in this study, the general acceptance showed positive effect over behavioural intention. These findings corroborate the notion that participants' positive evaluations (e.g., perceiving DMS as useful and trustworthy) are crucial determinants of their intention to utilise DMS.

As highlighted in various DMS studies (e.g., Coyne et al., 2024; Ehsani et al., 2024; Guttman & Gesser-Edelsburg, 2011; Guttman & Lotan, 2011; Jannusch et al., 2021; Presta et al., 2022), users express concerns regarding the systems and the processes of data collection, storage, and handling. This study identified that concerns demonstrated a negative, albeit small, effect on behavioural intention compared to other significant variables. This finding is consistent with the results of Ehsani et al. (2024), which indicate that privacy concerns had weaker relations with DMS acceptance than perceived usefulness (benefits). The findings corroborate those of Gruchmann and Jazairy (2025) regarding the acceptance of road-facing dashcams by truck drivers, indicating that perceived benefits, as linked with the general acceptance factor, are a more significant determinant of intention than concerns about data privacy. As multiple data sources may be required for more efficient and effective monitoring systems (Jannusch et al., 2021; Khan & Lee, 2019), the trade-off with collection and privacy concerns may be more pronounced in user acceptance.

Two interaction effects of modest yet significant magnitude were identified between age and acceptance, and age and concerns. The analysis indicated that age does not independently influence behavioural intention when acceptance and concerns are considered; rather, its effect is contingent upon extreme levels of these attitudes. Specifically, age is inversely related to behavioural intention among individuals exhibiting low acceptance or high concern, while it is positively associated with behavioural intention among those with very high acceptance or very low concern. This finding has direct implications for system utilisation, suggesting that, among users with low acceptance or high concern, older individuals may underutilise the systems due to lower behavioural intention. Conversely, among users with high acceptance or low concern, younger users may exhibit over-reliance on the system. These results underscore a complex interaction between demographic factors and attitudes in determining behavioural outcomes.

The findings may also help develop interventions aimed at enhancing DMS acceptance by targeting elements of acceptance and concerns. In the context of policy and industry, it may be advantageous to explicitly address concerns, and a different strategic focus on performance and trust may be more appropriate in certain cases. In a similar vein, Coyne et al. (2024) proposed that providing drivers with information regarding data sharing and the reliability of the systems could mitigate potential concerns about these systems. Furthermore, Turner et al. (2010) posited that behavioural intention serves as a more accurate predictor of actual technology use than perceived ease of use. Given the substantial percentage of variance explained by acceptance in predicting behavioural intention, addressing users' perceptions could significantly enhance the future utilisation of DMS technologies.

Furthermore, although country-level variance was minimal, policymakers should remain cognisant of the disparities in policy and practice that exist across countries, which may necessitate region-specific approaches when promoting DMS technologies. In this context, there is a lack of comparable cross-country statistics regarding drivers' personal exposure to conditionally automated driving systems and/or driver monitoring systems. Currently, the utilisation of DMS is not widespread; a recent study by Ehsani et al. (2024) reported that only 20 % of adults in the United States use DMS. This situation is anticipated to evolve as policy and market deployment progress. For instance, in Europe, the European New Car Assessment Programme (Euro NCAP, 2022) has introduced driver monitoring system assessment protocols that incentivise manufacturer adoption. Beginning in 2026, newly manufactured automobiles in Europe will be equipped with a DMS to enhance road safety and reduce risks associated with driver inattention or impairment (Euro NCAP, 2024). Additionally, in the United Kingdom, the Automated Vehicles Act (2025) establishes a framework for the safe deployment of automated driving systems. Collectively, these developments are expected to enhance the integration of automated driving systems and driver monitoring systems, thereby increasing real-world exposure and potentially influencing cross-country differences over time, as national implementation and industry practices evolve.

#### 4.2. Limitations and implications for future research

While this study offers valuable insights into DMS acceptance across diverse international settings, several limitations warrant acknowledgement. Firstly, the reliance on self-report survey data may introduce common method bias and potentially compromise the accuracy of the measured constructs, as participants' responses could be influenced by social desirability or other response biases. Secondly, the cross-sectional design restricts the ability to draw causal inferences regarding the relationships between the acceptance factors and behavioural intention. Furthermore, while the use of a random intercept for country accounted for between-country variability, future research could explore other contextual factors that might exert a more pronounced impact.

One methodological consideration in this study is that our operational definition of DMS encompasses two separate functions: driver state detection and vehicle response. Consequently, participants' acceptance and concern ratings reflect their views on both elements, making it difficult to separate these components. Future research could explore the attitudes toward monitoring and interventions functions individually to gain a more detailed understanding. Another consideration is that the study examined only a

limited number of constructs. As demonstrated by previous research (e.g., Marangunić, & Granić, 2015; Nordhoff et al., 2021), there exist multiple theoretically relevant but distinct latent factors contributing to acceptance and behavioural intention. While our findings provide evidence for a general acceptance factor cooperating trust, performance expectancy, and perceived ease of use, the results also reveal the distinct structure of concerns. Further empirical research is necessary to explore the general acceptance factor comprehensively. Furthermore, the negative latent variances observed in the two second-order factors model indicate potential over-specification. It is plausible that the higher-order structure (merging concerns and acceptance into two distinct second-order factors) does not hold with the current number of items. Moreover, certain items (e.g., the reversed PEU items) exhibited low loadings, necessitating their exclusion. Furthermore, although the two-factor structure demonstrates robustness across countries, the phrasing of the questionnaire may still introduce a minor degree of method variance. Despite the fact that concern items were formulated as content-specific statements rather than mere negations, the potential for method variance due to wording cannot be entirely dismissed, including residual effects from item polarity. This suggests that further refinement of the measurement including the framing of the items may be warranted.

Furthermore, we did not measure participants' previous experience with driver monitoring systems specifically or automated driving systems in general. Familiarity with these technologies could influence perceptions and attitudes (Charness et al., 2018; Öztürk et al., 2024; Pan & Zheng, 2025). Future research should aim to capture and analyse knowledge and experience aspects to gain a better understanding of the potential differences between users with varying levels of experience.

It should also be noted that most of the previous research on the GAF discussed in this paper originates from studies on automated vehicle acceptance (e.g., Aasvik et al., 2024; de Winter & Nordhoff, 2022). Although both automated vehicles and DMS pertain broadly to technology acceptance in transport, they are perceived to be different by users (Coyne et al., 2024), and the constructs underlying acceptance may differ due to their distinct functionalities. Thus, reliance on automated vehicle literature constitutes a potential limitation in the theoretical framing of the current study. Further research specifically targeting the acceptance of DMS technology is therefore warranted to clarify and expand theoretical understanding.

Returning to the initial discussion on the dimensionality of acceptance, as previously stated, the findings generally support the overarching acceptance factor while also indicating support for other factors influencing behavioural intention. Although further empirical research is warranted, the current study, building on the work of Aasvik et al. (2024) and de Winter and Nordhoff (2022), identifies the general acceptance factor as the most significant influence on behavioural intention and highlights concerns as a distinct factor. Drawing on the multi-layer, multi-dimensional approach by Nordhoff et al. (2019), it is suggested that simplifying the measurement of acceptance and identifying other independent contextual factors, such as concerns, would benefit both theoretical and practical research. Moreover, considering the interaction effects of age, it can be posited that, when testing models, the role of moderating factors may be crucial in capturing unique results that deviate from general trends (e.g., Chen et al., 2024). This could also lead to a more empirical question into the existence of multidimensionality concerning acceptance. Therefore, we propose simplifying the acceptance measurement and placing greater emphasis on the interaction effects between acceptance and other factors in predicting behavioural intention. Further empirical research and refinement of measurements are necessary to address this. For instance, employing simpler measurements that focus on distinct aspects could result in a more refined assessment of acceptance with fewer items (e.g., one question related to performance expectancy, one addressing trust, one concerning perceived ease of use, and other empirically identified constructs).

### CRediT authorship contribution statement

**İbrahim Öztürk:** Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Esko Lehtonen:** Writing – review & editing, Project administration, Methodology, Conceptualization. **Ruth Madigan:** Writing – review & editing, Methodology, Conceptualization. **Yee Mun Lee:** Writing – review & editing. **Elina Aittoniemi:** Writing – review & editing, Conceptualization. **Natasha Merat:** Writing – review & editing, Funding acquisition.

### 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.

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## Appendix A. . Item distribution per country

Item	Country	N	Missing	Mean	SD	Skewness	SE	Kurtosis	SE
PE1: I would find the DMS useful while driving	Germany	997	3	3.195	1.114	-0.380	0.077	-0.377	0.155
	Spain	997	2	3.504	1.013	-0.568	0.077	0.112	0.155
	France	999	2	3.041	1.171	-0.147	0.077	-0.745	0.155
	Japan	1000	0	3.150	0.815	-0.348	0.077	0.746	0.155
	Poland	996	2	3.291	0.947	-0.488	0.077	0.223	0.155
	Sweden	993	3	3.117	1.156	-0.237	0.078	-0.622	0.155
	United Kingdom	998	1	3.185	1.136	-0.454	0.077	-0.495	0.155
	United States	997	1	3.243	1.152	-0.389	0.077	-0.533	0.155
	China	1003	1	3.994	0.769	-0.690	0.077	1.054	0.154
	Germany	998	2	3.284	1.072	-0.416	0.077	-0.220	0.155
PE2: Using the DMS would help me to re-take control of the vehicle safely when required	Spain	998	1	3.546	0.963	-0.579	0.077	0.440	0.155
	France	998	3	3.099	1.106	-0.139	0.077	-0.583	0.155
	Japan	998	2	3.128	0.777	-0.355	0.077	1.102	0.155
	Poland	997	1	3.318	0.922	-0.571	0.077	0.305	0.155
	Sweden	992	4	3.128	1.135	-0.244	0.078	-0.496	0.155
	United Kingdom	997	2	3.340	1.016	-0.592	0.077	0.094	0.155
	United States	995	3	3.400	1.058	-0.520	0.078	-0.050	0.155
	China	1003	1	3.877	0.818	-0.649	0.077	0.644	0.154
	Germany	999	1	3.251	1.079	-0.426	0.077	-0.317	0.155
	Spain	999	0	3.462	1.008	-0.547	0.077	0.236	0.155
PE3: I think that the DMS would reduce the risk of being involved in a traffic accident	France	996	5	3.085	1.129	-0.122	0.077	-0.591	0.155
	Japan	1000	0	3.147	0.795	-0.305	0.077	0.804	0.155
	Poland	998	0	3.321	0.958	-0.459	0.077	0.206	0.155
	Sweden	993	3	3.168	1.140	-0.243	0.078	-0.562	0.155
	United Kingdom	996	3	3.252	1.069	-0.421	0.077	-0.248	0.155
	United States	997	1	3.332	1.088	-0.378	0.077	-0.354	0.155
	China	1004	0	3.929	0.785	-0.619	0.077	0.710	0.154
	Germany	997	3	3.251	0.983	-0.322	0.077	0.092	0.155
	Spain	997	2	3.332	0.928	-0.380	0.077	0.439	0.155
	France	999	2	3.035	1.079	-0.146	0.077	-0.382	0.155
PEU1: I think the DMS will be easy to interact with	Japan	996	4	2.952	0.769	-0.264	0.077	0.976	0.155
	Poland	996	2	3.222	0.874	-0.437	0.077	0.297	0.155
	Sweden	992	4	3.049	1.078	-0.239	0.078	-0.319	0.155
	United Kingdom	996	3	3.200	1.041	-0.412	0.077	-0.161	0.155
	United States	996	2	3.301	1.082	-0.344	0.077	-0.405	0.155
	China	1002	2	3.746	0.770	-0.422	0.077	0.448	0.154
	Germany	998	2	3.310	1.010	-0.351	0.077	-0.040	0.155
	Spain	996	3	3.465	0.975	-0.446	0.077	0.069	0.155
	France	998	3	3.131	1.061	-0.253	0.077	-0.423	0.155
	Japan	998	2	2.916	0.769	-0.373	0.077	1.080	0.155
PEU2: I think the DMS will be easy to understand	Poland	996	2	3.278	0.877	-0.518	0.077	0.438	0.155
	Sweden	993	3	3.083	1.117	-0.163	0.078	-0.477	0.155
	United Kingdom	997	2	3.207	1.044	-0.399	0.077	-0.317	0.155
	United States	998	0	3.310	1.111	-0.400	0.077	-0.404	0.155
	China	1003	1	3.812	0.810	-0.558	0.077	0.471	0.154
	Germany	995	5	2.946	1.131	-0.031	0.078	-0.688	0.155
	Spain	998	1	2.979	1.052	-0.072	0.077	-0.365	0.155
	France	997	4	3.001	1.182	0.035	0.077	-0.685	0.155
	Japan	998	2	3.047	0.805	-0.005	0.077	0.628	0.155
	Poland	996	2	2.787	0.973	-0.016	0.077	-0.323	0.155
PEU3* (reversed): I think the DMS will be annoying	Sweden	992	4	2.902	1.143	0.062	0.078	-0.546	0.155
	United Kingdom	996	3	2.635	1.093	0.142	0.077	-0.734	0.155
	United States	997	1	2.698	1.127	0.229	0.077	-0.674	0.155
	China	1004	0	3.519	0.983	-0.321	0.077	-0.317	0.154
	Germany	997	3	2.976	1.042	0.043	0.077	-0.488	0.155
	Spain	997	2	3.041	1.171	-0.147	0.077	-0.745	0.155
	France	999	2	3.041	1.171	-0.147	0.077	-0.745	0.155
	Japan	1000	0	3.150	0.815	-0.348	0.077	0.746	0.155
	Poland	996	2	3.291	0.947	-0.488	0.077	0.223	0.155
	Sweden	993	3	3.117	1.156	-0.237	0.078	-0.622	0.155
PEU4* (reversed): I think the DMS will be distracting	United Kingdom	998	1	3.185	1.136	-0.454	0.077	-0.495	0.155
	United States	997	1	3.243	1.152	-0.389	0.077	-0.533	0.155
	China	1003	1	3.994	0.769	-0.690	0.077	1.054	0.154
	Germany	998	2	3.284	1.072	-0.416	0.077	-0.220	0.155
	Spain	998	1	3.546	0.963	-0.579	0.077	0.440	0.155
	France	998	3	3.099	1.106	-0.139	0.077	-0.583	0.155
	Japan	998	2	3.128	0.777	-0.355	0.077	1.102	0.155
	Poland	997	1	3.318	0.922	-0.571	0.077	0.305	0.155
	Sweden	992	4	3.128	1.135	-0.244	0.078	-0.496	0.155
	United Kingdom	997	2	3.340	1.016	-0.592	0.077	0.094	0.155

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Item	Country	N	Missing	Mean	SD	Skewness	SE	Kurtosis	SE
TRT1: I will trust the information I receive from the DMS	Spain	996	3	2.945	1.054	0.079	0.077	-0.432	0.155
	France	998	3	3.239	1.102	0.111	0.077	-0.585	0.155
	Japan	999	1	3.148	0.754	0.071	0.077	1.113	0.155
	Poland	997	1	2.870	0.924	0.047	0.077	-0.242	0.155
	Sweden	992	4	2.930	1.117	0.055	0.078	-0.526	0.155
	United Kingdom	996	3	2.662	1.064	0.170	0.077	-0.590	0.155
	United States	994	4	2.735	1.117	0.170	0.078	-0.699	0.155
	China	1003	1	3.287	0.988	-0.220	0.077	-0.467	0.154
	Germany	997	3	3.160	1.049	-0.345	0.077	-0.243	0.155
	Spain	998	1	3.406	0.966	-0.478	0.077	0.289	0.155
	France	998	3	2.977	1.090	-0.173	0.077	-0.541	0.155
	Japan	997	3	3.046	0.746	-0.322	0.077	1.176	0.155
	Poland	996	2	3.092	0.929	-0.395	0.077	0.184	0.155
	Sweden	992	4	2.970	1.101	-0.104	0.078	-0.585	0.155
	United Kingdom	996	3	3.113	1.061	-0.399	0.077	-0.375	0.155
	United States	997	1	3.177	1.088	-0.331	0.077	-0.394	0.155
TRT2: I think I can rely on the DMS	China	1003	1	3.695	0.807	-0.453	0.077	0.224	0.154
	Germany	993	7	3.142	1.069	-0.250	0.078	-0.341	0.155
	Spain	998	1	3.276	1.026	-0.409	0.077	-0.005	0.155
	France	1000	1	2.915	1.126	-0.170	0.077	-0.625	0.155
	Japan	999	1	3.098	0.796	-0.536	0.077	1.005	0.155
	Poland	997	1	3.124	0.924	-0.341	0.077	0.093	0.155
	Sweden	992	4	2.897	1.150	-0.149	0.078	-0.731	0.155
	United Kingdom	996	3	3.035	1.094	-0.291	0.077	-0.506	0.155
	United States	997	1	3.131	1.123	-0.290	0.077	-0.507	0.155
	China	1004	0	3.417	0.911	-0.325	0.077	-0.209	0.154
	Germany	998	2	3.060	1.153	-0.271	0.077	-0.597	0.155
	Spain	996	3	3.050	1.097	-0.186	0.077	-0.583	0.155
	France	1000	1	2.799	1.251	0.018	0.077	-0.958	0.155
	Japan	1000	0	2.978	0.820	-0.189	0.077	0.416	0.155
	Poland	997	1	2.943	1.017	-0.299	0.077	-0.441	0.155
	Sweden	995	1	2.755	1.191	0.031	0.078	-0.824	0.155
TRT3: I would feel more comfortable doing other things (e.g. looking at my phone) with the DMS on	United Kingdom	998	1	2.849	1.183	-0.116	0.077	-0.949	0.155
	United States	997	1	3.019	1.203	-0.165	0.077	-0.839	0.155
	China	1004	0	3.631	0.919	-0.510	0.077	0.044	0.154
	Germany	998	2	3.339	1.132	-0.347	0.077	-0.508	0.155
	Spain	997	2	3.470	1.085	-0.448	0.077	-0.266	0.155
	France	996	5	3.257	1.220	-0.191	0.077	-0.816	0.155
	Japan	999	1	3.182	0.877	-0.219	0.077	0.326	0.155
	Poland	997	1	3.517	1.029	-0.335	0.077	-0.384	0.155
	Sweden	993	3	3.043	1.214	-0.086	0.078	-0.778	0.155
	United Kingdom	996	3	3.413	1.094	-0.332	0.077	-0.521	0.155
	United States	997	1	3.321	1.154	-0.260	0.077	-0.720	0.155
	China	1004	0	3.286	1.019	-0.430	0.077	-0.318	0.154
	Germany	999	1	3.405	1.186	-0.391	0.077	-0.647	0.155
	Spain	997	2	3.411	1.095	-0.348	0.077	-0.448	0.155
	France	999	2	3.232	1.253	-0.142	0.077	-0.902	0.155
	Japan	998	2	3.110	0.872	-0.161	0.077	0.374	0.155
CC1: I am worried that the DMS is recording my facial image data in real time	Poland	997	1	3.483	1.030	-0.298	0.077	-0.387	0.155
	Sweden	993	3	3.180	1.218	-0.167	0.078	-0.744	0.155
	United Kingdom	997	2	3.459	1.141	-0.389	0.077	-0.616	0.155
	United States	998	0	3.442	1.166	-0.371	0.077	-0.674	0.155
	China	1003	1	3.084	1.027	-0.129	0.077	-0.542	0.154
	Germany	998	2	3.391	1.186	-0.361	0.077	-0.696	0.155
	Spain	997	2	3.523	1.095	-0.446	0.077	-0.344	0.155
	France	999	2	3.259	1.222	-0.185	0.077	-0.831	0.155
	Japan	996	4	3.178	0.886	-0.146	0.077	0.321	0.155
	United States	998	0	3.442	1.166	-0.371	0.077	-0.674	0.155
	China	1003	1	3.084	1.027	-0.129	0.077	-0.542	0.154
	Germany	998	2	3.391	1.186	-0.361	0.077	-0.696	0.155
	Spain	997	2	3.523	1.095	-0.446	0.077	-0.344	0.155
	France	999	2	3.259	1.222	-0.185	0.077	-0.831	0.155
	Japan	996	4	3.178	0.886	-0.146	0.077	0.321	0.155
	United States	998	0	3.442	1.166	-0.371	0.077	-0.674	0.155
CC2: It bothers me that the DMS is recording my facial image data in real time	China	1004	0	3.631	0.919	-0.510	0.077	0.044	0.154
	Germany	998	2	3.339	1.132	-0.347	0.077	-0.508	0.155
	Spain	997	2	3.470	1.085	-0.448	0.077	-0.266	0.155
	France	996	5	3.257	1.220	-0.191	0.077	-0.816	0.155
	Japan	999	1	3.182	0.877	-0.219	0.077	0.326	0.155
	Poland	997	1	3.517	1.029	-0.335	0.077	-0.384	0.155
	Sweden	993	3	3.043	1.214	-0.086	0.078	-0.778	0.155
	United Kingdom	996	3	3.413	1.094	-0.332	0.077	-0.521	0.155
	United States	997	1	3.321	1.154	-0.260	0.077	-0.720	0.155
	China	1004	0	3.286	1.019	-0.430	0.077	-0.318	0.154
	Germany	999	1	3.405	1.186	-0.391	0.077	-0.647	0.155
	Spain	997	2	3.411	1.095	-0.348	0.077	-0.448	0.155
	France	999	2	3.232	1.253	-0.142	0.077	-0.902	0.155
	Japan	998	2	3.110	0.872	-0.161	0.077	0.374	0.155
	Poland	997	1	3.483	1.030	-0.298	0.077	-0.387	0.155
	Sweden	993	3	3.180	1.218	-0.167	0.078	-0.744	0.155
CC3: I am concerned that the DMS is collecting too much personal information about me	United Kingdom	997	2	3.459	1.141	-0.389	0.077	-0.616	0.155
	United States	998	0	3.442	1.166	-0.371	0.077	-0.674	0.155
	China	1003	1	3.084	1.027	-0.129	0.077	-0.542	0.154
	Germany	998	2	3.391	1.186	-0.361	0.077	-0.696	0.155
	Spain	997	2	3.523	1.095	-0.446	0.077	-0.344	0.155
	France	999	2	3.259	1.222	-0.185	0.077	-0.831	0.155
	Japan	996	4	3.178	0.886	-0.146	0.077	0.321	0.155
	United States	998	0	3.442	1.166	-0.371	0.077	-0.674	0.155
	China	1003	1	3.084	1.027	-0.129	0.077	-0.542	0.154
	Germany	998	2	3.391	1.186	-0.361	0.077	-0.696	0.155
	Spain	997	2	3.523	1.095	-0.446	0.077	-0.344	0.155
	France	999	2	3.259	1.222	-0.185	0.077	-0.831	0.155
	Japan	996	4	3.178	0.886	-0.146	0.077	0.321	0.155
	United States	998	0	3.442	1.166	-0.371	0.077	-0.674	0.155
	China	1003	1	3.084	1.027	-0.129	0.077	-0.542	0.154
	Germany	998	2	3.391	1.186	-0.361	0.077	-0.696	0.155
	Spain	997	2	3.523	1.095	-0.446	0.077	-0.344	0.155
	France	999	2	3.259	1.222	-0.185	0.077	-0.831	0.155
	Japan	996	4	3.178	0.886	-0.146	0.077	0.321	0.155

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Item	Country	N	Missing	Mean	SD	Skewness	Skewness SE	Kurtosis	Kurtosis SE
SU1: I am concerned that the manufacturer of the DMS will sell my facial image data to other companies e.g. insurers	Poland	998	0	3.603	1.016	−0.492	0.077	−0.144	0.155
	Sweden	996	0	3.148	1.249	−0.098	0.077	−0.905	0.155
	United Kingdom	996	3	3.495	1.088	−0.335	0.077	−0.635	0.155
	United States	998	0	3.476	1.148	−0.401	0.077	−0.614	0.155
	China	1004	0	3.398	1.026	−0.446	0.077	−0.326	0.154
	Germany	998	2	3.386	1.143	−0.366	0.077	−0.540	0.155
	Spain	998	1	3.582	1.106	−0.503	0.077	−0.376	0.155
	France	997	4	3.260	1.243	−0.166	0.077	−0.919	0.155
	Japan	998	2	3.103	0.864	−0.172	0.077	0.635	0.155
	Poland	996	2	3.609	1.018	−0.450	0.077	−0.211	0.155
	Sweden	994	2	3.101	1.197	−0.134	0.078	−0.704	0.155
	United Kingdom	997	2	3.373	1.117	−0.310	0.077	−0.571	0.155
	United States	998	0	3.334	1.165	−0.219	0.077	−0.743	0.155
	China	1004	0	3.372	1.077	−0.468	0.077	−0.453	0.154
SU2: I am concerned that my facial image data will be used for other purposes while using the DMS	Germany	997	3	3.373	1.149	−0.362	0.077	−0.570	0.155
	Spain	997	2	3.560	1.091	−0.539	0.077	−0.197	0.155
	France	999	2	3.279	1.247	−0.186	0.077	−0.915	0.155
	Japan	999	1	3.196	0.908	−0.204	0.077	0.185	0.155
	Poland	996	2	3.627	1.004	−0.484	0.077	−0.095	0.155
	Sweden	993	3	3.138	1.241	−0.165	0.078	−0.816	0.155
	United Kingdom	995	4	3.457	1.078	−0.401	0.078	−0.416	0.155
	United States	998	0	3.410	1.136	−0.317	0.077	−0.656	0.155
	China	1004	0	3.363	1.071	−0.463	0.077	−0.432	0.154
	Germany	997	3	3.343	1.133	−0.315	0.077	−0.574	0.155
	Spain	998	1	3.579	1.132	−0.552	0.077	−0.311	0.155
	France	996	5	3.280	1.239	−0.191	0.077	−0.876	0.155
	Japan	998	2	3.228	0.897	−0.130	0.077	0.269	0.155
	Poland	998	0	3.614	1.030	−0.482	0.077	−0.221	0.155
SU3: I am concerned that the manufacturer of the DMS will share my facial image data with a third party without my authorisation	Sweden	992	4	3.104	1.224	−0.143	0.078	−0.791	0.155
	United Kingdom	997	2	3.417	1.098	−0.306	0.077	−0.576	0.155
	United States	996	2	3.397	1.152	−0.286	0.077	−0.717	0.155
	China	1003	1	3.401	1.060	−0.500	0.077	−0.331	0.154
	Germany	998	2	3.433	1.074	−0.343	0.077	−0.375	0.155
	Spain	998	1	3.472	1.059	−0.401	0.077	−0.282	0.155
	France	997	4	3.328	1.192	−0.205	0.077	−0.804	0.155
	Japan	999	1	3.241	0.872	−0.161	0.077	0.511	0.155
	Poland	994	4	3.562	0.931	−0.212	0.078	−0.203	0.155
	Sweden	991	5	3.310	1.160	−0.245	0.078	−0.649	0.155
	United Kingdom	998	1	3.436	1.056	−0.330	0.077	−0.387	0.155
	United States	998	0	3.471	1.132	−0.390	0.077	−0.547	0.155
	China	1004	0	3.093	1.085	−0.147	0.077	−0.612	0.154
	Germany	999	1	3.358	1.165	−0.330	0.077	−0.647	0.155
PI1: I believe that hackers can easily break into the DMS and get my facial image data	Spain	998	1	3.594	1.111	−0.522	0.077	−0.352	0.155
	France	999	2	3.269	1.230	−0.216	0.077	−0.846	0.155
	Japan	999	1	3.338	0.940	−0.241	0.077	0.059	0.155
	Poland	995	3	3.616	1.015	−0.370	0.078	−0.405	0.155
	Sweden	993	3	3.097	1.220	−0.125	0.078	−0.789	0.155
	United Kingdom	997	2	3.371	1.137	−0.348	0.077	−0.616	0.155
	United States	997	1	3.376	1.154	−0.321	0.077	−0.682	0.155
	China	1004	0	3.345	1.077	−0.459	0.077	−0.479	0.154
	Germany	998	2	3.343	1.135	−0.321	0.077	−0.562	0.155
	Spain	998	1	3.398	1.060	−0.355	0.077	−0.225	0.155
	France	1000	1	3.226	1.181	−0.160	0.077	−0.720	0.155
	Japan	999	1	3.176	0.819	−0.181	0.077	0.751	0.155
	Poland	997	1	3.456	0.998	−0.238	0.077	−0.319	0.155
	Sweden	993	3	3.122	1.168	−0.071	0.078	−0.681	0.155

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Item	Country	N	Missing	Mean	SD	Skewness	SE	Kurtosis	SE
BI1: I would use a car that had a DMS	United Kingdom	997	2	3.447	1.054	-0.279	0.077	-0.523	0.155
	United States	998	0	3.398	1.120	-0.262	0.077	-0.633	0.155
	China	1003	1	3.163	1.019	-0.233	0.077	-0.400	0.154
	Germany	997	3	3.126	1.154	-0.354	0.077	-0.582	0.155
	Spain	998	1	3.368	1.072	-0.469	0.077	-0.148	0.155
	France	998	3	2.916	1.202	-0.088	0.077	-0.810	0.155
	Japan	999	1	2.972	0.849	-0.380	0.077	0.614	0.155
	Poland	997	1	3.115	1.035	-0.488	0.077	-0.176	0.155
	Sweden	993	3	2.981	1.218	-0.134	0.078	-0.789	0.155
	United Kingdom	995	4	3.090	1.164	-0.357	0.078	-0.643	0.155
BI2: I would be happy for the DMS to monitor my driving	United States	996	2	3.169	1.201	-0.292	0.077	-0.726	0.155
	China	1004	0	3.783	0.794	-0.358	0.077	0.094	0.154
	Germany	996	4	3.089	1.147	-0.275	0.077	-0.669	0.155
	Spain	998	1	3.267	1.059	-0.395	0.077	-0.217	0.155
	France	999	2	2.901	1.175	-0.086	0.077	-0.765	0.155
	Japan	997	3	2.981	0.842	-0.358	0.077	0.469	0.155
	Poland	997	1	3.003	1.054	-0.269	0.077	-0.521	0.155
	Sweden	994	2	2.956	1.187	-0.164	0.078	-0.792	0.155
	United Kingdom	996	3	3.078	1.166	-0.385	0.077	-0.768	0.155
	United States	998	0	3.146	1.183	-0.241	0.077	-0.705	0.155
BI3: If I had a DMS, I would take its' advice	China	1004	0	3.730	0.860	-0.601	0.077	0.336	0.154
	Germany	999	1	3.320	1.010	-0.451	0.077	0.082	0.155
	Spain	999	0	3.449	0.956	-0.504	0.077	0.343	0.155
	France	997	4	3.104	1.061	-0.214	0.077	-0.407	0.155
	Japan	999	1	3.164	0.776	-0.409	0.077	1.046	0.155
	Poland	997	1	3.249	0.950	-0.493	0.077	0.145	0.155
	Sweden	992	4	3.224	1.123	-0.234	0.078	-0.489	0.155
	United Kingdom	995	4	3.292	1.029	-0.519	0.078	0.047	0.155
	United States	998	0	3.251	1.090	-0.407	0.077	-0.266	0.155
	China	1004	0	3.826	0.785	-0.574	0.077	0.677	0.154

## Appendix B. . Measurement models

### B1: Measurement model for model 1

Latent	Observed	Estimate	SE	95 % Confidence Intervals		$\beta$	$\beta$ 95 % Confidence Intervals		p
				Lower	Upper		Lower	Upper	
Acceptance (Ordinal $\alpha = 0.840$ , AVE = 0.471)	PE1	1.000	0.000	1.000	1.000	0.672	0.660	0.684	
	PE2	0.858	0.010	0.838	0.877	0.576	0.562	0.590	<.001
	PE3	0.874	0.011	0.853	0.895	0.587	0.573	0.602	<.001
	PEU1	0.843	0.011	0.822	0.864	0.567	0.551	0.582	<.001
	PEU2	0.832	0.011	0.811	0.853	0.559	0.544	0.574	<.001
	TRT1	0.987	0.010	0.968	1.006	0.663	0.651	0.676	<.001
	TRT2	0.963	0.010	0.944	0.983	0.647	0.634	0.661	<.001
	TRT3	0.704	0.012	0.680	0.727	0.473	0.455	0.490	<.001
	CC1	-1.150	0.011	-1.171	-1.128	-0.773	-0.782	-0.763	<.001
	CC2	-1.079	0.011	-1.101	-1.057	-0.725	-0.737	-0.714	<.001
	CC3	-1.142	0.011	-1.165	-1.120	-0.768	-0.777	-0.758	<.001
	SU1	-1.162	0.011	-1.184	-1.140	-0.781	-0.790	-0.772	<.001
	SU2	-1.190	0.011	-1.212	-1.168	-0.800	-0.808	-0.791	<.001
	SU3	-1.171	0.011	-1.193	-1.149	-0.787	-0.796	-0.778	<.001
	PI1	-1.016	0.012	-1.039	-0.993	-0.683	-0.696	-0.671	<.001
	PI2	-1.164	0.011	-1.186	-1.142	-0.782	-0.791	-0.773	<.001
	PI3	-1.051	0.011	-1.073	-1.029	-0.706	-0.718	-0.695	<.001

Note. AVE: Average Variance Extracted.

## B2: Model 2

## Measurement model for model 2

Latent	Observed	Estimate	SE	95 % Confidence Intervals		$\beta$	$\beta$ 95 % Confidence Intervals		p
				Lower	Upper		Lower	Upper	
Performance expectancy (Ordinal $\alpha = 0.848$ , AVE = 0.651)	PE1	1.000	0.000	1.000	1.000	0.852	0.842	0.862	
	PE2	0.917	0.008	0.902	0.932	0.781	0.770	0.793	<.001
	PE3	0.922	0.008	0.906	0.938	0.786	0.773	0.798	<.001
Perceived ease of use (Ordinal $\alpha = 0.782$ , AVE = 0.642)	PEU1	1.000	0.000	1.000	1.000	0.804	0.792	0.817	
	PEU2	0.992	0.010	0.973	1.012	0.798	0.786	0.810	<.001
Trust (Ordinal $\alpha = 0.809$ , AVE = 0.592)	TRT1	1.000	0.000	1.000	1.000	0.827	0.817	0.837	
	TRT2	0.975	0.008	0.960	0.991	0.806	0.795	0.818	<.001
	TRT3	0.804	0.010	0.785	0.824	0.665	0.649	0.681	<.001
Collection concerns (Ordinal $\alpha = 0.859$ , AVE = 0.671)	CC1	1.000	0.000	1.000	1.000	0.835	0.825	0.844	
	CC2	0.951	0.007	0.937	0.964	0.794	0.782	0.805	<.001
	CC3	0.993	0.006	0.981	1.006	0.829	0.820	0.839	<.001
Secondary use concerns (Ordinal $\alpha = 0.886$ , AVE = 0.723)	SU1	1.000	0.000	1.000	1.000	0.844	0.835	0.853	
	SU2	1.015	0.006	1.004	1.026	0.857	0.848	0.865	<.001
	SU3	1.007	0.006	0.996	1.018	0.850	0.841	0.858	<.001
Perceived insecurity (Ordinal $\alpha = 0.830$ , AVE = 0.620)	PI1	1.000	0.000	1.000	1.000	0.751	0.739	0.764	
	PI2	1.108	0.009	1.090	1.125	0.832	0.823	0.842	<.001
	PI3	1.032	0.009	1.014	1.050	0.776	0.764	0.787	<.001

## Variance and covariances matrix for Model 2.

Variable 1	Variable 2	Estimate	SE	95 % Confidence Intervals		$\beta$	$\beta$ 95 % Confidence Intervals		p
				Lower	Upper		Lower	Upper	
PE	PE	0.726	0.008	0.709	0.742	1.000	1.000	1.000	<.001
PEU	PEU	0.647	0.010	0.627	0.667	1.000	1.000	1.000	<.001
TRT	TRT	0.684	0.009	0.667	0.701	1.000	1.000	1.000	<.001
CC	CC	0.697	0.008	0.681	0.712	1.000	1.000	1.000	<.001
SU	SU	0.712	0.007	0.698	0.727	1.000	1.000	1.000	<.001
PI	PI	0.565	0.010	0.546	0.583	1.000	1.000	1.000	<.001
PE	PEU	0.620	0.008	0.604	0.635	0.904	0.893	0.916	<.001
PE	TRT	0.680	0.007	0.666	0.693	0.965	0.957	0.972	<.001
PE	CC	-0.117	0.011	-0.138	-0.095	-0.164	-0.194	-0.135	<.001
PE	SU	-0.078	0.011	-0.100	-0.057	-0.109	-0.139	-0.079	<.001
PE	PI	-0.098	0.010	-0.118	-0.078	-0.153	-0.183	-0.122	<.001
PEU	TRT	0.602	0.008	0.587	0.618	0.906	0.893	0.918	<.001
PEU	CC	-0.110	0.011	-0.131	-0.089	-0.164	-0.195	-0.133	<.001
PEU	SU	-0.072	0.011	-0.094	-0.051	-0.106	-0.138	-0.075	<.001
PEU	PI	-0.091	0.010	-0.111	-0.072	-0.151	-0.183	-0.119	<.001
TRT	CC	-0.177	0.011	-0.198	-0.157	-0.257	-0.286	-0.228	<.001
TRT	SU	-0.154	0.011	-0.175	-0.133	-0.221	-0.251	-0.191	<.001
TRT	PI	-0.158	0.010	-0.177	-0.138	-0.254	-0.284	-0.223	<.001
CC	SU	0.681	0.007	0.668	0.694	0.966	0.960	0.972	<.001
CC	PI	0.621	0.007	0.607	0.636	0.991	0.984	0.997	<.001
SU	PI	0.628	0.007	0.614	0.642	0.990	0.984	0.996	<.001

## B3: Model 3

## Measurement model for Model 3.

Latent	Observed	Estimate	SE	95 % Confidence Intervals		$\beta$	$\beta$ 95 % Confidence Intervals		p
				Lower	Upper		Lower	Upper	
Performance expectancy (Ordinal $\alpha = 0.848$ , AVE = 0.651)	PE1	1.000	0.000	1.000	1.000	0.853	0.843	0.863	
	PE2	0.915	0.008	0.900	0.930	0.781	0.769	0.793	<.001
	PE3	0.920	0.008	0.905	0.936	0.785	0.773	0.798	<.001
Perceived ease of use (Ordinal $\alpha = 0.782$ , AVE = 0.642)	PEU1	1.000	0.000	1.000	1.000	0.805	0.792	0.817	

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Latent	Observed	Estimate	SE	95 % Confidence Intervals		$\beta$	$\beta$ 95 % Confidence Intervals		p
				Lower	Upper		Lower	Upper	
Trust (Ordinal $\alpha = 0.809$ , AVE = 0.592)	PEU2	0.992	0.010	0.972	1.012	0.798	0.786	0.810	<.001
	TRT1	1.000	0.000	1.000	1.000	0.826	0.816	0.837	<.001
	TRT2	0.974	0.008	0.959	0.990	0.805	0.794	0.817	<.001
	TRT3	0.808	0.010	0.788	0.827	0.668	0.651	0.684	<.001
Collection concerns (Ordinal $\alpha = 0.859$ , AVE = 0.671)	CC1	1.000	0.000	1.000	1.000	0.835	0.826	0.844	<.001
	CC2	0.950	0.007	0.937	0.964	0.793	0.782	0.804	<.001
	CC3	0.993	0.006	0.981	1.006	0.829	0.820	0.839	<.001
Secondary use concerns (Ordinal $\alpha = 0.886$ , AVE = 0.723)	SU1	1.000	0.000	1.000	1.000	0.844	0.835	0.852	<.001
	SU2	1.015	0.006	1.004	1.027	0.857	0.849	0.865	<.001
	SU3	1.007	0.006	0.996	1.018	0.850	0.841	0.858	<.001
Perceived insecurity (Ordinal $\alpha = 0.830$ , AVE = 0.620)	PI1	1.000	0.000	1.000	1.000	0.751	0.739	0.764	<.001
	PI2	1.108	0.009	1.090	1.126	0.832	0.823	0.842	<.001
	PI3	1.032	0.009	1.014	1.050	0.776	0.764	0.787	<.001
Concerns	CC	1.000	0.000	1.000	1.000	0.987	0.982	0.992	<.001
	SU	1.002	0.007	0.989	1.015	0.978	0.973	0.983	<.001
Acceptance	PI	0.920	0.008	0.904	0.936	1.009	1.004	1.014	<.001
	PE	1.000	0.000	1.000	1.000	0.961	0.953	0.968	<.001
	PEU	0.899	0.009	0.880	0.917	0.915	0.905	0.926	<.001
	TRT	1.018	0.009	1.000	1.036	1.010	1.002	1.017	<.001

**Variance and covariances matrix for Model 3.**

Variable 1	Variable 2	Estimate	SE	95 % Confidence Intervals		$\beta$	$\beta$ 95 % Confidence Intervals		p
				Lower	Upper		Lower	Upper	
PE	PE	0.056	0.006	0.045	0.067	0.077	0.062	0.092	<.001
PEU	PEU	0.105	0.007	0.092	0.118	0.162	0.142	0.182	<.001
TRT	TRT	-0.013	0.005	-0.024	-0.002	-0.019	-0.035	-0.004	0.016
CC	CC	0.018	0.003	0.012	0.024	0.026	0.017	0.035	<.001
SU	SU	0.031	0.003	0.024	0.037	0.043	0.034	0.052	<.001
PI	PI	-0.010	0.003	-0.016	-0.004	-0.018	-0.028	-0.007	<.001
Concerns	Concerns	0.679	0.008	0.663	0.695	1.000	1.000	1.000	<.001
Acceptance	Acceptance	0.672	0.009	0.654	0.689	1.000	1.000	1.000	<.001
Concerns	Acceptance	-0.127	0.010	-0.146	-0.107	-0.188	-0.216	-0.159	<.001

**B3: Model 4****Measurement model for model 4**

Latent	Observed	Estimate	SE	95 % Confidence Intervals		$\beta$	$\beta$ 95 % Confidence Intervals		p
				Lower	Upper		Lower	Upper	
Acceptance (Ordinal $\alpha = 0.920$ , AVE = 0.596)	PE1	1.000	0.000	1.000	1.000	0.836	0.826	0.845	<.001
	PE2	0.918	0.008	0.903	0.933	0.767	0.755	0.779	<.001
	PE3	0.923	0.008	0.908	0.939	0.772	0.759	0.784	<.001
	PEU1	0.903	0.008	0.887	0.919	0.755	0.742	0.768	<.001
	PEU2	0.897	0.008	0.881	0.912	0.749	0.737	0.762	<.001
	TRT1	0.981	0.007	0.968	0.995	0.820	0.810	0.830	<.001
	TRT2	0.957	0.007	0.942	0.971	0.800	0.788	0.811	<.001
	TRT3	0.794	0.010	0.775	0.812	0.664	0.647	0.680	<.001
Concerns (Ordinal $\alpha = 0.946$ , AVE = 0.662)	CC1	1.000	0.000	1.000	1.000	0.827	0.817	0.836	<.001
	CC2	0.951	0.007	0.938	0.965	0.787	0.776	0.798	<.001
	CC3	0.993	0.006	0.981	1.005	0.821	0.812	0.830	<.001
	SU1	1.011	0.006	0.999	1.023	0.836	0.827	0.844	<.001
	SU2	1.025	0.006	1.014	1.037	0.848	0.840	0.856	<.001
	SU3	1.017	0.006	1.006	1.029	0.841	0.833	0.850	<.001
	PI1	0.909	0.008	0.894	0.924	0.752	0.739	0.764	<.001
	PI2	1.007	0.006	0.996	1.019	0.833	0.824	0.842	<.001
	PI3	0.939	0.007	0.925	0.952	0.776	0.765	0.787	<.001

**Variance and covariances matrix for Model 4.**

Variable 1	Variable 2	Estimate	SE	95 % Confidence Intervals		$\beta$	$\beta$ 95 % Confidence Intervals		p
				Lower	Upper		Lower	Upper	
Acceptance	Acceptance	0.699	0.008	0.683	0.715	1.000	1.000	1.000	<.001
Concerns	Concerns	0.684	0.008	0.668	0.699	1.000	1.000	1.000	<.001
Acceptance	Concerns	-0.128	0.010	-0.147	-0.108	-0.185	-0.213	-0.156	<.001

## Appendix C. . Dwass-Steel-Critchlow-Fligner pairwise comparisons

Country	Country	Acceptance		Concerns		Behavioural Intention	
		W	p	W	p	W	p
Germany	Spain	6.618	<.001	4.651	0.028	6.218	<.001
Germany	France	-8.724	<.001	-4.228	0.069	-6.976	<.001
Germany	Japan	-8.985	<.001	-7.899	<.001	-6.707	<.001
Germany	Poland	-0.687	1.000	5.715	0.002	-1.711	0.955
Germany	Sweden	-7.924	<.001	-8.913	<.001	-4.543	0.036
Germany	United Kingdom	-1.701	0.956	1.960	0.904	0.144	1.000
Germany	United States	1.069	0.998	0.159	1.000	0.702	1.000
Germany	China	23.265	<.001	-2.443	0.730	21.756	<.001
Spain	France	-15.295	<.001	-8.970	<.001	-13.229	<.001
Spain	Japan	-16.998	<.001	-13.898	<.001	-14.422	<.001
Spain	Poland	-7.794	<.001	1.015	0.999	-8.239	<.001
Spain	Sweden	-14.486	<.001	-13.876	<.001	-10.740	<.001
Spain	United Kingdom	-8.225	<.001	-2.737	0.589	-5.835	0.001
Spain	United States	-5.250	0.006	-4.520	0.038	-5.237	0.007
Spain	China	17.453	<.001	-7.552	<.001	16.354	<.001
France	Japan	2.343	0.773	-2.200	0.829	2.106	0.861
France	Poland	8.796	<.001	10.133	<.001	5.587	0.003
France	Sweden	0.837	1.000	-4.601	0.031	2.410	0.744
France	United Kingdom	6.730	<.001	6.218	<.001	6.809	<.001
France	United States	9.316	<.001	4.287	0.061	7.379	<.001
France	China	30.325	<.001	2.268	0.803	27.699	<.001
Japan	Poland	9.222	<.001	14.814	<.001	5.214	0.007
Japan	Sweden	-1.209	0.995	-3.450	0.263	0.704	1.000
Japan	United Kingdom	6.868	<.001	10.708	<.001	7.066	<.001
Japan	United States	9.335	<.001	7.563	<.001	7.082	<.001
Japan	China	35.721	<.001	7.022	<.001	32.580	<.001
Poland	Sweden	-7.917	<.001	-15.099	<.001	-3.071	0.425
Poland	United Kingdom	-1.102	0.997	-3.846	0.141	1.931	0.911
Poland	United States	1.758	0.947	-5.687	0.002	2.448	0.728
Poland	China	25.759	<.001	-8.646	<.001	24.511	<.001
Sweden	United Kingdom	5.988	<.001	11.088	<.001	4.464	0.042
Sweden	United States	8.575	<.001	9.036	<.001	4.947	0.014
Sweden	China	29.742	<.001	7.348	<.001	25.282	<.001
United Kingdom	United States	2.814	0.551	-1.710	0.955	0.628	1.000
United Kingdom	China	24.531	<.001	-4.791	0.020	21.127	<.001
United States	China	20.909	<.001	-2.799	0.558	19.932	<.001

Note. Bold figures indicate significant country differences.

## Data availability

Data will be made available on request.

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