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Does acceptance of driver monitoring systems differ across countries? A latent profile analysis approach[☆]

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ABSTRACT

Driver Monitoring Systems (DMS) are poised to become a standard safety feature in new vehicles, with regulations in regions such as the European Union mandating their inclusion. Yet little is known about how privacy and security concerns influence their acceptance. This study investigated attitudes towards DMS among 9025 licensed drivers from nine countries (Germany, Spain, France, Japan, Poland, Sweden, United Kingdom, United States, and China). Participants rated their acceptance, concerns (including data collection, secondary use, and perceived insecurity), and behavioural intention to use DMS. Through Latent Profile Analysis, five distinct user profiles were identified: Enthusiasts, Somewhat enthusiastic, Moderate, Sceptical, and Resistant, each exhibiting systematic differences in acceptance, concerns, and behavioural intentions. Cross-national comparisons revealed significant cultural variations, with Enthusiasts and Somewhat enthusiastic profiles being more prevalent in China, whereas Resistant and Sceptical profiles were disproportionately represented in France, United Kingdom, and Sweden. Notably, age and gender effects were significant, as older drivers and women were more likely to belong to the resistant profile. These findings underscore the necessity for targeted interventions, transparent data handling policies, and culturally tailored communication strategies to enhance user acceptance of DMS and the widespread adoption as part of the broader transition towards automated and connected driving systems.

1. Introduction

Advancements in vehicle automation and driver-assistance systems are transforming the automotive landscape and facilitating enhanced safety and convenience. Among these emerging technologies, driver monitoring systems (DMS) have attracted significant attention from industry stakeholders and researchers. A DMS typically observes and evaluates a driver's alertness, distraction, readiness to resume vehicle control, and general fitness to operate a vehicle, using sensors and cameras to collect real-time data (Gonçalves et al., 2024; Jannusch et al., 2021; Khan & Lee, 2019; Presta et al., 2022). Regulatory bodies in numerous regions, including the European Union, have taken regulatory actions to acknowledge the potential safety benefits of this technology. For example, the European Commission (2024) has made drowsiness detection mandatory for new vehicles from 2024 onwards. From 2026, newly manufactured automobiles in Europe are anticipated to be equipped with a DMS to enhance road safety and mitigate risks associated with driver inattention or impairment (European New Car Assessment Programme, 2024). Currently, DMS use is relatively uncommon (a recent study by Ehsani et al., 2024, reported that only 20% of adults in the US use DMS), and users have demonstrated limited awareness of information collected through in-vehicle systems (e.g., Bella et al., 2021). This is not surprising as it is a relatively new technology.

Despite these promising advancements, the successful integration of DMS into everyday driving is contingent upon user acceptance. Previous research on emerging technologies (e.g., Adnan et al., 2018; Coyne et al., 2024; Damsara and de Barros, 2025; Feng and Qin, 2025; Hansen et al., 2025; Lee and Hess, 2022; Nordhoff et al., 2019; Nordhoff and Lehtonen, 2025; Öztürk et al., 2023; Rahman et al., 2018; Wang et al., 2020; Derek Hsien Wei, 2017), including DMS, has demonstrated that users' acceptance is influenced by multiple factors (e.g., perceived usefulness, trust in the system, and concerns regarding data privacy). These studies (e.g.,

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Rejali et al., 2023; Kaye et al., 2020) have employed various theoretical frameworks and models, including the Theory of Planned Behaviour (Ajzen, 1991), the Technology Acceptance Model (Venkatesh & Davis, 2000), and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003), to incorporate these factors. Although these models predominantly emphasise utility-driven beliefs regarding the technology (e.g., perceived ease of use or perceived usefulness), users' concerns about the system (e.g., concerns about data collection and sharing), which play a fundamental role in determining the subsequent adoption and utilisation of these technologies (e.g., Coyne et al., 2024; Kusyanti et al., 2022; Liljamo et al., 2018), are not adequately addressed in these models. Understanding these concerns could potentially increase use of the technology (Ehsani et al., 2024).

In contemporary society, a substantial amount of information is generated through online activities, such as internet searches and social media browsing. Individuals' willingness to share data is contingent upon the type of data and the associated costs and benefits of data sharing (Schudy & Utikal, 2017). Individuals' concerns regarding privacy vary depending on the specific activity involved (Bergström, 2015). For example, in the realm of health-related data, research has highlighted concerns about data sharing and its secondary use (Murphy et al., 2021; Shah et al., 2019; Whiddett et al., 2006). This raises questions about the nature of the data that should be collected by DMS, the entities with whom it is shared, and the extent to which users can exercise control over their data (e.g., Ackermann et al., 2022; Murphy et al., 2021; Shah et al., 2019). Data produced while driving may include sensitive information, such as location, driving behaviour, and other in-vehicle activities, whether or not they are directly related to driving. Our understanding of these issues within the road safety context remains limited.

Similarly, the use of a DMS may elicit concerns about the real-time collection of sensitive information, potential secondary uses of such data, and the perceived insecurity or vulnerability of the technology to unauthorised access (e.g., Chu et al., 2023; Coyne et al., 2024; Levshun et al., 2022). Studies have shown that adults have safety and privacy concerns for themselves (Coyne et al., 2024; Derek Hsien Wei, 2017) and for their children (Guttman & Gesser-Edelsburg, 2011; Guttman & Lotan, 2011), particularly due to the invasiveness of driver-monitoring technologies. In an attempt to conceptualise the concerns associated with facial image-based DMS, based on the Concern for Information Privacy scale by Smith et al. (1996), Chu et al. (2023) identified secondary use, collection concern, and perceived insecurity as lower-level factors associated with privacy concerns (higher-order factor), which were negatively associated with acceptance. This apprehension about privacy and security may undermine users' trust and reduce their willingness to adopt new in-vehicle systems.

Demographic characteristics and cultural norms may influence acceptance of new vehicle technologies such as automated driving systems (e.g. Edelmann et al., 2021; Nordhoff et al., 2019; Öztürk et al., 2025), and it is likely that these factors could also influence attitudes towards DMS in a similar manner. For example, Smyth et al. (2021) found that women reported higher levels of anxiety and performance expectancy from driver state monitoring than men, whereas age did not demonstrate any effect on various aspects such as performance expectancy, effort expectancy, and anxiety.

Furthermore, variations in regulatory environments, societal values, and prior exposure to automation technologies across countries could contribute to variations in users' attitudes toward DMS. Current literature is at a very early stage in addressing these differences. Therefore, examining how these concerns manifest in different demographic segments and geographic regions can provide a more nuanced understanding of user acceptance, informing more targeted design, communication, and policy strategies. Although DMS are designed to be used in both conventional manually driven vehicles and future automated driving systems, the focus of this research is on their use with automated driving systems. Specifically, the study aims to:

1) Segment drivers into distinct profiles using latent profile analysis of acceptance, concerns, and behavioural intention toward Driver Monitoring Systems,

2) Compare the prevalence of these profiles across nine countries, and

3) Examine demographic influences (age and gender) on profile membership.

2. Methods

2.1. Participants

The study was conducted with a total of 9025 participants across nine countries (Germany [DE], Spain [ES], France [FR], Japan [JP], Poland [PL], Sweden [SE], United Kingdom [UK], United States [USA], and China [CN]). The age and gender distribution of the participants are presented in Table 1.

2.2. Measurements

At the beginning of the survey section, the DMS was defined as follows: "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 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 requested to indicate their level of agreement with 22 statements (see Öztürk et al., 2026; Appendix A) measuring seven constructs i.e., collection concerns (Chu et al., 2023; Smith et al., 1996), secondary use concerns (Chu et al., 2023; Smith et al., 1996), perceived insecurity (Chu et al., 2023; Cichy et al., 2021), trust (Ghazizadeh et al., 2012), performance expectancy (Smyth et al., 2021), perceived ease of use (Ghazizadeh et al., 2012), and behavioural intention (Ghazizadeh et al., 2012). A 5-point Likert scale from *strongly disagree* to *strongly agree* was used to capture responses.

Following the detailed examination of various models delineating the factorial structure of the measurement instrument employed (see Öztürk et al., 2026, for details), a three-factor structure was adopted in the present study. The first factor, *Acceptance* (Cronbach's alpha = 0.90), comprises eight items that address trust, performance expectancy, and perceived ease of use concerning the DMS, adapted from Smyth et al. (2021) and Ghazizadeh et al. (2012). The second factor, *Concerns* (Cronbach's alpha = 0.93), includes nine items adapted from Chu et al. (2023), Cichy et al. (2021), and Smith et al. (1996). These items address concerns regarding the information collected (e.g., facial image/personal information), the secondary use of data collected by third parties or other companies, and the perceived insecurity of the system. Besides these two factors, three items (e.g., "I would use a car that had a DMS") adapted from Ghazizadeh et al. (2012) were used to measure behavioural intention (i.e., willingness to use DMS; Cronbach's alpha = 0.82). The descriptives per country are presented in Table 2.

2.3. Procedure

This online survey investigating drivers' attitudes toward automated driving systems and driver monitoring systems was conducted as part of the Hi-Drive project (Horizon Europe: 101006664) across nine countries

Table 1
Country-based age and gender descriptives of the sample.

Country	*n*	Age					Gender			
		n	*M*	*SD*	Min.	Max.	Woman	Man	Other	Preferred not to say
Germany	1001	972	48.38	16.42	18	85	500	500	1	0
Spain	1002	984	47.27	14.84	18	85	490	509	0	1
France	1002	979	48.20	17.13	18	82	514	487	0	1
Japan	1005	926	49.31	14.13	18	81	496	504	2	2
Poland	1003	968	46.02	15.15	18	82	494	504	2	2
Sweden	1002	956	47.96	16.92	18	85	520	476	2	4
United Kingdom	1002	985	46.97	17.04	18	85	493	506	2	1
United States	1004	955	45.49	16.49	18	85	505	493	5	1
China	1004	997	35.94	8.92	18	70	482	522	0	0

Table 2
Country-based descriptives of acceptance, concerns, and behavioural intention.

Construct	*Country*	*n*	*M*	*SD*
Acceptance	Germany	1000	3.21	0.83
	Spain	1002	3.38	0.76
	France	1002	3.01	0.84
	Japan	1005	3.05	0.58
	Poland	1003	3.20	0.72
	Sweden	1002	3.01	0.86
	United Kingdom	1002	3.15	0.85
	United States	1004	3.24	0.87
	China	1004	3.76	0.57
Concerns	Germany	1001	3.37	0.96
	Spain	1002	3.51	0.89
	France	1002	3.27	0.98
	Japan	1005	3.19	0.70
	Poland	1003	3.56	0.83
	Sweden	1002	3.14	0.95
	United Kingdom	1001	3.43	0.89
	United States	1004	3.40	0.90
	China	1004	3.28	0.83
Behavioural intention	Germany	1001	3.18	0.94
	Spain	1002	3.36	0.87
	France	1001	2.97	0.97
	Japan	1004	3.04	0.67
	Poland	1003	3.12	0.88
	Sweden	1001	3.05	0.99
	United Kingdom	1001	3.16	0.98
	United States	1004	3.19	1.00
	China	1004	3.78	0.65

from 17 to 29 May 2024. The study adheres to the guidelines provided by the Finnish National Board on Research Integrity TENK (https://tenk.fi/sites/default/files/2021–01/Ethical_review_in_human_sciences_2020.pdf). In line with TENK regulations, the study was exempt from review board approval, as it did not involve interventions in participants' physical integrity, exposure to unusually strong stimuli, recruitment of vulnerable groups, or the collection of sensitive personal data. All participants provided informed consent before the survey, and participation was entirely voluntary. The research did not compromise participants' (or the researchers') daily routines, physical well-being, or safety.

Data collection was conducted by the Finnish market research company INNOLINK. The survey instrument was developed in English by the research team and subsequently translated into other languages by the company. Each of the translated versions was subsequently checked by another independent researcher who was unfamiliar with the survey but knowledgeable in the field and fluent in both English and another language. The cross-language verification was completed for each language separately. The company was not involved in either the survey design or the analysis stage. All participants were volunteers and received compensation from the survey company for being a part of their participant pool. Compensation (fixed payment or prize-based incentive) was calibrated to reflect the approximate survey duration (around 8 min). The web panel sample was collected as a census-representative sample, stratified by gender, age, and region. All participants were required to hold a valid driver license for passenger vehicles, as this was the sole eligibility criterion applied. All invalid cases (including partial responses and survey drop-outs) were removed by the research company prior to data delivery.

2.4. Data analysis

The analysis was conducted using the Jamovi 2.7.13 programme (The Jamovi Project, 2025; R Core Team, 2024) with the tidyLPA (Rosenberg et al., 2021) and snowCluster (Seol, 2024) modules for latent profile analysis (LPA). The tidyLPA package was used to estimate latent profile models, including model specification. Additionally, the snowCluster package enabled the bias-adjusted three-step procedures (BCH/DCAT) to examine the relationships between latent profile membership and distal variables. The approach has previously been used to understand willingness to use automated shuttle buses (e.g., Schandl et al., 2025) and risky behaviours (e.g., Braitman & Braitman, 2017; Jesuíno et al., 2021).

Due to their small sample sizes, the gender categories "other" ($n = 14$) and "preferred not to say" ($n = 12$) were omitted from further analysis. An additional five participants were also excluded due to missing responses to one or more indicator factors (i.e., acceptance, concerns, or behavioural intention). This resulted in a final sample of 8990 participants. A small number of participants ($< 5\%$) did not report age or gender information. Participants with missing demographic information (see Table 1) were excluded from the covariate-based comparisons (e.g., age or gender comparison per profile membership). Given the extremely low proportion of missing values and the absence of any systematic pattern, the missing data were considered insignificant (Graham, 2009).

To achieve the research objective (Section 3.1), a three-step latent profile analysis was conducted in accordance with the methodology proposed by Asparouhov and Muthén (2014). This approach is highly recommended for investigating the relationships between latent profiles and external variables, while also accounting for classification uncertainty. **Step 1:** A latent profile model was estimated using participants' scores on acceptance, concerns, and behavioural intention with equal variances and zero covariances. These continuous indicators were modelled within a Gaussian mixture framework to identify distinct subpopulations (profiles) within the total sample. **Step 2:** Based on the estimated model, participants were assigned to latent profiles using posterior class membership probabilities. This probabilistic assignment reflects the uncertainty in classification, rather than relying solely on modal membership. In other words, each participant was assigned a probability of belonging to each of the profiles, instead of being assigned to a single profile. **Step 3:** Associations between latent profile membership and external covariates (country, age, and gender) were examined using the three-step approach. This method is superior to traditional one-step or naive assignment procedures because it explicitly adjusts for measurement error and incorporates posterior probabilities, thereby reducing bias in estimates of relationships between profiles and distal variables.

In the three sets of analyses conducted (profile-by-country, profile-by-age, profile-by-gender), each analysis consisted of 10 pairwise comparisons. Consequently, a Bonferroni correction was applied within each family of comparisons, resulting in an adjusted alpha level of $0.05/10 = 0.005$. To mitigate the problem of inflated Type-I error, which can occur due to large sample sizes and strong correlations between variables (refer to Giner-Sorolla et al., 2024; Lakens, 2022 for more details), we applied a more conservative threshold of $p_{\text{bonf}} < 0.001$.

3. Results

3.1. Profiles of DMS acceptance

Models consisting of four to eight classes were assessed and compared based on fit indices, simplicity, and interpretability. The fit indices examined included the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC), with lower scores indicating a better model fit. The Bootstrap Likelihood Ratio Test (BLRT) p-value was used to evaluate whether the current model provided a significantly improved fit compared to a model with one less category. Entropy was considered as a measure of classification accuracy, where higher values suggested more distinct separation (e.g., Kim, 2014; Wang et al., 2017). Across the models, AIC and BIC values decreased as the number of classes increased, a common occurrence with larger sample sizes. However, classification quality markedly declined beyond five classes, as evidenced by entropy (decreasing from 0.871 at five classes to 0.742 at six classes) and minimum posterior probabilities (0.881 at five classes versus 0.535 at six classes). The five-class solution offered the optimal balance of fit and interpretability, exhibiting the highest entropy and an acceptable smallest class size (6.3%). Although the BLRT remained significant at all stages ($p = 0.0099$), the emergence of micro-classes and diminished classification certainty in more complex models suggested overfitting. Consequently, the five-class model was retained as the final solution (Table 3).

The five-class solution was delineated by distinct profiles based on acceptance, concerns, and behavioural intention. The largest profile, Profile 1 (**Moderate**), encompassed 43.1% of the sample ($n = 3873$) and exhibited moderate levels of intention and acceptance, accompanied by moderate concerns. The second largest profile, Profile 3 (**Somewhat enthusiastic**), comprised 30.5% ($n = 2745$) of participants, demonstrating above-average intention and acceptance with moderate concerns. Profile 5 (**Sceptical)** constituted 12.2% ($n = 1097$) of the sample, characterised by lower intention and acceptance alongside heightened concerns. Profile 2 (**Enthusiasts**) accounted for 7.9% ($n = 708$), displaying very high intention and acceptance with comparatively lower concerns, whereas Profile 4 (**Resistant**) was the smallest group at 6.3% ($n = 567$), defined by very low intention and acceptance and high concerns. Mean scores for each indicator by profile are presented in Table 4.

The density plot (Fig. 1) depicts the distribution of scores for Acceptance, Concerns, and Behavioural Intention across the five latent profiles on the overall sample distribution (represented by the black line). The evident multimodal patterns corroborate the existence of distinct profiles.

Table 3
Fit indices for LPA.

Classes	4	5	6	7	8
LogLik	−28679	−27811	−27798	−27469	−27010
AIC	57394.7	55665.2	55648.3	54997.8	54,088
AWE	57738.7	56,086	56146.2	55572.5	54739.6
BIC	57522.6	55821.5	55,833	55210.9	54329.5
CAIC	57540.6	55843.5	55,859	55240.9	54363.5
SABIC	57465.4	55751.6	55750.4	55115.6	54221.5
Entropy	0.84504	0.8706	0.7416	0.73656	0.7576
prob_min	0.83596	0.8805	0.53493	0.05351	0.33188
prob_max	0.94442	0.95917	0.9524	0.95791	0.94459
n_min	0.08265	0.06307	0.06085	0.02614	0.01224
n_max	0.47531	0.43081	0.29266	0.37586	0.31101
BLRT_val	1425.37	1737.09	650.072	1451.67	1463.16
BLRT_p	0.0099	0.0099	0.0099	0.0099	0.0099

Note. LogLik: log-likelihood, AIC: Akaike Information Criterion, AWE: Approximate Weight of Evidence Criterion, BIC: Bayesian Information Criterion, CAIC: Consistent Akaike Information Criterion, SABIC: Sample-Size Adjusted Bayesian Information Criterion, prob: posterior class probability, n: size of the smallest and largest class, BLRT: Bootstrapped Likelihood Ratio Test Statistic and p-value.

3.2. Demographic comparison of latent profiles

A bias-adjusted three-step analysis (BCH/DCAT) was conducted to assess whether latent profile membership varied by country (Table 5). The omnibus test yielded significant results, $\chi^2(32) = 911.18, p < 0.001$, indicating that profile prevalence differed across countries. The association was of small to moderate magnitude, with Cramer's V = 0.159. Weighted profile-by-country distributions revealed systematic differences (Table 6). For instance, Japan was notably overrepresented in the Moderate profile and underrepresented in the profiles of Enthusiasts, Somewhat enthusiastic, and Resistant, whereas China exhibited a pronounced inclination toward the Somewhat enthusiastic and Enthusiasts profiles, with minimal representation in the Resistant profile. France demonstrated higher proportions in the Resistant and Sceptical profiles and lower in the Somewhat enthusiastic profile, while many countries (e.g., Germany and Spain) showed a tendency toward Moderate and Somewhat enthusiastic profiles. These patterns suggest significant cross-national variation in latent profiles.

Pairwise contrasts (Table 6) showed that the most substantial separations involved Enthusiasts vs. Sceptical and Resistant. Enthusiasts and Sceptical/Resistant profiles differ considerably across countries. Other notable contrasts included Somewhat enthusiastic vs. Resistant and Sceptical profiles. All pairwise tests remained significant after Benjamini–Hochberg and Bonferroni adjustments, except for Resistant vs. Sceptical profiles.

A bias-adjusted three-step analysis revealed significant age differences across latent profiles, $F(4, 9946.9) = 98.03$, $p < 0.001$ (Table 7). The BCH-weighted means demonstrated that the Resistant profile exhibited the highest mean age, followed by the Sceptical, Moderate, and the younger profiles of Enthusiasts and Somewhat enthusiastic.

Pairwise BCH comparisons (Table 8) confirmed that the Resistant profile was older than all other profiles, and the Sceptical profile was older than the Moderate, Enthusiasts, and Somewhat enthusiastic profiles. Effect sizes were small for comparisons involving adjacent mid-level profiles (e.g., Moderate vs. Enthusiasts) and medium to large for comparisons involving the Resistant profile.

Table 4
Mean scores for each indicator by profile.

	Acceptance		Concerns		Behavioural intention	
Profile	Estimate	SE	Estimate	SE	Estimate	SE
Profile 1 (Moderate)	3.07	0.01	3.32	0.01	3.04	0.01
Profile 2 (Enthusiasts)	4.53	0.02	2.91	0.06	4.72	0.02
Profile 3 (Somewhat enthusiastic)	3.78	0.01	3.30	0.02	3.90	0.01
Profile 4 (Resistant)	1.39	0.02	3.97	0.06	1.22	0.02
Profile 5 (Sceptical)	2.47	0.02	3.55	0.04	2.10	0.02

Note. Estimates of variance: Acceptance = 0.120 (SE = 0.004), Concerns = 0.754 (SE = 0.013), and Behavioural intention = 0.108 (SE = 0.004).

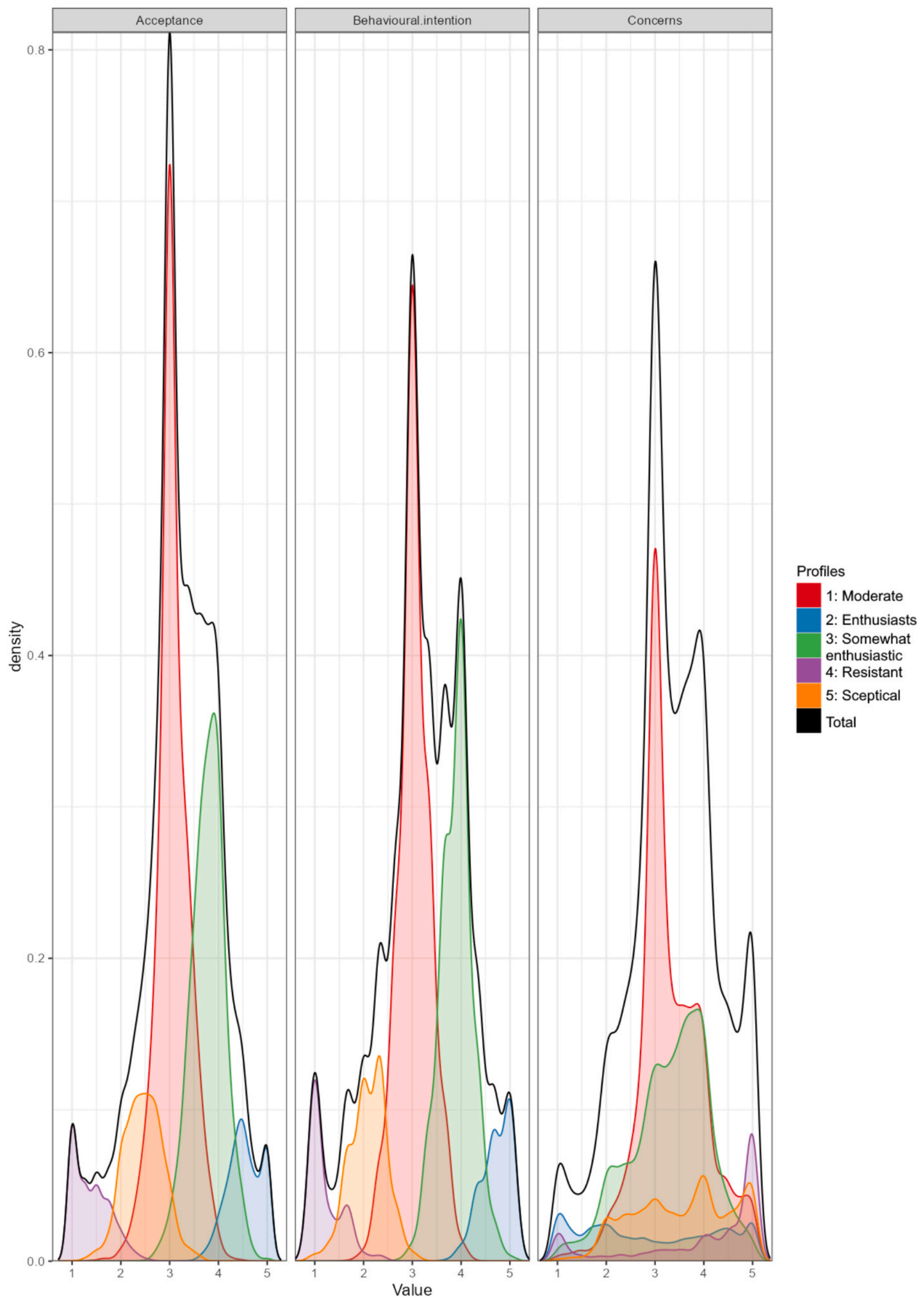

Fig. 1. Density plot of the latent profiles.

Table 5
Profile–by–country distribution (weighted counts).

Profiles	Germany	Spain	France	Japan	Poland	Sweden	United Kingdom	United States	China
Profile 1 (Moderate)	416.09	413.15	429.63	644.36	451.89	456.69	380.61	404.95	271.92
Profile 2 (Enthusiasts)	78.97	98.04	62.06	16.45	43.18	74.75	71.28	108.53	171.08
Profile 3 (Somewhat enthusiastic)	304.49	355.53	222.44	189.75	309.59	217.00	319.78	275.91	534.41
Profile 4 (Resistant)	76.05	41.41	91.11	33.00	55.36	96.11	91.51	78.79	3.00
Profile 5 (Sceptical)	123.40	90.88	194.76	115.44	137.98	150.45	134.82	129.82	23.60

A bias-adjusted three-step analysis revealed a significant association between sex and latent profile membership, $\chi^2(4) = 28.38$, $p < 0.001$, Cramer's V = 0.056 (Table 8). The BCH-weighted distributions (Table 9) indicated that men were more prevalent in the Enthusiasts, Somewhat enthusiastic, and Resistant categories, whereas women were more prevalent in the Moderate and Sceptical categories.

Pairwise tests (Table 10) confirmed the strongest separation for Moderate vs. Enthusiasts, where Enthusiasts had a higher proportion of men compared to Moderate.

Table 6
Pairwise country contrasts between profiles.

Contrast	χ2	df	p_{BH}	p_{bonf}	V
Profile 1 vs Profile 2	300.85	8	< 0.001	< 0.001	0.256
Profile 1 vs Profile 3	376.42	8	< 0.001	< 0.001	0.239
Profile 1 vs Profile 4	126.75	8	< 0.001	< 0.001	0.169
Profile 1 vs Profile 5	99.58	8	< 0.001	< 0.001	0.142
Profile 2 vs Profile 3	59.88	8	< 0.001	< 0.001	0.132
Profile 2 vs Profile 4	191.32	8	< 0.001	< 0.001	0.385
Profile 2 vs Profile 5	296.00	8	< 0.001	< 0.001	0.403
Profile 3 vs Profile 4	206.04	8	< 0.001	< 0.001	0.250
Profile 3 vs Profile 5	286.80	8	< 0.001	< 0.001	0.274
Profile 4 vs Profile 5	28.51	8	< 0.001	0.004	0.131

Notes. Profile 1: Moderate; Profile 2: Enthusiasts; Profile 3: Somewhat enthusiastic; Profile 4: Resistant; Profile 5: Sceptical. p_{BH} = Benjamini–Hochberg adjusted *p*; p_{bonf} = Bonferroni adjusted *p*; V = Cramer's V (effect size).

Table 7
Profile–by–age comparison.

Profile (Label)	Mean Age	SE	N_eff
Profile 1 (Moderate)	45.90	0.25	4165.9
Profile 2 (Enthusiasts)	43.85	0.50	835.1
Profile 3 (Somewhat enthusiastic)	43.84	0.27	3084.9
Profile 4 (Resistant)	55.06	0.64	589.3
Profile 5 (Sceptical)	49.63	0.46	1276.7

Table 8
Pairwise profile comparisons for age.

Contrast	z	p_{BH}	p_{bonf}	Cohen's *d*
Profile 1 vs Profile 2	3.690	< 0.001	0.002	0.131
Profile 1 vs Profile 3	5.592	< 0.001	< 0.001	0.132
Profile 1 vs Profile 4	−13.312	< 0.001	< 0.001	−0.579
Profile 1 vs Profile 5	−7.193	< 0.001	< 0.001	−0.234
Profile 2 vs Profile 3	0.024	0.981	1.00	0.001
Profile 2 vs Profile 4	−13.795	< 0.001	< 0.001	−0.753
Profile 2 vs Profile 5	−8.561	< 0.001	< 0.001	−0.371
Profile 3 vs Profile 4	−16.057	< 0.001	< 0.001	−0.734
Profile 3 vs Profile 5	−10.865	< 0.001	< 0.001	−0.372
Profile 4 vs Profile 5	6.875	< 0.001	< 0.001	0.337

Notes. Profile 1: Moderate; Profile 2: Enthusiasts; Profile 3: Somewhat enthusiastic; Profile 4: Resistant; Profile 5: Sceptical. p_{BH} = Benjamini–Hochberg adjusted *p*; p_{bonf} = Bonferroni adjusted *p*; V = Cramer's V (effect size).

Table 9
Profile–by–sex distribution (weighted counts).

Profile (label)	Man	Woman
Profile 1 (Moderate)	1849.2	2020.1
Profile 2 (Enthusiasts)	413.9	310.5
Profile 3 (Somewhat enthusiastic)	1400.2	1328.7
Profile 4 (Resistant)	303.4	263.0
Profile 5 (Sceptical)	531.4	569.7

Table 10
Pairwise profile contrasts by sex.

Contrast	χ2	df	p_{BH}	p_{bonf}	V
Profile 1 vs Profile 2	21.309	1	< 0.001	< 0.001	0.068
Profile 1 vs Profile 3	7.916	1	0.013	0.049	0.035
Profile 1 vs Profile 4	6.595	1	0.021	0.102	0.039
Profile 1 vs Profile 5	0.075	1	0.785	1.000	0.004
Profile 2 vs Profile 3	7.794	1	0.013	0.052	0.048
Profile 2 vs Profile 4	1.640	1	0.250	1.000	0.036
Profile 2 vs Profile 5	13.789	1	0.001	0.002	0.087
Profile 3 vs Profile 4	0.958	1	0.364	1.000	0.017
Profile 3 vs Profile 5	2.919	1	0.125	0.875	0.028
Profile 4 vs Profile 5	4.215	1	0.067	0.401	0.050

Notes. Profile 1: Moderate; Profile 2: Enthusiasts; Profile 3: Somewhat enthusiastic; Profile 4: Resistant; Profile 5: Sceptical. P_{BH} = Benjamini–Hochberg adjusted *p*; p_{bonf} = Bonferroni adjusted *p*; V = Cramer's V (effect size).

4. Discussion

This study investigated drivers' attitudes toward DMS through the application of latent profile analysis, thereby identifying distinct subgroups of potential users. Subsequently, variations across countries and demographic factors were examined within five identified profiles.

This study offers novel insights into the variation in drivers' acceptance by identifying five distinct user profiles: Enthusiasts, Somewhat enthusiastic, Moderate, Sceptical, and Resistant. These profiles exhibit systematic differences in acceptance, concerns, and behavioural intentions, with non-linear patterns across profiles. The LPA results showed that these profiles are not merely positioned along a linear continuum of "pro-anti-technology"; instead, they demonstrate nuanced, non-linear relationships between concerns and acceptance constructs. While the distinctions between profiles are more pronounced for acceptance and behavioural intention, concerns were somewhat less varied, suggesting that apprehension can coexist with positive efficacy beliefs about DMS. This pattern aligns with a "privacy calculus" perspective, wherein individuals assess perceived benefits against perceived risks rather than uniformly rejecting technologies that raise concerns (e.g., Ackermann et al., 2022; Yan et al., 2026).

Variable-centred models, such as the TAM and the UTAUT, typically predict monotonic relationships between perceived benefits/risks and adoption intentions. Our profile-centred analysis complements these models by revealing heterogeneous configurations of beliefs across different subpopulations. The conceptual coexistence of high acceptance and behavioural intention alongside significant concern can be elucidated by the risk–benefit balancing framework. Specifically, perceived safety benefits may not inherently outweigh the discomfort associated with being recorded, or scepticism regarding data stewardship. This phenomenon may also indicate a form of conditional acceptance, in which acceptance and trust depend on factors such as the data-processing method, the entities with access to the data (OEMs, insurers, third parties), and the available controls (opt-in, consent granularity, retention policies). In the absence of assurances, acceptance and behavioural intention may remain limited, even when the functional utility is acknowledged.

Significant cross-country variations were observed in the general distribution of participants across profiles. The Enthusiast and Somewhat enthusiastic profiles were more prevalent in China, whereas the Resistant and Sceptical profiles were disproportionately represented in France, the United Kingdom, and Sweden. The most significant divergences were observed between Enthusiasts and both Sceptical and Resistant profiles, indicating considerable cross-national variability in these extreme positions. This finding suggests that cultural and regulatory contexts exert the greatest influence on the extremes of the acceptance spectrum rather than on mid-level profiles. Furthermore, comparisons between Somewhat enthusiastic and the two most resistant profiles also yielded medium effect sizes, reinforcing that moderate-to-high acceptance is not uniformly distributed across countries. These country disparities may be attributed to legal frameworks, data protection regulations, and societal attitudes towards privacy. The higher degree of individualism in Western countries compared to Japan and China has been shown to correlate with elevated privacy concerns in Western society (Wang et al., 2020). The mandatory implementation of these systems in manufactured vehicles may engender discomfort for a specific subset of users in certain countries. This sensitivity also aligns with cross-cultural differences in privacy calculus (Trepte et al., 2017). While the majority of individuals may be inclined to try these systems, a notable minority remains resistant, and it is imperative to address their concerns.

Age and gender effects further underscore the complexity of profiles, with older drivers and women more likely to belong to the resistant profile. The observation that older drivers are more frequently categorised within Resistant or Sceptical profiles aligns with previous research indicating a lower acceptance of automated vehicles among older adults (e.g., Haghzare et al., 2021; Lajunen & Sullman, 2021; Owens et al., 2015; Öztürk et al., 2025). This phenomenon can be partially influenced by anxiety (Nguyen et al., 2023), exposure (Classen et al., 2021), and perceived vulnerability of automated driving systems to cyber-attacks (Kinero et al., 2025). Older drivers' heightened sensitivity to potential privacy and security threats associated with novel in-vehicle technologies could possibly be due to reduced familiarity with such technologies or concerns regarding personal data utilisation. Given the potential benefits of DMS for older drivers (e.g. Coyne et al., 2024), the elevated level of concern may impede its implementation. In contrast, younger drivers are often classified within Enthusiast or Somewhat enthusiastic profiles. This behaviour is consistent with early-adopter patterns observed in related technologies (Hardman et al., 2019; Louw et al., 2021).

Gender differences, with women more frequently represented in Moderate/Sceptical profiles and men more in Enthusiast/Somewhat enthusiastic profiles, correspond with existing evidence indicating that women are less likely to adopt similar technologies than men (e.g., Greenwood & Baldwin, 2022; Hohenberger et al., 2016; Rice & Winter, 2019; Smyth et al., 2021; Son et al., 2015). This is also in line with women having greater concerns regarding connected and automated vehicles (Lee & Hess, 2022). These differences do not suggest a uniform reluctance among women; rather, they indicate that interventions should be attuned to the tone of communication, agency, and context of use.

4.1. Limitations

Despite the advantages of employing a large, multi-national sample and a robust latent profile analysis, several limitations warrant consideration. Firstly, the cross-sectional design limits causal inference; thus, future longitudinal or experimental research is necessary to explore how experience with DMS affects profile membership and attitudes over time. Secondly, although the sample was balanced for age and gender within each country, demographic variations, such as the younger average age in the Chinese sample, may have impacted cross-country comparisons.

In contrast to traditional clustering methodologies that depend on rigid cut-off values or heuristic grouping, LPA offers a model-based, probabilistic framework that incorporates measurement error and classification uncertainty. This approach is particularly crucial in the context of technology acceptance, where attitudes are continuous and interrelated rather than categorical. LPA facilitates the identification of distinct subpopulations based on these multidimensional indicators without imposing arbitrary thresholds, thereby enhancing both interpretability and statistical rigour. Despite these advantages, the identified profiles depend on the specific indicators used (e.g., acceptance, concerns, behavioural intention). Incorporating additional constructs, such as technology anxiety, prior experience, or individual values, could yield more detailed segmentation. The study did not account for participants' prior experience with automated driving systems and DMS technologies. Thus, the findings may have been influenced by such previous exposure (e.g., Al Haddad et al., 2024). Therefore, we recommend interpreting the results with caution and suggest that future research consider prior experience with these systems as a potential confounding variable.

As previously noted, the study did not evaluate user profiles based on a specific model or theory. Given the diverse concerns identified among potential users (Coyne et al., 2024) and the need for more up-to-date models of user acceptance of vehicle technologies (Damsara & de Barros, 2025), future research should prioritise examining the acceptance of DMS technologies from both theoretical and practical perspectives. Finally, the findings of the study are limited to the definition of DMS provided to participants. As demonstrated by Bernhard and Hecht (2022) and Presta et al. (2022), the adoption of systems by individuals may vary as a function of data collection methodology. People exhibit a preference for less obtrusive systems (such as cameras) over wearable sensors (Presta et al., 2022). A potential avenue for future research is to investigate in depth the concerns associated with various forms of data collection.

4.2. Implications and future suggestions

As discussed by Jannusch et al. (2021), DMS promises significant safety benefits to reduce aberrant driver behaviours, including distracted driving. Even the presence of a camera system may have an effect on reducing aberrant behaviours. Despite these potential benefits, the profiles identified in this paper should be assessed from the users' perspective. For example, a recent study examining truck drivers' acceptance of road-facing dashcams found that perceived benefits of the technology play a more significant role in acceptance than privacy concerns (Gruchmann & Jazairy, 2025). However, the current study identified two subsets of potential users who exhibited significant concerns and demonstrated lower levels of acceptance and behavioural intention to use DMS. While privacy concerns may be less pronounced regarding road-facing cameras, in-vehicle monitoring appears to be a substantial concern for certain user profiles. Addressing these concerns could yield immediate and significant benefits for the future utilisation of these systems.

A DMS collects a variety of data concerning behavioural metrics, such as eye gaze and steering patterns, which are utilised to assess the driver's state, including distraction, fatigue, or unresponsiveness (Palao et al., 2023). The study's findings indicate that users express significant concerns regarding the data collected. Therefore, it is imperative to provide users with transparent information about different types of concerns (e.g., real-time image processing, secondary data processing by others or data protection) addressed in this study. Additionally, the secondary use of data by manufacturers, insurance companies, or fleet management may necessitate further consultation with users to determine the optimal approach to balance user preferences and stakeholder requirements. Although the form of data processing may be system-dependent and vary across manufacturers or countries due to policy differences, the use of this data raises concerns that necessitate stringent data protection measures and transparent policies on data collection, storage, and sharing.

The consistent evidence of age and gender differences in the acceptance of various vehicle technologies (e.g., Greenwood & Baldwin, 2022; Weigl et al., 2023) suggests that manufacturers and policymakers should consider the potentially differing needs of women, men and different age groups, and consider targeted communication strategies for each of these groups. Providing clear, non-technical explanations of data collection, processing, and privacy protection may help alleviate concerns, particularly among users in Resistant and Sceptical profiles. For instance, Greenwood and Baldwin (2022) found that older adults and women perceived themselves as less knowledgeable about automated driving systems compared to younger adults and males. They also found that older users prefer more factual information and avoid social media as a source of information. Communication strategies that emphasise transparency in data handling may be particularly effective for women and the elderly in the Sceptical profile. However, tailored messages should also avoid perpetuating stereotypes. Exposure-based strategies, such as hands-on demonstrations or trial opportunities, can acknowledge these concerns and help reduce initial apprehensions, thereby supporting broader acceptability. This approach may also address the generally lower confidence observed in women regarding their ability to use and learn technology efficiently (Cai et al., 2017).

5. Conclusion

This study used a large, multi-country sample to identify distinct profiles of DMS acceptance and examined how these profiles varied across demographic groups and country contexts. While several findings align with existing evidence from related domains, such as automated driving systems, the contribution of this study lies in advancing beyond variable-centred analyses to a person-centred segmentation of users, specifically applied to the acceptance of DMS. Through the application of LPA, nuanced combinations of acceptance, concerns, and behavioural intentions were revealed, which do not conform to a simple pro- versus anti-technology continuum. This profiling approach supports the coexistence of high acceptance with significant concerns within certain user groups, offering a more refined understanding of end-user heterogeneity. Furthermore, the profiles are unevenly distributed across countries. These findings emphasise the importance of tailoring communication and design strategies and policy approaches to user profiles rather than treating the public as a homogeneous group.

CRediT authorship contribution statement

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

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 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.

Please rate the extent to which you agree or disagree with the following statements in relation to a DMS:

Table A.1
Items and associated constructs.

No	*Item*	*Construct*
1	I would use a car that had a DMS	Behavioural intention
2	I would be happy for the DMS to monitor my driving	
3	If I had a DMS, I would take its' advice	
4	I will trust the information I receive from the DMS	Acceptance
5	I think I can rely on the DMS	
6	I would feel more comfortable doing other things (e.g. looking at my phone) with the DMS on	
7	I would find the DMS useful while driving	
8	Using the DMS would help me to re-take control of the vehicle safely when required	
9	I think that the DMS would reduce the risk of being involved in a traffic accident	
10	I think the DMS will be easy to interact with	
11	I think the DMS will be easy to understand	
12	I am worried that the DMS is recording my facial image data in real time	Concerns
13	It bothers me that the DMS is recording my facial image data in real time	
14	I am concerned that the DMS is collecting too much personal information about me	
15	I am concerned that the manufacturer of the DMS will sell my facial image data to other companies e.g. insurers	
16	I am concerned that my facial image data will be used for other purposes while using the DMS	
17	I am concerned that the manufacturer of the DMS will share my facial image data with a third party without my authorization	
18	I believe that hackers can easily break into the DMS and get my facial image data	
19	I am concerned that my facial data will be leaked	
20	I believe that using a DMS poses a real risk to the protection of personal information	
21*	I think the DMS will be annoying	
22*	I think the DMS will be distracting	

Note. Items marked with an asterisk (*) are excluded from the constructs following factorial analysis (refer to Öztürk et al., 2026, for further details).

Data availability

Data will be made available on request.

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