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Privacy Concern and Acceptability of Driver Monitoring System

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ABSTRACT

A Driver Monitoring System (DMS) is designed to monitor and evaluate driver states, including distraction, fatigue, and drowsiness. It issues warnings when necessary and can provide countermeasures to promote driving safety. Our study aimed to gauge the perceptions of Chinese drivers regarding DMS-induced privacy concern and their acceptance of this technology. We conducted a one-way between-subjects design to assess the impact of different DMS types—facial image-based, electroencephalogram (EEG) signals-based, electrocardiogram (ECG) signals-based, and vehicle motion-based—on privacy concern and acceptance via an online survey (N = 486). The findings showed that participants expressed moderate privacy concern but displayed a positive attitude towards DMS. They exhibited a preference for the vehicle motion-based DMS, which uses indirect methods for monitoring. Acceptance of DMS was higher among individuals who perceived the data as sensitive and lower among those with pronounced privacy concern. Our research may provide practical implications for the development of DMS.

Keywords: Driver monitoring system, Privacy concern, General acceptance, Data sensitivity

INTRODUCTION

It is reported that a predominant proportion of traffic accidents, over 90% in both the United States (Dingus et al., 2016) and China (Huang et al., 2018), are attributable to human-related factors. While vehicle automation technology continues to advance, most vehicles on the market still necessitate that drivers monitor the vehicle, road, and surrounding environment to ensure safety. The driver monitoring system (DMS) is developed to track driver's attention status. If it detects signs of fatigue or distraction, it implements countermeasures, such as playing music, to enhance driving safety (Dong et al., 2011).

DMS can be categorized into three types. The first type involves monitoring drivers using driver-facing cameras. This DMS type (e.g., Nakamura et al., 2013) identifies driver states by analyzing factors such as eye movements (e.g., eye closure and blink frequency), facial expressions (e.g., frowning), and head movements (e.g., frequent nodding and head rotation). The second type utilizes contact-based, non-invasive equipment or wearable devices to gather physiological data, like electroencephalogram (EEG) signals (Chen et al., 2015) or electrocardiogram (ECG) signals (Vicente et al., 2016). These signals can reflect a driver's drowsiness, fatigue, and stress levels. The third type relies on vehicle motion and utilizes road-facing cameras to monitor driver states. Indicators like irregular steering-wheel angles and erratic vehicle tracking might suggest driver fatigue (Zhong et al., 2007). Vehicle motion assists in determining if the vehicle is under effective control, thereby indirectly identifying driver states.

Current technology facilitates the monitoring of driver's behavior. It is crucial to ascertain whether drivers accept this technology. Picco et al. (2023) investigated user acceptance among Dutch drivers, revealing moderate enthusiasm and low sensitivity towards data collection. These drivers express a relative preference for data collection methods based on speed and forward-facing video footage (Picco et al., 2023). A survey on the basis of Universal Theory of Acceptance and Use of Technology framework explored the acceptability of DMS, and the behavioral intention of this technology is influenced by effort expectancy, performance expectancy, social influence, attitudes to using new technology, and anxiety (Smyth et al., 2021). Notably, a primary determinant of acceptance is privacy concern (Picco et al., 2023). Privacy-invasive conditions can discomfort users (Bloom et al., 2017), and data collection may lead to privacy breaches and potential security risks.

The current study aims to understand Chinese drivers' perceptions regarding privacy concern and acceptance, thereby aiding in evaluating the potential adoption of DMS. We classified DMS into four categories based on their primary characteristics: facial image-based DMS, EEG signals-based DMS, ECG signals-based DMS, and vehicle motion-based DMS. We conducted an online questionnaire to explore drivers' data sensitivity, collection concern, secondary use, perceived insecurity, perceived usefulness, trust, and behavioral intention.

METHOD

Materials and Procedure

The questionnaire consists of two parts. The first collects the participants' degree of (dis)agreement with DMS-related items and the second section gathers demographic information.

In the first part, participants were asked to express their (dis)agreement with each item about the involved DMS. A Likert scale ranging from 1 (totally disagree) to 7 (totally agree) was used to measure seven dimensions of data sensitivity (DS), collection concern (CC), secondary use (SU), perceived insecurity (PI), perceived usefulness (PU), trust (Tru), and behavioral intention (BI) with 19 items (see Table 1). Collection concern and secondary use were derived from the Concern for Information Privacy scale developed by Smith et al. (1996), with modifications made based on the specific context of this study. The items related to perceived usefulness, trust, and behavioral intention to use were adapted from the questionnaire used by Xu et al. (2018).

Demographic information was collected in the second section. Participants were asked to provide their gender, age, education level, occupation, monthly income, level of knowledge about DMS, years of driving experience, and average annual driving distance in the last two years. After answering demographic questions, participants answered an attention-check question about the type of DMS they had read about earlier and those who failed the attention check would be removed.

Each participant was randomly assigned to one of the four DMS type conditions. The questionnaire commenced with a succinct introduction to the relevant DMS type, including its name, functions, and methods of data collection. For example, for the facial image-based DMS condition, participants read that "This system employs on-board cameras to continuously gather facial data, including the eye closure, blinking, gaze direction, and yawning. This data is subsequently processed and analyzed to assess the driver's level of distraction and fatigue. If the system detects that the driver has a certain degree of distraction or fatigue, it issues a warning." Subsequently, participants were required to answer how much they agreed with the 19 items. The questionnaire ended up with demographic questions. An example of the questionnaire items for the facial image-based DMS condition is shown in Table 1.

Table 1. An example of the questionnaire items for the facial image-based DMS condition.

Seven dimensions and corresponding items
Data sensitivity (DS) (Kehr et al., 2015)
DS1: I think facial image data is very sensitive.
Collection concern (CC) (Smith et al., 1996)
CC1: I am worried that this system is recording my facial image data in real time.
CC2: It bothers me that this system is recording my facial image data in real time.
CC3: I am concerned that this system is collecting too much personal information about me.
Secondary use (SU) (Smith et al., 1996)
SU1: I am concerned that the manufacturer of this system will sell my facial image data to other companies.
SU2: I am concerned that my facial image data will be used for other purposes while using this system.
SU3: I am concerned that the manufacturer of this system will share my facial image data with a third party without my authorization.
Perceived insecurity (PI) (Cichy et al., 2021)
PI1: I believe that hackers can easily break into this system and get my facial image data.
PI2: I am concerned that my facial data will be leaked.
PI3: I believe that using this system poses a real risk to the protection of personal information.
Perceived usefulness (PU) (Xu et al., 2018)
PU1: I think using this system can make my driving easier.
PU2: I think using this system can improve my driving safety performance.
PU3: Overall, this system is useful for me.
Trust (Tru) (Xu et al., 2018)
Tru1: I think this system is dependable.
Tru2: I think this system is reliable.
Tru3: Overall, I can trust this system.
Behavioral intention (BI) (Xu et al., 2018)
BI1: I intend to buy this system.
BI2: I intend to use this system.
BI3: I will recommend family members and friends to use this system.

Note: "this system" refers to the facial image-based DMS.

Participants

We run this study via an online survey platform in China (Sojump; https://www.sojump.com). In total, 654 participants completed the survey. However, 133 failed the attention check, 29 did not possess a driving license, and the gap between age and driving experience (in years) for six participants was less than 18 years (a person under 18 years old cannot apply for a driving license according to Chinese traffic law). Among the remaining 486 participants (303 female; mean age = 30.2 years), 125 were under the facial image-based DMS condition, 121 were under the EEG signals-based DMS condition, 122 were under the ECG signals-based DMS condition, and 118 were under the vehicle motion-based DMS condition. The distribution of all demographic variables did not differ significantly among the four conditions (ps > .05).

RESULTS

Material, data, code, and results are publicly available (https://osf.io/86txu/?view_only=1dc6196d16444394b81f2aafc4b91229).

Factor Analysis

These 19 items were subjected to an exploratory factor analysis. The Kaiser-Meyer-Olkin measure of sampling adequacy, KMO = .94, and Bartlett's Test of Sphericity, $\chi^2(171)= 6126.86$, $p < .001$, suggesting that correlations between these items were sufficiently large for factor analyses. Unexpectedly, a scree plot and parallel analysis (Horn, 1965) indicated that three factors should be retained. We conducted a weighted least squares factor extraction method and oblique rotation. The results showed that factor I was comprised of nine items from pre-assumed collection concern, secondary use, and perceived insecurity, and it explained 30% of the variance, which was named privacy concern by us; factor II was comprised of nine items from perceived usefulness, trust, and behavioral intention, and it explained 26% of the variance, which was named general acceptance following a similar observation by de Winter and Nordhoff (2022); factor III was comprised of one item and it explained 4% of the variance, named data sensitivity (Kehr et al., 2015). Factor loadings of each item on each factor are listed in Table 2. There is no common method bias issue, as indicated by the results of the unrotated factor analysis, which show that no single factor accounts for more than 50% of the variance (Podsakoff et al., 2003).

The exploratory factor analysis indicates that our three pre-assumed factors (collection concern, secondary use, perceived insecurity) was factored into a single factor (privacy concern). Thus, we assumed privacy concern to be a second-order construct and the three factors as first-order constructs. Similarly, this assumption applied to general acceptance and its relevant three factors. To validate our assumptions, we then constructed a second-order factor model with a confirmatory factor analysis (see Figure 1). Several fit indices were examined in assessing the goodness-of-fit of the model ($\chi^2/df = 1.78$, Root Mean Square Error of Approximation = 0.04, Goodness of Fit Index = 0.95, Adjusted Goodness of Fit Index = 0.93, Tucker-Lewis

Table 2. Factor matrix of exploratory factor analysis.

Item	Factor I	Factor II	Factor III
DS1	.00	.03	**.89**
CC1	**.73**	−.06	.05
CC2	**.64**	−.04	.06
CC3	**.79**	−.05	.04
SU1	**.89**	.07	−.05
SU2	**.87**	.05	−.07
SU3	**.85**	.02	−.03
PI1	**.70**	−.05	.01
PI2	**.88**	.05	−.04
PI3	**.79**	.00	.02
PU1	−.04	**.55**	.10
PU2	−.01	**.60**	.10
PU3	.11	**.76**	.01
Tru1	−.02	**.77**	−.04
Tru2	−.03	**.73**	−.08
Tru3	−.02	**.79**	−.06
BI1	.00	**.80**	.00
BI2	.04	**.87**	−.02
BI3	−.06	**.71**	−.01

Note. DS = data sensitivity; CC = collection concern; SU = secondary use; PI = perceived insecurity; PU = perceived usefulness; Tru = trust; BI = behavioral intention.

Index = 0.98, Normed Fit Index = 0.96, Comparative Fit Index = 0.98) and indicated an acceptable fitness (Schumacker and Lomax, 2004).

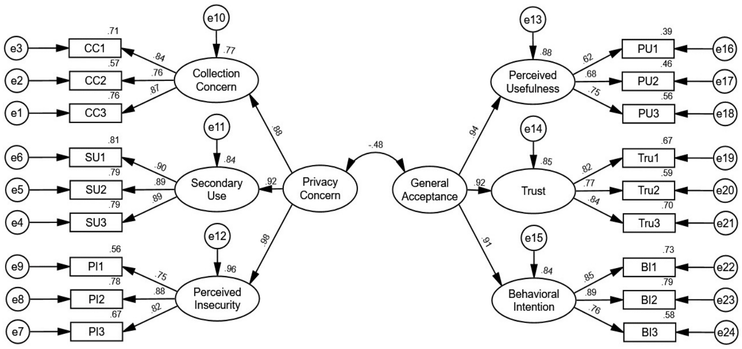

Figure 1: A second-order factor model with a confirmatory factor analysis.

In Table 3, all factor loadings were greater than .60, indicating acceptable indicator reliability. All factors had acceptable internal consistency (Cronbach's α and Composite Reliability greater than .70) (George and Mallery, 2003). Most factors' average variance extracted (AVE) were above .50, except for perceived usefulness with .46 (close to .50), indicating that the questionnaire achieved acceptable convergent validity (Hair et al., 2014). The square roots of AVE (Privacy concern: .93; General acceptance: .92) were greater than the absolute value of the associated inter-construct correlation coefficient ($r = -.48$), indicating acceptable discriminant validity. Thus, the second-order factor model was adequate.

Table 3. A second-order factor model structure fit index.

Construct and item		FL	AVE	CR	Cronbach's α
Privacy concern	Collection concern	.88	.86	.95	
	Secondary use	.92			
	Perceived insecurity	.98			
General acceptance	Perceived usefulness	.94	.85	.95	
	Trust	.92			
	Behavioral intention	.91			
Collection concern	CC1	.84	.68	.86	.87
	CC2	.76			
	CC3	.87			
Secondary use	SU1	.90	.79	.92	.92
	SU2	.89			
	SU3	.89			
Perceived insecurity	PI1	.75	.67	.86	.86
	PI2	.88			
	PI3	.82			
Perceived usefulness	PU1	.62	.46	.72	.71
	PU2	.68			
	PU3	.75			
Trust	Tru1	.82	.65	.85	.85
	Tru2	.77			
	Tru3	.84			
Behavioral intention	BI1	.85	.69	.87	.87
	BI2	.89			
	BI3	.76			

Note. FL = factor loading; CR = composite reliability; AVE = average variance extracted.

Impact of DMS Type on Data Sensitivity, Privacy Concern, and General Acceptance

Average scores of data sensitivity, privacy concern, and general acceptance were 5.59 (SD = 0.96), 4.55 (SD = 1.29), and 5.34 (SD = 0.88), respectively. On average, participants' opinions towards data sensitivity and general acceptance were between "somewhat agree" and "agree", indicating that they thought data collected by DMS were sensitive and they intended to accept DMS. As for privacy concern, attitude between "neutral" and "somewhat agree" showed moderate privacy concern.

Then, a one-way between-subjects analysis of variance (ANOVA) test was conducted to compare the effect of DMS type on data sensitivity, privacy concern, and general acceptance. The results revealed no significant main effects of DMS type on data sensitivity ($F(3, 482) = 1.35$, $p = .257$, $\eta^2\text{p} = .008$), privacy concern ($F(3, 482) = 1.09$, $p = .354$, $\eta^2\text{p} = .007$), and general acceptance ($F(3, 482) = 2.48$, $p = .060$, $\eta^2\text{p} = .015$), indicating that data required by the four types were statistically equally sensitive for participants, and DMS type did not significantly affect participants' privacy concern and general acceptance.

Pairwise comparisons through Fisher's least significant difference (LSD) method revealed that general acceptance of vehicle motion-based DMS was significantly higher than the other three types (see Figure 2; vehicle motion-based DMS vs. facial image-based DMS: $\Delta M = 0.26$, $t(482) = 2.27$, $p = .024$, Cohen's $d = 0.291$; vehicle motion-based DMS vs. EEG signals-based DMS: $\Delta M = 0.25$, $t(482) = 2.18$, $p = .030$, Cohen's $d = 0.281$; vehicle motion-based DMS vs. ECG signals-based DMS: $\Delta M = 0.26$, $t(482) = 2.27$, $p = .024$, Cohen's $d = 0.293$).

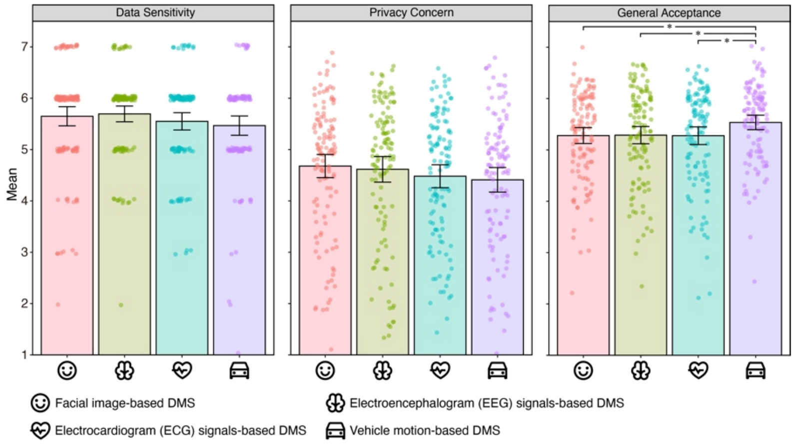

Figure 2: Mean values of the data sensitivity, privacy concern, and general acceptance on each DMS type. Error bars = ± 2 standard errors. $^{*}p < .05$ (two-tailed).

In addition, we also focused on the impact of DMS type on pre-determined factors, which constitute privacy concern and general acceptance. A one-way between-subjects ANOVA revealed that there were no significant main effects of DMS type on collection concern, secondary use, and perceived insecurity ($ps > .05$). Similarly, as for perceived usefulness, trust, and behavioral intention, which compose general acceptance, there were also no significant main effects of DMS type ($ps > .05$). Pairwise comparisons through LSD method suggested that vehicle motion-based DMS was perceived more useful than facial image-based DMS ($\Delta M = 0.27$, $t(482) = 2.37$, $p = .018$, Cohen's $d = 0.304$) and ECG signals-based DMS ($\Delta M = 0.22$, $t(482) = 1.98$, $p = .049$, Cohen's $d = 0.255$). In addition, participants trusted vehicle motion-based DMS more than the other three types of DMS ($ps < .05$).

Data Sensitivity and Privacy Concern Influence General Acceptance

Linear regression analysis was conducted to explore whether demographic variables, data sensitivity, and privacy concern impact general acceptance (see Table 4). Data sensitivity was a positive predictor of general acceptance ($b = 0.24$, $t = 7.01$, $p < .001$), indicating that participants who perceived the

Table 4. The regression coefficient (unstandardized beta, *b*) of linear regression model.

Variables	Four DMS types	Facial image-based DMS	EEG signals-based DMS	ECG signals-based DMS	Vehicle motion-based DMS
Gender[a]	0.07	0.06	0.12	−0.04	0.03
Age	0.01	0.02	0.01	0.00	0.00
Education[b]	−0.25*	−0.34	−0.10	−0.44	−0.29
Occupation[c]	0.10	0.38	−0.20	0.15	0.23
Monthly income[d]	0.19*	0.18	0.07	0.25	0.22
Heard of DMS[e]	0.34***	0.52**	0.50***	0.45**	−0.21
Driving experience	−0.04**	−0.01	−0.03	−0.07*	−0.04
Average kilometers driven per year[f]	0.29***	0.18	0.29*	0.38*	0.26
Data sensitivity	0.24***	0.19**	0.35***	0.36***	0.13*
Privacy concern	−0.28***	−0.24***	−0.34***	−0.28***	−0.25***

Note. [a]Male = 0, female = 1; [b]Undergraduate or graduate = 1, others = 0; [c]Civil servant or public-sector employee = 1, others = 0; [d]≤10, 000 Chinese Yuan per month = 0, others = 1; [e]Never heard = 0, have theoretical knowledge about the operating principles of DMS = 1, have used = 2; [f]>10,000 km/year = 1, others = 0. Other variables are continuous. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

data used in DMS as more sensitive had a higher acceptance level for DMS. Participants who were concerned their privacy more had a lower acceptance for DMS ($b = -0.28$, $t = -10.81$, $p < .001$). The influence of data sensitivity and privacy concern on general acceptance showed the same trend across four conditions. In terms of demographic variables, linear regression analysis revealed that participants who had lower education level ($b = -0.25$, $t = -2.53$, $p = .012$), more monthly income ($b = 0.19$, $t = 2.57$, $p = .010$), heard of or even used DMS before ($b = 0.34$, $t = 4.52$, $p < .001$), had less driving experience (the year held driving license) ($b = -0.04$, $t = -2.90$, $p = .004$), and drove more per year (in the last two years) on average ($b = 0.29$, $t = 3.76$, $p < .001$) had higher acceptance.

DISCUSSION

This study examined data sensitivity, privacy concern, and general acceptance of four DMS types among Chinese drivers through an online survey. The findings suggest that participants viewed the data collected by DMS as sensitive and had moderate concern about privacy. However, they were inclined to accept DMS. Notably, participants perceived DMS based on vehicle motion, an indirect monitoring method, as more useful and trustworthy. Concerning the factors that influenced acceptance, participants who perceived the data as being more sensitive tended to be more receptive to DMS, while those with more privacy concern showed lower acceptance.

Drivers displayed moderate privacy concern, indicating that while they are not excessively anxious about privacy, they do recognize potential risks. Nevertheless, they generally have a positive attitude towards DMS, mirroring the findings of Picco et al. (2023). One possible reason is that the safety benefits drivers might gain from DMS could lead them to tolerate some risks associated with privacy leakage. However, positive attitudes do not necessarily lead to actual purchases. In real-world scenarios, the decision to buy is influenced by factors such as actual driving experience, the effectiveness of the DMS, and trust in its manufacturer.

Compared to collecting data from facial images, EEG, and ECG, drivers are more receptive to the collection of vehicle motion information. However, the efficacy of vehicle motion-based DMS is debatable. While vehicle motion data can be analyzed to obtain speed, acceleration, or deceleration patterns, it has limitations in identifying risky driving behaviors. Such data might not adequately address instances of driver inattention inside the vehicle (Jannusch et al., 2021).

Participants who perceived the data as more sensitive demonstrated a higher acceptance level for DMS. At first glance, this may appear counterintuitive, as one might expect that individuals who view the data as sensitive would exercise more caution towards DMS. However, a plausible interpretation is that drivers who perceive the data as sensitive also understand that such data can accurately reflect their driving behavior. Consequently, DMS could potentially discern the genuine driver states from a plethora of personalized data, leading to effective, tailored countermeasures. We also studied the impact of demographic factors on overall acceptance. Drivers with a lower educational background, higher monthly income, previous awareness or use of DMS, less driving experience, and higher annual mileage displayed greater acceptance. Drivers with less education might lack familiarity with DMS and, therefore, be more inclined to embrace this new technology. Affluent drivers tend to be more open to trying out new products (Gilsenan, 2021). Drivers who have heard of or previously used DMS are likely less apprehensive about its use and effectiveness due to their past experience. Novice drivers with fewer years of driving experience might be more receptive to DMS, especially since the technology is advertised as enhancing driving safety. Moreover, frequent drivers, who face more risks on the road, may be inclined to seek technologies that improve safety.

This study has practical implications. Overall, the acceptance of DMS by Chinese drivers highlights the potential applications of this technology. However, drivers' privacy concern suggest a need to develop policies that enhance the protection of private information collected by DMS. This study also has limitations. The online survey we conducted lacks ecological validity and should be supplemented by field experiments.

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