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A hierarchical cluster analysis of young drivers based on their perceived risk and frequency of texting while driving

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Abstract

Introduction: The present study attempted to provide a proof-of-concept of usefulness of cluster analysis for identifying distinct and practically meaningful subgroups of drivers who differed in their perceived risk and frequency of texting while driving (TWD).

Method: Using a hierarchical cluster analysis, which involves sequential steps in which individual cases are merged together one at a time based on their similarities, the study first attempted to identify distinct subgroups of drivers who differed in their perceived risk and frequency of TWD. To further evaluate the meaningfulness of the subgroups identified, the subgroups were compared in terms of levels of trait impulsivity and impulsive decision making for each gender.

Results: The study identified the following three distinct subgroups: (a) drivers who perceive TWD as risky but frequently engage in TWD; (b) drivers who perceive TWD as risky and infrequently engage in TWD; and (c) drivers who perceive TWD as not so risky and frequently engage in TWD. The subgroup of male, but not female, drivers who perceive TWD as risky but frequently engage in TWD showed significantly higher levels of trait impulsivity, but not impulsive decision making, than the other two subgroups.

Discussion: This is the first demonstration that drivers who frequently engage in TWD can be categorized into two distinct subgroups that differ in terms of the perceived risk of TWD.

Practical applications: For drivers who perceived TWD as risky yet frequently engage in TWD, the present study suggests that different intervention strategies may be needed for each gender.

Keywords

Texting while driving; Perceived risk; Impulsivity; Cluster analysis; College students

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Declaration of Competing Interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

1. Introduction

It is estimated that 28,000 people were injured in crashes involving mobile phone use in 2019 in the United States (National Highway Traffic Safety Administration, 2021). Despite its obvious risk, mobile phone use while driving is still ubiquitous. An observational study revealed that 23% of drivers were using their mobile phones and 9% of them were texting (Kruger et al., 2018). Texting while driving (TWD) is a particularly dangerous form of distracted driving because it involves visual (e.g., looking away from the roadway), manual (e.g., taking a hand off the steering wheel), and cognitive (e.g., thinking about something other than driving) forms of distraction (Sherin et al., 2014). A study utilizing naturalistic observations with on-board cameras revealed that TWD led to 3.87 times more crashes or near-crashes among novice drivers (Klauer et al., 2014; see also Caird et al., 2008, 2014; Simmons et al., 2016; Stavrinos et al., 2018, for meta-analyses on effect of cell-phone use on driving outcomes).

Transportation researchers have identified various situational factors associated with TWD. These include: (a) when the distance to the destination is farther (e.g., Hayashi et al., 2016); (b) while stopped at a red light (e.g., Bernstein & Bernstein, 2015) or while driving at slower speed (e.g., Oviedo-Trespalacios et al., 2017); (c) while driving under intense road conditions (e.g., Atchley et al., 2011) or when the chance of motor-vehicle crashes is higher (e.g., Hayashi, Fessler, et al., 2018); (d) when the amount of fine for TWD is higher (e.g., Hayashi, Friedel, et al., 2019a); and (e) when the message received while driving is very important (e.g., Foreman et al., 2021) or the social relationship to the sender is closer (Foreman et al., 2019).

One noteworthy finding in the literature is that *perceived* risk of motor-vehicle crashes due to TWD is not a reliable predictor of TWD. Some studies have found that perceived risk is a very weak predictor of TWD (Atchley et al., 2011), a predictor of TWD in females but not in males (Struckman-Johnson et al., 2015), or a predictor of intentions to engage in TWD (Brown et al., 2019). A majority of studies, however, have found that higher perceived risk is not associated with lower engagement or intentions of TWD (e.g., Berenbaum et al., 2019; Oviedo-Trespalacios, King, et al., 2017; Rupp et al., 2016; Sullman et al., 2018), which is consistent with the finding that drivers engage in TWD despite being aware of its danger (e.g., Atchley et al., 2011; Harrison, 2011; Hayashi et al., 2015; Terry & Terry, 2016).

To better understand the discrepant findings in the literature, the present study further explored the relationship between perceived risk of TWD and engagement in TWD in college students (one of the main target populations for the problem of TWD; Feldman et al., 2011). If the discrepant findings on the relation between perceived risk and TWD stemmed from the heterogeneity of perceived risk among drivers who frequently engage in TWD, it should be that some drivers who frequently TWD perceive TWD as very risky, whereas others perceive TWD as not so risky. To test this possibility, this study proposes that cluster analysis is useful.

Cluster analysis refers to grouping entities based on their similarities in terms of selected variables, such that members of the resulting groups are homogeneous to other members of the same group yet heterogeneous to those of the different groups (Clatworthy et al., 2005). An important advantage of cluster analysis is that classification can be performed objectively by assigning the variables equal numeric weights to help minimize *a priori* bias (Haldar et al., 2008). In this study a hierarchical cluster analysis was conducted, which involves a series of sequential steps in which individual cases are merged together one at a time based on their similarities (Clatworthy et al., 2005; Yim & Ramdeen, 2015). The primary purpose of the present study was to provide a proof-of-concept of usefulness of hierarchical cluster analysis for identifying distinct and practically meaningful subgroups of drivers who differed in their perceived risk and frequency of TWD. It was hypothesized that the hierarchical cluster analysis would result in the identification of distinct subgroups of drivers who would differ significantly in their perceived risk and frequency of TWD.

If such subgroups of drivers are identified, a next logical step is to evaluate the meaningfulness of the identified subgroups by investigating what factor(s) would differentiate them. To this end, it is important to recall the impulsive nature of TWD that drivers engage in TWD despite being aware of its danger (e.g., Atchley et al., 2011). Consistent with this, various studies (e.g., Hayashi et al., 2015; Pearson et al., 2013; Struckman-Johnson et al., 2015; but see Hayashi et al., 2016) have found that higher frequencies of TWD are significantly associated with higher levels of trait impulsivity (i.e., a predisposition toward rapid, unplanned reactions despite their negative consequences; Moeller et al., 2001) as well as impulsive decision making (i.e., a propensity to forego a future but larger reward to obtain an immediate but smaller reward; Green & Myerson, 2004). Based on these studies, the present study further explored whether subgroups of drivers who differ in their perceived risk and frequency of TWD would differ in terms of trait impulsivity and impulsive decision making. In addition, given the gender difference observed in the relationship between trait impulsivity and TWD (Struckman-Johnson et al., 2015), as well as the relationship between impulsive decision making and other problematic mobile phone use (e.g., Blessington & Hayashi, 2020), the comparisons among clusters were conducted separately for each gender. Because these were exploratory investigations based on the results of the cluster analysis, the study had no hypotheses to test for these analyses.

2. Material and methods

2.1. Participants

One hundred and seventy undergraduate students, who were enrolled in introductory psychology courses at a university in the northeastern United States, participated. The sample size wad determined based on similar studies (e.g., Hayashi, Friedel, et al., 2019b; Ortiz-Peregrina et al., 2020). The participants received course credit for their participation. Students who (a) had no history of driving (n = 29), (b) did not complete all surveys (n = 3), and (c) failed attention checks (n = 2) were excluded, and their data were not analyzed. The remaining sample consisted of 59 males and 77 females, and their mean age, years of higher education, and years driving were 19.5 (SD = 4.3), 1.5 (SD = 1.4), and 3.0 (SD = 4.0), respectively. The present study is a part of the larger survey and portions of the present data were reported in different studies with different goals and analyses (e.g., Hayashi et al., 2017; Hayashi, Foreman, et al., 2018).

2.2. Procedure

Sessions were conducted in a large classroom. The participants completed questionnaires on demographic information, perceived risk and frequency of TWD, trait impulsivity, and impulsive decision making. The Institutional Review Board at the first author's affiliated university reviewed the study protocol and deemed the study exempt.

2.2.1. Demographic and TWD questionnaires—In addition to the basic demographic information such as age, gender, years of higher education, and years driving, participants completed a questionnaire that included two sets of three questions adopted from Atchley et al. (2011), which measured perceived risk and frequency of three modes of TWD (initiating, replying, and reading). The questions employed a 7-point Likert scale ranging 1 (*not at all*) to 7 (*extremely*) for perceived risk (e.g., "In general, how dangerous is it to initiate a text while driving?") and from 1 (*never*) to 7 (*always*) for frequency (e.g., "How often do (did) you reply to a text while driving?"). Means across three modes of TWD were calculated and used for analyses. Cronbach's a's with the present sample were 0.908 for perceived risk and 0.910 for frequency.

2.2.2. Trait impulsivity—Trait impulsivity was assessed by the Barratt Impulsiveness Scale (BIS-11; Patton et al., 1995), which is a self-reported measure of trait impulsivity that consists of 30 questions with a 4-point Likert scale ranging from 1 (*rarely/never*) to 4 (*almost always/always*). Questions with negatively worded items were reverse coded, and higher scores indicate higher levels of impulsivity. The BIS has three subscales: *attentional impulsivity* (inability to focus attention), *motor impulsivity* (acting without thinking), and *non-planning impulsivity* (lack of future orientation or forethought; Meule, 2013). To make the scores of the subscales directly comparable, the raw scores were transformed into standardized scores with the minimum and maximum set to 0.0 and 1.0, respectively. Cronbach's α's with the present sample were 0.819 for the total score, 0.693 for attentional impulsivity, 0.583 for motor impulsivity, and 0.693 for non-planning impulsivity.

2.2.3. Impulsive decision making—The degree of impulsive decision making was assessed by the Monetary Choice Questionnaire (MCQ; Kirby et al., 1999). The MCQ includes a fixed set of 27 choices between smaller but immediate monetary rewards and larger but delayed rewards. For example, participants were asked, "Would you prefer (a) $55 today or (b) $75 in 61 days?" and they indicated which alternative they would prefer by circling it. The delays ranged from 7 to 186 days. Based on the patterns of choices, a discounting rate (k) is estimated (see Kirby et al., 1999, for scoring details). A discounting rate reflects the degree to which the subjective value of the delayed reward is discounted as a function of the time to its receipt, and higher k values indicate greater degree of impulsive decision making. The k values obtained from an MCQ can range from 0.00016 to 0.25. Because the k values in the present study were distributed exponentially, as with other studies (e.g., Kirby et al., 1999), the values were natural-log transformed for analyses.

2.3. Statistical analysis

A hierarchical cluster analysis was conducted to identify the subgroups of students who differed in terms of perceived risk and frequency of TWD. The mean scores of both scales were entered into the analysis, with Ward's method as the method of clustering, squared Euclidian distances as the measure of the distance, and z-score conversion as the method of standardization (Clatworthy et al., 2005; Yim & Ramdeen, 2015). The number of clusters was determined by the inverse scree technique, in which a sudden change in coefficient values was identified by the visual inspection of the values (Yim & Ramdeen, 2015).

With respect to the comparison across the subgroups, gender was analyzed by the chi-square test. Continuous variables were analyzed by a one-way analysis of variable (ANOVA) or by a Welch ANOVA if the assumption of homogeneity of variances, as assessed by Levene's test for equality of variances, was violated. Post-hoc pairwise comparisons were performed by the Tukey test or by the Games-Howell test if the assumption of homogeneity of variances was violated. Gender differences within a subgroup were analyzed by the independent-samples t test. All statistical analyses were performed with SPSS Version 27. The statistical significance level was set at 0.05.

3. Results

Fig. 1 shows the coefficient values of the cluster analysis as a function of the number of clusters. There was a robust increase in coefficient values (i.e., "jump") as the analysis shifted between the model with three clusters and the one with two clusters, suggesting that the model with three clusters best fits the present data. Fig. 2 shows perceived risk and frequency of TWD of each participant as a function of the clusters. Overall, the three clusters show distinct patterns in terms of the scores of perceived risk and frequency of TWD. Cluster 1 was characterized by high risk and relatively high frequency (hereafter, *High-Risk-High-Frequency* subgroup). Cluster 2 was characterized by high risk and low frequency (*High-Risk-Low-Frequency* subgroup). Cluster 3 was characterized by relatively low risk and relatively high frequency (*Low-Risk-High-Frequency* subgroup).

Table 1 shows the demographic characteristics for the three clusters. There was a statistically significant difference across the clusters for gender, $\chi^2(2) = 6.14$, p =.046, but no statistically significant differences were found for age, $F(2, 133) = 0.62$, p =.542; years of higher education, $F(2, 133) = 1.26$, p =.287; and years driving, $F(2, 133) = 0.16$, p =.856.

Table 2 shows the results of the ANOVA on the BIS and MCQ scores conducted separately for each gender. For females, no significant differences among the clusters were observed on all measures, whereas for males, significant differences were observed on the BIS motor impulsivity and total scores. The results of the post-hoc comparisons (Table 3) revealed that for both measures, the High-Risk-High-Frequency subgroup showed significantly greater impulsivity than the High-Risk-Low-Frequency and Low-Risk-High-Frequency subgroups (p's < 0.05).

Lastly, to confirm that splitting each cluster based on gender did not invalidate the clustering, gender differences on perceived risk and frequency of TWD were analyzed for each cluster. The results revealed that there were no gender differences on both measures for all clusters (p's > 0.05).

4. Discussion

Using a hierarchical cluster analysis, the present study explored whether college students could be categorized into distinct subgroups based on their perceived risk and frequency of TWD. The results revealed the following distinct subgroups: (a) drivers who perceive TWD as risky but frequently engage in TWD; (b) drivers who perceive TWD as risky and infrequently engage in TWD; and (c) drivers who perceive TWD as not so risky and frequently engage in TWD. To the best of our knowledge, this is the first demonstration that drivers who frequently engage in TWD can be categorized into two distinct subgroups that differ in terms of the perceived risk of TWD, suggesting that hierarchical cluster analysis is a useful research tool for identifying and profiling distinct, practically meaningful subgroups of drivers.

We believe this finding could potentially reconcile the discrepant findings on the relationship between perceived risk and frequency of TWD (e.g., Atchley et al., 2011 vs. Oviedo-Trespalacios, King, et al., 2017). Simply put, if a sample has a higher proportion of drivers who perceive TWD as risky but frequently engage in TWD, then it becomes more difficult to detect the significant negative relationship between perceived risk and frequency of TWD. Given the hypothetical nature of this argument, however, it is advisable for future research to further examine this hypothesis.

Another important finding of the present study is that male drivers, but not female drivers, who perceive TWD as risky but frequently engage in TWD showed significantly higher levels of trait impulsivity—but not impulsive decision making—than drivers who perceive TWD as risky and infrequently engage in TWD or those who perceive TWD as not so risky and frequently engage in TWD. This finding has three important implications. First, the differences between genders, as well as between trait impulsivity and impulsive decision making, may be relevant to the results of a meta-analysis that significant sex differences were observed with trait impulsivity (i.e., males being more impulsive than females) but not with impulsive decision making (Cross et al., 2011). Second, the gender moderation in the relationship between trait impulsivity and TWD in the present study would suggest that the significant positive relationship between trait impulsivity and TWD frequency reported in the literature (e.g., Pearson et al., 2013) is likely to be driven by male impulsive drivers who frequently engage in TWD. Third, the gender moderation would also suggest that intervention strategies targeting the impulsive nature of TWD may need to be trailed for each gender (details discussed follow).

4.1. Implications for policies to reduce TWD

The present study has important implications for policies on effective and efficient intervention strategies to reduce TWD. First, the present finding that some drivers frequently engage in TWD yet perceive it as not so risky demonstrated the importance of an educational approach that increases their perceived risk of TWD. As an example, Hayashi, Foreman, et al. (2019) experimentally demonstrated that a video-based threat-appeal intervention, in which drivers are exposed to a threatening message about the risk of TWD, is effective in reducing drivers' impulsive decisions associated with TWD through the enhanced feeling of potential regret deriving from negative consequences of TWD.

It is important to note, however, that frequent engagement in TWD may occur first for a variety of reasons, which then lowers drivers' perceived risk through the resolution of cognitive dissonance—the psychologically uncomfortable state of having inconsistent attitudes and/or behaviors (Festinger, 1957). That is, if drivers choose to frequently engage in TWD despite perceiving it is risky (i.e., inconsistency between the behavior and the attitude), they may perceive TWD to be less risky than it actually is (Atchley et al., 2011). If the behavior of TWD shapes drivers' perception of riskiness in this manner, some forms of behavioral interventions, such as contingency management, may be promising. Contingency management is a therapeutic technique in which a reward is delivered contingent on desirable behavioral change (Higgins et al., 2008). A pilot study demonstrated the feasibility and effectiveness of a smartphone-based application that implemented a contingency-management intervention, in which teen drivers earned points exchangeable for various rewards for miles driven without interacting with their phones (Henk et al., 2021).

Second, to maximize the effectiveness and efficiency of intervention strategies for TWD, it is essential to avoid a "one size fits all" approach (cf. Becker et al., 2012). The present study provides important insights for tailoring interventions for TWD. For male drivers who perceived TWD as risky yet frequently engage in TWD, some interventions that prevent drivers from "acting without thinking" (Meule, 2013) may be effective because this type of driver showed high levels of motor impulsivity. One potential approach is a precommitment strategy (Rachlin & Green, 1972), in which drivers commit to not engaging in TWD prior to starting to drive by, for example, turning on an application that silences text messages and other notifications while driving (e.g., the *Drive Focus* function available on iOS). Because mere availability of the application is shown to be insufficient to promote its use (Reagan & Cicchino, 2020), incentivizing its use through contingency-management strategies mentioned above may be needed to maximize the successful implementation of the precommitment strategy.

Another approach that may be effective for male drivers who perceived TWD as risky yet frequently engage in TWD is an executive function training that strengthens inhibitory control over the impulsive act of TWD. For example, trainees may learn to withhold responses that are initially very likely to occur to cues associated with text messaging and learn to respond to neutral cues as rapidly as possible (i.e., go/no go task; Allom et al., 2016). This approach may be potentially useful because (a) a meta-analysis has shown the effectiveness of executive function training in reducing various impulsive behaviors (Allom et al., 2016), and (b) lower levels of executive functioning were associated with higher frequency of TWD (e.g., Hayashi et al., 2017; Hayashi, Foreman, et al., 2018). Nevertheless, because no study has tested a response-inhibition training to reduce TWD, future research is needed to evaluate its effectiveness as well as feasibility.

Lastly, because female drivers who perceive TWD as risky yet frequently engage in TWD do not show high levels of motor impulsivity, different intervention strategies may be needed to target these drivers. In this vein, the findings of Feldman et al. (2011) are informative. The researchers found that female drivers lower in mindfulness reported more frequent TWD, and this relationship was mediated by the degree to which they engage in text messaging as a way to regulate unpleasant emotions. This suggests that mindfulness-based approaches, which increase awareness and acceptance of negative emotions (Bowen et al., 2014) and promote greater situational awareness (Kass et al., 2011), may be useful for female drivers (cf. Koppel et al., 2019). Future research is needed to evaluate the effectiveness of mindfulness interventions in reducing TWD, potentially in combination with other intervention strategies discussed above.

4.2. Limitations

Some limitations of the present study need to be discussed. First, as a major limitation of the present study, the present sample was small and exclusively consisted of college students. It is possible that the findings obtained in the present study might have been due to the small and homogeneous sample. Please note, however, that the effect size for the motor impulsivity subscale in males was considered large (Cohen, 1988), and that college students are an important target population for TWD. Therefore, the present sample would be acceptable for this exploratory study for the purpose of the proof of concept of utility of the cluster analysis. Nevertheless, it is strongly recommended that future research examines the replicability and generalizability of the present findings with a larger and more diverse sample of drivers of all ages. Second, TWD frequency was based on self-reported data. Although self-reports may be sufficient for the purpose of conducting a cluster analysis and identifying distinct subgroups, it is still advisable for future research to supplement the self-reported data with data obtained from observational studies. Third, because the present study is cross-sectional in nature, no causal relationship between impulsivity and TWD should be inferred in a strict sense. Future studies that employ a longitudinal design may be warranted to evaluate the exact role of impulsivity.

4.3. Conclusion

The present study provided a proof-of-concept of usefulness of hierarchical cluster analysis, which resulted in the successful identification of three distinct subgroups of drivers who differed significantly in their perceived risk and frequency of TWD. Another major finding of the present study is that the subgroup of male drivers who perceived TWD as risky yet frequently engage in TWD showed the higher level of motor impulsivity, but not impulsive decision making, than the other two subgroups. Although the present study helps to develop intervention strategies tailored for different subgroups of drivers, it is important for future research to extend the present study and further the understanding of the etiological mechanism(s) underlying TWD. As an example, a longitudinal study may be needed to examine how perceived risk and trait impulsivity would interact on predicting the frequency of TWD. It is also important for future research to extend the present paradigm to other forms of distracted driving as well as other risky driving behaviors (e.g., driving under the influence of drugs). These studies should further contribute to the development of individualized interventions to improve roadside safety.

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Biography

Yusuke Hayashi, PhD, is an Associate Professor of Psychology at the Pennsylvania State University, Hazleton. He earned his PhD in Psychology from West Virginia University. His research has focused on solving various technology-related societal problems, such as texting while driving and media multitasking. Using a behavioral economic approach, he is interested in better understanding the decision-making mechanisms underlying these issues and developing effective prevention and intervention strategies using the improved knowledge.

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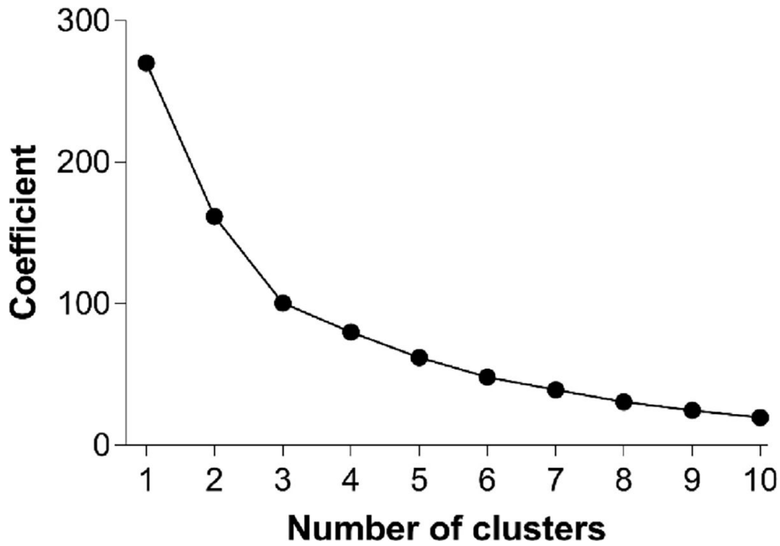

Fig. 1.
Scree Plots of the Cluster Analysis.

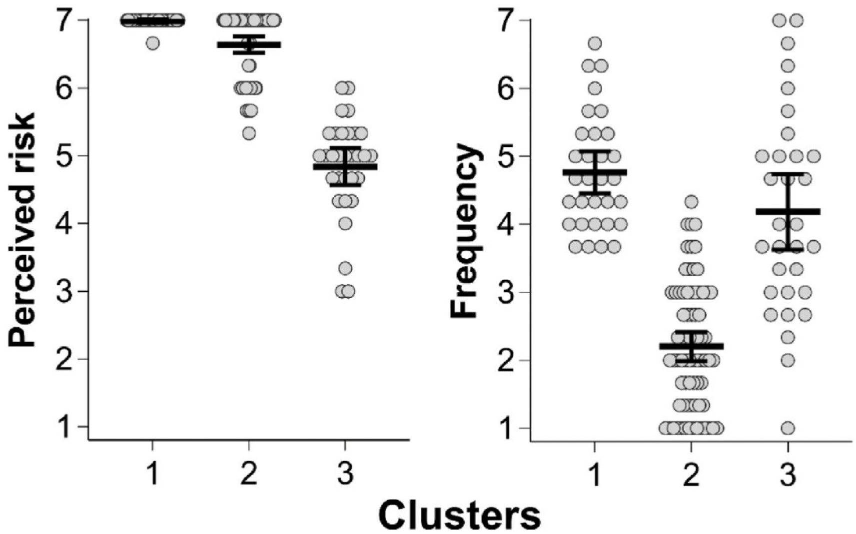

Fig. 2. Perceived Risk and Frequency of Texting while Driving for All Clusters

Note. Horizontal lines and error bars indicate means and 95% confidence intervals, respectively. Cluster 1 = High-Risk-High-Frequency subgroup. Cluster 2 = High-Risk-Low-Frequency subgroup. Cluster 3 = Low-Risk-High-Frequency subgroup.

Table 1

Demographic Characteristics for All Clusters.

Characteristics	Cluster 1	Cluster 2	Cluster 3
Gender*			
Female	17	48	12
Male	14	26	19
Age in years	18.9 (0.8)	19.9 (5.6)	19.3 (2.4)
Years of higher education	1.2 (0.6)	1.6 (1.9)	1.3 (0.6)
Years driving	2.8 (1.1)	3.2 (5.2)	2.8 (2.1)

Note. The numbers are means (and *SDs*) except for Gender. Cluster 1 = High-Risk-High-Frequency subgroup. Cluster 2 = High-Risk-Low-Frequency subgroup. Cluster 3 = Low-Risk-High-Frequency subgroup.

* $p < .05$ (chi-square test).

Table 2

ANOVA Results of the BIS and MCQ Scores among Clusters for Each Gender.

		Female					Male				
Measures	**Cluster**	***M***	**95% CI**	***F*(2, 74)**	***p***	**η2**	***M***	**95% CI**	***F*(2, 56)**	***p***	**η2**
BIS: Attentional	1	0.42	[0.34, 0.51]	1.71	0.187	0.04	0.50	[0.42, 0.58]	2.24	0.116	0.07
	2	0.42	[0.36, 0.47]				0.41	[0.34, 0.48]			
	3	0.53	[0.41, 0.64]				0.39	[0.31, 0.46]			
BIS: Motor	1	0.41	[0.33, 0.49]	1.53	0.224	0.04	0.44	[0.36, 0.52]	5.82	**0.005**	0.17
	2	0.35	[0.32, 0.38]				0.30	[0.25, 0.36]			
	3	0.37	[0.30, 0.44]				0.32	[0.27, 0.36]			
BIS: Non-planning	1	0.42	[0.35, 0.49]	1.21	0.303	0.03	0.43	[0.37, 0.49]	0.94	0.395	0.03
	2	0.38	[0.33, 0.42]				0.36	[0.31, 0.42]			
	3	0.45	[0.35, 0.55]				0.37	[0.29, 0.46]			
BIS: Total	1	0.42	[0.36, 0.48]	1.59	0.211	0.04	0.45	[0.40, 0.51]	4.02	**0.023**	0.13
	2	0.38	[0.35, 0.41]				0.35	[0.31, 0.40]			
	3	0.44	[0.37, 0.51]				0.36	[0.30, 0.41]			
MCQ	1	−4.89	[−5.73, −4.04]	0.51	0.600	0.01	−3.66	[−4.42, −2.91]	1.07	0.352	0.04
	2	−4.35	[−4.93, −3.77]				−3.30	[−3.68, −2.92]			
	3	−4.53	[−5.54, −3.51]				−3.75	[−4.30, −3.20]			

Note. Cluster 1 = High-Risk-High-Frequency subgroup. Cluster 2 = High-Risk-Low-Frequency subgroup. Cluster 3 = Low-Risk-High-Frequency subgroup. Bold numbers indicate statistical significance.

Table 3

Post-Hoc Comparisons of the BIS Scores among Clusters for Males.

Measures	**Comparison**	Δ	**SE**	p	**95% CI**
BIS: Motor	C1 vs. C2	0.13	0.04	**0.005**	[0.04, 0.23]
	C1 vs. C3	0.12	0.04	**0.020**	[0.02, 0.23]
	C2 vs. C3	−0.01	0.04	0.934	[−0.10, 0.08]
BIS: Total	C1 vs. C2	0.10	0.04	**0.029**	[0.01, 0.19]
	C1 vs. C3	0.09	0.04	**0.049**	[0.00, 0.19]
	C2 vs. C3	0.00	0.03	0.997	[−0.08, 0.08]

Note. Δ = mean difference. C1 = High-Risk-High-Frequency subgroup. C2 = High-Risk-Low-Frequency subgroup. C3 = Low-Risk-High-Frequency subgroup. Bold numbers indicate statistical significance.