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Role of trait impulsivity in distracted driving and walking: A Cluster analysis

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ABSTRACT

Introduction: The present study examined whether college students could be categorized into distinct subgroups that differed in their distracted driving and walking frequencies. *Method:* A sample of 277 college students participated in this study. They completed an online survey measuring their frequencies of distracted driving and walking, trait impulsivity (relatively stable characteristics of individuals to act spontaneously without considering the potential consequences), and behavioral impulsivity (process-oriented construct reflecting impulsive decision-making). Using hierarchical cluster analysis with component scores derived from a principal component analysis for distracted driving and walking frequencies, the following four subgroups were identified and named based on relative differences in frequencies: (a) the Low-Distraction subgroup, (b) the Distracted-Walking subgroup, (c) the Distracted-Driving subgroup, and (d) the High-Distraction subgroup. These subgroups were then compared to the extent to which they differed in levels of trait and behavioral impulsivity. *Results:* The results of the multinomial regression analyses, including cell phone use as a covariate, revealed that the differences between the Low-Distraction subgroup and other subgroups were significantly predicted by increased attentional impulsivity for other subgroups. Additionally, the difference between the Distracted-Walking and High-Distraction subgroups was significantly predicted by increased motor impulsivity for the High-Distraction subgroup. Implications for new intervention strategies targeting these impulsivity processes are discussed in relation to existing intervention strategies.

1. Introduction

In today's constantly connected world, an increase in multitasking technology has also increased distractions. For example, some students attempt to stay connected in the classroom while listening to the lecture and taking notes (Dontre, 2021). Similarly, some employees often find themselves juggling between work-related and unrelated tasks throughout the day (Mercado et al., 2017). This multitasking habit may extend to the moments when we are in transition, such as driving a vehicle or walking down the street. These distractions can quickly escalate into a significant safety issue, with 8% of fatal crashes and 12% of injury crashes in 2022 identified as distraction-affected (National Center for Statistics and Analysis, 2024). A review of observational studies revealed that drivers use a mobile phone while driving between 1% and 10% of the time (Huemer et al., 2018). The prevalence of pedestrians using mobile phones while crossing the road varied widely across countries, but in the United States the percentage ranged from 6% to 32% (Yadav & Velaga, 2022).

Distraction during driving and walking refers to diverting a traveler's attention from the primary task of navigating the roadway environment (Kirley et al., 2023), which can take various forms. While visual distractions (e.g., looking away from the roadway) and cognitive distractions (e.g., thinking about something other than driving and walking) are involved in both distracted driving and walking, manual (e.g., taking a hand off the steering wheel) distractions and aural distractions (e.g., listening off the road) are especially relevant for distracted driving and walking, respectively (Sherin et al., 2014; Stavrinos et al., 2018). Recent reviews and meta-analyses concluded that technological distraction negatively affects driving performance by impairing drivers' attention (e.g., Soares et al., 2021; Voinea et al., 2023). Similar conclusions were drawn on distracted walking: mobile technology use increases injury risk for pedestrians (e.g., Simmons et al., 2020). For example, 26% of

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respondents reported they had been involved in distracted-walking incidents, such as bumping into something without injury (American Academy of Orthopaedic Surgeons, 2015).

To combat these safety concerns, previous research has identified various predictors, some of which are common in both distracted driving and walking. For example, (general) mobile phone use frequency and texting automaticity/habit have been identified as important predictors for both behaviors (e.g., Panek et al., 2015; Tontodonato & Drinkard, 2021). Similarly, problematic mobile phone use and fear of missing out (e.g., Liu et al., 2023; Rahmillah et al., 2023; Sinha & Serin, 2024), as well as a strong need or demand for mobile phone use (e.g., Foreman et al., 2021; Hayashi, Friedel, et al., 2019a, 2019b; Tontodonato & Drinkard, 2021), are common predictors. Concerning cognitive and behavioral factors, self-control levels and impulsive decision-making are also common predictors (e.g., Hayashi et al., 2015, 2016; Hayashi, Foreman, et al., 2019; Igaki et al., 2019; Panek et al., 2015; but see Hayashi et al., 2017; Romanowich et al., 2021). Lastly, various studies utilizing the Theory of Planned Behavior (TPB) framework have shown that TPB variables, such as subjective norm, attitude, and perceived behavioral control, can predict both behaviors (e.g., Bazargan-Hejazi et al., 2017; Liu et al., 2023). Interestingly, perceived danger generally predicts distracted walking (e.g., Tontodonato & Drinkard, 2021), but its role in distracted driving is somewhat mixed (see Hayashi et al., 2023, for a brief review).

These common predictors suggest that distracted driving and walking may share common psychological/behavioral mechanisms. Indeed, Romanowich et al. (2021) reported that distracted driving and walking were significantly positively correlated with each other (r = 0.42). However, it is not clear how likely these two risky behaviors co-occur. For example, is there a subgroup of mobile phone users who frequently engage in one behavior but not the other? Or, are users who engage in one risky behavior always engaging in the other? Profiling user groups for detailed risky behavior patterns should provide a useful framework for understanding the underlying behavioral mechanisms and tailoring intervention strategies optimized for groups with unique profiles.

The first purpose of the present study, therefore, was to obtain detailed behavioral profiles for drivers and pedestrians based on technology-related distracted driving and walking frequencies. To achieve this, we believe cluster analysis, an unsupervised machine-learning technique that categorizes cases based on similarities across selected variables, is useful. Given that distracted driving and distracted walking are conceptually distinct and at least partially independent behaviors, it is possible that individuals may fall into one of the four subgroups: those who engage in both, only one, or neither. Accordingly, a four-group structure may emerge when clustering individuals based on their reported behaviors across these two dimensions, but it remains unclear which subgroups are more prevalent.

If such driver/pedestrian subgroups are identified, the next logical step is to examine what factor(s), if any, would differentiate between the subgroups. In this vein, it is important to highlight that some drivers and pedestrians engage in distracted driving and walking, respectively, despite being aware of the danger (e.g., Atchley et al., 2011; Tontodonato & Drinkard, 2021). This discrepancy between belief and behavior is essential for developing effective intervention strategies (Panek et al., 2015), and it underscores the potential influence of impulsivity on these behaviors (cf. Romanowich et al., 2021). Therefore, this study explored whether the subgroups would differ in their impulsivity levels.

Impulsivity is a complex, multi-asset construct involving distinct psychological processes (e.g., Strickland & Johnson, 2021), which can be studied as trait or behavioral impulsivity (e.g., Herman et al., 2018). Trait impulsivity is a relatively stable individual characteristic, and it reflects a general tendency to act spontaneously without considering potential consequences (Whiteside & Lynam, 2001). Behavioral impulsivity, on the other hand, is a process-oriented construct that can be divided into two major dimensions: impulsive action and impulsive decision-making. Impulsive action occurs due to response disinhibition or the inability to inhibit inappropriate or unwanted behaviors. Impulsive decision-making involves choosing instant gratification over long-term benefits due to the subjective devaluation of future rewards (Weafer et al., 2013).

As described above, previous research has identified the trait of self-control, considered to be an antipode of impulsivity, and impulsive decision-making as common predictors for distracted driving and walking (e.g., Hayashi et al., 2015; Igaki et al., 2019; Panek et al., 2015). Additionally, previous research has established that trait impulsivity and executive dysfunction, another related construct, are unique predictors for distracted driving (e.g., Hayashi et al., 2017, 2018; Struckman-Johnson et al., 2015). However, relatively less empirical attention has been given to the relationship between impulsivity and distracted walking. Notably, no previous research has concurrently examined the relative importance of trait impulsivity in both distracted driving and walking. This gap in the existing literature should be filled to fully understand the similarities and differences between distracted driving and walking.

The second purpose of the present study was to examine whether cluster differences, if identified successfully, can be explained by trait impulsivity, behavioral impulsivity, or both, over and above cellphone use frequency. This was to gain insights into whether distracted driving and walking would share common underlying psychological processes associated with impulsivity, and if so, which impulsivity processes are more closely aligned with specific cluster differences. For example, if two groups of drivers and pedestrians are identified, one with infrequent distracted driving but frequent distracted walking and another with frequent distracted driving and walking, the present study aimed to identify variables that could account for such group differences. Because this was an exploratory investigation, we had no specific hypotheses to test.

2. Materials and methods

2.1. Participants

A total of 277 undergraduate students enrolled in introductory psychology courses between Fall 2018 and Fall 2023 at a Northeastern United States university participated and received course credit. Exclusions were made for students without a driver's license ($n = 51$) and those who did not complete questionnaires about texting while driving or walking ($n = 7$). This study was part of a larger survey, and portions of the data have been reported in other studies with distinct goals and analyses (Hayashi et al., 2023; Hayashi & Tahmasbi, 2020, 2022).

2.2. Procedure

All surveys for this study were conducted online using Qualtrics (Provo, UT). After consenting to participate, participants completed questionnaires on demographics (age, years of higher education, driver's license status, years of driving experience, days of driving per month, and daily cell phone usage hours), distracted driving and walking frequency, trait impulsivity, and impulsive decision-making. The study protocol was reviewed and deemed exempt by the Institutional Review Board at the first author's affiliated university.

2.2.1. Distracted driving and walking

The questionnaire featured six questions assessing distracted driving and walking frequency, using a 5-point scale ranging from 1 (*never*), 2 (*seldom/occasionally*), 3 (*sometimes*), 4 (*often/usually*), to 5 (*always*). For distracted driving, participants were first asked about how frequently they typed something on a mobile phone while driving at any speed and then while stopped at a red light. Additionally, two questions asked how frequently they read something on the phone in these same two driving contexts. Regarding distracted walking, participants answered two questions about how frequently they use mobile phones while walking down the street and while crossing the street. See Supplementary Material A for the questions used.

2.2.2. Trait impulsivity

Trait impulsivity was measured using the Barratt Impulsiveness Scale (BIS-11; Patton et al., 1995), a self-reported scale comprising 30 items rated on a 4-point Likert scale from 1 (*rarely/never*) to 4 (*almost always/always*). The BIS consists of three subcomponents: *attentional impulsivity* (inability to focus attention; e.g., "I don't pay attention;" possible raw score range: 8–32), *motor impulsivity* (inability to inhibit inappropriate responses; e.g., "I do things without thinking;" range: 11–44), and *non-planning impulsivity* (lack of future orientation or forethought; e.g., "I say things without thinking;" range: 11–44) (Chowdhury et al., 2017; Meule, 2013). Negatively worded items were reverse-coded, with higher scores indicating greater impulsivity. Cronbach's alpha with the present sample was 0.727 for attentional impulsivity, 0.731 for motor impulsivity, and 0.684 for non-planning impulsivity, which are similar to those reported in previous studies with college students (e.g., Levine et al., 2013).

2.2.3. Impulsive decision making

During the delay-discounting task, adapted from Jones and Rachlin (2009) and modified for the present study, participants were presented with 55 choices involving hypothetical monetary rewards. They chose between smaller immediate amounts that ranged from $99 to $1 ($99, $90, $80, $70, $60, $50, $40, $30, $20, $10, and $1 presented in this order) and a larger delayed amount of $100, available after varying delays (1 week, 1 month, 6 months, 1 year, or 5 years, in this order). On each screen featuring a single delay value, participants made 11 choices between the two rewards, with the smaller immediate amounts and the larger delayed amounts listed in columns on the left and right, respectively. On each trial (e.g., $99 now vs. $100 in 1 week), participants indicated their choice by clicking a radio button next to each amount. Indifference points—where the subjective value of immediate and delayed rewards equalize—were calculated following Rachlin et al. (1991). To evaluate the degree of delay discounting, the area under the curve based on log-transformed delay values (AUC_{logd}) was calculated following Borges et al. (2016). Twenty-two participants showed non-systematic response patterns, as determined by Criterion 1 of Johnson and Bickel (2008), and their data were excluded from subsequent analyses of delay-discounting data. Studies on delay discounting often reveal nonsystematic response patterns influenced by various idiosyncratic factors, such as random responding (e.g., Hayashi & Glodowski, 2023), and the exclusion of such non-systematic data is common practice. Also, the exclusion rate for this study (10%) is analogous to that in previous studies using college students (see Smith et al., 2018, for a meta-analysis).

2.3. Statistical analysis

We used a principal component analysis (PCA), a dimensionality-reduction technique that increases data interpretability while minimizing information loss (Jolliffe & Cadima, 2016), to summarize distracted driving and walking responses. The six response scores (typing while driving, typing while stopped, reading while driving, reading while stopped, phone use while walking, and phone use while crossing) were entered into the analysis. The principal components were extracted using the correlation matrix. The number of principal components was determined by considering the eigenvalues, the percentage of variance explained, and the scree plot (Cattell, 1966; Kaiser, 1960). A varimax orthogonal rotation was used to aid interpretability. The principal component scores derived from this analysis were utilized in subsequent analyses examining distracted driving and walking frequencies.

A hierarchical cluster analysis was performed to categorize students based on their frequency of distracted driving and walking behaviors. The analysis incorporated the principal component scores, utilizing Ward's method for clustering, squared Euclidian distances as the distance measure, and z-score for standardization, following the methods outlined in Clatworthy et al. (2005) and Yim and Ramdeen (2015). The number of clusters was determined utilizing the inverse scree plot (Yim & Ramdeen, 2015).

Comparisons across subgroups were performed by one-way analysis of variance (ANOVA) or by Welch's ANOVA if the assumption of homogeneity of variances was violated, as assessed by Levene's test for equality of variances. Post-hoc pairwise comparisons were conducted using the Tukey test or the Games-Howell test if the assumption of homogeneity of variances was not met. Lastly, to evaluate the relative contributions of the impulsivity-related variables on the cluster membership, a multinomial logistic regression analysis was performed, with daily hours of cellphone use included as a covariate. The assumptions for all statistical tests were checked, and no violations were found. All analyses were conducted using SPSS Version 29, and the statistical significance level was set at 0.05.

3. Results

Table 1 shows the demographic information of the entire sample. Table 2 shows eigenvalues and the percentage of variance explained by the PCA. The left panel of Fig. 1 shows the scree plot. Because there was a robust increase in eigenvalues as the analysis shifted from two components to one component and two components accounted for about 80% of the cumulative variance, principal components 1 and 2 were retained, although the eigenvalue with two components was slightly smaller than 1. Table 3 shows component loadings in the rotated component matrix and communalities. The results supported a two-component model; principal components 1 and 2 are referred to as *Distracted Driving* and *Distracted Walking*, respectively.

The right panel of Fig. 1 shows the cluster analysis coefficient values as a function of the number of possible clusters. There was a relatively distinct increase in coefficient values as the analysis shifted from the model with four clusters to the model with three clusters, suggesting that the model with four clusters best fit the present data. Table 1 shows the demographic characteristics for the four clusters. There was a statistically significant difference across the clusters for daily mobile phone usage, $F(3, 215) = 4.25$, $p = 0.006$, partial $\eta^2 = 0.056$, but no statistically significant differences were found for other demographic variables (p's > 0.05).

Fig. 2 shows distracted driving and walking frequencies for each participant. The results of the (Welch) ANOVA revealed the clusters

Table 1
Demographic Characteristics.

Characteristics	Entire sample	Cluster 1	Cluster 2	Cluster 3	Cluster 4
n (%)	219 (100)	59 (26.9)	39 (17.8)	101 (46.1)	20 (9.1)
Age in years	19.8 (5.1)	19.9 (3.9)	19.9 (7.0)	20.0 (5.2)	19.0 (1.9)
Years of higher education	1.2 (1.1)	1.2 (1.1)	1.1 (0.9)	1.3 (1.1)	1.0 (1.1)
Years of driving experience	3.5 (4.2)	3.3 (4.5)	4.0 (5.2)	3.5 (4.0)	3.0 (1.9)
Days of driving per month	22.3 (9.8)	22.2 (10.6)	18.9 (10.6)	23.2 (9.0)	25.3 (8.1)
Daily phone usage hours**	6.2 (3.6)	5.9 (3.7)	7.5 (3.6)	5.6 (3.1)	7.8 (4.5)

Note. The numbers are means (and *SDs*), unless otherwise noted. Cluster 1 = Low-Distraction subgroup. Cluster 2 = Distracted-Walking subgroup. Cluster 3 = Distracted-Driving subgroup. Cluster 4 = High-Distraction subgroup. **$p < 0.01$ on ANOVA across the four clusters (Cluster 2 > Cluster 3 on Tukey test, $p = 0.03$).

Table 2
Eigenvalues and Variance Explained.

Component	Eigenvalue	Variance Explained	
		%	Cumulative %
1	3.723	62.0	62.0
2	0.973	16.2	78.3
3	0.583	9.7	88.0
4	0.336	5.6	93.6
5	0.275	4.6	98.2
6	0.110	1.8	100.0

differed significantly on distracted driving frequency, $F(3, 65.3) = 261.4$, $p < 0.001$, partial $\eta^2 = 0.701$, and distracted walking frequency, $F(3, 215) = 89.4$, $p < 0.001$, partial $\eta^2 = 0.555$. Table 4 shows the post-hoc comparison results. Overall, the four clusters show distinct patterns for distracted driving and walking frequency. Cluster 1 was characterized by a low frequency for both behaviors (hereafter, the *Low-Distraction* subgroup). Cluster 2 was characterized by a low frequency for distracted driving and a high frequency for distracted walking (the *Distracted-Walking* subgroup). Cluster 3 was characterized by a moderate frequency for distracted driving and a low frequency for distracted walking (the *Distracted-Driving* subgroup). Finally, Cluster 4 was characterized by a high frequency for both behaviors (the *High-Distraction* subgroup).

Regarding the comparisons of the scores for the BIS subscales and AUC_{logd} values across clusters, the results of the (Welch) ANOVA revealed that the clusters differed significantly on all the BIS subscales (p's < 0.001) but not on the AUC_{logd} values ($p = 0.372$; detailed results are available in Supplementary Material B).

Lastly, the multinomial logistic regression analysis revealed that the entire model was statistically significant, $\chi^2(15) = 47.27$, $p < 0.001$, Pseudo R^2 (Nagelkerke) $= 0.233$. Table 5 shows the estimated coefficients from the analyses, indicating the impact of each predictor on the likelihood of each subgroup, relative to the reference subgroup chosen for each block of analyses. The difference between the Low-Distraction subgroup (C1) and other subgroups was significantly predicted by increased attentional impulsivity for other subgroups (p's < 0.01, odds ratios = 1.19–1.30). In other words, for every one-unit increase in the raw attentional impulsivity score, the odds of belonging to one of the other subgroups (rather than the Low-Distraction subgroup) increased by 19% to 30%. In addition, the difference between the Distracted-Walking subgroup (C2) and the High-Distraction (C4) subgroups was significantly predicted by increased motor impulsivity for the High-Distraction subgroup ($p = 0.033$, odds ratio = 1.14). Finally, significant differences were also observed with cell phone use (hours) in the following three comparisons: (a) between the Low-Distraction (C1) and Distracted-Walking (C2) subgroups ($p = 0.019$, odds ratio = 1.17); (b) between the Distracted-Walking (C2) and Distracted-Driving (C3) subgroups ($p = 0.007$, odds ratio = 0.86); and (c) between the Distracted-Driving (C3) and High-Distraction (C4) subgroups ($p = 0.043$, odds ratio = 1.15).

4. Discussion

Using a hierarchical cluster analysis, the present study explored whether college students could be grouped into distinct subgroups that differed in their distracted driving and walking frequencies, which resulted in these four subgroups: (a) the Low-Distraction subgroup, (b) the Distracted-Walking subgroup, (c) the Distracted-Driving subgroup, and (d) the High-Distraction subgroup. It is noteworthy that, to the best of our knowledge, this is the first study reporting the existence of subgroups whose frequencies did not positively correlate between distracted driving and walking (i.e., the Distracted-Walking and Distracted-Driving subgroups), indicating that distracted driving and walking do not necessarily co-occur in the same direction.

The multinomial regression analysis revealed that attentional impulsivity is important to predict cluster membership: the differences between the Low-Distraction subgroup and other subgroups were significantly predicted by increased attentional impulsivity for the other three subgroups, over and above mere cell phone usage. This is consistent with a previous study demonstrating that drivers who frequently text while driving show higher levels of attentional impulsivity (Hayashi et al., 2017). Nevertheless, the present study extends the previous studies by demonstrating that attentional impulsivity plays an important role in *both* distracted driving and walking.

In addition, other interesting comparisons emerged between the Low-Distraction and Distracted-Driving subgroups. Both subgroups were infrequent cell phone users (Table 1) who also infrequently engaged in distracted walking. Nevertheless, one subgroup frequently engaged in distracted driving while the other did not. This difference was predicted by increased attentional impulsivity for the Distracted-Driving subgroup, suggesting that among infrequent cell phone users (who also infrequently engage in distracted walking), the inattentional

Table 3
Component Loadings and Communalities.

Items	Component Loadings		Communalities
	1	2	
Typing while driving	0.882	0.165	0.805
Typing while stopped	0.877	0.251	0.832
Reading while driving	0.852	0.194	0.763
Reading while stopped	0.834	0.338	0.810
Phone use while walking	0.223	0.844	0.763
Phone use while crossing	0.211	0.825	0.724

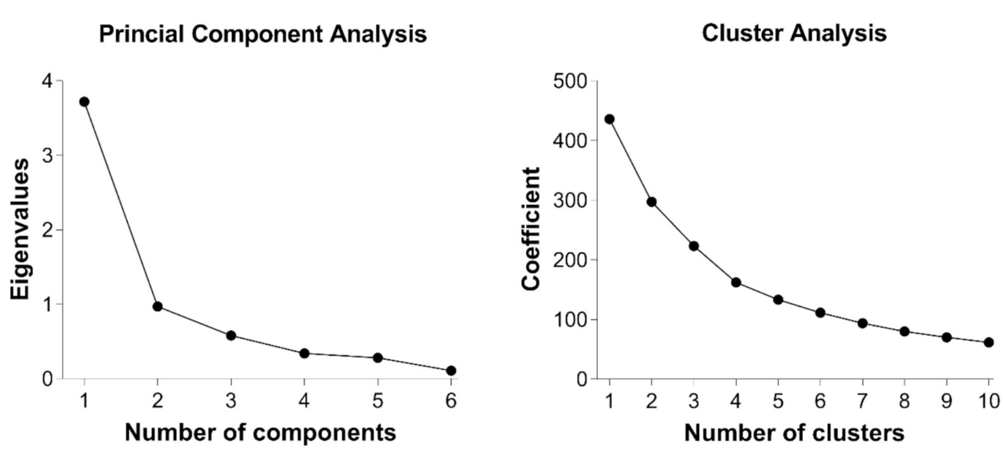

Fig. 1. Scree Plots for the Principal Component Analysis and the Cluster Analysis.

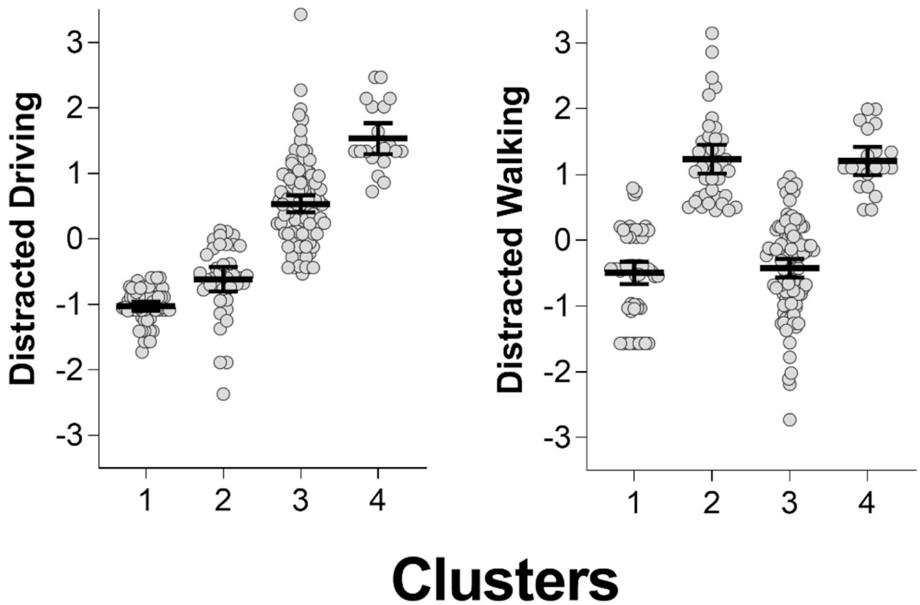

Fig. 2. *Frequencies of Distracted Driving and Walking for All Clusters. Note.* Horizontal lines and error bars indicate means and 95% confidence intervals of the means, respectively. Cluster 1 = Low-Distraction subgroup. Cluster 2 = Distracted-Walking subgroup. Cluster 3 = Distracted-Driving subgroup. Cluster 4 = High-Distraction subgroup.

Table 4
Post-Hoc Comparisons of Frequencies of Distracted Driving and Walking among Clusters.

Measures	Comparison	Δ	*SE*	*p*	95% CI
Driving	C1 & C2	−0.41	0.10	**< 0.001**	[-0.67, −0.15]
	C1 & C3	−1.56	0.07	**< 0.001**	[-1.75, −1.37]
	C1 & C4	−2.56	0.12	**< 0.001**	[-2.89, −2.23]
	C2 & C3	−1.15	0.11	**< 0.001**	[-1.45, −0.85]
	C2 & C4	−2.15	0.15	**< 0.001**	[-2.54, −1.76]
	C3 & C4	−1.00	0.13	**< 0.001**	[-1.35, −0.65]
Walking	C1 & C2	−1.73	0.14	**< 0.001**	[-2.09, −1.37]
	C1 & C3	−0.07	0.11	0.910	[-0.36, 0.21]
	C1 & C4	−1.70	0.17	**< 0.001**	[-2.15, −1.25]
	C2 & C3	1.66	0.13	**< 0.001**	[1.33, 1.98]
	C2 & C4	0.03	0.18	1.000	[-0.45, 0.51]
	C3 & C4	−1.63	0.16	**< 0.001**	[-2.05, −1.20]

Note. The *p* values and 95% CI's were adjusted for multiple comparisons according to the Tukey or Games-Howell procedure. *Δ* = Mean difference. C1 = Low-Distraction subgroup. C2 = Distracted-Walking subgroup. C3 = Distracted-Driving subgroup. C4 = High-Distraction subgroup. Bold numbers indicate statistical significance.

process is an important factor influencing whether or not they would engage in distracted driving.

Another interesting comparison was between the Distracted-Walking and High-Distraction subgroups, both of which were frequent cell phone users (Table 1) and who also frequently engaged in distracted walking. Nevertheless, one subgroup frequently engaged in distracted driving, while the other did not, and this difference was predicted by increased motor impulsivity for the High-Distraction subgroup. This may suggest that among frequent cell phone users (who also frequently engage in distracted walking), motor impulsivity is an important factor influencing whether or not they would engage in distracted driving.

Lastly, some subgroup differences, such as between the Distracted-Driving and High-Distraction subgroups, were predicted by the difference in hours of cell phone use, suggesting that some variance in distracted driving and walking can be accounted for by general cell phone use. This aligns with findings from Panek et al. (2015), who found that general texting frequency is a significant and unique predictor of texting frequency while driving and walking. It is essential to acknowledge that distracted driving and walking represent complex behavioral phenomena involving multiple dynamically interacting processes. By understanding and addressing the multifaceted nature of these distractions, more comprehensive and effective strategies can be developed for these problems.

4.1. *Implications for interventions*

The present findings provide important implications for developing effective prevention and intervention strategies. First, given that attentional impulsivity significantly predicted the differences between the Low-Distraction subgroup and the other three subgroups, attentional impulsivity, or inability to focus attention or concentrate (Meule, 2013), can be an important intervention target for both distracted driving and walking. In this vein, it is important to note that such an inattentional process reflects executive control deficits (Kim et al., 2024), which may lead to automatic/habitual mobile phone use. Therefore, implementing mindfulness-based interventions, which can enhance executive control by improving awareness (Tang et al., 2012), is promising for reducing distracted driving and walking. Such interventions would work for drivers/pedestrians whose mobile phone use while driving and walking is automatic/habitual (Panek et al., 2015), aligning with Liu et al. (2022) that a brief mindfulness intervention reduced problematic smartphone use.

Second, given that motor impulsivity significantly predicted the differences between the Distracted-Walking and High-Distraction subgroups, motor impulsivity, or the inability to inhibit inappropriate responses (Chowdhury et al., 2017), can be an important intervention target for distracted driving, especially for frequent cell phone users. Some drivers who frequently engage in distracted driving perceive the behavior as dangerous, yet they engage in it anyway (Hayashi et al., 2023). One potential approach for these drivers is executive function training, in which trainees learn to withhold impulsive responses to target cues and respond to neutral cues as rapidly as possible (go/no go task; Allom et al., 2016). A meta-analysis has shown that this training is effective in reducing various impulsive behaviors (Allom et al., 2016). Given that drivers who frequently engage in distracted driving show lower levels of executive functioning (e.g., Hayashi et al., 2017;

Table 5
Multinomial Logistic Regression Predicting Cluster Membership.

	C1 vs. C2			C1 vs. C3			C1 vs. C4		
	OR	95% CI	*p*	OR	95% CI	*p*	OR	95% CI	*p*
Intercept	–	–	**0.019**	–	–	**0.030**	–	–	**< 0.001**
Cell hours	1.17	[1.03, 1.32]	**0.019**	1.00	[0.89, 1.12]	0.991	1.15	[0.99, 1.34]	0.073
Attentional	1.26	[1.10, 1.44]	**< 0.001**	1.19	[1.06, 1.33]	**0.002**	1.30	[1.10, 1.55]	**0.003**
Motor	0.95	[0.85, 1.06]	0.326	1.00	[0.92, 1.09]	0.955	1.08	[0.96, 1.21]	0.194
Non-planning	0.99	[0.89, 1.10]	0.850	1.02	[0.94, 1.11]	0.628	0.99	[0.86, 1.13]	0.884
AUC_{logd}	0.46	[0.07, 2.88]	0.409	0.44	[0.10, 1.92]	0.276	0.14	[0.01, 1.64]	0.117
				C2 vs. C3			C2 vs. C4		
				OR	95% CI	*p*	OR	95% CI	*p*
Intercept				–	–	0.469	–	–	0.065
Cell hours				0.86	[0.77, 0.96]	**0.007**	0.99	[0.86, 1.13]	0.873
Attentional				0.95	[0.84, 1.06]	0.341	1.04	[0.88, 1.23]	0.679
Motor				1.05	[0.96, 1.16]	0.277	1.14	[1.01, 1.28]	**0.033**
Non-planning				1.03	[0.94, 1.14]	0.523	1.00	[0.87, 1.15]	0.997
AUC_{logd}				0.96	[0.18, 5.04]	0.958	0.30	[0.02, 3.66]	0.344
							C3 vs. C4		
							OR	95% CI	*p*
Intercept							–	–	**0.010**
Cell hours							1.15	[1.00, 1.32]	**0.043**
Attentional							1.10	[0.94, 1.28]	0.245
Motor							1.08	[0.98, 1.20]	0.118
Non-planning							0.97	[0.86, 1.10]	0.621
AUC_{logd}							0.31	[0.03, 3.10]	0.320

Note. Clusters 1, 2, and 3 served as the reference for the top, middle, and bottom blocks of analyses, respectively. OR = Odds Ratio. CI = confidence interval. C1 = Low-Distraction subgroup. C2 = Distracted-Walking subgroup. C3 = Distracted-Driving subgroup. C4 = High-Distraction subgroup. Bold numbers indicate statistical significance.

Hayashi, Foreman, et al., 2018), this training may be effective in reducing distracted driving.

Another approach for reducing distracted driving is a precommitment strategy (Rachlin & Green, 1972), in which they commit to not engaging in distracted driving by, for example, turning on a smartphone application that silences text messages and other notifications while driving (e.g., the *Driving Focus* function available on iOS). Because mere availability is insufficient to promote application use (Javid et al., 2023; Reagan & Cicchino, 2020), other strategies should be supplemented. One such strategy is to incentivize the use of the application. A randomized control trial revealed that a precommitment strategy was more effective when combined with a financial incentive (Ebert et al., 2024). Another strategy, which acknowledges a limitation of the intervention strategies at individual levels, is to utilize High Visibility Enforcement (HVE) campaigns, in which law enforcement targets high-crash or high-violation areas and widely publicizes the enforcement to maximize general deterrence (Kirley et al., 2023). For example, the precommitment strategies could be applied to informational and warning stops by police officers: police may ask if a stopped driver is willing to activate the anti-distraction application on their phone, and instructions on how to do so could be included on the informational flyer.

4.2. Limitations

Several limitations of the present study are noteworthy. First, using a cross-sectional design precludes any causal inferences between attentional/motor impulsivity and distracted driving/waking. For example, it is not clear from our results whether increased impulsivity causes frequent distraction behaviors or whether frequent mobile phone use, including distracted driving and walking, causes increased impulsivity (cf. Ferraro et al., 2012). Alternatively, it is possible that the relationship between levels of impulsivity and distracted driving and walking frequencies is caused by a third factor. Examining the exact mechanism underlying the significant relationships detected in this study is an important topic for future research, which may be achieved by, for example, employing a longitudinal research design.

Second, the present study employed self-reported data for both distracted driving and walking. It is possible that participants may underreport socially undesirable behavior (Wentland, 1993). However, the self-reported data were used only to identify clusters of users in the present study. Also, if the self-reported data had been subject to underreporting bias (and cluster differences had been artificially reduced), it would make it more difficult to reject the null hypothesis that clusters do not differ. Therefore, we believe the overall conclusions of the present study are tenable. Nevertheless, using smartphone-based software that can automatically detect and measure the occurrences of distracted driving and walking would be a great addition to future research (see Arafat et al., 2023; Papatheocharous et al., 2023 for review).

Third, the data collection took place over a long period, which may have affected the uniformity of the sample. In particular, the COVID-19 pandemic occurred during this time, and it is possible that the cohorts before and after the event differ in some ways. Although the results of the independent samples *t*-tests comparing the pre- and post-pandemic cohorts revealed no significant differences on any study variables ($p > 0.05$), this factor may need to be taken into consideration when interpreting the results.

Fourth, the present sample exclusively consisted of college students, and the sample size was relatively small. Because college students are a relatively homogeneous group, may be less impulsive than other populations (cf. Patton et al., 1995; Stanford et al., 1996), and tend to have lower traffic mortality rates both as drivers and as pedestrians (Harper et al., 2015), the generalizability of the present findings should be approached with caution. However, young college students are a critical demographic for both distracted driving and walking (Atchley et al., 2011; Lennon et al., 2017). In this sense, while the use of college students is a limitation, it also serves as a strength by focusing on an important target population (cf. Feldman et al., 2011). Nevertheless, it is advisable for future research to examine the external validity of this study by employing a more diverse and larger sample.

Lastly, although distracted driving and walking might share similar behavioral/cognitive processes, they pose very different risks—differences that were not fully recognized in this study. Distracted pedestrians primarily endanger themselves, whereas distracted drivers pose a significant risk to the life and property of those around them (Ralph & Girardeau, 2020), particularly due to the increased size and weight of vehicles over the past 50 years (United States Environmental Protection Agency, 2024) that increases the probability of a serious injury or fatality (Montfort & Mueller, 2024). Furthermore, many distracted walking features (e.g., misjudging gaps, crossing against signals, failing to look both left and right, walking slowly, etc.) also apply to our most vulnerable pedestrians, such as children, the elderly, and those with sensory or mobility impairments (Ralph & Girardeau, 2020), yet the present study did not recognize this important factor. Efforts to improve safety for pedestrians should consider the needs of these vulnerable populations if they are to be both effective and equitable (Eisenberg et al., 2022; Gamache et al., 2019), which requires not just a single intervention but comprehensive changes to how transportation environments are designed (Michael et al., 2021).

4.3. Conclusions and future research

Future research should evaluate the intervention strategies proposed in this study, as well as examine the motivational/functional processes underlying distracted driving and walking. According to Elhai et al. (2017), problematic mobile phone use initially arises from positive reinforcement, where individuals enjoy benefits such as mood enhancement. As usage intensifies, some users experience negative emotions or withdrawal-like symptoms when not using their phones, and mobile phone use serves as the only way to alleviate them—a state of dependency through negative reinforcement (Kruger & Djerf, 2017). A similar approach could enhance our understanding of the processes underlying distracted driving and walking, focusing on the emotional and social dynamics in these behaviors. By comprehensively addressing all mobile-phone-related issues together, including the impact of social interactions (cf. Foreman et al., 2019), this strategy should effectively mitigate risks associated with mobile phone use in various contexts.

Author note

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CRediT authorship contribution statement

Yusuke Hayashi: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Paul Romanowich:** Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization. **Jonathan M. Hochmuth:** Writing – review & editing, Writing – original draft. **Oliver Wirth:** Writing – review & editing, Writing – original draft.

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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jsr.2025.08.004.

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