

Patterns of distracted driving behaviors among young adult drivers: Exploring relationships with personality variables



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ABSTRACT

The current study sought to identify naturally occurring profiles of distracted driving behaviors; to distinguish personality traits associated with these profiles; and lastly to examine relationships between distracted driving behaviors and perception of risk. Self-reported information on distracted driving behaviors (i.e., frequency of engagement and perceived level of distraction) and personality characteristics were collected online from 266 young adult drivers from two academic institutions. The most commonly reported distracting behaviors were talking with passengers, programming music, eating or drinking, and using navigation. Latent profile analysis revealed 3 profile classes of distracted driving, with the personality trait of extraversion emerging as a consistent predictive indicator of level of distracted driving, including in high-risk situations such as inclement weather and in free-flowing, high speed traffic. In terms of level of perceived risk, the profile class with the lowest engagement in distracted driving behavior tended to rate the behaviors at most distracting, relative to higher-engagement groups. The profile class that engaged in the highest level of distracted driving reported such behaviors as moderately distracting, despite engaging in them. This class also yielded the highest levels of extraversion, suggesting that this personality trait may relate to consistently higher levels of distracted driving behaviors, despite perceiving them as risky. This information may be useful for identifying young adults at highest risk of engaging in distracted driving, as well as for tailoring initiatives to decrease rates of distracted driving, potentially cutting down incidents in this high-risk population.

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1. Introduction

In the United States, young drivers have disproportionately high numbers of motor vehicle crash deaths relative to the number of miles they drive, compared with other age groups (Insurance Institute for Highway Safety [IIHS], 2013). In fact motor vehicle crashes are the leading cause of death among young adults ages 16–30 (National Center for Injury Prevention & Control, 2015). Coupled with the finding that young drivers are more likely than older drivers to talk or text on cell phones when driving (IIHS, 2015), distracted driving, particularly among young drivers, has garnered much attention.

A 2010 national telephone survey of over 6000 drivers ages 18 and older found that among drivers in the youngest age group (18–35), the most frequently reported distracting behaviors including talking with passengers, adjusting the radio,

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using a navigation system or phone for directions, using a portable music player, eating or drinking, and making and answering phone calls (Tison, Chaudhary, & Cosgrove, 2011). However, most research on distracted driving has focused primarily on driver cell phone use.

Among drivers of all ages, cell phone use when driving is high. In a national online survey of over 2700 drivers ages 16 and older, more than 69% of drivers reported talking on a cell phone while driving during the past month. Moreover, the percentage is higher among younger drivers. Among drivers ages 19–24, 72% reported talking on cell phones when driving during the past month; 50% reported reading texts or e-mails, and 41% reported typing or sending texts or e-mails (AAA Foundation for Traffic Safety, 2015). Results from another national survey of over 1,200 drivers suggest that drivers ages 25–29 were most likely to talk daily on a cell phone when driving (39%), compared with 20% among drivers ages 18–24 and 24% among those ages 30–59 (Braitman & McCartt, 2010).

Higher rates of distracted driving among young drivers are confirmed with observational studies as well. For example, in a 2014 national observational study of drivers observed while stopped at intersections, 5.8% of drivers ages 16–24 were observed talking on hand-held phones. This compares with 4.3% of drivers ages 25–69, and 0.8% of drivers ages 70 and older. Nearly 5% of drivers ages 16–24 were observed manipulating their phone, compared with 2% of drivers ages 25–69. Data were not sufficient to provide estimates for drivers 70 and older manipulating phones (National Highway Traffic Safety Administration, 2015).

These increased rates of phone use by young adults are potentially problematic. Studies have revealed an increased crash risk from interacting with phones while driving. Two epidemiological studies found a four-fold risk of injury or property-damage crash for drivers talking on phones (McEvoy et al., 2005). Farmer, Braitman, and Lund (2010) used this estimated crash risk (McEvoy et al., 2005; Redelmeier & Tibshirani, 1997), paired with a national survey of over 1,200 drivers, to examine population attributable risk for driver cell phone use. It was estimated that driver phone use may account for 22% of all police-reported crashes.

More recent research, however, suggests that risk may be lower than estimated by these studies. A naturalistic study of 105 drivers over a one year-period took a detailed look at cell phone use. Findings revealed a 17% increase in crash- or near-crash-risk when using a phone, although most of the increase was attributable to dialing, answering, or reaching for the phone (Farmer, Klauer, McClafferty, & Guo, 2015).

How cell phone use and other distracting behaviors directly translate into crash risk has been explored in driving simulator research with young drivers. For example, Pradhan et al. (2005) documented that younger drivers are worse at acquiring relevant information during high-risk driving scenarios, leading to fewer mitigating actions for those risks. Eye movements indicated younger drivers scan risk-relevant elements (e.g., a hedge near a crosswalk) less often than older drivers, and engage in behaviors indicating recognition of the potential risk (e.g., stopping prior to the crosswalk in case a pedestrian emerges from behind the hedge) less often as well. Another simulator study found that texting while driving leads to substantial driving impairments, including more time looking away from the road, increased cognitive workload, and decrements in speed monitoring, regardless of phone type (Young, Rudin-Brown, Patten, Ceci, & Lenné, 2014). Even when using hands-free phones for conversations, eye movements indicate drivers reduced their attention from the visual scene and had delayed reactions to vehicles braking in front of them (Strayer, Drews, & Johnston, 2003). It appears there may be multiple mechanisms at play contributing to increased crash risk for distracted driving.

Although it is challenging to identify the precise role of distracted driving in crashes, it is clear from research that there is an increased crash risk with distraction, and that young drivers are particularly vulnerable, given their higher cell phone use rates (AAA Foundation for Traffic Safety, 2015; National Highway Traffic Safety Administration, 2015, coupled with their increased risk of police-reported and fatal crash rates per mile driven, relative to older drivers (IIHS, 2013).

While rates of cell phone-related distracted driving are higher among young adult drivers, it is clear not all young adult drivers engage in these behaviors. Further, although cell phone use is the primary focus of many distraction studies, there is some evidence that other forms of distraction may more prevalent (Tison et al., 2011). A better understanding of the most common types of young driver distractions, as well as the personality characteristics of young drivers who actively engage in distracted driving may lead to more effective countermeasures for reducing or curbing such behaviors.

Surprisingly, there is little research specifically on the relationship between personality variables and distracted driving. One such study reported that attachment to one's phone correlated with self-reported distracted driving behaviors (Weller, Shackelford, Dieckmann, & Slovic, 2013). Bone and Mowen (2006) examined personality traits of self-reported distracted driving among college students. Need for arousal was positively correlated with distracted driving behavior, whereas negative relationships were observed for conscientiousness, need for learning, and health motivation.

Given the paucity of research identifying all relevant distracted driving behaviors as well as who is most susceptible to these behaviors, the current study explored self-reported distracted driving behaviors among college students, particularly in relation to personality variables – namely, the “Big Five” personality dimensions, a widely accepted and comprehensive taxonomy of personality, which includes traits of neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness (McCrae & Costa, 2008). In particular we hypothesized that conscientiousness would negatively correlate with distracted driving behaviors. There is some preliminary evidence that conscientiousness is associated with a reduction in risky or aggressive driving behaviors (e.g., Bone & Mowen, 2006; Schwebel, Severson, Ball, & Rizzo, 2006), as well as other unsafe health behaviors, such as smoking (Hampson, Andrews, Barckley, Lightenstein, & Lee, 2000).

Accordingly, the current study sought to identify naturally occurring profiles of distracted driving behaviors (aim 1) as well as to identify risk or protective factors (i.e., personality traits) associated with these profiles (aim 2). Lastly, we sought

to examine relationships between distracted driving behaviors and perception of risk. To our knowledge, no one has explored how distracting young drivers believe this wide range of specific behaviors to be. Therefore, we explored whether drivers who tend to engage in other tasks while driving perceive these behaviors to be more or less distracting, relative to other drivers (aim 3).

2. Method

2.1. Participants

Detailed information about distracted driving behaviors was collected from 266 young adult drivers recruited from two academic institutions. Roughly half (50.4%) were from a midsized public university in Virginia, and the remaining half were recruited from a small liberal arts college in Missouri. Demographic and main variables of interest did not differ between the schools and so the two samples were combined. The mean age of participants was 20.56 ($SD = 3.07$; Median = 20.00). The sample was predominantly White (67.3%); the remaining participants reported the following racial identities: 23% African-American, 3% Latino, 1% Native American; 3% 'Other'; and 1% did not report information on race. All participants were licensed drivers, and the average length of licensure was 4.5 years ($SD = 3.19$, Median = 4.00).

2.2. Procedure

Participants were recruited using an online study management portal at the Virginia institution, and through psychology courses at the Missouri institution. Interested participants were provided a hyperlink that led to an online survey. Details of the study were provided at the start of the survey. After providing consent, participants completed the measures described below. Course credit was offered as compensation for participants at both institutions.

2.3. Measures

2.3.1. Distracted driving

The distracted driving items were created by the researchers. Thirty-five items assessed the frequency with which respondents engage in potentially distracting activities while driving, ranging from 1 (*Never*) to 5 (*Every time I drive*). Items were developed by the researchers in consultation with colleagues and students. Sample activities include: Make hand-held phone calls; Make hands-free phone calls; Read text messages; Send text messages; Program music; Look at a paper map; Watch videos; Access the internet to check news; Put on makeup or other grooming; Talk with a passenger; and Eat or drink. Participants next rated the same 35 items in terms of their level of distraction, ranging from 1 (*Not distracting*) to 5 (*Very distracting*). Participants also indicated whether they talked on their phone, texted, or used their phone in other ways under known high-risk conditions (i.e., during rush hour, free-flowing high speed traffic, stop-and-go traffic, at night, and in bad weather). A total risk score was created by summing endorsement of these activities with weighting for level of distraction (1 = talk, 2 = text or other).

2.3.2. Personality

Respondents also completed the Big Five Inventory (BFI; Benet-Martinez & John, 1998; John, Donahue, & Kentle, 1991; John, Naumann, & Soto, 2008), a measure of the "Big Five" personality variables – agreeableness (e.g., cold and aloof [*reverse scored*], rude to others [*reverse scored*]) (9 items, $\alpha = .77$), conscientiousness (e.g., somewhat careless [*reverse scored*], disorganized [*reverse scored*]) (9 items, $\alpha = .78$), neuroticism (e.g., relaxed [*reverse scored*], not easily upset [*reverse scored*]) (8 items, $\alpha = .79$), extraversion (e.g., reserved [*reverse scored*], sometimes shy [*reverse scored*]) (8 items, $\alpha = .87$), and openness to experience (e.g., prefers work that is routine [*reverse scored*], has few artistic interests [*reverse scored*]) (10 items, $\alpha = .75$). Participants indicated how strongly they believed a list of characteristics applied to them, from 1 (*Disagree strongly*) to 5 (*Agree strongly*).

2.4. Analyses

Descriptive statistics were examined for the 35 distracted driving behaviors, including mean frequency of use, variance of that frequency, and mean distracting rating. Based on this information, the top 14 distracted driving behaviors were identified. These behaviors were used as indicators in a latent profile analysis, conducted using Mplus version 6.1 (Muthén & Muthén, 1998–2010) to address the first aim of the study. Latent profile analysis assumes an underlying construct that accounts for participants' responses to observed continuous indicators. The profiles identified minimize within-class variability on observed variables while maximizing between-class differences. A series of models are estimated specifying a different number of classes each time; the ideal number of classes is determined using model fit indices. For the present study, the ideal number of classes was determined using a combination of information criteria (Bayesian Information Criterion [BIC; Schwartz, 1978], and sample-size adjusted Bayesian information criterion [aBIC; Sclove, 1987]) as well as relative entropy values, the Lo-Mendell-Rubin (LMR) likelihood ratio test (Lo, Mendell, & Rubin, 2001), bootstrapped likelihood ratio

test (BLRT; McLachlan & Peel, 2000), proportional class size, and interpretability of the identified classes. Lower BIC and aBIC values indicate better fit, whereas higher relative entropy values indicate higher certainty of classification. The LMR likelihood ratio test and BLRT assess if the current number of classes for that model (k) is a significant improvement compared to one less class ($k - 1$) for each model tested. Relatively small probabilities (p) support the current model being tested, whereas larger probability values support the model with fewer classes. Models were conducted for $c = 1$ through $c = 6$ classes based on mean frequency of the top 14 distracted driving behaviors.

Posterior probability-based multiple imputations were used for the Wald tests to compare classes across demographic characteristics as well as across personality variables and for the mean distraction rating of the 14 top behaviors. These analyses are an improvement over analyses based on most likely class membership because they yield unbiased mean estimates for each latent class on the variables of interest (Asparouhov, 2007; Asparouhov & Muthén, 2014). A multiple regression was also conducted to assess the influence of personality on total risk scores.

3. Results

Means and standard deviations for the most frequently-reported distracted-driving behaviors are shown in Table 1. The most commonly reported behaviors were talking with passengers, programming music, eating or drinking, and using navigation. Cell phone use was less common; when drivers did use their phone, it was typically to answer calls (using a hand-held phone) or to read text messages. Drivers making or answering calls tended to do so on hand-held phones more often than hands-free. Of the most commonly reported behaviors, participants rated reading social media and sending and reading text messages as the most distracting, followed by accessing the internet or applications for traffic or banking information.

3.1. Latent profiles of distracted driving behaviors

Model fit information was examined for the latent class analysis models (see Table 2). Though BLRT is often the best fit indicator (Nylund, Asparouhov, & Muthén, 2007), it is not unusual for BLRT to return values of zero beyond any reasonable number of classes, particularly for complex data such as these, in which case the LMR likelihood ratio test is preferable, which points to the model with $c = 3$ classes as ideal in the current study. Though statistical information criteria and relative entropy were better for models with more classes, the LMR likelihood ratio test performs better under these conditions with complex models, including many indicators and unbalanced class proportions such as the current data (Nylund et al., 2007). Similarly, as we moved beyond 3 classes, the proportion of participants in the smallest group dropped drastically to less than 5%, which is likely too small to be meaningful. Taking all fit indices into account, the model with three classes was identified as the best fitting model relative to the others examined.

Class 1 ($n = 77$; 28.9%), named the “low engagement” class, had the lowest engagement in distracted driving behaviors. Class 2 ($n = 142$; 53.3%), named the “medium engagement” class, was comprised of the majority of the sample, and represented medial levels of distracted driving behaviors. Finally, Class 3 ($n = 47$; 17.8%), named the “high engagement” class, had the highest engagement in distracted driving behaviors. See Table 3 for the means and standard deviations of each distracting behavior by class. Fig. 1 represents the general profile for each class. As seen in Table 3 and Fig. 1, making and taking hands-free calls were relatively rare for all three classes. However, the classes differed in almost all other behaviors. Class 1 (the “low engagement” class) did not engage much in taking or receiving calls by any methods, nor texting, reading social

Table 1

Mean frequency and distraction ratings of participants' most commonly reported distracted-driving behaviors.

Indicator	Frequency of behavior ^a		Distraction rating of behavior ^b	
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Make Calls - Hand Held	2.77	0.96	3.20	1.21
Make Calls - Hands Free	2.09	1.12	2.61	1.22
Take Calls - Hand Held	2.88	1.03	3.12	1.19
Take Calls - Hands Free	2.05	1.15	2.63	1.24
Read Texts	2.85	1.12	4.06	1.04
Send Texts	2.61	1.17	4.25	0.98
Program Music	3.43	1.40	3.04	1.22
Read Social Media	1.75	0.99	4.29	1.02
Navigate (GPS)	3.10	1.03	3.06	1.19
Access Internet - Traffic	1.70	0.98	3.97	1.15
Access Internet - Banking	1.69	0.96	4.07	1.13
Talk with Passenger(s)	3.90	1.02	2.48	1.31
Find in Bag	2.57	1.04	3.61	1.08
Eat or Drink	3.25	0.94	2.85	1.18

^a 1 = Never; 2 = Rarely; 3 = Sometimes; 4 = Frequently; 5 = Every time I drive.

^b 1 = Not distracting; 5 = Very distracting (Labels for values of 2–4 were not given).

Table 2

Model fit based on number of classes.

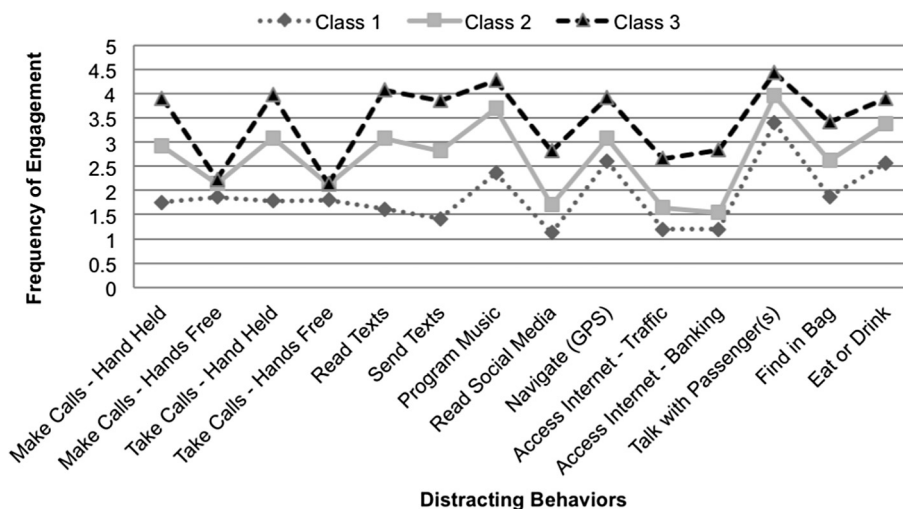
Classes	BIC	Adjusted BIC	Relative entropy	LMR LRT <i>p</i>	BLRT	Proportion of smallest group
1	11064.536	10975.760	–	–	–	–
2	10407.469	10271.135	.897	.0000	.0000	.37516
3	10189.458	10005.565	.893	.0880	.0000	.17765
4	10132.504	9901.053	.887	.7256	.0000	.18298
5	10062.739	9783.730	.915	.2991	.0000	.04737
6	10024.242	9697.674	.920	.5923	.0000	.03463

Note. BIC = Bayesian Information Criterion, LMR LRT = Lo-Mendell-Rubin likelihood ratio test, BLRT = bootstrapped likelihood ratio test. Entropy, LMR LRT, and BLRT are not available for models with only one class.

Table 3

Frequency of distracting behavior indicator means by latent class.

Indicator	Latent class 1		Latent class 2		Latent class 3	
	<i>M</i>	<i>SE</i>	<i>M</i>	<i>SE</i>	<i>M</i>	<i>SE</i>
Make Calls - Hand Held	1.76	0.12	2.93	0.09	3.92	0.15
Make Calls - Hands Free	1.87	0.14	2.16	0.11	2.25	0.25
Take Calls - Hand Held	1.79	0.14	3.10	0.09	3.99	0.18
Take Calls - Hands Free	1.82	0.15	2.14	0.11	2.15	0.24
Read Texts	1.63	0.11	3.10	0.11	4.09	0.25
Send Texts	1.43	0.09	2.84	0.13	3.87	0.26
Program Music	2.37	0.16	3.72	0.14	4.29	0.14
Read Social Media	1.13	0.04	1.71	0.10	2.84	0.31
Navigate (GPS)	2.61	0.14	3.10	0.10	3.93	0.12
Access Internet - Traffic	1.20	0.07	1.65	0.10	2.68	0.27
Access Internet - Banking	1.20	0.06	1.56	0.12	2.86	0.24
Talk with Passenger(s)	3.41	0.16	3.98	0.08	4.46	0.14
Find in Bag	1.88	0.13	2.64	0.09	3.44	0.20
Eat or Drink	2.57	0.13	3.40	0.09	3.91	0.11

**Fig. 1.** Frequency of engaging in distracting behaviors by latent class.

media, searching through bags, or accessing the internet for traffic or banking information. However, they did engage somewhat in programming music, navigation, and eating or drinking. Their most frequent behavior was talking with passengers. With the exceptions of using hands-free devices, class 2 engaged more often than class 1 in all other behaviors, and class 3 (the “high engagement” class) engaged the most often in all other behaviors. These differences are most pronounced for reading and sending text messages, as these are very low frequency for class 1 (*M*’s = 1.63 and 1.43, respectively), and fairly high for class 3 (*M*’s = 4.09 and 3.87, respectively).

Table 4

Demographic information by latent class.

Variable	Latent class 1		Latent class 2		Latent class 3		χ^2	p
	Count	(%)	Count	(%)	Count	(%)		
Sex							2.42	.298
Male	24	(32.0)	46	(32.4)	9	(20.5)		
Female	51	(68.0)	96	(67.6)	35	(79.5)		
Ethnicity							14.58	.068
Caucasian/White	45	(60.8)	106	(75.7)	28	(62.2)		
African-American/Black	23	(31.1)	24	(17.1)	14	(31.1)		
Asian or Pacific Islander	3	(4.1)	2	(1.4)	0	(0.0)		
Native American	2	(2.7)	1	(0.7)	0	(0.0)		
Other	1	(1.4)	7	(5.0)	3	(6.7)		
Hispanic							2.76	.251
Yes	2	(2.7)	10	(7.0)	1	(2.2)		
No	71	(97.3)	132	(93.0)	44	(97.8)		
Year in School							8.96	.345
Freshman	22	(29.7)	44	(30.8)	7	(15.6)		
Sophomore	13	(17.6)	30	(21.0)	12	(26.7)		
Junior	22	(29.7)	43	(30.1)	19	(42.2)		
Senior	16	(21.6)	26	(18.2)	7	(15.6)		
Other	1	(1.4)	0	(0.0)	0	(0.0)		
Relationship Status							2.76	.251
Single	60	(83.3)	97	(68.3)	31	(68.9)		
Married	6	(8.3)	2	(1.4)	2	(4.4)		
Committed relationship	6	(8.3)	41	(28.9)	12	(26.7)		
Other	0	(0.0)	2	(1.4)	0	(0.0)		
School							3.99	.136
Virginia	41	(53.9)	65	(45.1)	28	(60.9)		
Missouri	35	(46.1)	79	(54.9)	18	(39.1)		

As seen in Table 4, classes did not differ significantly based on gender, year in school, relationship status, or school attended. While the differences based on ethnicity were not significant, there did appear to be more Caucasian/White participants and fewer African-American/Black participants in class 2 compared to the other classes.

3.2. Personality associations

Results for the Wald tests of mean equalities using posterior probability-based multiple imputations are seen in Table 5. As shown, there were no differences among the classes based on agreeableness, conscientiousness, or neuroticism. However, strong differences were observed based on extraversion, with Class 1 (the “low engagement” class) scoring significantly lower on extraversion than either Class 2 or Class 3 (the “medium” and “high engagement” classes). In addition, though the overall test for openness was non-significant, individual class comparisons indicated that Class 1 (the “low engagement” class) scored significantly higher on openness than Class 3 (the “high engagement” class).

Additionally, the five personality variables were included as predictors in a regression with the high risk behaviors total score (e.g., texting in bad weather, using your phone in stop-and-go traffic, etc.) as the outcome. As seen in Table 6, only extraversion emerged as a significant predictor when controlling for all other personality variables.

Table 5

Mean equalities on personality constructs by latent classes using posterior probability-based multiple imputations.

Variable	Latent class 1		Latent class 2		Latent class 3		χ^2	p
	M	(SE)	M	(SE)	M	(SE)		
Extraversion	3.10 ^a	0.09	3.40 ^b	0.07	3.60 ^b	0.12	10.41	.005
Agreeableness	3.87	0.07	3.92	0.05	3.82	0.08	1.39	.498
Conscientiousness	3.69	0.07	3.67	0.05	3.68	0.09	0.07	.966
Neuroticism	2.88	0.08	2.69	0.06	2.89	0.09	5.71	.058
Openness	3.60 ^a	0.06	3.45 ^{ab}	0.05	3.35 ^b	0.08	5.54	.063

Note. Means with differing superscripts within rows are significantly different at the $p < .05$ level using posterior probability-based multiple imputations. Values for the overall chi-squares are included in the table. Note that there were 2 degrees of freedom for each overall test and 1 degree of freedom for each pairwise test.

Table 6

Influence of personality traits on high risk behaviors total score.

Predictor	<i>B</i>	<i>SE</i>	β	<i>t</i>	<i>p</i>	r_{sp}^2
Extraversion	0.81	0.36	0.145	2.26	.024	.019
Agreeableness	−0.82	0.52	−0.104	−1.58	.116	.009
Conscientiousness	−0.65	0.50	−0.086	−1.32	.189	.006
Neuroticism	0.03	0.43	0.005	0.07	.945	.000
Openness	−0.43	0.51	−0.052	−0.84	.400	.003

Note. r_{sp}^2 = squared semi-partial correlation.

3.3. Mean distraction rating

Additional Wald tests of mean equalities indicated that strong differences were observed based on mean distraction rating across the 14 behaviors, with Class 1 (the “low engagement” class; $M = 3.68$, $SD = 0.10$) rating the behaviors as significantly more distracting than Class 2 (the “medium engagement” class; $M = 3.22$, $SD = 0.07$). Class 3 (the “high engagement” class; $M = 3.36$, $SD = 0.15$) fell between the two groups and was not significantly different from either. Therefore, Class 1 rated the behaviors as most distracting and reported in engaging in them the least. Class 2 rated the behaviors as least distracting and reported engaging in them generally more often than Class 1. Interestingly, Class 3 rated these behaviors as fairly distracting, but reported engaging in them most frequently.

4. Discussion

The current study identified 14 distracted driving behaviors that were relatively highly endorsed by young adults. It is interesting to note that there was wide variety in the types of distractions that young drivers reported engaging in, and that cell phones were one common distraction among many. This finding is consistent with [Tison et al. \(2011\)](#), who reported a variety of forms of distraction among young drivers.

A latent profile analysis of those 14 behaviors resulted in 3 classes or profile patterns of behavior. It is interesting to note that while some variables had high engagement across all groups (e.g., navigating, talking with passengers) and some had low engagement across all groups (e.g., hands-free conversations, reading social media), the majority of behaviors varied a great deal across classes. Surprisingly, conscientiousness was unrelated to frequency of distracted driving. Instead, extraversion emerged as a risk factor predictive of engaging in high risk behaviors while driving. Notably, extraversion not only significantly predicted level of engagement in distracted driving behaviors in general, but it was also the only significant personality predictor of distracted driving in high-risk driving situations, including during rush hour, free-flowing high speed traffic, and in poor weather conditions. Representative traits of extraversion include being affectionate, talkative, active, and fun-loving ([McCrae & Costa, 2003](#)). As such, extraverts may find it difficult to be disconnected from others while driving, and may feel compelled to interact with others (e.g., talking with passengers, texting, conversing on the phone, using social media, using the radio, etc.).

It is interesting to consider both level of engagement as well as mean distraction ratings among the three classes. Class 1 included drivers who reportedly engaged least in distracted driving behaviors, and yielded the highest distraction ratings. Hence, it appears as though they may avoid such behaviors because they are perceived as highly distracting. However, from the current study it cannot be determined for sure whether perception of risk determines the behavior, or whether, perhaps, these drivers tend not to engage in distracting behaviors in general, and therefore due to lack of this experience, presume that the behaviors are risky. Regardless of the direction of this relationship, little intervention is likely required among this group. Class 2 fell in the middle in terms of frequency of distracted driving behaviors, and among the 3 classes, provided the lowest perceived distraction ratings.

What may be the most interesting is the paradox of class 3, who rated the behaviors fairly high in terms of perceived level of distraction (fell in the middle in terms of distraction ratings, behind class 1 [the “low engagement group”]), and yet reported the highest engagement in such behaviors. This group also yielded the highest extraversion scores, suggesting that perhaps highly extraverted individuals are more compelled to talk or text while driving despite reporting that such behaviors are potentially distracting. This group may be the most appropriate for intervention, and understanding the personality profiles of individuals in this group may be helpful in terms of tailoring the approach of such programs. While interventions designed to improve driving focus and attention are becoming faster and more streamlined (e.g., [Yamani, Samuel, Knodler, & Fisher, 2016](#)), they are still time consuming and not yet widely adopted. Identifying the most at-risk drivers allows interventions to be more tailored, and resources can be efficiently managed to target the group with the most to gain.

The current study is not without limitations. Findings should be interpreted with caution given relatively small samples, and the use of self-report rather than direct observation. However, a unique aspect of the current study is that the sample included participants from two institutions of different types (i.e., small private liberal arts college versus a mid-size state university), and from distinct geographic regions. The end result was a relatively diverse sample. Future research should replicate these findings across larger samples and multiple populations.

4.1. Conclusions

An online survey deployed at two institutions examined the most highly endorsed distracted driving behaviors by young adults. Three profiles of behavior engagement were identified, with extraversion emerging as a consistent predictive indicator of the highest-risk profile of distracted driving behaviors. This information could be used to identify young adults at the highest risk of engaging in distracted driving, as well as to tailor initiatives to decrease rates of distracted driving, potentially reducing distraction-related crashes in this high-risk population.

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