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Texting while driving: A discrete choice experiment

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ABSTRACT

Texting while driving is one of the most dangerous types of distracted driving and contributes to a large number of transportation incidents and fatalities each year. Drivers text while driving despite being aware of the risks. Although some factors related to the decision to text while driving have been elucidated, more remains to be investigated in order to better predict and prevent texting while driving. To study decision making involved in reading a text message while driving, we conducted a discrete choice experiment with 345 adult participants recruited from Amazon's Mechanical Turk. Participants were presented with multiple choice sets, each involving two different scenarios, and asked to choose the scenario in which they would be more likely to text while driving. The attributes of the scenarios were the relationship to the text-message sender, the road conditions, and the importance of the message. The attributes varied systematically across the choice sets. Participants were more likely to read a text message while driving if the sender of the message was a significant other, the message was perceived to be very important, and the participant was driving on rural roads. Discrete choice experiments offer a promising approach to studying decision making in drivers and other populations because they allow for an analysis of multiple factors simultaneously and the trade-offs among different choices.

1. Introduction

Distracted driving, or engaging in secondary tasks while driving, results in significant loss of life and monetary damages. In 2018, distracted driving resulted in 2841 deaths in the United States {National Highway Traffic Safety Administration, 2020 #2936}. Districted driving accounted for $39.7 billion or 16 % of all economic costs from motor vehicle crashes in 2010 (Blincoe et al., 2015). Distracted driving can involve three types of distraction: visual, manual, or cognitive (National Highway Traffic Safety Administration, 2017). Common distractions include reaching for an object (visual and manual), eating (manual), or talking to a passenger (cognitive). In 2017, 14 % of fatal crashes caused by distracted driving involved cell phone use (National Center for Statistics and Analysis, 2019). Cell phone use while driving has been found to be just as dangerous as driving under the influence of alcohol. A driving simulations study comparing drivers talking on a phone and drivers with a blood alcohol concentration of 0.08 % found that the distracted drivers suffered performance deficits that were just as profound as the drivers under in the influence of alcohol (Strayer et al., 2006).

One of the most pernicious forms of distracted driving is texting while driving (TWD) because it involves visual, manual, and cognitive distractions (Alosco et al., 2012). During a simulated driving task, 66 % of drivers exhibited lane excursions while texting (Rumschlag et al., 2015), and in another simulation study, TWD led to five times more crashes than driving without texting (Bendak, 2015). A study examining the effects of texting on the simulated driving performance of young drivers found that in the TWD condition, drivers spent up to 400 % more time not looking at the road compared to conditions in which they were not texting (Hosking et al., 2009). A meta-analysis of driving simulation studies concluded that reading and typing text messages while driving diverts attention away from the road, increases response time to hazards, and increases the risk of crashing (Caird et al., 2014). Despite the risks, TWD remains prevalent. In a large naturalistic study, 23 % of drivers were observed using their phones and 9 % of drivers were observed TWD (Kruger et al., 2018). Several surveys have also indicated a similar pattern. A survey of U.S. drivers found that for 30 days prior to the survey 48 % and 33 % reported reading or writing texts while driving, respectively (Gliklich et al., 2016). In an online survey of drivers aged 18–64 years old, 31 % reported that they had read or sent text or e-mail messages while driving in the last 30 days (Naumann and Dellinger, 2013).

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Drivers text while driving despite being aware of the risks. College students reported TWD with relative frequency despite also agreeing that it is dangerous and should be illegal (Harrison, 2011) and that it is just as dangerous as driving while legally intoxicated (Terry and Terry, 2016). In another study surveying young drivers, the majority of respondents reported that initiating, replying to, and reading a text while driving were more dangerous than talking on a cell phone. The respondents in that study also rated reading a text while driving as a dangerous behavior (a mean score of 4.63 on a scale from 1 to 7), yet 92 % of the young drivers reported reading a text while driving (Atchley et al., 2011). Research also suggests that drivers are more likely to text while driving farther from their destination (Hayashi et al., 2018, 2016), while stopped at a red light (Bernstein and Bernstein, 2015), or while driving at slower speeds (Oviedo-Trespalacios et al., 2017). Although some of these factors related to the decision to text while driving have been elucidated, more remains to be investigated in order to better predict and prevent texting while driving.

Behavioral economics has been one tool that has been used more recently to quantify some of the factors that affect the decision to text while driving. Behavioral economics has been defined as "the application of economic concepts and approaches to the molar study of individuals' choices and decisions" (Bickel et al., 2014, p. 643). The behavioral economic process of *discounting* has been used to conceptualize TWD; *discounting* refers to the process by which delayed or probabilistic outcome loses its value as a function of the delay to or probability of the receipt of the outcome, respectively. Individuals who more steeply discount delayed outcomes are more likely to engage in text messaging while driving (Hayashi et al., 2015). Additionally, discounting can quantify the likelihood with which people are willing to wait to respond to a text message when driving (Hayashi et al., 2016). A similar study examined how the likelihood of a car crash affected the likelihood of waiting to respond to a text message (Hayashi et al., 2018).

1.1. Discrete choice experiments

Although the decision to text while driving likely involves numerous factors, previous studies have only examined some of the factors, usually in isolation of other factors, or studies have compared multiple quantitative outcomes (e.g., distance and probability of a car crash). One method for examining choice behavior that is frequently used in other fields but has not been as broadly applied with safety-related choices is discrete choice experiments (DCEs). With a DCE, one can easily arrange choices among options that differ according to both qualitative and quantitative factors. The approach is also well-suited to choice contexts that include multiple factors that are inextricable or may potentially interact with one another. The goal of the present study was to assess the effects of multiple factors simultaneously on the likelihood of TWD by using a DCE.

DCEs are a behavioral economic approach to systematically assess individual preferences among products or services, and they have been widely implemented in marketing (Chandukala et al., 2008), health economics (de Bekker-Grob et al., 2012), and environmental valuation (Hoyos, 2010), among other fields. For example, a participant in a DCE might be asked to choose between two different products (e.g., cell phones that differ in screen size, storage amount, and price) or two different services (e.g., diabetes treatment programs that differ in length, content, and cost). In a DCE, two or more alternatives presented to the participant are termed a "choice set", and the characteristics or features of each alternative are termed "attributes". A typical DCE is comprised of multiple choice sets in which the attributes of the alternatives are systematically varied. Analysis of the participants' choice patterns across the choice sets can reveal the influence of the different attributes on choice. Additionally, DCEs can be used to understand any trade-offs among the attributes that affect preferences. Previous studies investigating texting while driving have not evaluated multiple qualitative variables (e.g., weather, road conditions, etc.) simultaneously, and the DCE is an appropriate methodology with which to do so.

DCEs were first proposed by McFadden (1974) and are rooted in the *random utility theory* (Thurstone, 1927) of behavior. As it relates to DCEs, the random utility theory proposes that each choice alternative being considered has a latent "utility" and individuals will always choose the choice alternative that has the greatest utility. As utility is a latent construct, it is not directly observable, but it can be derived by studying choice patterns (J. J. Louviere, 2001). Discrete choice experiments are designed to systematically vary the attributes associated with choice sets to determine the utility derived (or lost) by each attribute. The derived measures of utility consist of two components: systematic utility and random utility (J. J. Louviere et al., 2010). The systematic component consists of the attributes of the alternatives and the characteristics of the individual. The random component consists of the factors responsible for the preference that cannot be identified (for example, if they went unmeasured) and measurement error that is an inherent part of any measurement procedure (J. Louviere et al., 2000). The basic axiom of random utility theory is:

$$U_{ni} = V_{ni} + \varepsilon_{ni}$$

where U_{ni} is the latent, unobservable utility that person n associates with choice alternative i, V_{ni} is the systematic, explainable component of utility that individual n associates with choice alternative i, and ε_{ni} is the random component.

1.2. Study objectives

The present study applied the behavioral economic framework of DCEs to study decision making involved in reading a text message while driving. Participants were presented with multiple choice sets, each involving two different scenarios, and asked to choose the scenario in which they would be more likely to text while driving. The attributes of the scenarios were varied systematically across the choice sets. To select the attributes to include, we conducted reviews of the relevant literature and consulted with subject matter experts. Previous research has found that individuals are more likely to respond to a text immediately rather than waiting to reply when the text sender is closer to them in social distance (e.g., a significant other) in both driving (Foreman et al., 2019) and non-driving contexts (Atchley and Warden, 2012). Other factors, such as the perceived importance of a phone call (Nelson et al., 2009) and road conditions (Atchley et al., 2011) have been found to be a strong predictor of talking on the phone while driving. Both middle-aged adults (Engelberg et al., 2015) and younger adults (Schroeder and Sims, 2014) report TWD at high rates while stopped at red lights. Therefore, we selected relationship to the text message sender, the perceived importance of the message, and road conditions as the attributes for the DCE.

In addition, we compared a sample of drivers who did and did not drive for work to assess whether this factor interacts with the aforementioned factors on the decision to text while driving. Motor vehicle crashes are the leading cause of workplace fatalities (U.S. Department of Labor, 2019), and driver distraction has been shown to increase the likelihood of motor vehicle crashes among commercial large-truck drivers (Peng and Boyle, 2012; Zhu et al., 2011) and increase the likelihood that a crash will be fatal (Bunn et al., 2005). Employees who drive for organizations with stronger safety climates and greater management support for safe driving have reported lower rates of distracted driving (Wills et al., 2006) and distracted-related crashes (Swedler et al., 2015). It is conceivable that those who drive for work within an organization that emphasizes safe driving may engage in safer driving practices outside of work. Therefore, it would be important to evaluate whether there were any differences in choice behavior between those who did and did not drive for work in our sample.

The main objective of the present study was to assess the most important factors that influence drivers' decisions to read a text while driving. Based on the existing evidence, we hypothesized that the relationship to the sender would have the greatest utility in the selection of choice scenarios, followed by the perceived importance of the message and the road conditions. The design and implementation of a DCE to study TWD allowed for a simultaneous assessment of multiple categorical attributes that may affect the decision to read a text while driving in contrast to previous studies in which small numbers of continuous variables were examined independently (e.g., distance to destination and probability of a crash). A secondary objective was to conduct an exploratory analysis of the choices of participants who report driving for work and assess whether their choices differed from those of participants who did not drive for work.

2. Methods

2.1. Participants

Participants ($N = 345$) were recruited from Amazon's Mechanical Turk (MTurk), an online crowdsourcing platform in which individuals are compensated for completing short tasks or surveys (termed human intelligence tasks; HIT). Although a sample size of 100 participants is typically sufficient for DCEs (Pearmain and Kroes, 1990), we wanted ensure sufficient power for evaluating interaction effects. Participants were eligible for the HIT of this study if they lived in the United States, were over 18 years of age, possessed a U.S. driver's license, and owned or possessed a cell phone capable of sending or receiving text messages. Participants self-reported on each of the eligibility criteria. Individuals who drive for work also had to be employed outside of completing tasks on MTurk and drove a vehicle for work other than commuting. The survey HIT was only available to those who consistently completed HITs with a high degree of accuracy (i.e., 95 % of previously completed HITs accepted as satisfactory). The survey also included questions that were attention checks (see below), and data from participants who did not pass attention checks or who did not answer all of the questions were dropped from the analysis ($n = 20$). Participants were compensated $1.00 for successful completion of the survey. The research was conducted with approval from Pennsylvania State University's Institutional Review Board.

2.2. Materials

The survey was hosted on Qualtrics (Qualtrics XM, Provo, UT). Various sections of the survey, described below, were presented to participants in a pseudorandom order, as determined by Qualtrics's randomization function. The survey questions contained within each section were presented in a fixed order.

The survey consisted of demographic questions (age, gender, race, ethnicity, and education), a brief assessment of the respondent's driving habits, and the DCE. Other items that were included in the survey but are not relevant for the present study were the Distracted Driving Survey (Bergmark et al., 2016), the Barratt Impulsiveness Scale (BIS) (Patton et al., 1995) and an eight-item delay discounting questionnaire (Gray et al., 2014). The respondents were asked if they were employed outside of completing HITs on MTurk and whether they drove for work, not including commuting to and from home.

2.3. Discrete choice experiment

Another section of the survey consisted of a DCE. The DCE was constructed based on a well-cited guidance document (e.g., Johnson et al., 2013). As an important first step, we conducted a review of the relevant literature related to TWD and consulted subject matter experts to develop a list of potential attributes and levels. The list of potential attributes and levels was then refined to the final three attributes and associated levels (see Table 1).

Considering the small number of attributes and levels, it was not possible to include all of the attributes in each choice profile while still keeping the total number choice sets to a minimum number necessary for the analysis. One consideration for determining the array of choice sets and the arrangement of those choice sets (i.e., choice alternatives in each question) is that including pairwise comparisons of every permutation of attributes and levels is often impractical, and, therefore, researchers must rely on a limited array of profiles in the final DCE. For example, with our attributes and levels, if all possible combinations of attributes and levels in Table 1 were compared in a two-alternative design, then there would be 36 (4 * 3 * 3) possible profiles and 630 (36 * (36−1) / 2) possible combinations of two-alternative choice questions. There are several techniques to determine a limited array of profiles across choice sets that will lead to sufficient information for later statistical analysis (Johnson et al., 2013; Street et al., 2008). We elected to use a Bayesian D-optimal design constructed by JMP software (SAS Institute, Cary, North Carolina, USA). The final design resulted in 2 blocks of 12 choice sets with 2 choice profiles per set; all three attributes were permitted to vary within a choice set. Participants were randomly assigned to see only one of the two blocks of choice sets. A screenshot of one question from the DCE is shown in Fig. 1 as an example.

Table 1
The attributes, levels, and definitions.

Attribute	Level	Definition
Relationship to Sender		
	Family Member	
	Significant Other	
	Boss	
	Casual Friend	
Road Conditions		
	City/Heavy Traffic	"City streets with numerous stop lights; traveling 0–25 miles per hour"
	Highway/ Moderate Traffic	"Interstate roads; traveling 55–70 miles per hour"
	Rural/Light Traffic	"Curvy, 2-lane roads; traveling 35–50 miles per hour"
Importance		
	Very Important	
	Moderately Important	
	Not Important	

2.4. Data analysis

The analyses for the DCE portion of the survey was conducted with NLogit (Econometric Software, Inc., Plainview, NY). Sociodemographic characteristics that were included in the DCE analysis were modeled as non-random categorical parameters which were dummy coded. The levels for each attribute were also dummy coded. We first conducted analyses using the multinomial logit model based on the following equation: $V = \beta_0 + \beta_1 \mathrm{RELATIONSHIP} + \beta_2 \mathrm{ROAD} + \beta_3 \mathrm{IMPORTANCE} + \varepsilon$, where V is the utility of a given driving scenario, β_0 is a constant reflecting a right- or left-side bias in scenario selection, and β_1, β_2, and β_3 are coefficients indicating the relative importance of each of the attributes. To account for the presence of preference heterogeneity across participants, we then estimated a mixed-logit model that included random effects as well as fixed effects because the random effects can often account for potential variation in relative preferences across participants (Hauber et al., 2016). This is in contrast to the multinomial logit model, which assumes homogeneous preferences across participants (Train, 2009). A mixed-logit model is similar to a mixed-effects regression in that some coefficients are fixed and others are random. The mixed-logit estimation relies on boot-strapped estimators. For our estimation, we specified 2000 Halton draws, indicating that the obtained choice data were a panel (i.e., multiple choices by each participant), and that there was unobserved preference heterogeneity. Initially,

Fig. 1. A screenshot of a DCE question presented to participants during the survey.

the mixed-logit models were estimated with random effects for each attribute and level. To determine the most parsimonious model, if the distribution of a random parameter was not statistically significant (at $p < .05$), then the specification of the parameter was reverted to a fixed effect. The final model (reported below) included N fixed effects and M random effects. We calculated marginal effects for each level based on the final mixed model (Hensher et al., 2005).

3. Results

The demographic characteristics of the respondents are shown in Table 2. Approximately half of the respondents were male (51.1 %), white (83.1 %), non-Hispanic (92.6 %), and had at least some college education (91.4 %). Approximately 50 % of the sample drove for work.

The parameter estimates for the multinomial and mixed-logit models are in Table 3. In the mixed logit model, all attribute parameters were initially specified as random linear parameters with normal distributions. In the initial mixed logit, only two of the random parameters (Very Important and Moderately Important) had significant standard deviations, indicating that there was significant variance in those parameters from the mean and thus a fixed parameter was not appropriate. Therefore, the attributes with significant standard deviations were retained as random parameters and attributes with non-significant standard deviations were reverted to fixed parameters. To assess the differences in choices between those who do and do not drive for work, the Drive for Work variable was included in the mixed-model as an interaction term. It is also important to note that the reported regression coefficients relate the attribute levels to the utility associated with responding to a text message that has that attribute. A positive regression coefficient indicates that utility is gained by responding to a text message with that feature and, all else being equal, on average a person is more likely to respond to a text message that has that feature. A negative regression coefficient indicates that utility is lost by responding to a text message with that feature and, all else being equal, on average a person is less likely to respond to a text message that has that feature. A significant coefficient ($p < .05$) indicates that the attribute level had a significant effect on the decision to text while driving relative to the base case level, and the sign of the coefficient indicates the direction of the effect.

Table 2
Demographic Characteristics of the Sample.

Characteristic		Mean (±SD) or number (%)	
	Age	36.2	(±11.8)
Gender			
	Male	166	(51.1)
	Female	159	(48.9)
Race			
	White	270	(83.1)
	Black or African-American	30	(0.9)
	Asian	18	(5.5)
	American Indian or Alaska Native	6	(1.8)
	Native Hawaiian or Other Pacific Islander	0	(0.0)
	Other	7	(2.6)
Ethnicity			
	Non-Hispanic	301	(92.6)
	Hispanic	23	(7.1)
	No Response	1	(0.3)
Education			
	Less than high School	1	(0.3)
	High School/GED	27	(8.3)
	Some College	85	(26.2)
	2-Year College	47	(14.5)
	4-Year College	123	(37.8)
	Graduate Degree	42	(12.9)
Drive for Work			
	Yes	161	(49.5)
	No	164	(50.5)

In the multinomial logit model, all of the regression coefficients were significant. With regard to the effects of the sender on the decision to read a text message while driving relative to the reference case (Casual Friend), Significant Other (β: 1.24, 95 % CI 1.08–1.39) had the greatest impact on utility, followed by Family Member (β: 1.21, 95 % CI 1.05–1.37) and Boss (β: 0.58, 95 % CI 0.43 to 0.72). In terms of the importance of the text message, in comparison to the reference case (Not Important), Very Important (β: 2.03, 95 % CI 1.86–2.20) messages had the greatest influence on utility followed by Moderately Important (β: 1.05, 95 % CI: 0.89–1.20) messages. In terms of the road condition, in comparison to the reference case (Rural), Highway (β: −0.40, 95 % CI −0.53 to −0.27) roads had the greatest influence on utility followed by City (β: −0.19, 95 % CI: −0.33 to −0.07) roads.

The pattern of results obtained with the mixed-logit model were similar to the pattern of results obtained with the multinomial logit model. In the mixed logit model, the coefficients for Moderately Important and Very Important were random effects indicating that there was preference heterogeneity across participants for the strength of the importance of the message in the decision to read a text while driving. This preference heterogeneity indicates that the pattern of results for the multinomial logit model, particularly the coefficients associated with Moderately Important and Very Important text messages, are not accurate.

For the Driving Status by attribute level interactions with the mixed-logit model, there were several significant interactions. In terms of sender, relative to the reference case (Not Drive for Work × Casual Friend), Drive for Work × Family Member (β: −0.86 95 % CI: −1.33 to −0.39) and Drive for Work × Significant Other (β: −0.75, 95 % CI: −1.28 to −0.22) had significantly less of an impact on the utility of a scenario. In terms of importance of the message, relative to the reference case (Not Drive for Work × Not Important), Drive for Work x Very Important (β: −0.75, 95 % CI: −1.28 to −0.22) and Drive for Work × Moderately Important (β: −0.75, 95 % CI: −1.28 to −0.22) also had significantly less of an influence on utility. Additionally, relative to the reference case (Not Drive for Work × Rural), Drive for Work × Highway (β: 0.51, 95 % CI: 0.08 to 0.93) and Drive for Work × City (β: 0.56, 95 % CI: 0.07–1.05) roads had significantly more of an impact on the utility of a texting scenario. The Drive for Work × Boss interaction coefficient was not statistically significant.

The marginal effect of each attribute level on the decision to read a text while driving—expressed as the change in the choice probability—is shown in Fig. 2. These marginal probabilities indicate how each attribute level affects the likelihood of reading a text message relative to the basal level of reading a text message while driving. For example, a participant was 27 % more likely to read a text message if it was very important relative to their baseline likelihood of reading a text message. Thus, these marginal effects represent the translation of the

Table 3
Beta coefficients and 95 % confidence intervals for the multinomial logit model (left) and mixed-logit model (right).

	Multinomial logit model				Mixed logit model							
Attributes/statics	Mean	95 % CI		*P* value	Mean	95 % CI		*P* value	SD	95 % CI		*P* value
Relationship												
Family Member	1.21*	1.05	1.37	.0000	2.22*	1.82	2.62	.0000	–	–	–	
Significant Other	1.24*	1.08	1.39	.0000	2.39*	1.92	2.86	.0000	–	–	–	
Boss	0.58*	0.43	0.72	.0000	1.28*	0.86	1.71	.0000	–	–	–	
Casual Friend	–	–	–	–	–	–	–	–	–	–	–	
Road												
Highway	−0.40*	−0.53	−0.27	.0000	−0.95*	−1.29	−0.61	.0000	–	–	–	
City	−0.19*	−0.33	−0.06	.0035	−0.93*	−1.33	−0.53	.0000	–	–	–	
Rural	–	–	–	–	–	–	–	–	–	–	–	
Importance of Text												
Very Important	2.03*	1.86	2.20	.0000	8.14*	5.35	10.94	.0000	6.68*	3.97	9.39	.0000
Mod Important	1.05*	0.90	1.21	.0000	2.99*	2.08	3.89	.0000	2.31*	1.21	3.42	.0000
Not Important	–	–	–	–	–	–	–	–	–	–	–	
Drive for Work												
× Family Member					−0.86*	−1.33	−0.40	.0003	–	–	–	
× Significant Other					−0.74*	−1.28	−0.22	.0058	–	–	–	
× Boss					−0.51	−1.04	0.01	.0561	–	–	–	
x Casual Friend					–	–	–	–	–	–	–	
x Highway					0.51*	0.08	0.93	.0198	–	–	–	
x City					0.56*	0.07	1.05	.0242	–	–	–	
x Rural					–	–	–	–	–	–	–	
x Very Important					−2.37*	−3.63	−1.10	.0003	–	–	–	
x Mod Important					−0.75*	−1.42	−0.08	.0290	–	–	–	
x Not Important					–	–	–	–	–	–	–	
AIC	4294.8				4208.3							
Pseudo R^2	0.21				0.23							
Observations	3900				3900							
Sample Size	325				325							

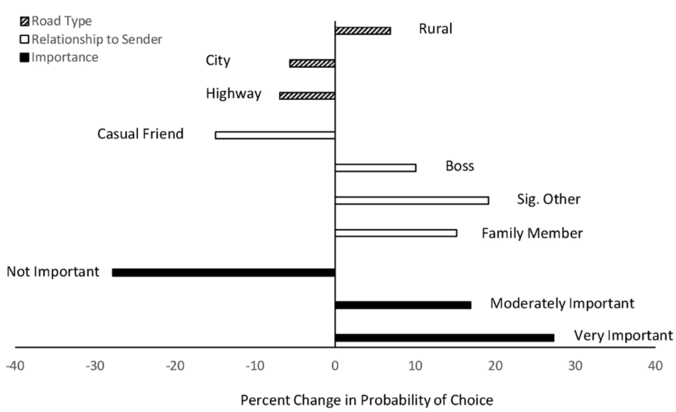

Fig. 2. The percent change in the probability of the choice to read a text while driving in comparison to the reference case (on a Rural Road when you receive a Not Important text from a Casual Friend).

mixed-logit utility function coefficients into how those attribute levels affect the choice to read a text message. The levels for Importance had the largest effect on choice and the Road Type had the smallest effect on choice. If the text in the scenario was Very Important, the scenario was 27 % more likely to be chosen. If the text in the scenario was Moderately or Not Important the scenario was 17 % more likely and 27 % less likely to be chosen, respectively. For the Relationship to the Sender attribute, if Family Member, Significant Other, or Boss was in the scenario, then that scenario was more likely to be chosen, but if Casual Friend was in the scenario, then it was 14 % less likely to be selected.

4. Discussion

4.1. Factors affecting the decision to text while driving

In the present study, a DCE was used to investigate the decision making of drivers when faced with hypothetical TWD scenarios. When drivers were asked under which of two circumstances they are most likely to read a text message, the factor that had the greatest effect on choice was the importance of the message. These results are consistent with previous studies that found that the perceived importance of a phone call was a strong predictor of talking on a cellphone while driving (Nelson et al., 2009).

The sender of the text message had a smaller but still significant effect on drivers' decisions to read a text message. The present findings are consistent with other studies on social distance. For example, when the sender of a message or a caller was more socially distant, teen drivers were more likely to ignore texts (McDonald and Sommers, 2015) and less likely to talk on the phone (LaVoie et al., 2016) while driving. In a study that examined texting while driving and social distance, participants were more likely to text while driving as the sender became closer to them in social distance (e.g., dearest friend or relative) (Foreman et al., 2019). The present findings are also consistent with texting behavior outside of a driving context, as a study by Atchley and Warden (2012) that participants were more willing to wait to reply to a text message from someone who was more socially distant compared to senders who were closer to them in social distance.

In the present study, drivers were less likely to read a text message in city traffic (i.e., stop-and-go) compared to highway or rural road conditions. These results contrast the finding that young adult drivers reported that they were more likely to read a text message when stopped at a stop sign as well as in "calm" road conditions, and less likely to read a text message on the highway or in "intense" road conditions (Atchley et al., 2011). The divergence in our results from the prior study may have occurred because the road conditions in the present study included both road type (city, highway, or rural) and amount of traffic (heavy, moderate, or light). It is possible that participants may not have read or completely comprehended the definitions for the different levels of road conditions that were provided. If we had fully separated the type of road conditions (e.g., congested, not congested) from the actions of the cars on that road (e.g., stopped traffic, slow traffic, fast traffic, etc.) then the results may have been consistent with previous research.

The analyses comparing participants who drove for work and those who do not drive for work were exploratory, and thus our conclusions are also limited. The utility of the attributes in the DCE scenarios were significantly different for those who drove for work compared to those who did not drive for work based on the significant interactions between Drive for Work and the levels of the attributes. Compared to those who did not drive for work, participants who drove for work derived less utility from the relationship of the sender (Family Member and Significant Other) and the importance of the message (Very Important and Moderately Important) and derived greater utility from the road conditions (City/Heavy Traffic and Highway/Moderate Traffic). Although the difference in the coefficients between the two groups were statistically significant, the reasons for these differences are unknown. Future studies could ask about the rules concerning distracted driving at their jobs because the policies and practices within organizations related to TWD may affect workers' driving behavior at work and outside of work. Perhaps stricter policies around cellphone use while driving within workplaces would encourage those who drive for work to behave more safely during non-work driving. Additionally, including the amount of a potential fine for being caught TWD as an attribute could have helped to differentiate the groups. It is possible that those who drive for work are less risk averse while driving than those who do not, and there is evidence that those who drive for work in a company vehicle are involved in more car accidents than those who use a personal vehicle (Clarke et al., 2005; Downs et al., 1999). The DCE in the present study only asked about decision making associated with TWD during non-work activities (e.g., personal errands), whereas decision making may differ depending on whose car is being driven or whether the driver is currently working.

Although the present study was primarily a demonstration of the DCE methodology with drivers' decision making, there may be some implications for public policy and guidance. The results indicate that the factor with the greatest effect on the decision to read a text message while driving was the importance of the message, and message importance has been a focus of some insurance campaigns. For example, in 2018, many Allstate Insurance slogans included the phrase, "No text is important enough to risk a life," in their social media advertisements for that company's *Drivewise* program (Kevin Olp: Allstate Insurance, 2018). In relation to texting while driving for work, a study of a cohort of individuals who drive for work found that one of the predictors of safety performance was management commitment to fleet and driver safety (Wills et al., 2006). Therefore, adherence to company texting while driving policies by managers and supervisors (e.g., not sending drivers text messages while they are known to be driving) may help ensure a safer climate for their driving workers.

4.2. Study limitations and future directions

There are several limitations to the present study. First, the amount of information that could be extracted from the DCE design was somewhat limited given that only three attributes were included in the study design. In any well-designed DCE, there is a tradeoff between the number of attributes and levels in the study design and the amount of cognitive burden imposed on the participants. If there are too many attributes, then the quality of the data may suffer because the participants are not attending to all of the attributes (Alemu et al., 2013). Future research could investigate a greater number of attributes, perhaps by using a partial profile design in which only a select number of attributes are presented to each participant (Kessels et al., 2011). Although these designs do require a relatively large number of participants, the design decreases the potential cognitive burden on the participants while still allowing the researchers to examine a larger number of attributes.

A second limitation was that all of the attributes studied were categorical variables. Including a continuous variable, like cost of a driving citation, permits the computation of equivalence calculations, such as maximum acceptable risk (Bridges et al., 2011). In the present study, inclusion of a variable like a monetary fine or penalty for TWD could have expanded the present analysis beyond only ranking the importance of the attributes and levels. Future research could incorporate continuous variables, such as risk of a crash or the amount of a fine, into a discrete choice experiment to assess how much risk would be tolerated under different texting scenarios.

Third, there was no "opt out" option in which the participant could select neither scenario. In the present study participants were forced to make a choice between texting in two different scenarios. It is quite possible that some participants would not have responded to a text message under any condition in a more naturalistic or real-life situation. This may have limited the realism of the DCE choice sets because, in real life, drivers can always choose to not engage in cellphone use while driving. Future studies could expand the DCE methodology to include writing text messages and other types of cellphone use while driving and include continuous variables and opt-out options to increase both the potential implications of the findings and the realism of the DCE, respectively.

Additionally, our sample was relatively young (the mean age was 36.2) and was primarily composed of non-Hispanic whites who had at least some college education. Although the demographic characteristics of drivers were not a focus of the present study, future research could examine differences in decision making across diverse groups.

DCEs can further expand avenues of research on distracted driving. In addition to assessing driver decision making and behavior, DCEs can also be used to assess preferences among different driver monitoring technologies, such as smartphone applications that block calls and screen notifications of email and text messages while driving. For example, a DCE could evaluate the acceptability of attributes of potential new technologies, such as the ease of use and cost of a new smartphone application, related to decreasing or preventing cellphone use while driving, especially considering that some current technologies (e.g., software that blocks phone use while driving) have not been adopted by drivers outside of research study protocols (Creaser et al., 2015;

Funkhouser and Sayer, 2013). Similarly, DCEs can be used with relevant driver populations to evaluate the potential effectiveness of new public service campaigns in changing driver behavior (cf. Hayashi et al. (2019)). The aspects of a potential campaign, such as the tagline, included statistics (e.g., X number of drivers crash due to texting), and message framing (e.g., negative or positive), could be manipulated and shown to samples of drivers to assess under which combination of attributes they would be more compelled to alter their texting-while-driving behavior.

4.3. Conclusions

The present study demonstrated the use of a DCE to examine decision making of drivers related to reading text messages while driving. When choosing between two hypothetical scenarios in which the relevant factors were evaluated simultaneously, participants were more likely to read a text message while driving if the sender of the message was a significant other, the message was perceived to be very important, and the participant was driving on rural roads. DCEs offer a promising approach to studying decision making in drivers and other populations because they allow for an analysis of multiple factors simultaneously and the trade-offs among different choices. DCE methods provide safety researchers with additional survey designs and analytical tools to more effectively assess factors that directly influence safety-related decisions and behavior, which would contribute to the development of effective prevention and intervention strategies for the problem.

Disclaimer

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CRediT authorship contribution statement

Anne M. Foreman: Conceptualization, Methodology, Formal analysis, Writing - original draft. **Jonathan E. Friedel:** Formal analysis, Writing - original draft. **Yusuke Hayashi:** Conceptualization, Methodology, Writing - review & editing. **Oliver Wirth:** Methodology, Writing - original draft, Supervision.

Declaration of Competing Interest

The authors have no conflicts of interest to declare. All co-authors have seen and agree with the contents of the manuscript and there is no financial interest to report. The submission is original work and is not under review at any other publication.

Appendix B. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.aap.2020.105823.

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