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ORIGINAL ARTICLE

A Behavioral Economic Analysis of Demand for Texting while Driving

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Abstract

The overarching goal of the present study was to determine whether a behavioral economic framework of demand analysis is applicable to texting while driving. To this end, we developed a novel hypothetical task in which participants receive a text message while driving, and they rated the likelihood of replying to a text message immediately versus waiting to reply until arriving at a destination when the fine for texting while driving ranged from $1 to $300. The scenario presented two delays to a destination (15 min and 60 min). For drivers who self-reported a higher frequency of texting while driving the demand for social interaction from texting was more intense and less elastic. Demand was also more intense and less elastic under the 60-min delay condition. The results of this proof-of-concept study suggest that behavioral economic demand analyses are potentially useful for understanding and predicting texting while driving.

Keywords Texting while driving · Demand analysis · Distracted driving · Behavioral economics · College students

Various statistics indicate that distracted driving is a major public health issue. In 2015 in the United States, for example, 3,477 people were killed and 391,000 people were injured in motor vehicle crashes caused by distracted driving (National Highway Traffic Safety Administration [NHTSA], 2017a). Even worse, these numbers are believed to be underreported due to inherent difficulties in identifying the exact cause of motor vehicle crashes when mobile phone use was involved (National Safety Council [NSC], 2013). According to the NSC's estimate, 341,000 to 910,000 motor vehicle crashes in 2013 in the United States are likely to be attributable to texting while driving alone (NSC, 2015). Despite its dangers, 31.4% and 40.2% of drivers in the United States reported that they have sent and read a text message while driving in the past 30 days (AAA Foundation for Traffic Safety, 2017).

To date, legislation to prohibit all drivers from texting while driving has been adopted in 47 states and the District of Columbia (Governors Highway Safety Association, 2018); however, the evidence of the effectiveness of these laws in reducing texting while driving is somewhat mixed (see Delgado, Wanner, & McDonald, 2016, for review). Educational campaigns, such as *U Drive. U Text. U Pay.* (NHTSA, 2017b), are other strategies that have been implemented to reduce texting while driving (see Cismaru & Nimegeers, 2017, for review). Despite the popularity of such campaigns in the media, there is no direct evidence that supports the effectiveness of these campaigns in reducing texting while driving (Delgado et al., 2016).

In efforts to identify other approaches, it is important to note a hallmark of this problem—that drivers send and read text messages while driving despite being aware of its danger (Atchley, Atwood, & Boulton, 2011). The impulsive nature of texting while driving is associated with the behavioral economic principle *delay discounting,* which refers to the process by which the decision maker subjectively devalues future events (Madden & Bickel, 2010). From a delay-discounting perspective, texting while driving can be conceptualized as an impulsive choice for an immediate reinforcer (i.e., immediate social interaction obtained while driving) conjoined with the increased[1] probability of a punisher (i.e., a greater chance of a motor vehicle crash) over a self-controlled choice for a delayed reinforcer conjoined with no probability of that punisher

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[1] The term "increased" is used to indicate the change in the probability of a motor vehicle crash due to texting while driving from the basal probability of a crash due to driving without texting. Note that the consequences of interest here concern only texting behavior. Therefore, the basal probability of a crash (by itself) is not referenced in our description for the sake of simplicity.

(i.e., delayed social interaction obtained when not driving without a chance of a motor vehicle crash). This delay discounting conceptualization of texting while driving has been empirically supported in previous studies (Hayashi, Fessler, Friedel, Foreman, & Wirth, 2018; Hayashi, Miller, Foreman, & Wirth, 2016; Hayashi, Russo, & Wirth, 2015).

When it comes to impulsive decision making, delay discounting is not the only process involved. In substance use disorders, for example, the reinforcer-pathology model (Bickel, Jarmolowicz, Mueller, & Gatchalian, 2011) posits that substance abuse is a function of persistent high valuation of a drug as a reinforcer (as assessed by demand analysis) as well as excessive preference for receiving the reinforcer in the short term (as assessed by delay discounting). Substantial empirical evidence suggests that these two factors (a) are closely related to suboptimal choice patterns associated with substance abuse, (b) are predictive of the outcomes of the interventions, and (c) can be the direct target of interventions in clinical settings (Bickel, Johnson, Koffarnus, MacKillop, & Murphy, 2014). Whether or not texting while driving can be regarded a form of behavioral addiction is debatable (Kardefelt-Winther et al., 2017) and it is beyond the scope of this article. Nevertheless, the similarity between texting while driving and other addictive and impulsive behaviors would suggest that the reinforcer-pathology model is potentially useful for texting while driving. In the present article, we propose that analyzing the valuation of a social reinforcer associated with texting while driving (i.e., analysis of demand for social interaction from texting in a driving context) is an essential part of a comprehensive approach towards better understanding the behavior of texting while driving.

Demand is a fundamental concept in economics and it refers to the amount of a commodity consumed at a given price. In behavioral economics, price is defined broadly, which could include monetary cost, effort, or time needed to obtain a commodity. Demand is often displayed graphically with the amount of a commodity consumed plotted as a function of its price, which is typically called a demand curve. A demand curve usually demonstrates the *law of demand*, which refers to the decrease in consumption of a commodity as its price increases (Samuelson & Nordhaus, 1985). Demand curve analysis allows for quantifying how much an individual values a certain commodity as well as examining how a demand curve is altered by various independent variables. For example, a demand curve analysis could be used to determine how a person values sugar versus artificial sweetener as the effort to obtain the commodities increases.

Two important indices obtained from a demand curve analysis are demand *intensity* and demand *elasticity*. Demand intensity refers to the level of consumption of a commodity when the price of the commodity is zero or very low (i.e., consumption with little or no constraint). Demand intensity may indicate the subjective hedonic value of a commodity (e.g., liking or enjoyment), but it cannot necessarily predict consumption at higher prices (Bickel et al., 2014). The other important index is demand elasticity, which refers to the sensitivity of consumption to changes in price. Demand is said to be *elastic* if the proportional change in consumption is greater than the corresponding proportional change in prices (i.e., *higher* sensitivity to price increases), whereas demand is said to be *inelastic* if the proportional change in consumption is less than the corresponding proportional change in price (i.e., *lower* sensitivity to price increases) (Hursh, 1980, 1984). In the literature on substance use disorders, demand elasticity is linked to drug abuse liability (Koffarnus & Kaplan, 2017), which refers to "a drug's potential to serve as a reinforcer and the strength of that reinforcer function in comparison with other drugs" (Hursh & Winger, 1995, p. 373).

Again, one aspect of substance use disorders, according to the reinforcer-pathology model (Bickel et al., 2014), is that the relative reinforcing efficacy of drugs is persistently high in comparison to the reinforcing efficacy of other commodities. The relative reinforcing efficacy can be assessed as either or both of the total amount of consumption of a commodity (i.e., intensity) and the total amount of resources allocated to obtain a commodity (i.e., elasticity). The multidimensional nature of drugs as a reinforcer can be well accounted for by demand analysis (Johnson & Bickel, 2006). Previous research has demonstrated the utility of demand analysis with various drugs, such as heroin (e.g., Jacobs & Bickel, 1999), cocaine (e.g., Bruner & Johnson, 2014), alcohol (e.g., Murphy & MacKillop, 2006), and cigarettes (e.g., MacKillop et al., 2008). In addition, demand analysis has been successfully applied to various nondrug reinforcers, such as food (e.g., Epstein, Salvy, Carr, Dearing, & Bickel, 2010), indoor tanning (e.g., Reed, Kaplan, Becirevic, Roma, & Hursh, 2016), gambling (e.g., Weinstock, Mulhauser, Oremus, & D'Agostino, 2016), and internet access (e.g., Broadbent & Dakki, 2015).

The extensive literature linking demand analysis and various addictive and impulsive behaviors, in combination with the aforementioned similarity between texting while driving and other addictive and impulsive behaviors, would provide a compelling rationale to examine the utility of demand analysis in texting while driving. The overarching goal of the present study, therefore, was to determine whether the behavioral economic framework associated with demand analysis is applicable to texting while driving. To this end, we developed a novel hypothetical texting task in which, after receiving a text message while driving, participants rated the likelihood of replying to the text message immediately under various conditions differing in the amounts of a fine for the traffic violation of texting while driving. Consistent with previous studies, the reinforcing value of a social reinforcer associated with texting while driving was operationalized using microeconomic demand curve analysis, which characterizes the relation between "consumption" of social interaction from texting while driving and its potential financial cost (i.e., a fine for texting while driving).

Given the overarching goal of the present study, the present study examined whether drivers who frequently text while driving show greater demand for social interaction from texting while driving than those who infrequently text while driving. A particular interest was to determine whether drivers who frequently text while driving can be characterized by (a) high intensity of demand for social interaction from texting while driving, (b) low elasticity of the demand, or (c) both. Differentiating these characteristics is important for understanding the nature of texting while driving. According to Koffarnus and Kaplan (2017), demand intensity and elasticity are associated with use level (excessiveness) and dependence severity (persistence), respectively. Therefore, intense but elastic demand for texting while driving (i.e., texting being high at the lowest fine but sensitive to increase in fine) would be consistent with the notion that texting while driving is essentially excessive behavior, whereas nonintense but inelastic demand (i.e., texting being low at the lowest fine but insensitive to increase in fine) would be consistent with the notion that texting while driving possesses the persistent nature. As an alternative, both intense and inelastic demand (i.e., texting being high at the lowest fine and insensitive to increase in fine) would suggest that texting while driving is characterized by both its excessiveness and persistence, as with other impulsivity-related problems such as substance use disorders.

Method

Participants

Sixty-three undergraduate students at Pennsylvania State University, Hazleton who enrolled in introductory psychology courses participated in this study. Course credit was offered for their participation. Students who reported that they did not have a valid driving license ($n = 9$) on the demographic survey (described below) were excluded from the study and their data were not analyzed. Based on the criteria developed by Stein, Koffarnus, Snider, Quisenberry, and Bickel (2015), students who showed nonsystematic patterns of responding ($n = 5$) were also excluded from the study (the details described below). The remaining sample was composed of 21 males and 28 females. Their mean age, years of higher education, and years driving were 19.7 ($SD = 3.4$; ranging from 18 to 39), 1.9 ($SD = 1.2$; ranging from 1 to 5), and 3.2 ($SD = 3.4$; ranging from 0 to 23). The institutional review board of the Pennsylvania State University approved the study protocol.

Procedure

All surveys were hosted online by Qualtrics (Provo, UT). Participants received an email through the Qualtrics website that contained a link to the online survey. After they read the descriptions of the present study and clicked an "Agree to participate" button as the informed consent process, they completed a demographic questionnaire and a hypothetical demand task with a texting while driving scenario.

Demographic questionnaire The questionnaire had questions for age, gender, years of higher education, whether they have a valid driver's license, and years of driving with a license. The questionnaire also included four questions on the frequency of texting while driving. The first question was "How often do you type something on your cell phone (e.g., text messages, emails, social media posts) while you are driving at any speed?" followed by "How often do you type something on your cell phone (e.g., text messages, emails, social media posts) while you are stopped at a red light?" The other two questions were similar, but instead of asking how often they "type" on their phone, they asked how often they "read." The questions employed a 5-point Likert scale ranging from 1 (*Never*), 2 (*Rarely*), 3 (*Some of the times*), 4 (*Most of the times*), to 5 (*Every time I drive*).

Hypothetical texting task As mentioned previously, the novel hypothetical texting task in the present study was developed based on previous studies using *likelihood* of purchase to quantify demand (e.g., Reed et al., 2016; Roma, Hursh, & Hudja, 2016), as opposed to traditional demand analyses in which demand is quantified using *amount* of purchase. Using visual analog scales, participants rated their likelihood of waiting to reply to a text message for a certain period of time versus replying immediately. The following instruction was presented on each trial:

> Suppose that texting while driving is illegal in your state and the police will impose a fine (but no other penalty) if they see you texting while driving.
> Imagine that you are driving, and your significant other (or your best friend) has just sent a text message saying "text me asap" when you are [delay] away from your destination. Given the current road conditions, there is a very low (0.01%) chance of having a car accident if you reply to the message, but it is unknown how likely the police will catch you texting while driving.
> Please rate how likely you are to wait until you arrive at the destination versus replying now if the fine for texting while driving is [amount].

The visual analog scale, located immediately below the instruction, was a horizontal line labeled from 0 to 100 in increments of 10 and it had the descriptive anchors *definitely wait* on the left side and *definitely reply now* on the right side. The participants indicated their likelihood of replying immediately by dragging the slider bar of the visual analog scale (the initial position of the slider bar on each trial was 50). Two delay values (15 min and 60 min) were used, with 15 min presented first. Within each delay condition, the delay value remained constant, but the amount of the fine varied across trials in this order: $1, $5, $10, $20, $30, $45, $60, $80, $100, $125, $150, $200, $250, and $300. Therefore, the entire task consisted of 2 blocks of 14 trials (total 28 trials).

Dependent measures The hypothetical texting task provides the following demand indices: demand elasticity, demand intensity, breakpoint, $P_{\max}$, and $O_{\max}$. First, demand elasticity in the present study refers to sensitivity of texting while driving to increases in the amount of the fine. Lower demand elasticity indicates smaller reduction in likelihood of replying (i.e., insensitivity) as the amounts of the fine increase. Second, demand intensity refers to the degree of texting while driving at the lowest amount of the fine ($1 in the present study). Higher demand intensity indicates higher likelihood of texting when the amount of the fine is $1. Third, breakpoint is defined as the smallest amount of the fine at which the likelihood of texting while driving reaches zero (or $300 if participants reported they would text while driving at the highest amount). For the group level analyses, break point is defined as the smallest amount of the fine at which the mean likelihood is smaller than 2.0. This nonzero value was arbitrarily chosen because the mean likelihood did not reach zero in both groups under both conditions. Fourth, P_{max} refers to the price at which the expenditure (or response output) is maximized. In the present study, expenditure is calculated by multiplying a given amount of the fine and the likelihood of texting while driving (transformed into a proportion, 0-1) at the amount (e.g., $50 if the amount of the fine is $100 and the likelihood is 50). Finally, O_{max} refers to the maximum expenditure at P_{max}.

All reinforcement indices except for demand elasticity were based on observed data. When two amounts of the fine generated the same $O_{\max}$ value, the $P_{\max}$ value was calculated by averaging the two amounts. When the likelihood of replying to a text message was zero at all amounts of the fine, the smallest amount ($1) served as the P_{max} value. Demand elasticity was derived by fitting both group and individual data to the exponentiated version of Hursh and Silberberg's (2008) exponential demand equation developed by Koffarnus, Franck, Stein, and Bickel (2015) using least squares nonlinear regression performed with the Solver function in Microsoft Excel 2016:

$$Q = Q_0 \cdot 10^{k\left(e^{-\alpha Q_0 C}-1\right)} \tag{1}$$

where Q is likelihood of replying to a text message of a given amount of the fine C, Q_0 is demand intensity (cf. an observed value is used for this study), α is demand elasticity, and k is a constant that denotes the range of likelihood of texting while driving in log units (in this study $k = 2$ for all analyses). The exponentiated version was chosen because it allows for inclusion of zero values in the analyses (Koffarnus et al., 2015). For group aggregate demand curves (see Fig. 2), Eq. 1 was fit to geometric means of the likelihood data (cf. geometric mean is calculated by taking the n-th root of the product of n numbers). Geometric means were employed because the likelihood data were not normally distributed, and we wanted to use every likelihood data point as the scaling factor. Because the likelihood data contain 0, a constant of 1 was added to all values prior calculating the product of the values and the constant was subtracted from the resultant geometric mean (see Becirevic et al., 2017, for the same arrangement in calculating geometric means).

In addition to these demand indices, essential value (*EV*, Hursh, 2014) was calculated based on the following formula:

$$EV = \frac{1}{\left(100 \cdot \alpha \cdot k^{1.5}\right)} \tag{2}$$

where the parameters are the same as in Eq. 1.[2] Essential value represents the normalized value of a reinforcer relatively independently of the values of k and Q_0 (Hursh & Silberberg, 2008) and the higher value indicates less elasticity. In the present study, we use essential values to represent the elasticity of the demand (see below for details).

Exclusion Criteria for Nonsystematic Responding

As mentioned previously, based on the criteria developed by Stein et al. (2015), the data from five participants who showed nonsystematic patterns of responding were excluded from analyses. The following criteria were used to flag nonsystematic data for further consideration: (a) trend (less than a 0.025 log-unit reduction in consumption per log-unit range from the first to last price), (b) bounce (local increase in consumption by 25% or more of the initial consumption at the lowest price), and (c) reversal from zero (reoccurrence of consumption at higher price after no consumption at two or more consecutive prices). We excluded the data that violated the bounce and reversal-from-zero criteria but relaxed the trend criterion for two reasons. First, as discussed in Stein et al. (2015), the data that violate the trend criterion may represent important information depending on the nature of a study. In the present study, we believe choices of not texting at all (i.e., exclusive choice of 0 as the likelihood of replying) or texting all the times (i.e., exclusive choice of 100) while driving represent important information. Second, in this exploratory study, the

[2] It is important to note that the exponent of 1.5 in Eq. 2 was determined for Hursh and Silberberg's (2008) exponential demand equation, and an equivalent for Koffarnus et al.'s (2015) exponentiated equation has not been determined yet. In this study, we use the exponent of 1.5 in calculating EV's because our primary focus is to compare the groups and conditions within this study, but the readers are cautioned that the absolute values of the EV's in the present study may not be appropriate for comparisons across studies.

selection of the parameters (the amount from \$1 to \$300) was arbitrary. The data might have not violated the trend criterion if larger values had been used.

Group Assignment and Statistical Analysis

The participants were stratified into two groups: the High-Texting While Driving (High-TWD) group (n = 25) and the Low-TWD group (n = 24) (see Iacobucci, Posavac, Kardes, Schneider, & Popovich, 2015, for the justification for this group assignment). The group assignment was based on the mean ratings of (a) typing and reading while driving at any speed and then (b) typing and reading while stopped at a red light. The participants with upper and lower half of the scores were assigned to the High-TWD and Low-TWD groups, respectively.

For demographic measures, gender was analyzed with a chi-square test. Continuous variables were analyzed with an independent samples t-test. The Mann-Whitney U test was used to compare the five demand indices between the High-TWD and Low-TWD groups because the data were not normally distributed. The Wilcoxon signed-rank test was used to compare the indices across two delay conditions. All statistical tests were performed with SPSS Version 24 with the statistical significance level of .05. Confidence intervals were calculated GraphPad Prism Version 7.

Results

Table 1 shows the demographic characteristics. No significant differences among groups were found for gender, $\chi^2(1)$ = 1.70, p =.680; age, $t(47)$ = -.53, p = .597; years of higher education, $t(47)$ = 1.14, p = .262; or years driving, $t(47)$ = -.84, p = .403.

The left panel of Fig. 1 shows the geometric means of the likelihood of replying to a text message as a function of amounts of the fine and best-fitting demand curves for the High-TWD and Low-TWD groups under the 15- and 60-min delay conditions. For both groups and under both conditions, Eq. 1 described the data well (R^2's ≥ .97), and the likelihood of replying decreased with increases in amounts of the fine. The right panel of Fig. 1 shows potential expenditure for replying to a text message as a function of amounts of the fine for the High-TWD and Low-TWD groups under the 15- and 60-min delay conditions.

Table 1 Demographic characteristics for TWD and non-TWD groups

Characteristics	High-TWD	Low-TWD
Gender		
Male	10	11
Female	15	13
Age in years	19.5 (2.3)	20.0 (4.3)
Years of higher education	2.0 (1.4)	1.7 (0.9)
Years driving	2.8 (2.0)	3.6 (4.4)
TWD frequency (driving)[a]	3.1 (0.6)	1.6 (0.5)
TWD frequency (stopped)[a]	3.4 (0.7)	2.7 (0.8)

The numbers are means (and standard deviations) except for gender. TWD = Texting while driving. [a] Mean differences depict the results of the stratification

As shown at the legend of Fig. 1, at the group level of analyses, demand for replying to a text message while driving was more intense (i.e., higher observed Q_0 value) for the High-TWD group than for the Low-TWD group (the difference between the High-TWD and Low-TWD groups for the 15-min delay condition, hereafter referred to as $\Delta_{\text{H-L\_15}}$, was 38.0, and the same difference for the 60-min delay condition, hereafter referred to as $\Delta_{\text{H-L\_60}}$, was 46.5). Also, the demand was less elastic (i.e., lower log(α) value and higher essential value) for the High-TWD group than for the Low-TWD group (for log(α), $\Delta_{\text{H-L\_15}}$ and $\Delta_{\text{H-L\_60}}$ were -0.7 and -0.8, respectively, and for essential value, $\Delta_{\text{H-L\_15}}$ and $\Delta_{\text{H-L\_60}}$ were 19.8 and 36.2, respectively). This indicates that the High-TWD group was more likely to reply at the lowest amount of the fine and was less sensitive to increases in the amounts of the fine. Likewise, the demand was more intense under the 60-min delay condition than under the 15-min condition both for the High-TWD group (the difference between the 60-min and 15-min delay conditions for the High-TWD group, hereafter referred to as $\Delta_{\text{60-15\_H}}$, was 13.3) and for the Low-TWD group (the same difference for the Low-TWD group, hereafter referred to as $\Delta_{\text{60-15\_L}}$, was 4.8). The demand was also less elastic under the 60-min delay condition than under the 15-min condition both for the High-TWD group ($\Delta_{\text{60-15\_H}}$ was -0.3 for log(α) and 18.8 for essential value) and for the Low-TWD group ($\Delta_{\text{60-15\_L}}$ was -0.2 for log(α) and 2.4 for essential value). The breakpoint, observed P_{max}, and observed O_{max} values show a similar pattern: The values were the highest for the High-TWD group under the 60-min delay condition (see the legend of Fig. 1 for details).

To further analyze the difference between the groups as well as across the conditions, the demand indices were calculated based on the data obtained from each participant. In this process, Eq. 1 could not be fitted to the data from 14 participants (5 for the High-TWD group and 9 for the Low-TWD group) in either or both of the delay conditions because the likelihood of replying did not differ across amounts of the fine. These data were excluded for the analysis of the elasticity parameter (α). Eleven out of the 14 participants showed a null demand function (i.e., zero likelihood of replying at all amounts of the fine). Because the essential value in the case of null demand can be considered zero (see Reed et al., 2016, for the same arrangement), the data from the 11 participants were included in the analysis of essential value. This resulted

Group (condition)	log(α)	EV	Q_0	BP	P_{max}	O_{max}	R^2
● High-TWD (60 min)	-4.1	43.3	63.3	300	45	14.2	.99
□ High-TWD (15 min)	-3.8	24.5	50.0	200	20	7.8	.99
● Low-TWD (60 min)	-3.3	7.1	16.8	80	20	2.6	.98
□ Low-TWD (15 min)	-3.1	4.7	12.0	45	20	1.7	.97

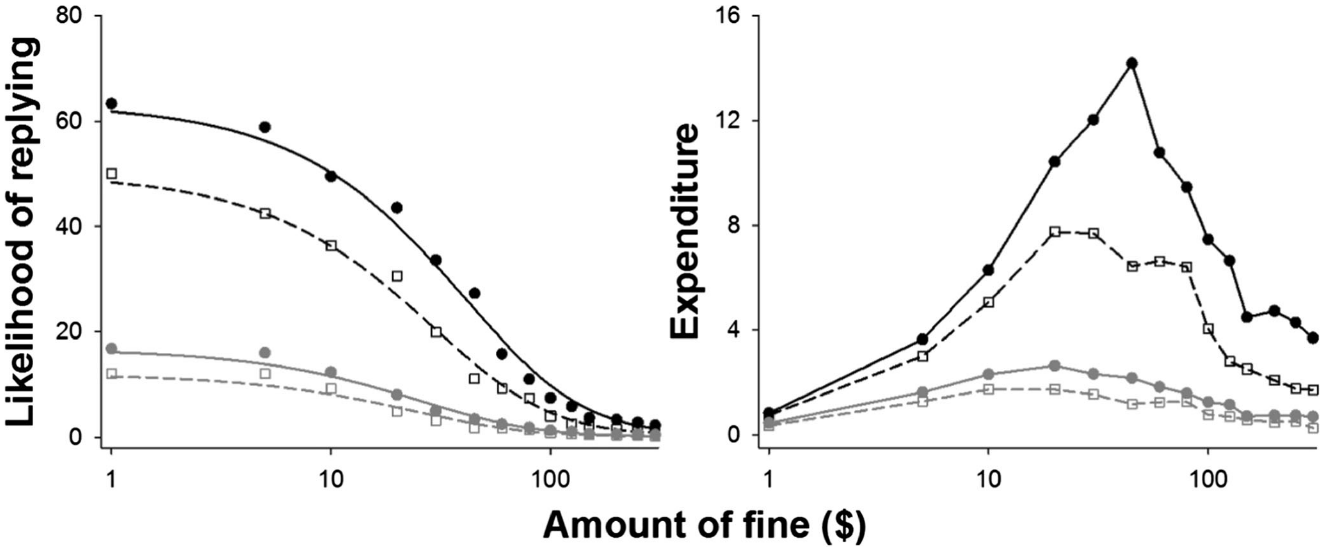


Fig. 1. Likelihood of replying to a text message and best-fitting demand curves (left panel) and expenditure (right panel) as a function of amounts of the fine and for the High-TWD and Low-TWD groups under the 15- and 60-min delay conditions. EV = Essential value. BP = Breakpoint

in exclusion of the data from two participants in the High-TWD group (due to exclusive choice of 100 likelihood of replying at all amounts of the fine) and one participant in the Low-TWD group (due to exclusive choice of 50 likelihood of replying).

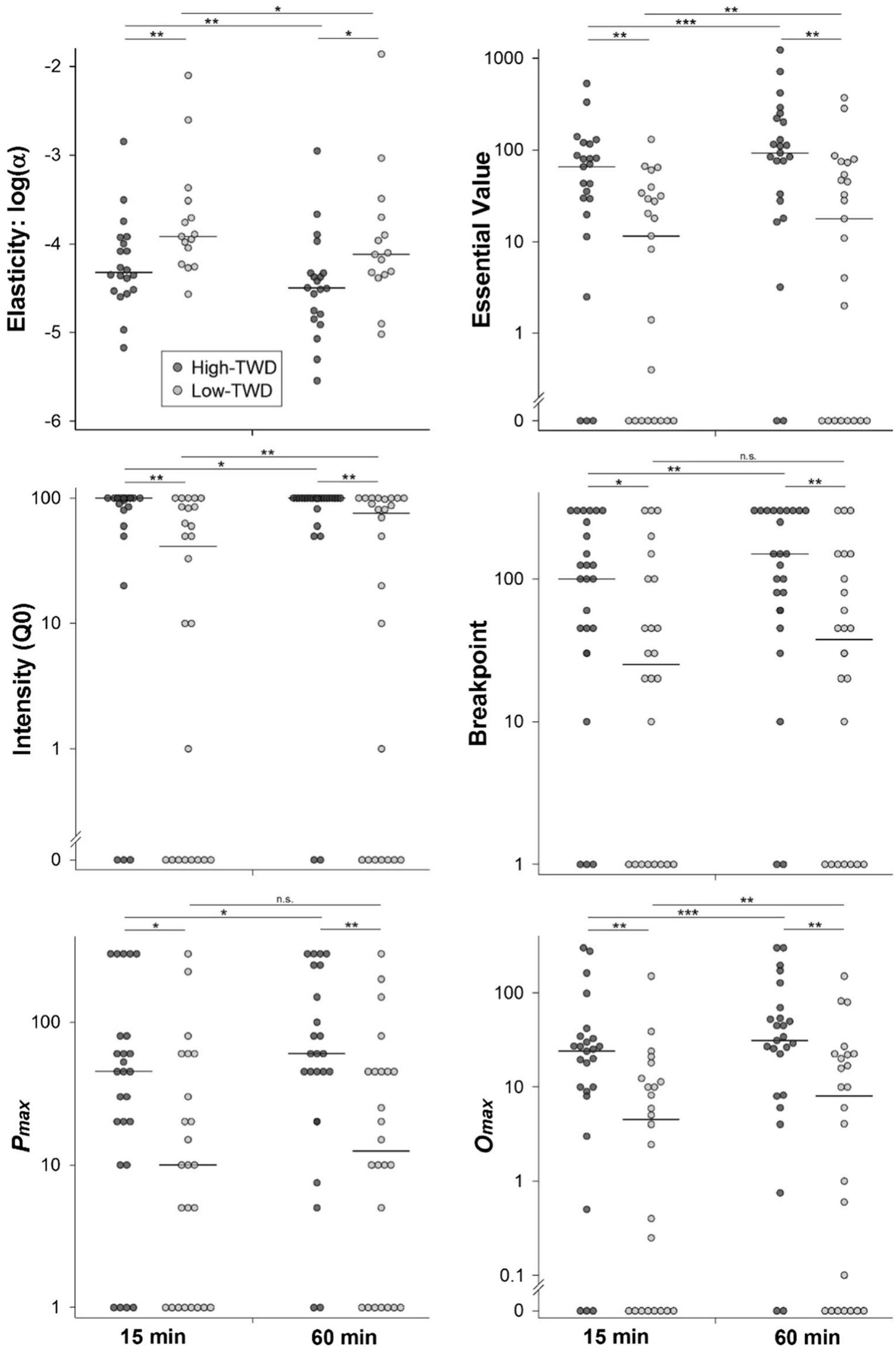
Figure 2 shows the median and individual data points for demand elasticity (α), essential value, demand intensity (observed Q_0), breakpoint, observed P_{max}, and observed O_{max} for the High-TWD and Low-TWD groups under the 15- and 60-min delay conditions. Table 2 shows the results of the Mann-Whitney U test that compared these demand indices between the High-TWD and Low-TWD groups. Table 3 shows the results of the Wilcoxon signed-rank test that compared the indices across two delay conditions. Overall, these results are consistent with the aforementioned group analyses: demand for replying to a text message while driving was the most intense (i.e., the highest observed Q_0 value) and the least elastic (i.e., the lowest α value and the highest essential value) for the High-TWD group under the 60-min delay condition. The breakpoint, observed P_{max}, and observed O_{max} values show the same pattern, with an exception that the difference in breakpoint and observed P_{max} between the two delay conditions was not significant for the Low-TWD group.

Discussion

The overarching goal of the present study was to examine whether a behavioral economic framework of demand analysis is applicable to the public health challenge of texting while driving. To this end, we developed the novel hypothetical texting task that allowed for assessing various behavioral economic demand indices for text while driving. In general, drivers who frequently text while driving show greater demand for social interaction from texting in the hypothetical driving context than those who infrequently text while driving. In particular, demand for social interaction from texting was more intense and less elastic for drivers who frequently text while driving (with the effect sizes being medium to close to large), suggesting that texting while driving is essentially excessive behavior that shows a persistent nature (cf. Koffarnus & Kaplan, 2017). In addition, the present study demonstrated that the demand assessed in the novel task was sensitive to, and varied in the predictive direction with, a variable known to affect texting while driving such as delay to a destination (with the effect sizes being medium to large), suggesting that the task possesses construct validity.

Overall, the present demand curves resembled those reported in previous studies with substance use disorders (e.g., Bickel et al., 2014; MacKillop, 2016) as well as various types of behavioral addiction (e.g., Broadbent & Dakki, 2015; Epstein, Salvy, et al., 2010; Reed et al., 2016; Weinstock et al., 2016). In addition, the demand curves in the present study were well described by a variation of Hursh and Silberberg's (2008) exponential demand equation. These results suggest that behavioral economic demand analysis serves as a viable method for assessing demand for social interaction from texting while driving, and it supports a

Fig. 2. Demand indices for the High-TWD and Low-TWD groups under the 15- and 60-min delay conditions. Horizontal bars represent the median. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$. n.s. = not significant



general conclusion that a behavioral economic framework is applicable to texting while driving.

Previous research has shown that texting while driving is fundamentally an impulsive choice that involves a trade-off between immediate and delayed reinforcers (Hayashi et al., 2016; Hayashi, Fessler, et al., 2018). The present study extends the literature by demonstrating that texting while driving is characterized by excessive valuation of a social reinforcer from texting (both excessiveness and persistence as measured by the intensity and elasticity of the demand, respectively). Taken together, these findings support the utility of the reinforcer-pathology model (Bickel et al., 2011) for understanding texting while driving: texting while driving may be characterized as a function of excessive preference for

Table 2 Comparisons of demand indices between high-TWD and low-TWD groups

Indices	Condition	*ΔMedian*	*ΔCI*	*U*	*p*	*r*
Elasticity	15-min	-0.4	[-0.7, -0.1]	68.00	.006	0.46
	60-min	-0.4	[-0.8, -0.1]	77.00	.015	0.41
Essential value	15-min	54.0	[11.0, 69.9]	400.00	.003	0.44
	60-min	75.0	[16.7, 112.4]	402.00	.002	0.45
Intensity	15-min	58.5	[0.0, 79.9]	445.00	.003	0.43
	60-min	24.5	[0.0, 59.9]	439.00	.003	0.43
Breakpoint	15-min	75.0	[0.0, 105.0]	417.00	.018	0.34
	60-min	112.5	[10.0, 150.0]	438.00	.005	0.40
P_{max}	15-min	35.0	[0.0, 47.5]	415.00	.020	0.33
	60-min	47.5	[5.0, 59.0]	434.00	.007	0.39
O_{max}	15-min	19.5	[3.1, 24.1]	447.00	.003	0.42
	60-min	23.2	[5.9, 40.0]	449.00	.003	0.43

ΔMedian = difference in medians between groups. *ΔCI* = 95% confidence interval on the differences in medians. *U* = Mann-Whitney's *U* value. *r* = effect size

receiving a social reinforcer from texting in the short term (as assessed by delay discounting) as well as persistent high valuation of the social reinforcer (as assessed by demand analysis). If texting while driving is similar to other impulsivity-related problems, such as substance abuse, in this essential manner, further attempts to extrapolate the behavioral economic demand principles to texting while driving may be successful. If so, it can serve as a novel conceptual framework in future research by providing (a) independent variables to predict and influence texting while driving, and (b) dependent variables that may allow us to analyze texting while driving in different contexts (Bickel et al., 2014).

Table 3. Comparisons of demand indices across 15-min and 60-min delay conditions

Indices	Group	*MedianΔ*	*CIΔ*	*Z*	*p*	*r*
Elasticity	High	-0.2	[-0.3, -0.1]	-3.25	.001	0.51
	Low	-0.2	[-0.4, -0.1]	-2.16	.031	0.39
Essential value	High	45.1	[5.0, 104.0]	3.95	<.001	0.58
	Low	2.4	[0.0, 14.8]	2.90	.004	0.43
Intensity	High	0.0	[0.0, 0.0]	2.38	.017	0.34
	Low	0.0	[0.0, 15.0]	2.81	.005	0.40
Breakpoint	High	0.0	[0.0, 35.0]	2.94	.003	0.42
	Low	0.0	[0.0, 0.0]	0.61	.539	0.09
P_{max}	High	0.0	[0.0, 20.0]	2.20	.028	0.31
	Low	0.0	[0.0, 5.0]	1.08	.278	0.16
O_{max}	High	9.0	[1.0, 22.5]	3.84	<.001	0.54
	Low	0.6	[0.0, 5.0]	2.84	.004	0.41

High = High-TWD. Low = Low-TWD. *MedianΔ* = median of differences between conditions. *CIΔ* = 95% confidence interval on the median of differences. *Z* = standardized static value for Wilcoxon signed-rank test. *r* = effect size

Potential Intervention Strategies

The present findings that texting while driving may share similar behavioral/cognitive mechanisms with other addictive and impulsive behaviors (i.e., excessive valuation of immediate reinforcer) suggest that similar intervention strategies may be useful for reducing texting while driving. According to Bickel et al. (2017), one way to treat reinforcer pathology is to strengthen executive control. For example, for alcohol-related problems, a computer-based executive function training that strengthens inhibitory control for alcohol-related cues (i.e., go/no go task) has been shown to decrease alcohol consumption in college students (e.g., Houben, Nederkoorn, Wiers, & Jansen, 2011). Given that texting while driving is associated with lower levels of executive function (Hayashi, Foreman, Friedel, & Wirth, 2018; Hayashi, Rivera, Modico, Foreman, & Wirth, 2017), a similar intervention strategy may be potentially useful. Support for this strategy also comes from a study by Beeli, Koeneke, Gasser, and Jancke (2008), in which dangerous driving behaviors in a simulator task were reduced by the application of the transcranial direct current stimulation (tDCS) on the dorsolateral prefrontal cortex, which is hypothesized to strengthen executive control.

Interventions utilizing episodic future thinking are another potential intervention strategy, which is also consistent with the reinforcer pathology model. Episodic future thinking refers to “an ability to project the self forward in time to pre-experience an event” (Atance & O’Neill, 2001, p. 537). Engaging in episodic future thinking produces a more salient representation of the future event being imagined, and its therapeutic effects have been well documented (see Bickel et al., 2017, for review). Approaches based on episodic future thinking have been shown to alter impulsive decision making (i.e., delay discounting) in obese participants (Daniel, Stanton, & Epstein, 2013a, 2013b), cigarette smokers (Stein et al., 2016; Stein et al., 2017), and pathological gamblers (Wiehler, Petzschner, Stephan, & Peters, 2017). The approaches have also been shown to reduce behavioral economic demand for food (Sze, Daniel, Kilanowski, Collins, & Epstein, 2015; Sze, Stein, Bickel, Paluch, & Epstein, 2017), alcohol (Bulley & Gullo, 2017; Snider, LaConte, & Bickel, 2016), and cigarettes (Stein, Tegge, Turner, & Bickel, 2018; Stein et al., 2016). Given the previous studies linking delay discounting with texting while driving (Hayashi et al., 2015, 2016; Hayashi, Fessler, et al., 2018) as well as the present study linking excessive valuation of texting with texting while driving, evaluating the effectiveness of episodic future thinking in reducing texting while driving should be an important future direction.

Toward the Development of Useful Research Tool

We believe the hypothetical demand task in the present study has the potential to serve as a useful research tool (cf. Sigurdsson, Taylor, & Wirth, 2013) that can contribute to the development of effective prevention and intervention strategies for texting while driving. There are three advantages that are worth mentioning. First, the research tool allows us to utilize an experimental approach, in which a variable of interest is manipulated and its effects on texting while driving can be analyzed. This is important not only to further our understanding of variables that affect texting while driving but also to develop effective prevention and intervention strategies for texting while driving. Toward this end, assessing the test–retest reliability of the present task is a logical next step (cf. Murphy, MacKillop, Skidmore, & Pederson, 2009).

Second, from an ethical and safety standpoint, the hypothetical nature of the present task is desirable if anything beyond observational studies needs to be conducted. That is, the hypothetical task allows investigators to experimentally study variables that may alter demand for texting while driving without having to expose drivers to the actual danger of texting while driving. Although the similar approach may be taken by using driving simulators (e.g., He et al., 2014), some practical constraints (e.g., cost) can be important limitations.

Finally, the hypothetical task can possess high scalability, which is also an important practical limitation of driving simulators. A growing number of studies using a hypothetical task have recruited participants with Amazon Mechanical Turk (MTurk), which allows for recruiting diverse samples efficiently (e.g., Johnson, Johnson, Rass, & Pacek, 2017). The scalability of a hypothetical task is particularly advantageous in terms of external validity of findings as well as implications for public policy (discussed below).

Limitations

Four limitations of the present study are noteworthy. First, the size of the sample was small and was exclusively composed of college students. Therefore, the present findings have to be interpreted with caution. It is strongly recommended that future research replicate the present study with a larger and more diverse sample and collect more demographic measures. It is important to note, however, that the present study is exploratory in nature and the primary focus is proof-of-concept of the utility of behavioral economic demand analysis for texting while driving. It is also important to note that, despite the small sample size, medium to large effect sizes were obtained for the primary dependent measures (i.e., demand intensity and elasticity). Therefore, we believe that the small and homogeneous sample would be acceptable given the nature of the present study.

Second, a hypothetical demand task relies on participants' verbal report of their choice as a proxy for actual choice, which raises the issue of correspondence between the verbal report and the actual patterns of choice (Jacobs & Bickel, 1999). It is important to note, however, that the question of correspondence is ultimately an empirical question (Jacobs & Bickel, 1999). Previous research has shown that there is close correspondence between choice under a hypothetical demand task and under a condition involving actual exposure to the consequences (Amlung & MacKillop, 2015; Amlung, Acker, Stojek, Murphy, & MacKillop, 2012; Wilson, Franck, Koffarnus, & Bickel, 2016). Other evidence comes from the studies demonstrating that demand assessed in a hypothetical task is predictive of the severity of dependence (e.g., Chase, MacKillop, & Hogarth, 2013; MacKillop et al., 2010) and treatment success (e.g., MacKillop & Murphy, 2007; Madden & Kalman, 2010). Taken together with the ethical issues of having participants actually engage in texting while driving, this empirical support in previous studies would justify the use of a hypothetical task as a viable option in studying texting while driving.

Third, as stated in the instructions of the present task, the likelihood of being caught by the police was unspecified. This arrangement was made to make the hypothetical task similar to an actual situation (i.e., we often cannot estimate the likelihood). Because of this arrangement, the fine (or the cost for replying) may be said to be probabilistic, unlike a traditional demand task in which the cost is not probabilistic. Therefore, the subjective value of cost, which is affected by the individual differences in estimation of the likelihood of being caught by the police, may differ across individuals, just like the subjective value of a particular amount of cost (e.g., loss of \$100) may differ across individuals. Although this is not ideal, we believe that this does not cause a serious issue in interpreting our data. This is because our primary focus in the present study was to characterize the nature of the demand for a social reinforcer from texting (i.e., intensity and elasticity), which can be achieved without considering the mechanisms. In other words, our primary focus is the functional relation between the demand and the cost as operationalized by the amount and whether or not the functional relation varies systematically across the High- and Low-TWD groups. Although it is important for future research to identify the exact mechanism through which the demand changed as a function of the cost, we believe that our arrangement of the probabilistic cost is justifiable, at least in this exploratory investigation. Nevertheless, it is important for future research to investigate how the probability of being caught by the police affects the demand for texting, which may interact with a history of being caught. It is also important to for future research to collect information about participants' financial status, which may provide an assessment of subjective value of loss of money due to the fine for texting while driving.

Finally, the frequencies of texting while driving are based on self-reported data. There are some tendencies that inappropriate behaviors are underreported (social desirability bias; Nederhof, 1985). In this sense, it is at least possible that some participants in the Low-TWD group are similar to those in the High-TWD group in terms of actual frequencies of texting while driving. This may account for some variabilities observed in the Low-TWD group (e.g., some participants in the Low-TWD group showed high intensity of the demand). Although the differences between two groups were robust enough to achieve statistical significance in the present study, it may be desirable for future research to employ more objective measures of texting while driving (e.g., observational data collected using an on-board camera; Klauer et al., 2014).

Conclusion: Public Policy Implications

The present study adds to the growing literature on behavioral economic approaches toward texting while driving by complementing prior investigations that have examined the role of delay and probability discounting in texting while driving (Hayashi et al., 2015, 2016; Hayashi, Fessler, et al., 2018). The results of the present study suggest that measures of demand intensity and elasticity can be useful for a more comprehensive understanding of individual differences in the valuation of social interaction obtained from texting while driving.

The present study also provides a rich source of information about sensitivity of texting while driving to varying amounts of monetary penalties, which contributes to a greater understanding of the economic factors that determine the maladaptive choice. That is, the present data are consistent with the notion that an increase in the amount of a fine for texting while driving can be an effective way to decrease the behavior. For this purpose, the value of P_{max}, the point at which the demand curve transitions from inelastic to elastic, provides an empirical basis for determining a potentially effective amount of the fine for texting while driving (cf. Hursh & Roma, 2013). From a policy-making perspective, P_{max} can be said to be a quantitative description of the point at which the amount of a fine becomes sufficiently high and maximizes its effectiveness in reducing texting while driving. Consistent with this notion, demand analysis has been employed to examine potential policy implications of other commodities, such as cigarettes (MacKillop et al., 2012), high caloric food (Epstein, Dearing, Roba, & Finkelstein, 2010), and reusable shopping bags (Kaplan, Gelino, & Reed, 2018). In addition, validation of this approach comes from Grace, Kivell, and Laugesen (2015), who demonstrated that demand elasticity from a hypothetical cigarette purchase task predicted consumption among smokers following increases in tobacco excise taxes. Taken together, once the present study is replicated with a more diverse and larger sample, it is possible that simulated demand curves can provide an important and possibly unique source of information about how individual drivers' behavior will change following an increase in the amount of a fine. In this manner, the present proof-of-concept study demonstrates great promise in paving the way for "empirical public policy" (Hursh & Roma, 2013) for texting while driving.

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Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

Ethical Approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed Consent Informed consent was obtained from all individual participants included in the study.

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