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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 designed to quantify the intensity and elasticity of the demand for social interaction from texting while driving. This task involved a scenario 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 amounts of a fine for texting while driving ranged from $1 to $300. To assess the construct validity of the task, the scenario presented two delays to a destination (15 min and 60 min). The demand for social interaction from texting was more intense (greater at the lowest amount of the fine) and less elastic (less sensitive to the increase in the amounts of the fine) for drivers who self-reported a higher frequency of texting while driving than for those who self-reported a lower frequency of texting while driving. Demand was also more intense and less elastic under the 60-min delay condition than under the 15-min 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

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Footnote

A Behavioral Economic Analysis of Demand for Texting while Driving Behavioral economics refers to the integration of behavioral science and microeconomic principles for the purpose of a functional analysis of economic processes (Hursh, 1980, 1984), which has provided "a translational framework for extending principles derived from laboratory studies to an understanding of consumer choice" (Hursh, 2014). In this extension, a conceptual bridge across the two fields is achieved by equating *the allocation of limited resources to consume one commodity over another* in microeconomics parlance with *the allocation of operant behavior among different competing reinforcers* in behavioral science parlance (Hursh, 1980, 1984). The latter framework has been successfully applied to various important societal problems, such as substance use disorders (Bickel, Johnson, Koffarnus, MacKillop, & Murphy, 2014; MacKillop, 2016), obesity (Epstein, Salvy, Carr, Dearing, & Bickel, 2010), and other health-related behaviors (Bickel, Moody, & Higgins, 2016). One common feature of these behavioral economic extensions is a conceptual, methodological, and analytical framework for assessing the efficacy of the reinforcer of interest. In the case of substance use disorders, for example, the identification of relative reinforcement efficacy of an abused drug is critical in determining its abuse liability (Jacobs & Bickel, 1999), and this translational strategy, based on the behavioral economic approach, has made significant contributions to the development of effective treatment strategies (e.g., Bickel et al., 2016). We propose that a similar translational strategy is useful for understanding, predicting, and reducing texting while driving as an emerging public health concern in society. The overarching goal of this paper is to demonstrate the utility of a behavioral economic approach, particularly demand analysis, as an initial step towards the development of effective prevention and intervention strategies for the problem.

Various statistics indicates 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). The behavior is particularly prevalent in young drivers such as college students. In the United States, more than 90% of college students surveyed reported they have engaged in texting while driving (Atchley, Atwood, & Boulton, 2011; Harrison, 2011).

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, 2017); however, the evidence of the effectiveness of these laws in reducing texting while driving is somewhat mixed (see Delgado, Wanner, & McDonald, 2016, for review). Some studies have shown that a texting ban was associated with the decreased number of fatalities and injuries due to motor vehicle crashes (Ferdinand et al., 2014, 2015), whereas other studies have shown that a texting ban was not associated with decreased frequencies of physically manipulating a phone while driving (Goodwin, O'Brien, & Foss, 2012), a reduction of motor vehicle crashes at all (Ehsani, Bingham, Ionides, & Childers, 2014), or a long-term reduction of motor vehicle crashes (Abouk & Adams, 2013). 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). Although there is little doubt that legislation and educational campaigns are worthwhile, the empirical research suggests that these approaches need to be supplemented with other efforts to be maximally effective in reducing or eliminating texting while driving.

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 et al., 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-control choice for a delayed reinforcer conjoined with no probability of that punisher (i.e., delayed social interaction obtained when not driving without a chance of a motor vehicle crash).

Previous studies have supported this delay discounting conceptualization of texting while driving. Hayashi, Russo, and Wirth (2015) found that drivers who frequently text while driving were more impulsive, as measured by the degree of delay discounting with hypothetical monetary reinforcers, than those who infrequently text while driving. In a subsequent study, Hayashi, Miller, Foreman, and Wirth (2016) examined whether opportunities to text while driving as a social reinforcer were subject to delay discounting. In a delay-discounting task with a hypothetical scenario, participants rated their likelihood of immediately replying to a text message received while driving versus waiting to reply until arriving at a destination. The participants also completed a delay-discounting task with hypothetical monetary reinforcers. The researchers found that the decrease in the subjective value of opportunities to reply to a text message as a function of delay was well described by the hyperbolic delay-discounting function. The researchers also found that the rates of delay discounting of the delayed opportunities to reply were greater for drivers who text frequently while driving than those who infrequently text while driving, although, contrary to Hayashi et al. (2015), the rates of discounting of hypothetical monetary reinforcers did not differ between the two groups of drivers. Finally, Hayashi, Fessler, Foreman, Friedel, and Wirth (2017) extended the previous studies to probability discounting. Also using a hypothetical scenario that presented several delays to a destination and probabilities of a motor vehicle crash, the researchers found that the subjective value of opportunities to reply to a text message decreased as a function of both the delay to the destination and the probability of a

[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.

motor vehicle crash. In addition, they found that drivers who frequently texting while driving showed greater rates of both delay and probability discounting.

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 et al., 2014). Whether or not texting while driving (or problematic mobile phone use more generally) can be regarded a form of behavioral addiction (Ascher & Levounis, 2015) is debatable (Kardefelt-Winther et al., 2017) and it is beyond the scope of this paper. Nevertheless, the similarity between texting while driving and other addictive and impulsive behaviors would suggest that the reinforcer pathology model, which has been shown to be effective for other impulsive and addictive behaviors, such as obesity (e.g., Epstein, Salvy, et al., 2010), is potentially useful for texting while driving. In the present paper, 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, predicting, and controlling 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 is increasing.

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), and this multi-dimensional 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), marijuana (e.g., Collins, Vincent, Yu, Liu, & Epstein, 2014), alcohol (e.g., Murphy & MacKillop, 2006), cigarettes (e.g., MacKillop et al., 2008), e-cigarettes (e.g., Johnson, Johnson, Rass, & Pacek, 2017), and prescription drugs (Pickover, Messina, Correia, Garza, & Murphy, 2016). In addition, demand analysis has been successfully applied to various non-drug reinforcers, such as food (e.g., Epstein et al., 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).

These extensive literatures 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. In other words, we sought to provide proof of concept for the applicability of demand analysis to texting while driving.

Based on previous studies using the measure *likelihood of purchase* to quantify demand (e.g., Roma, Hursh, & Hudja, 2016), 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). An underlying assumption is that demand for social interaction from texting while driving reflects the individual's valuation of opportunities to engage in texting while driving as a social reinforcer.

Given the overarching goal of the present study, the first purpose of the present study was to examine 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 demand can successfully differentiate between drivers who frequently text while driving and those who infrequently text while driving. Based on the previous studies linking texting while driving and delay discounting (e.g., Hayashi et al., 2015), it was hypothesized that drivers who frequently texted while driving would show greater demand for social interaction than those who infrequently texted while driving.

The second purpose of the present study 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 are important for understanding the nature of the behavior of texting while driving. According to Koffarnus and Kaplan (2017), demand intensity and elasticity, respectively, are associated with use (consumption) level and dependence severity. Therefore, intense but elastic demand for texting while driving would be consistent with the notion that texting while driving is essentially excessive behavior, whereas non-intense but inelastic demand would be consistent with the notion that texting while driving shows the persistent nature of other impulsivity-related problems, such as substance use disorders. Because this is an exploratory investigation, we had no *a priori* hypothesis.

Finally, the third purpose of the present study was to assess the construct validity of the novel demand task by testing whether a variable known to affect texting while driving, such as delay to a destination (e.g., Hayashi et al., 2016), can affect drivers' demand for social interaction from texting while driving. In the hypothetical scenarios, two delay conditions were presented: Drivers receive a text message when their arrival to a destination is 15 min or 60 min. Based on the previous studies on delay discounting and texting while driving (Hayashi et al., 2016, 2017), it was hypothesized that demand for texting while driving would be greater under the 60-min delay condition than under the 15-min delay condition.

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 at 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 agreeing to participate, 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, etc.) 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, etc.) 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., Roma et al., 2016). 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). 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 non-zero 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 and is the point at which demand shifts from inelastic to elastic. In the present study, P_{max} refers to the amount of the fine at which the potential expenditure is maximized due to texting while driving, as 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. 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:

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

where Q is likelihood of replying to a text message of a given amount of the fine C, Q_0 is demand intensity, 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 (Figure 2), Equation 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 zero, 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 & Silberberg, 2008) was calculated based on the following formula:

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

where the parameters are the same as in Equation 1. 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 criteria are used to flag nonsystematic data for further consideration based on three components: (a) trend (no reduction in consumption from the first to last price), (b) bounce (local increase in consumption when price increases), and (c) reversal from zero (reoccurrence of consumption at higher price after consumption reaches zero). 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 selection of the parameters (the amount from $1 to $300) was arbitrary. If larger values had been used, the data might have not violated the trend criterion.

Group assignment and statistical analysis

The participants were stratified into two groups: the Texting While Driving (TWD) group (n = 25) and the Non-TWD group (n = 24). 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 TWD and Non-TWD groups, respectively.

For demographic measures, gender was analyzed with a chi-square test. Continuous variables were analyzed with an independent sample t-test. The Mann-Whitney U test was used to compare the five demand indices between the TWD and Non-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 analyses were performed with SPSS Version 24. The statistical significance level was set at .05.

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 Figure 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 TWD and Non-TWD groups under the 15- and 60-min delay conditions. For both groups and under both conditions, Equation 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 Figure 1 shows potential expenditure for replying to a text message as a function of amounts of the fine for the TWD and Non-TWD groups under the 15- and 60-min delay conditions.

Demand for replying to a text message while driving was more intense (higher Q_0 value) and less elastic (lower α value and higher essential value) for the TWD group than for the Non-TWD group, indicating that the 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. Similarly, the demand was more intense and less elastic under the 60-min delay condition than under the 15-min condition. The breakpoint, P_{max}, and O_{max} values show a similar pattern: The values were the highest for the TWD group under the 60-min delay condition.

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, Equation 1 could not be fitted to the data from 14 participants (5 for the TWD group and 9 for the Non-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, Kaplan, Becirevic, Roma, & Hursh, 2016, for the same arrangement), the data from the 11 participants were included in the analysis of essential value. This resulted in exclusion of the data from two participants in the TWD group (due to exclusive choice of 100 likelihood of replying at all amounts of the fine) and one participant in the Non-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 (Q_0), breakpoint, P_{max}, and O_{max} for the TWD and Non-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 TWD and Non-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 Q_0 value) and the least elastic (i.e., the lowest α value and the highest essential value) for the TWD group under the 60-min delay condition. The breakpoint, P_{max}, and O_{max} values show the same pattern, with an exception that the difference in breakpoint and $Pmax$ between the two delay conditions was not significant for the Non-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, 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 (delay to a destination), 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 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 general conclusion that a behavioral economic framework is applicable to texting while driving.

Translational utility of the present study

We believe that the present study contributes to the literature on texting while driving by providing a translational framework for extending behavioral economic principles derived from rigorous experimental research to better understand, predict, and potentially reduce texting while driving. Particularly, in the present *use-inspired basic research*, which is defined as "basic research that seeks to extend the frontiers of understanding but is also inspired by considerations of use" (Stokes, 1997, p. 74), our goals were (a) to extrapolate the behavioral economic principles of demand to texting while driving and (b) to determine whether texting while driving is well characterized by the principles. Although this type of extrapolation is hypothetical in nature, and its success in terms of better prediction and control of the behavior is essentially an empirical question (Zuriff, 1985), we believe that this extrapolation is at least logically coherent because (a) "consumption" of social interaction from texting while driving obeyed the law of demand, (b) the demand curves were well described by a variation of Hursh and Silberberg's (2008) exponential demand equation, and (c) the hypothetical task in the present study showed some construct validity.

At this point, however, the judgement for the success of this extrapolation primarily relies on the face validity. Previous research has well established the robustness and fruitfulness of behavioral economic demand principles in understanding, preventing, and treating various impulsivity-related problems, such as substance use disorders (Bickel et al., 2014; MacKillop, 2016), obesity (Epstein, Salvy, et al., 2010), and other health-related behaviors (Bickel et al., 2016). If texting while driving is similar to other impulsivity-related problems in an essential manner, namely the role of excessive demand in impulsive choice, 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) conceptual categories that allow us to address new questions, (b) independent variables to predict and influence texting while driving, and (c) dependent variables that may allow us to analyze texting while driving in different lights (Bickel et al., 2014).

Texting while driving as impulsive choice

In the present task, we conceptualize texting while driving as fundamentally an impulsive choice, and this conceptualization has important implications. As with a recent conceptualization of addiction as a choice disorder (e.g., Heyman, 2009), we view texting while driving as a choice (or a behavioral allocation) controlled by competing reinforcement contingencies that involve a trade-off between immediate and delayed reinforcers. Note that conceptualizing texting while driving as a choice is not just a matter of perspective. Rather, it lies at the center of how to understand and ultimately influence the behavior (cf. Lamb, Maguire, Ginsburg, Pinkston, & France, 2016).Therefore, "choosing" becomes the *prima facie* focus of investigation (Lamb et al., 2016). Furthermore, viewing texting while driving as a choice can direct our focus on identifying environmental/contextual factors that affect those choices (Lamb et al., 2016), as opposed to internalizing the cause(s) within drivers (i.e., addictive personality).

In this process of externalizing the causes of texting while driving, it is important to note that a maladaptive choice or behavioral allocation is often implicit and habitual, rather than explicit and deliberative (Lamb & Ginsburg, 2017; cf. Kahneman, 2011). As with other habitual behaviors, the maladaptive behavioral allocation of texting while driving would likely occur in specific contexts (environments), such as the presence of cues that induce a "craving" for the reinforcer (cf. Becirevic, Reed, & Amlung, 2017; MacKillop, O'Hagen, et al., 2010). Thus, identifying the variables in the context that lead to those behavioral allocations should be a fruitful direction for future research. This practical approach has proved useful in research on various impulsivity-related problems, such as substance use disorders (e.g., Bickel et al., 2014; Lamb & Ginsburg, 2017). Given the aforementioned similarity between texting while driving and other impulsivity-related problems, we believe a similar approach is useful for texting while driving. As an initial step, refining and validating the novel demand task developed in the present study would be a high priority.

Toward the development of useful research tool

We believe the choice-based research tool (cf. Sigurdsson, Taylor, & Wirth, 2013) developed in the present study has the potential to contribute to the development of effective prevention and intervention strategies for texting while driving. There are three advantages for such a research tool 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 need 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 et al., 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).

Needless to say, a hypothetical task is not without problems. Most importantly, the very nature of being hypothetical can be a major limitation. That is, 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). Indeed, previous research on risk-taking has shown that individuals tend to take more risks when outcomes are hypothetical than when they are real (e.g., Irwin et al., 1992), although, as mentioned previously, it would be ethically problematic to have participants actually engage in texting while driving.

It is important to note that the correspondence between self-reported and actual behavior, or say-do correspondence, is under conditional stimulus control (Lattal & Doepke, 2001) and thus the question of correspondence is ultimately an empirical question (Jacobs & Bickel, 1999; cf. Zuriff, 1985). Previous research has shown that there is close correspondence between choice under a hypothetical demand task and that 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, Miranda, et al., 2010) and treatment success (e.g., MacKillop & Murphy, 2007; Madden & Kalman, 2010). Finally, concurrent and convergent validity of a hypothetical demand task has been established through the studies demonstrating that demand is related to other established scales or accurately predicts categorical differences (e.g., Higgins et al., 2017; MacKillop et al., 2008). Taken together with the construct validity of the present task discussed previously, the strong empirical support in other areas of research would support the use of a hypothetical task in texting while driving. Nevertheless, it is still an empirical question whether similar correspondence can be obtained with texting while driving, and thus future research should address this issue.

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, 2017). 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 support the conclusion 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) and high caloric food (Epstein, Dearing, Roba, & Finkelstein, 2010). 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) associated with texting while driving.

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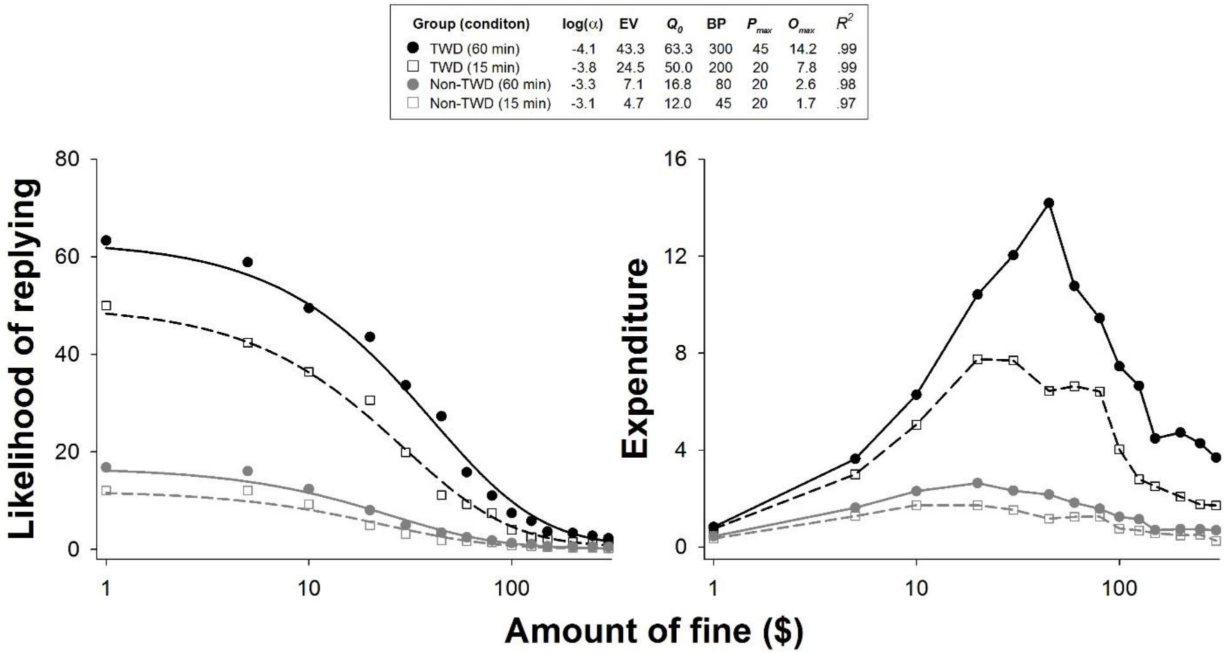

Figure 1.

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 TWD and Non-TWD groups under the 15- and 60-min delay conditions. EV = Essential value. BP = Breakpoint.

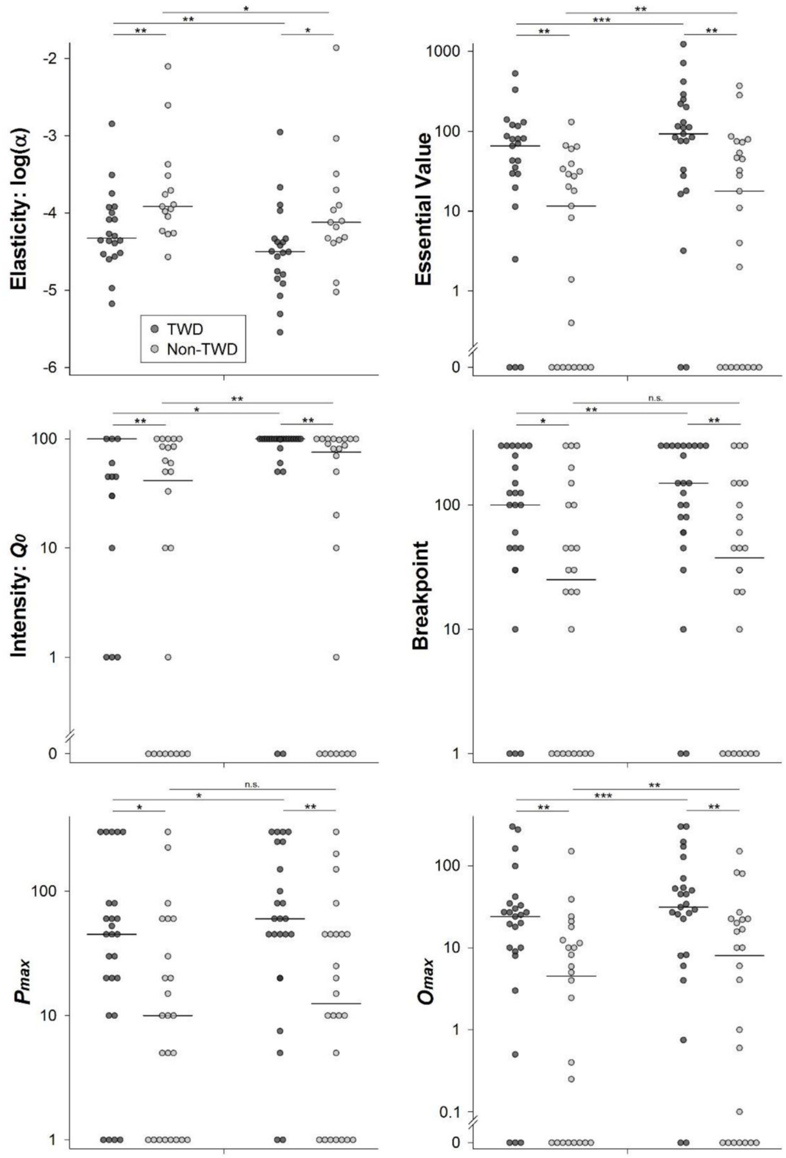

Figure 2.

Demand indices for the TWD and Non-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.

Table 1

Demographic Characteristics for TWD and Non-TWD Groups

Characteristics	TWD	Non-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)

Note. The numbers are means (and standard deviations) except for gender. TWD = Texting while driving.

[a]Mean differences depict the results of the stratification.

Table 2.

Comparisons of Demand Indices between TWD and Non-TWD Groups.

Indices	Condition	*U*	*p*	*r*
Elasticity	15-min	68.00	.006	0.46
	60-min	77.00	.015	0.41
Essential value	15-min	400.00	.003	0.44
	60-min	402.00	.002	0.45
Intensity	15-min	445.00	.003	0.43
	60-min	439.00	.003	0.43
Breakpoint	15-min	417.00	.018	0.34
	60-min	438.00	.005	0.40
P_{max}	15-min	415.00	.020	0.33
	60-min	434.00	.007	0.39
O_{max}	15-min	447.00	.003	0.42
	60-min	449.00	.003	0.43

Table 3.

Comparisons of Demand Indices across 15-min and 60-min Delay Conditions.

Indices	Group	*Z*	*p*	*r*
Elasticity	TWD	−3.25	.001	0.51
	Non-TWD	−2.16	.031	0.39
Essential value	TWD	3.95	<.000	0.58
	Non-TWD	2.90	.004	0.43
Intensity	TWD	2.38	.017	0.34
	Non-TWD	2.81	.005	0.40
Breakpoint	TWD	2.94	.003	0.42
	Non-TWD	0.61	.539	0.09
P_{max}	TWD	2.20	.028	0.31
	Non-TWD	1.08	.278	0.16
O_{max}	TWD	3.84	<.001	0.54
	Non-TWD	2.84	.004	0.41