10-2022

A behavioral economic demand analysis of media multitasking in the college classroom: A cluster analysis

Masahiro Toyama
Marshall University, toyama@marshall.edu

Yusuke Hayashi

Recommended Citation
Toyama, M., Hayashi, Y. A behavioral economic demand analysis of media multitasking in the college classroom: A cluster analysis. Current Psychology (2022). https://doi.org/10.1007/s12144-022-03894-2

A Behavioral Economic Demand Analysis of Media Multitasking in the College Classroom: A Cluster Analysis

Masahiro Toyama[1] and Yusuke Hayashi[2]

[1] Division of Natural Sciences & Mathematics, University of the Ozarks

[2] Division of Social Sciences and Education, Pennsylvania State University, Hazleton

Author Note

Masahiro Toyama (ORCID: 0000-0003-3012-1906), Division of Natural Sciences & Mathematics, University of the Ozarks, Clarksville, AR, USA (when the present study was conducted); Masahiro Toyama is now at Department of Psychology, Marshall University, Huntington, WV, USA; Yusuke Hayashi (ORCID: 0000-0002-2776-8461), Division of Social Sciences and Education, Pennsylvania State University, Hazleton, PA, USA.

Correspondence concerning this article should be addressed to Masahiro Toyama, Department of Psychology, Marshall University, One John Marshall Drive, Huntington, WV 25755, USA, E-mail: toyama@marshall.edu

Declarations

Funding

The current study did not receive any funding.

Conflicts of interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

Ethics approval

The institutional review board at the Pennsylvania State University reviewed the study protocol and deemed the study exempt.

Consent to participate

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

Availability of data and material

The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

Abstract

Media multitasking has brought concerns (e.g., lower productivity and performance) in multiple settings including college classrooms. The present study examined the behavior of texting in the classroom (TIC) by applying the behavioral economic demand theory while taking college students' different attitudes and behaviors of TIC into consideration. Undergraduate students (109 females and 73 males for valid data, whose average age was 19.4 [*SD* = 2.5]) completed questionnaires on demographic characteristics, TIC-related attitude and behavior, and a demand task with a hypothetical scenario, which aimed to quantify the value of social rewards from text messaging with demand intensity (i.e., excessiveness) and elasticity (i.e., persistence). A cluster analysis identified four distinct subgroups who had varying levels of attitude (i.e., perceiving TIC as appropriate or inappropriate) and frequency of TIC: Inappropriate-Low-Frequency, Inappropriate-High-Frequency, Appropriate-Moderate-Frequency, and Appropriate-High-Frequency subgroups. The subsequent analysis revealed that demand intensity and elasticity of the Inappropriate-Low-Frequency subgroup were significantly lower and higher, respectively, than those of the Inappropriate-High-Frequency and Appropriate-High-Frequency subgroups. In addition, in supplemental analyses of multiple regression, demand intensity, but not elasticity, significantly predicted frequencies of TIC. Considering these findings, excessive valuation of social rewards from text messaging, particularly characterized by its demand intensity, appears to play an important role in the frequency of TIC. The present study contributes to the literature on media multitasking by suggesting excessive valuation as a potential factor related to TIC and providing practical implications that can help explore effective interventions tailored for distinct types of college students who have varying TIC-related attitudes and behaviors.

Keywords: media multitasking, texting in the classroom, behavioral economics, demand analysis, cluster analysis, college students

A Behavioral Economic Demand Analysis of Media Multitasking in the College Classroom: A Cluster Analysis

As mobile phones are used almost everywhere across the world, nearly all (97%) people own a mobile phone in the United States (Pew Research Center, 2022). Related to the prevalence of mobile phone use, media multitasking, or using media (e.g., text messaging) while engaging in other media or non-media activities at the same time (van der Schuur et al., 2015), has brought some concerns in multiple settings. For example, previous research addressed problematic texting behaviors, such as texting while driving (e.g., Hayashi, Foreman, et al., 2019) and texting while walking (e.g., Igaki et al., 2019). Texting in the classroom (TIC) is another type of problematic texting behaviors (Hayashi, 2021) as texting has been reported as the most common in-class media multitasking activity using a mobile phone (e.g., Roberts et al., 2014). The present study focuses on examining cognitive and behavioral factors related to TIC among college students from a behavioral economic perspective.

According to previous research, college students engage in text messaging frequently, on average, spending 1.5 to 3.5 hours per day (Roberts et al., 2014; Rosen et al., 2013) and sending 77 to 97 text messages per day (Junco & Cotten, 2012; Lepp et al., 2014). In another study for college students (Olmsted & Terry, 2014), nearly all (97.5%) of their participants reported that they engaged in TIC at least occasionally. As media multitasking, such as TIC, can reduce productivity (Rubinstein et al., 2001; Sanbonmatsu et al, 2013), TIC has been found to be associated with poorer academic performance (Bjornsen & Archer, 2015; Ellis et al., 2010; Gingerich & Lineweaver, 2014). Thus, it is important to improve knowledge of TIC and related factors, which can help develop effective interventions to reduce TIC.

There are multiple factors related to TIC, which concern students' characteristics (e.g., motivation, personality, self-regulation, executive function) as well as instructors' behavior (Abel et al., 2012; Bolkan & Griffin, 2017; Hayashi & Nenstiel, 2021; Toyama & Hayashi, 2021a, 2021b; Wei et al., 2012; Wei & Wang, 2010). One of those factors that have been understudied is students' cognition about TIC, such as their attitude or perception of TIC being appropriate or inappropriate (Hayashi, 2021). While few studies had addressed this factor, Hayashi (2021) demonstrated some attitude-behavior discrepancy of TIC: college students who frequently engaged in TIC despite their perception of TIC as inappropriate showed greater degree of impulsive decision making (as determined by rates of delay discounting or subjective devaluation of future rewards) compared to those who infrequently engaged in TIC and/or those who perceived TIC as appropriate.

While TIC may involve multiple causes that can affect it in a complex way, this attitude-behavior discrepancy may be one of the hallmarks of TIC, which warrants further research. Thus, the present study focuses on specifically investigating this factor. For this investigation, we propose that a behavioral economic approach, which integrates behavioral science and principles of microeconomics for the purpose of functional analysis of economic processes (Hursh, 1980, 1984), can be useful. Particularly, one important feature of these behavioral economic research programs is a conceptual and methodological framework for quantifying excessive preference for a smaller but immediate reward, and this has been well characterized by the behavioral economic demand theory, according to which an impulsive behavior, as characterized by the attitude-behavior discrepancy, can be understood by the excessive valuation of the reward that maintains the impulsive behavior (cf. Bickel et al., 2014).

Demand is a fundamental economic concept referring to the amount of a commodity consumed at a given price. In demand analysis that allows for quantifying the subjective value of a commodity, a demand curve is often used to graphically show the amounts of a commodity consumed at varying prices. Two important indices generated from a demand analysis are demand intensity and change in demand elasticity (hereafter demand elasticity for the sake of simplicity; cf. Gilroy et al., 2020). Demand *intensity* refers to the consumption of a commodity at the lowest price (i.e., zero or the lowest available price) showing the consumption level when little or no constraint is added. This index is useful in addressing some problematic behaviors as it is related to the hedonic value one personally puts on a reward (e.g., how much they like or enjoy the reward) (Bickel et al., 2014). High demand intensity indicates excessiveness of consumption (Koffarnus & Kaplan, 2018). Despite its usefulness, demand intensity alone may not predict consumption at higher prices, so another index called demand *elasticity* should be examined together with demand intensity. Demand elasticity refers to how rapidly consumption decreases responding to increases in price (i.e., sensitivity of consumption to price increase). In opposition to an elastic demand, an *in*elastic demand can indicate lower sensitivity to increased prices or more persistence of consumption.

Previous studies (Hayashi & Blessington, 2021; Hayashi, Friedel, et al., 2019a) have shown that the behavioral economic demand theory could be applied to better understand the behavior of text messaging by addressing its excessiveness and persistence. That is, these studies have shown that both text-messaging while driving (Hayashi, Friedel, et al., 2019a) and text-message dependency (Hayashi & Blessington, 2021) can be characterized by higher intensity of demand for social interaction (i.e., excessiveness) as well as low elasticity of the demand (i.e., persistence), indicating that those who engage in the problematic text-message behaviors show greater valuation of social rewards from text messaging.

These literatures linking the text-messaging behaviors and the behavioral economic demand theory provide a compelling rationale to examine the utility of demand analysis in TIC. Specifically for TIC, what has not been addressed in previous research is whether students' attitude-behavior discrepancy as discussed earlier (or consistency between their attitude and behavior) can be well explained by their excessive valuation of social rewards associated with text messaging, as represented by two theoretically derived demand indices—demand intensity (i.e., excessiveness) and demand elasticity (i.e., persistence). Possibly, there may be different types of students in terms of their attitude and behavior of TIC (including students who has such attitude-behavior discrepancy versus other types of students), who may have varying characteristics with regard to the intensity and elasticity of demand for text messaging (in general, not specific to TIC). If this is the case, identifying specific groups of students who have different characteristics related to problematic texting behavior as indicated by their excessive valuation of social rewards would be helpful to develop effective interventions tailored for those different types of students to reduce their TIC. Thus, this direction of research applying the behavioral economic demand theory while addressing different attitudes and behaviors can have practical implications, but no previous studies, to our knowledge, has conducted such research.

The present study aimed to improve the knowledge of TIC using the behavioral economic demand theory while taking college students' different attitudes and behaviors of TIC into consideration. The overarching goal of the present study was to examine (a) whether there is a distinct subgroup of college students who demonstrate the attitude-behavior discrepancy in terms of TIC, and if so, (b) whether such a subgroup of students differ from other students in terms of their demand for social interaction from text messaging. Specifically, in an effort to evidence attitude-behavior discrepancies in college students' TIC, we first determined whether college students fell into discrete subgroups in terms of frequencies and attitudes of their TIC. To this end, we adopted a cluster analysis technique, which allowed us to identify naturally-occurring distinct subgroups based on similarities across selected variables, so that members of the resulting subgroups are as similar as possible to others within their subgroup and as different as possible to those in other subgroups (Clatworthy et al., 2005; Yim & Ramdeen, 2015). This is in contrast to previous studies (e.g., Hayashi, 2021) that employed simpler and more arbitrary classification approaches (e.g., median-split). It was hypothesized that college students would be grouped into distinct and practically meaningful subgroups that would differ in their levels of frequencies and attitudes of TIC, and one of such subgroups would be the one showing the attitude-behavior discrepancy (i.e., those who perceive TIC as inappropriate but still engage in TIC frequently).

If a subgroup of students who shows the attitude-behavior discrepancy is identified, a next logical step is to examine how the subgroup differs from other subgroups. Therefore, we compared a subgroup of students with the attitude-behavior discrepancy with other subgroups of students in terms of valuation of social rewards from text messaging, as represented by the intensity and elasticity of the demand. Based on the previous finding that students with the attitude-behavior discrepancy showed greater impulsive decision making (Hayashi, 2021), it was hypothesized that the subgroup of students with such attitude-behavior discrepancy would show greater valuation of social reward from text messaging, as represented by higher demand intensity (i.e., excessiveness) and lower elasticity (i.e., persistence), than other subgroups of students.

Method

Participants

We recruited 192 undergraduate students from introductory psychology courses at a university in the Northeastern United States for this study, and the students received course credit for their participation. Using the criteria developed by Stein et al. (2015), students who showed nonsystematic patterns of responding (n = 10) on the demand task were excluded from this study (details described below). The remaining sample consisted of 109 females and 73 males, and their mean age and years of higher education were 19.4 (SD = 2.5) and 1.4 (SD = 1.1), respectively.

Procedure

An online session was hosted on Qualtrics (Provo, UT). After agreeing to participate, the participants completed questionnaires on their demographic information (age, gender, and years of higher education) and their in-class text-messaging behavior as well as a demand task with a hypothetical scenario. The present study is a part of the larger survey and portions of the present data were reported in different studies with different goals and analyses ([blinded for review]). The Institutional Review Board at the second author's affiliated university reviewed the study protocol and deemed the study exempt.

Questionnaire on In-Class Text-Messaging Behavior

The questionnaire included four questions about TIC. Two questions assessed the frequencies of their sending and reading a text message in the classroom separately (e.g., "How often do you <u>send</u> a conversation through text, email, and/or social media (e.g., Facebook) while you are in class?") using a 5-point Likert scale ranging from 1 (*never*), 2 (*seldom/occasionally*), 3 (*sometimes*), 4 (*often/usually*), to 5 (*always*). Total scores of the two questions were calculated, and higher scores indicate higher frequencies of TIC. Cronbach's alpha with the current sample was .89.

The other two questions assessed their attitudes toward sending and reading a text message in the classroom separately (e.g., "In general, how inappropriate is it to read a conversation through text, email, and/or social media (e.g., Facebook) while you are in class?") using a 5-point Likert scale ranging from 1 (*not at all*), 2 (*slightly*), 3 (*moderately*), 4 (*very*), to 5 (*extremely*). Total scores of the two questions were calculated, and higher scores indicate more unfavorable attitudes (i.e., inappropriateness) toward TIC. Cronbach's alpha with the current sample was .92.

Hypothetical Text-Messaging Demand Task

To assess the demand for text messaging in a general context, a hypothetical text-messaging demand task was developed based on similar previous studies (Hayashi, Friedel, et al., 2019a; Reed et al., 2016; Roma et al., 2016). In this task, the participants indicated their likelihood of paying an extra charge to continue sending and receiving text messages using a visual analog scale. The following instruction was given on each trial:

> Suppose you have a prepaid cell phone that has a maximum number of text messages you can send and receive for each month. Once you hit the maximum, you have no other way to send and receive text messages for the rest of the month unless you pay an extra charge to unlock the limit. Imagine that you hit the maximum but you still have 5 days left before the next month begins. If the extra charge to unlock the limit is [amount], how likely you are to pay the extra charge (rating: 100) versus waiting for 5 days without sending and receiving text messages (rating: 0)?

The visual analogue scale, a horizontal line anchored with 0 (*definitely wait*) and 100 (*definitely pay*) on the left and right edges of the line, respectively, was located immediately below the instruction. On each trial, the participants rated their likelihood of paying the extra charge by dragging the slider bar of the visual analogue scale. The amount of the extra charge varied across trials in this order: $0.10, $1, $3, $5, $10, $15, $20, $30, $40, $50, $60, and $80.

The demand task can provide two important demand indices, demand intensity and demand elasticity, that indicate the level of valuation of a reward of interest. In the present study, demand intensity refers to the level of demand for text messaging at the lowest amount of the extra charge, and it was based on the observed data (i.e., the likelihood of paying when the extra charge was $0.10). Higher demand intensity indicates higher likelihood of paying the extra charge.

Demand elasticity in the present study refers to sensitivity of the demand to increases in the amount of the extra charge, and it was represented by essential value (EV; Hursh, 2014), which was calculated in two steps. First, the value of the α parameter was derived by fitting group or individual data to the exponentiated version of the demand equation (Koffarnus et al., 2015) using least squares nonlinear regression:

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

where Q is likelihood of paying a given amount of the extra charge C, Q_0 is demand intensity, α is the rate of change in elasticity, and k is a constant that denotes the range of likelihood of paying the extra charge in log units (k = 2 for all analyses; Gilroy et al., 2018). We chose the exponentiated version because it allows for inclusion of zero values in the analyses (Koffarnus et al., 2015).

Second, using the α value derived, essential value was calculated based on the following formula:

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

where the parameters are the same as in Equation 1. Please note that higher essential values indicate *lower* demand elasticity (i.e., greater insensitivity or persistence of the likelihood despite increases in the price). We used essential values for the analysis of the demand elasticity because Equation 1 could not be fit to data from some participants due to the likelihood being 0 for all the amounts, but essential values for these participants could be conceptualized as zero (see Hayashi, Friedel, et al., 2019a; Reed et al., 2016, for similar arrangements).

Data Exclusion, Group Assignment, and Data Analyses

As mentioned previously, we applied the criteria developed by Stein et al. (2015) to identify non-systematic responders and the data from 10 participants were excluded from analyses. The criteria flag nonsystematic data for further consideration in these three categories: (a) trend: consumption (cf. likelihood in the present study) not reduced by more than 0.025 log-unit range from the first to last price; (b) bounce: the proportion of "jumps" (defined as increases in consumption from one price to another greater than 25% of the consumption at the first price) greater than 10% of all price increases; and (c) reversal from zero: reoccurrence of nonzero consumption once zero consumption at two consecutive prices are observed. We excluded all data that violated the bounce and reversal-from-zero criteria but relaxed the trend criterion and did not exclude the data with zero consumption (i.e., exclusive choice of 0 as the likelihood for paying the extra charge), as mentioned previously. The exclusion rate in the present study (5.2%) is comparable to that of the previous studies with similar arrangements (e.g., Reed et al., 2016).

To determine whether college students can be classified into distinct subgroups in terms of their attitudes and frequencies of TIC, a hierarchical cluster analysis, which involves a series of sequential steps in which individual cases are merged together one at a time based on their similarities (Greenacre & Primicerio, 2013), was conducted with Ward's method as the method of clustering, squared Euclidian distances as the measure of the distance, and z-score conversion as the method of standardization (see Clatworthy et al., 2005; Yim & Ramdeen, 2015, for more technical details and the rationale of the choices of the parameters). To determine the number of clusters, we used the inverse scree technique (Lathrop & Williams, 1987), in which a sudden change in coefficient values was detected by visual inspection (see Yim & Ramdeen, 2015, for more technical details).

Once distinct subgroups of students who differed in terms of their attitudes and frequencies of TIC, the subgroups were compared on the demographic variables, in-class text-messaging behavior, and demand indices. With respect to the statistical analyses of the demographic variables and measures on in-class text-messing behavior, gender was analyzed by a chi-square test. Continuous variables were analyzed by a one-way analysis of variable (ANOVA) or by the Welch ANOVA if the assumption of homogeneity of variances, as assessed by Levene's test for equality of variances, was violated. The post-hoc pairwise comparisons were performed by the Tukey test or by the Games-Howell test if the assumption of homogeneity of variances was violated. The two demand indices were analyzed with the Kruskal-Wallis test because some data were not normally distributed. The post-hoc pairwise comparisons were conducted using the Dunn test (Dunn, 1964) with Bonferroni corrections. Lastly, as supplemental analyses, multiple linear regression was performed to determine whether the demand intensity and elasticity would predict attitudes and frequencies of TIC. All statistical analyses were performed with SPSS Version 27. The statistical significance level was set at .05.

Results

Figure 1 shows a scree plot of the cluster analysis demonstrating the change in the coefficient values as a function of the number of clusters. There was a discontinuous or robust increase in coefficient values (i.e., “jump”) between three- and four-cluster models, suggesting the model with four clusters best fits the present data. Table 1 shows the demographic characteristics of the four clusters. There was a statistically significant difference across the clusters for age, $F(3, 96.7) = 3.26$, $p = .025$, partial $\eta 2 = .042$, but no statistically significant difference was found for gender, $\chi^2(3) = 5.27$, and years of higher education, $F(3, 178) = 0.47$, $p = .703$, partial $\eta 2 = .008$.

Figure 2 shows the inappropriateness and frequency of in-class text-messaging behavior of each participant. The results of the ANOVA revealed the clusters differed significantly on inappropriateness, Welch's $F(3, 95.7) = 128.37$, $p < .001$, partial $\eta 2 = .679$, and frequency, Welch's $F(3, 94.6) = 182.69$, $p < .001$, partial $\eta 2 = .715$. The results of the post-hoc comparisons are shown in Table 2. Overall, the four clusters show distinctive patterns in terms of inappropriateness and frequency of in-class text messaging. Participants in Cluster 1 were characterized by high inappropriateness and low frequency of in-class text messaging and are termed here as *Inappropriate-Low-Frequency* users. Participants in Cluster 2 were characterized by high inappropriateness and high frequency and are termed as *Inappropriate-High-Frequency* users. Participants in Cluster 3 were characterized by low inappropriateness and moderate frequency and are termed as *Appropriate-Moderate-Frequency* users. Finally, participants in

Cluster 4 were characterized by low inappropriateness and high frequency and are termed as *Appropriate-High-Frequency* us*ers*.

Figure 3 shows the group medians of the likelihood of paying the extra charge as a function of the amounts of the charge and best-fitting demand curves for all clusters. For all clusters, Equation 1 described the data very well (R^2's >.93). Demand for text messaging was less intense (i.e., lower Q_0 value) and more elastic (i.e., lower essential value) for the Inappropriate-Low-Frequent users than other three types of users, indicating that the Inappropriate-Low-Frequency users were less likely to continue text messaging at the lowest amount of the extra charge and were more sensitive to increase in the amounts of the charge.

To further analyze the difference across the clusters, the demand indices were calculated based on the data from each participant, and Figure 4 shows median demand intensity (Q_0) and demand elasticity (EV) for all clusters. The results of the Kruskal-Wallis test revealed significant differences across clusters on the demand intensity, $\chi^2(3) = 12.43$, $p = .006$, and the demand elasticity, $\chi^2(3) = 12.85$, $p = .005$. Table 3 shows the results of the post-hoc comparisons performed by the Dunn-Bonferroni test.

Lastly, as supplemental analyses, multiple liner regression predicting attitudes and frequencies of TIC as outcome variables was performed with the two demand indices as predictors. The results showed that demand intensity ($\beta = .26$, $t = 3.61$, $p < .001$), but not demand elasticity ($\beta = .14$, $t = 1.92$, $p = .056$), significantly predicted frequencies of TIC, and that both demand intensity ($\beta = -.08$, $t = -1.10$, $p = .275$) and demand elasticity ($\beta = -.04$, $t = -0.58$, $p = .566$) did not significantly predict attitudes of TIC.

Discussion

The present study aimed to examine the behavior of TIC among college students by applying the behavioral economic demand theory while taking their different attitudes and behaviors of TIC into account. As discussed in detail below, we specified practically meaningful subgroups of students with a cluster analysis and demonstrated significant differences related to excessiveness and persistence of text messaging (indicated by the demand intensity and elasticity, respectively) among the distinct subgroups.

The results of the present study supported our first hypothesis that college students would be grouped into distinct and practically meaningful subgroups that would differ in their levels of frequencies and attitudes of TIC, and one of such subgroups would show the attitude-behavior discrepancy (i.e., those who frequently engaged in TIC despite their perception of its inappropriateness), as shown by the results of our cluster analysis and the significant differences among the four distinct subgroups of college students who differed in the combination of levels of frequencies (“low,” “moderate,” or “high”) and attitudes (“appropriate” or “inappropriate”) of TIC. This finding based on the more sophisticated (and less arbitrary) classification technique extends previous research that reported such a discrepancy (e.g., Hayashi, 2021), which further illustrates the importance of investigating the underlying mechanism of the discrepancy.

For our second hypothesis that the subgroup of students with the attitude-behavior discrepancy (i.e., those who perceived TIC as inappropriate but still engaged in TIC frequently) would show greater valuation of social rewards from text messaging, as represented by higher demand intensity and lower elasticity than other subgroups, our results only partially support this hypothesis. When compared with the Inappropriate-Low-Frequency subgroup (who might be considered “good students” as they did not engage in TIC frequently perceiving it as inappropriate), the attitude-behavior-discrepancy subgroup showed higher demand intensity and lower elasticity as expected. However, the levels of the two demand indices of the attitude-behavior-discrepancy subgroup did not differ from those of the other two subgroups. Thus, while Hayashi (2021) demonstrated that such an attitude-frequency discrepancy for TIC was related to impulsive decision making, the present findings suggest that the excessive valuation of social rewards (i.e., demand) could not completely explain the attitude-frequency discrepancy.

It should be noted, however, that the results of this study may have been affected by some potential statistical and methodological issues. Specifically, while Figure 3 shows some apparent differences, for example, between the Inappropriate-High-Frequency subgroup (i.e., students with the attitude-behavior discrepancy) and Appropriate-Moderate-Frequency subgroup, they were not statistically significant. This may have been influenced by the lack of sufficient statistical power due to the relatively small sample size of this study. Additionally or alternatively, a ceiling effect may have affected the results: the similarity or insignificant difference in the demand curves among the three subgroups other than the “good-student” subgroup may have been because their demand indices, particularly demand intensity, were too close to the upper limit (i.e., the maximum likelihood in this study was 100). In other words, there may actually have been differences among these three subgroups, which could not be detected in the present study due to the lack of statistical power and/or the ceiling effect. These issues should be addressed in future research having larger numbers of samples and/or using alternative measures.

Nevertheless, with respect to the role of excessive demand for text messaging in the frequency of TIC (not in the attitude-behavior discrepancy), the present results of the multiple regression analyses that demand intensity, but not elasticity, significantly and independently predicted the frequency of TIC have an important implication. In contrast to the previous findings on other texting behaviors indicating that both higher demand intensity and lower demand elasticity were associated with higher texting while driving (Hayashi, Friedel, et al., 2019a) and greater text-message dependency (Hayashi & Blessington, 2021), the present study suggests that TIC may be characterized by excessiveness (i.e., high demand intensity), rather than persistence (i.e., low demand elasticity), of text messaging. This finding that excessive valuation, particularly demand intensity, of text messaging in general predicted the frequency of TIC can correspond to previous findings suggesting associations of habitual use of text messaging with the frequency of TIC (e.g., Wei & Wang 2010). Future research is needed to identify how exactly the attitudes toward TIC would interact with excessive valuation of social interaction from text messaging in influencing habitual use of text messaging.

Implications for Interventions

In addition to its contribution to furthering the knowledge of TIC, the present study offers two implications for potential interventions for TIC. First, the present finding of identifying distinct four subgroups of college students can be useful in exploring effective interventions to reduce TIC. For example, two subgroups identified in this study had different attitudes toward TIC but still engaged in TIC frequently, which suggests that changing only students' attitude may not be an effective intervention to reduce the frequency of TIC. In addition, considering the lower (or moderate) frequency of the other subgroup who perceived TIC as appropriate, such an undesirable attitude may not necessarily lead to the problematic behavior (i.e., high frequency of TIC). Thus, in order to reduce their frequency of TIC, it may be necessary to address students' other characteristics in addition to their attitude.

Second, if the demand, or excessive valuation, of text messaging plays an important role in the frequency of TIC as discussed earlier, one potentially effective intervention is episodic future thinking, which can help enhance the salience of future, long-term outcomes of a certain behavior (Bickel et al., 2017). Previous research has shown that engaging in episodic future thinking reduces demand for food in a similar hypothetical task (Sze et al., 2017). This approach may also be useful for reducing the demand for TIC, which may result in decreasing its frequency. Future research should examine the effectiveness of this intervention to reduce TIC. As distinct subgroups have been identified in the present study, the intervention should possibly be tailored for different types of students with varying attitudes and behaviors, rather than using a one-size-fits-all approach indiscriminately targeting “college students” as a whole.

Limitations

Despite the contributions of the present study to directing potential future research, there were some limitations to be noted. First, in addition to the small sample size as discussed earlier, the results of this study were based on data from students in a single university, although this was the first study, to our knowledge, that applied demand analysis to TIC. In order to generalize the findings, it should be replicated with larger and diverse samples from various universities. In addition, while the cluster analysis allowed us to identify practically meaningful subgroups of college students, it could not determine, due to our cross-sectional design, whether there was a causal relationship between the characteristics indicated by the demand indices (i.e., excessiveness and persistence of text messaging) and TIC (or its attitude and frequency). In order to develop effective interventions for TIC as discussed earlier, such a causal relationship would need to be identified. Thus, future research should adopt experimental designs to test the causality. Third, while the demand task in the present study showed good concurrent validity based on the significant association between TIC frequencies and the demand intensity, we did not evaluate other types of validity (e.g., convergent validity; MacKillop et al., 2008) as well as test-retest reliability of the task (Johnson, & Bruner, 2013). To improve the utility of the demand task, it is advisable for future research to further evaluate the validity and reliability of the task. Lastly, the demand task in the present study was hypothetical and thus discrepancies between hypothetical and actual choice patterns can occur (Jacobs & Bickel, 1999). It is important to note, however, that this issue is empirical in nature: Previous research using similar demand tasks has documented high correspondence between hypothetical and actual choices (Amlung & MacKillop, 2015; Amlung et al., 2012; Wilson et al., 2016). Given the strong empirical support, we believe the use of the hypothetical task in the present study would be acceptable, at least in this exploratory study.

Conclusion

In conclusion, the present study was the first, to our knowledge, that aimed to explain the behavior of TIC by applying behavioral economic demand analysis and identified excessive valuation for text messaging as a potential factor related to the frequency of TIC. Considering our findings, we provided practical implications that can help explore effective interventions for distinct types of college students who have varying TIC-related attitudes and behaviors. These findings contribute to the literature on media multitasking in the college classroom.

References

Abel, J. I., Buff, C. L., & Abel, J. P. (2012). Can they defer the cellular lure? College students' self-control and cell phone usage. *Review of Business Research*, *12*, 101–106. Retrieved from http://rbr-journal.org/domains/RBR-JOURNAL/

Amlung, M., & MacKillop, J. (2015). Further evidence of close correspondence for alcohol demand decision making for hypothetical and incentivized rewards. *Behavioural Processes*, *113*, 187–191. https://doi.org/10.1016/j.beproc.2015.02.012

Amlung, M. T., Acker, J., Stojek, M. K., Murphy, J. G., & MacKillop, J. (2012). Is talk "cheap"? An initial investigation of the equivalence of alcohol purchase task performance for hypothetical and actual rewards. *Alcoholism: Clinical and Experimental Research*, *36*, 716–724. https://doi.org/10.1111/j.1530-0277.2011.01656.x

Bickel, W. K., Johnson, M. W., Koffarnus, M. N., MacKillop, J., & Murphy, J. G. (2014). The behavioral economics of substance use disorders: Reinforcement pathologies and their repair. *Annual Review of Clinical Psychology*, *10*, 641–677. https://doi.org/10.1146/annurev-clinpsy-032813-153724

Bickel, W. K., Stein, J. S., Moody, L. N., Snider, S. E., Mellis, A. M., & Quisenberry, A. J. (2017). Toward narrative theory: Interventions for reinforcer pathology in health behavior. In J. R. Stevens (Ed.), *Impulsivity* (pp. 227–267). Springer International Publishing. https://doi.org/10.1007/978-3-319-51721-6_8

Bjornsen, C. A., & Archer, K. J. (2015). Relations between college students' cell phone use during class and grades. *Scholarship of Teaching & Learning in Psychology*, *1*, 326–336. https://doi.org/10.1037/stl0000045

Bolkan, S., & Griffin, D. J. (2017). Students' use of cell phones in class for off-task behaviors: The indirect impact of instructors' teaching behaviors through boredom and students' attitudes. *Communication Education*, *66*, 313–329. https://doi.org/10.1080/03634523.2016. 1241888

Chiesa, A., & Serretti, A. (2014). Are mindfulness-based interventions effective for substance use disorders? A systematic review of the evidence. *Substance Use & Misuse*, *49*, 492–512. https://doi.org/10.3109/10826084.2013.770027

Chiou, W.-B., & Wu, W.-H. (2017). Episodic future thinking involving the nonsmoking self can induce lower discounting and cigarette consumption. *Journal of Studies on Alcohol and Drugs, 78*(1), 106–112. https://doi.org/10.15288/jsad.2017.78.106

Clatworthy, J., Buick, D., Hankins, M., Weinman, J., & Horne, R. (2005). The use and reporting of cluster analysis in health psychology: A review. *British Journal of Health Psychology*, *10*, 329–358. https://doi.org/10.1348/135910705X25697

Daniel, T. O., Stanton, C. M., & Epstein, L. H. (2013). The future is now: Reducing impulsivity and energy intake using episodic future thinking. *Psychological Science*, *24*, 2339–2342. https://doi.org/10.1177/0956797613488780

Dunn, O. J. (1964). Multiple comparisons using rank sums. *Technometrics*, *6*, 241–252. https://doi.org/10.1080/00401706.1964.10490181

Ellis, Y., Daniels, B. W., & Jauregui, A. (2010). The effect of multitasking on the grade performance of business students. *Research in Higher Education Journal, 8*, 1–10 http://aabri.com/rhej.html

Gilroy, S. P., Kaplan, B. A., & Reed, D. D. (2020). Interpretation(s) of elasticity in operant demand. *Journal of the Experimental Analysis of Behavior*, *114*(1), 106–115. https://doi.org/10.1002/jeab.610

Gilroy, S. P., Kaplan, B. A., Reed, D. D., Koffarnus, M. N., & Hantula, D. A. (2018). The Demand Curve Analyzer: Behavioral economic software for applied research. *Journal of the Experimental Analysis of Behavior*, *110*(3), 553–568. https://doi.org/10.1002/jeab.479

Gingerich, A. C., & Lineweaver, T. T. (2014). OMG! Texting in class = u fail :(Empirical evidence that text messaging during class disrupts comprehension. *Teaching of Psychology, 41*, 44–51. https://doi.org/10.1177/0098628313514177

Greenacre, M., & Primicerio, R. (2013). *Multivariate analysis of ecological data*. Fundación BBVA.

Hayashi, Y. (2021). Attitude moderates the relation between frequency of media multitasking in the classroom and delay discounting. *The Psychological Record*, *71*(2), 211–218. https://doi.org/10.1007/s40732-020-00443-w

Hayashi, Y., & Blessington, G. P. (2021). Excessive valuation of social interaction in text-message dependency: A behavioral economic demand analysis. *The Psychological Record, 71*(2), 237–245. https://doi.org/10.1007/s40732-020-00418-x

Hayashi, Y., Friedel, J. E., Foreman, A. M., & Wirth, O. (2019a). A behavioral economic analysis of demand for texting while driving. *The Psychological Record, 69*(2), 225–237. https://doi.org/10.1007/s40732-019-00341-w

Hayashi, Y., Friedel, J. E., Foreman, A. M., & Wirth, O. (2019b). A cluster analysis of text message users based on their demand for text messaging: A behavioral economic approach. *Journal of the Experimental Analysis of Behavior*, *112*(3), 273–289. https://doi.org/10.1002/jeab.554

Hayashi, Y., Foreman, A. M., Friedel, J. E., & Wirth, O. (2019). Threat appeals reduce impulsive decision making associated with texting while driving: A behavioral economic approach. *PLOSONE*, *14*(3), e0213453. https://doi.org/10.1371/journal.pone.0213453

Hayashi, Y., & Nenstiel, J. N. (2021). Media multitasking in the classroom: Problematic mobile phone use and impulse control as predictors of texting in the classroom. *Current Psychology*, *40*, 4500–4506. https://doi.org/10.1007/s12144-019-00395-7

Hursh, S. R. (1980). Economic concepts for the analysis of behavior. *Journal of the Experimental Analysis of Behavior, 34*, 219–238. https://doi.org/10.1901/jeab.1980.34-219

Hursh, S. R. (1984). Behavioral economics. Journal of the Experimental Analysis of Behavior, 42, 435–452. https://doi.org/10.1901/jeab.1984.42-435

Hursh, S. R. (2014). Behavioral economics and the analysis of consumption and choice. In F. K. McSweeney & E. S. Murphy (Eds.), *The Wiley Blackwell handbook of operant and classical conditioning* (pp. 275–305). John Wiley & Sons.

Igaki, T., Romanowich, P., & Yamagishi, N. (2019). Using smartphones while walking is associated with delay but not social discounting. *The Psychological Record*, *69*, 513–524. https://doi.org/10.1007/s40732-019-00348-3

Jacobs, E. A., & Bickel, W. K. (1999). Modeling drug consumption in the clinic using simulation procedures: Demand for heroin and cigarettes in opioid-dependent outpatients. *Experimental and Clinical Psychopharmacology*, *7*, 412–426. https://doi.org/10.1037/1064-1297.7.4.412

Johnson, M. W., & Bruner, N. R. (2013). Test–retest reliability and gender differences in the Sexual Discounting Task among cocaine-dependent individuals. *Experimental and Clinical Psychopharmacology*, *21*, 277–286. https://doi.org/10.1037/a0033071

Junco, R., & Cotten, S. R. (2012). No A 4 U: The relation- ship between multitasking and academic performance. *Computers & Education*, *59*, 505–514. https://doi.org/10.1016/j.compedu.2011.12.023

Koffarnus, M. N., Franck, C. T., Stein, J. S., & Bickel, W. K. (2015). A modified exponential behavioral economic demand model to better describe consumption data. *Experimental and Clinical Psychopharmacology*, *23*, 504–512. https://doi.org/10.1037/pha0000045

Koffarnus, M. N., & Kaplan, B. A. (2018). Clinical models of decision making in addiction. *Pharmacology Biochemistry and Behavior*, *164*, 71–83. https://doi.org/10.1016/j.pbb.2017.08.010

Lathrop, R. G., & Williams, J. E. (1987). The reliability of inverse scree tests for cluster analysis. *Educational and Psychological Measurement*, *47*, 953–959. https://doi.org/10.1177/0013164487474010

Lepp, A., Barkley, J. E., & Karpinski, A. C. (2014). The relationship between cell phone use, academic performance, anxiety, and satisfaction with life in college students. *Computers in Human Behavior*, *31*, 343–350. https://doi.org/10.1016/j.chb.2013.10.049

MacKillop, J., Murphy, J. G., Ray, L. A., Eisenberg, D. T. A., Lisman, S. A., Lum, J. K., & Wilson, D. S. (2008). Further validation of a cigarette purchase task for assessing the relative reinforcing efficacy of nicotine in college smokers. *Experimental & Clinical Psychopharmacology, 16*, 57–65. https://doi.org/10.1037/1064- 1297.16.1.57

Olmsted, N. M., & Terry, C. P. (2014). Who's texting in class? A look at behavioral and psychological predictors. *Psi Chi Journal of Psychological Research, 19*, 183–190. https://doi.org/10.24839/2164-8204.JN19.4.183

Pew Research Center. (2022). *Mobile fact sheet.* Retrieved from http:// www.pewinternet.org/fact-sheet/mobile/

Roberts, J. A., Yaya, L. H. P., & Manolis, C. (2014). The invisible ad- diction: Cell-phone activities and addiction among male and female college students. *Journal of Behavioral Addictions, 3*, 254–265. https://doi.org/10.1556/JBA.3.2014.015

Roma, P. G., Hursh, S. R., & Hudja, S. (2016). Hypothetical purchase task questionnaires for behavioral economic assessments of value and motivation. *Managerial and Decision Economics*, *37*, 306–323. https://doi.org/10.1002/mde.2718

Rosen, L. D., Carrier, L. M., & Cheever, N. A. (2013). Facebook and texting made me do it: Media-induced task-switching while studying. *Computers in Human Behavior, 29*, 948–958. https://doi.org/10.1016/j.chb.2012.12.001

Rubinstein, J. S., Meyer, D. E., & Evans, J. E. (2001). Executive control of cognitive processes in task switching. *Journal of Experimental Psychology. Human Perception & Performance, 27*, 763–797. https://doi.org/10.1037//0096-1523.27.4.763

Sanbonmatsu, D.M., Strayer, D. L., Medeiros-Ward, N., &Watson, J.M. (2013). Who multi-tasks and why? Multi-tasking ability, perceived multi-tasking ability, impulsivity, and sensation seeking. *PLoSOne*, *8*(1), e54402. https://doi.org/10.1371/journal.pone.0054402

Snider, S. E., LaConte, S. M., & Bickel, W. K. (2016). Episodic future thinking: Expansion of the temporal window in individuals with alcohol dependence. *Alcoholism: Clinical and Experimental Research*, *40*(7), 1558–1566. https://doi.org/10.1111/acer.13112

Stein, J. S., Koffarnus, M. N., Snider, S. E., Quisenberry, A. J., & Bickel, W. K. (2015). Identification and management of nonsystematic purchase-task data: Towards best practice. *Experimental and Clinical Psychopharmacology*, *23*, 377–386. https://doi.org/10.1037/pha0000020

Stein, J. S., Tegge, A. N., Turner, J. K., & Bickel, W. K. (2018). Episodic future thinking reduces delay discounting and cigarette demand: an investigation of the good-subject effect. *Journal of Behavioral Medicine*, *41*(2), 269–276. https://doi.org/10.1007/s10865-017-9908-1

Stein, J. S., Wilson, A. G., Koffarnus, M. N., Daniel, T. O., Epstein, L. H., & Bickel, W. K. (2016). Unstuck in time: Episodic future thinking reduces delay discounting and cigarette smoking. *Psychopharmacology*, *233*(21–22), 3771–3778. https://doi.org/10.1007/s00213-016-4410-y

Sze, Y. Y., Stein, J. S., Bickel, W. K., Paluch, R. A., & Epstein, L. H. (2017). Bleak present, bright future: Online episodic future thinking, scarcity, delay discounting, and food demand. *Clinical Psychological Science*, *5*(4), 683–697. https://doi.org/10.1177/2167702617696511

Toyama, M., & Hayashi, Y. (2021a). Links of personality traits to media multitasking: Conscientiousness predicts mobile phone use in the college classroom. *Current Psychology*. Advance online publication. https://doi.org/10.1007/s12144-020-01258-2

Toyama, M., & Hayashi, Y. (2021b). Personality and media multitasking in the college classroom: Context-dependent implications of conscientiousness and agreeableness. *Current Psychology*. Advance online publication. https://doi.org/10.1007/s12144-021-01793-6

van der Schuur, W. A., Baumgartner, S. E., Sumter, S. R., & Valkenburg, P. M. (2015). The consequences of media multitasking for youth: A review. *Computers in Human Behavior*, *53*, 204–215. https://doi.org/10.1016/j.chb.2015.06.035

Yim, O., & Ramdeen, K. T. (2015). Hierarchical cluster analysis: Comparison of three linkage measures and application to psychological data. *The Quantitative Methods for Psychology*, *11*, 8–21. https://doi.org/10.20982/tqmp.11.1.p008

Wei, F.-Y. F., & Wang, Y. K. (2010). Students' silent messages: Can teacher verbal and nonverbal immediacy moderate student use of text messaging in class? *Communication Education*, *59*, 475–496. https://doi.org/10.1080/03634523.2010.496092

Wei, F.-Y. F., Wang, Y. K., & Klausner, M. (2012). Rethinking college students' self-regulation and sustained attention: Does text messaging during class influence cognitive learning? *Communication Education*, *61*, 185–204. https://doi.org/10.1080/03634523.2012. 672755

Wilson, A. G., Franck, C. T., Koffarnus, M. N., & Bickel, W. K. (2016). Behavioral economics of cigarette purchase tasks: Within-subject comparison of real, potentially real, and hypothetical cigarettes. *Nicotine & Tobacco Research*, *18*, 524–530. https://doi.org/10.1093/ntr/ntv154

Table 1

Demographic Characteristics for All Clusters

Characteristics	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Gender				
Female	23	29	33	24
Male	22	10	26	15
Age in years*	19.7 (2.6)	18.8 (1.0)	19.9 (3.6)	18.8 (1.0)
Years of higher education	1.4 (1.1)	1.3 (1.0)	1.5 (1.3)	1.2 (1.1)

Note. The numbers are means (and *SD's*) except for Gender. Cluster 1 = Inappropriate-Low-Frequency subgroup. Cluster 2 = Inappropriate-High-Frequency subgroup. Cluster 3 = Appropriate-Moderate-Frequency subgroup. Cluster 4 = Appropriate-High-Frequency subgroup.

*p < .05.

Table 2

Post-Hoc Comparisons of In-Class Text Messaging among Clusters

Measures	Comparison	*Δ*	*SE*	*p*	95% CI
Inappropriateness	C1 & C2	0.52	0.24	.135	[-0.10, 1.14]
	C1 & C3	4.05	0.26	< **.001**	[3.36, 4.74]
	C1 & C4	3.88	0.29	< **.001**	[3.12, 4.63]
	C2 & C3	3.53	0.25	< **.001**	[2.89, 4.18]
	C2 & C4	3.36	0.27	< **.001**	[2.64, 4.07]
	C3 & C4	-0.18	0.30	.934	[-0.95, 0.60]
Frequency	C1 & C2	-4.17	0.28	< **.001**	[-4.92, -3.43]
	C1 & C3	-1.27	0.24	< **.001**	[-1.88, -0.66]
	C1 & C4	-4.74	0.22	< **.001**	[-5.32, -4.15]
	C2 & C3	2.90	0.29	< **.001**	[2.14, 3.66]
	C2 & C4	-0.56	0.28	0.188	[-1.30, 0.170]
	C3 & C4	-3.47	0.23	< **.001**	[-4.07, -2.86]

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

Table 3

Post-Hoc Comparisons of Demand Indices among Clusters

Indices	Comparison	*Z*	*p*	*r*
Intensity	C1 & C2	-2.70	**0.041**	0.29
	C1 & C3	-1.24	1.000	0.12
	C1 & C4	-3.06	**0.013**	0.33
	C2 & C3	1.68	0.562	0.17
	C2 & C4	0.35	1.000	0.04
	C3 & C4	-2.06	0.237	0.21
Elasticity	C1 & C2	-2.70	**0.042**	0.29
	C1 & C3	-2.15	0.190	0.21
	C1 & C4	-3.34	**0.005**	0.36
	C2 & C3	0.80	1.000	0.08
	C2 & C4	0.62	1.000	0.07
	C3 & C4	-1.48	0.827	0.15

Note. The *p* values were adjusted for multiple comparisons according to the Bonferroni procedure. C1 = Inappropriate-Low-Frequency subgroup. C2 = Inappropriate-High-Frequency subgroup. C3 = Appropriate-Moderate-Frequency subgroup. C4 = Appropriate-High-Frequency subgroup. Bold numbers indicate statistical significance.

Figure 1

Scree Plot of the Cluster Analysis

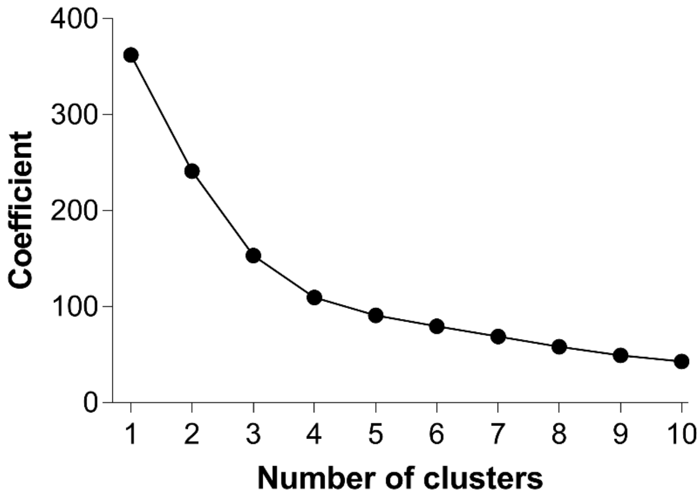
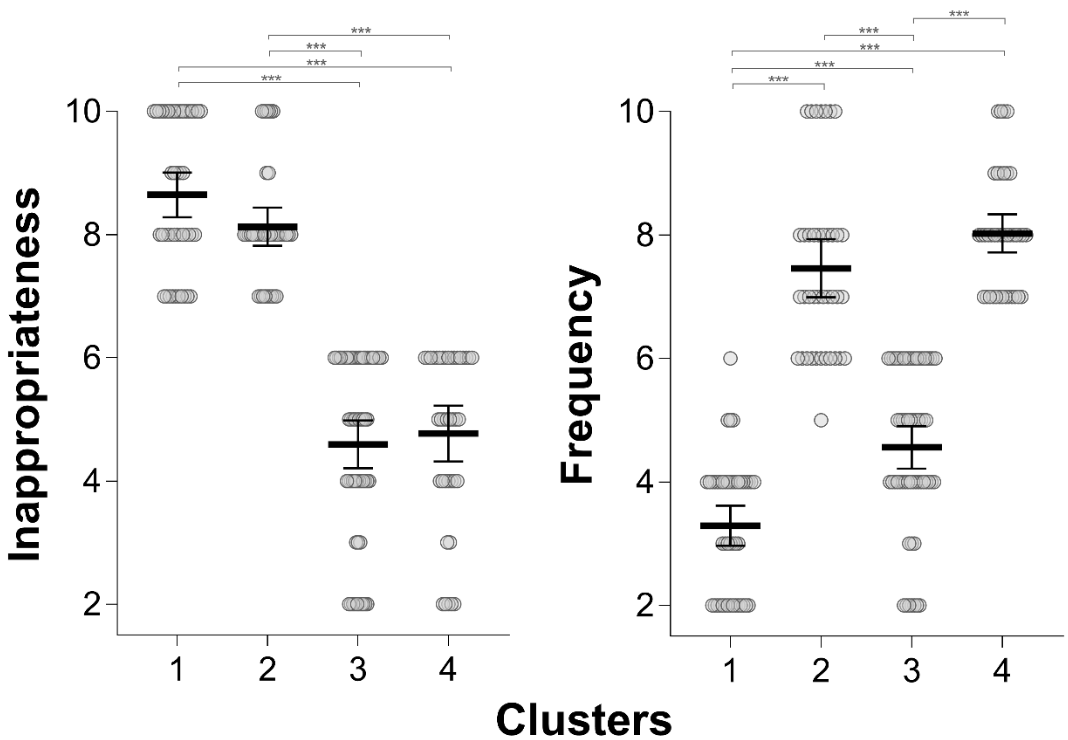


Figure 2

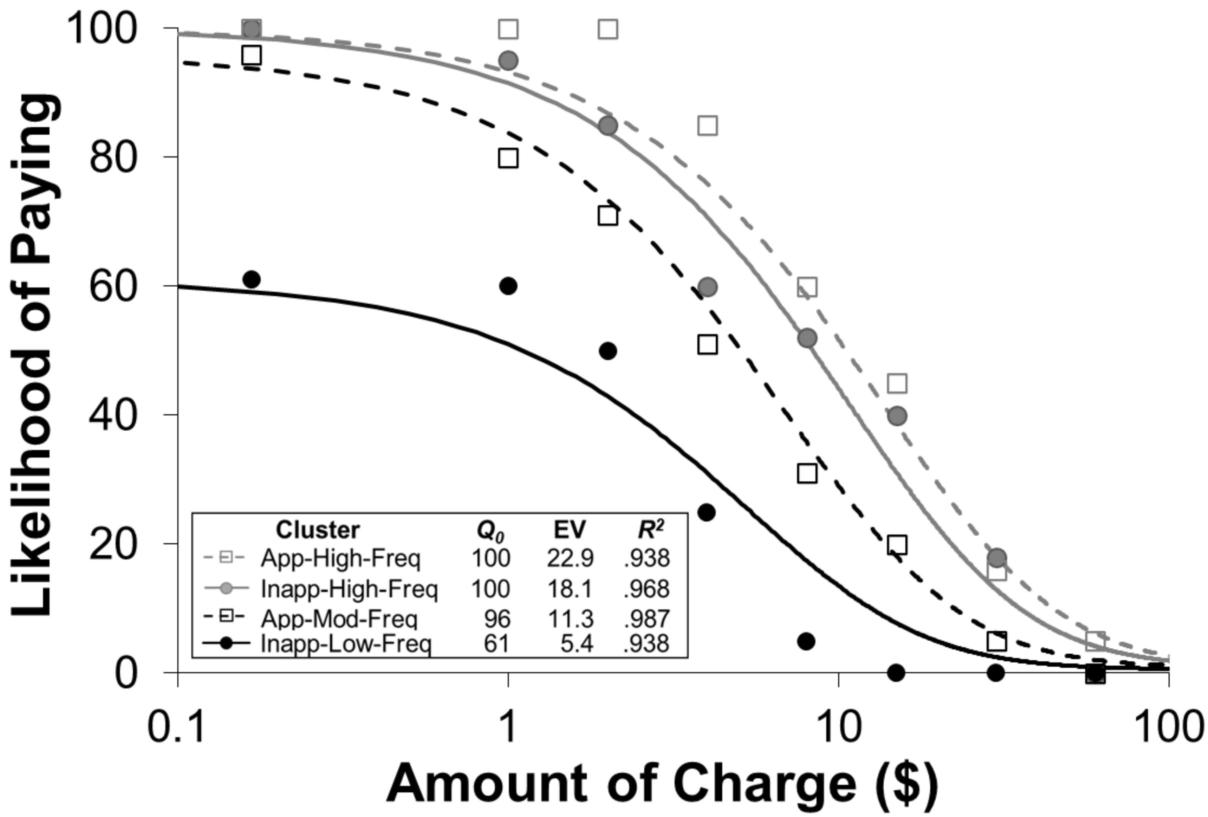
Inappropriateness and Frequency of In-Class Text-Messaging Behavior for All Clusters



Note. Error bars indicate 95% confidence intervals and thick horizontal lines within the error bars indicate means. Cluster 1 = Inappropriate-Low-Frequency subgroup. Cluster 2 = Inappropriate-High-Frequency subgroup. Cluster 3 = Appropriate-Moderate-Frequency subgroup. Cluster 4 = Appropriate-High-Frequency subgroup. $^{***}p < .001$.

Figure 3

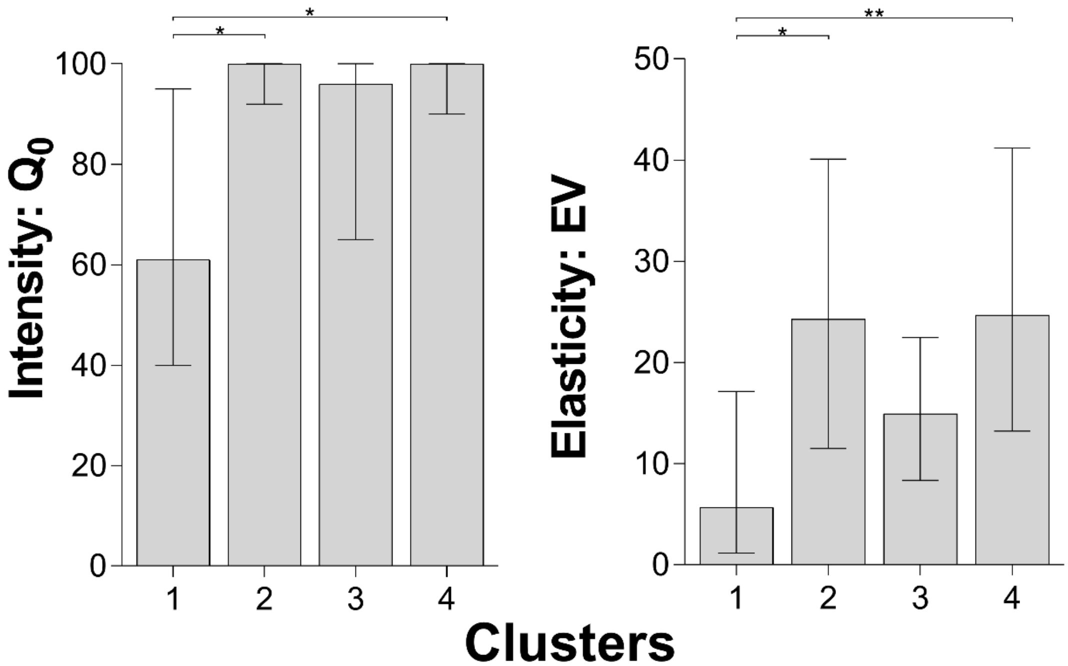
Likelihood of Paying the Extra Charge and Best-Fitting Demand Curves as a Function of the Amounts of the Extra Charge



Note. EV = essential value.

Figure 4

Median Demand Intensity and Elasticity for All Clusters



Note. Error bars indicate 95% confidence intervals. Cluster 1 = Inappropriate-Low-Frequency subgroup. Cluster 2 = Inappropriate-High-Frequency subgroup. Cluster 3 = Appropriate-Moderate-Frequency subgroup. Cluster 4 = Appropriate-High-Frequency subgroup. $^{*}p$ <.05. $^{**}p$ <.01.