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Collecting Text Messages from College Students:
Evaluating a Novel Methodology

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Abstract

Social interaction, particularly in older adolescents, increasingly involves computer-mediated communication. Although studies of public computer-mediated communication are increasingly common, studies of private text messaging remain rare. As approaches for obtaining such data evolve with technological advances, developmental scientists need designs in which to use such approaches that reduce sampling biases in both participants and text messages. In this study (n=854; 46% male; 22% African American, 60% European American), we examined selection biases in the participant sample (i.e., factors associated with actual participation), procedural biases in the participant sample (i.e., factors related to failed data capture due to technological or procedural issues), and selection biases in the sample of text messages (i.e., based on self-reported reasons for texting). Findings from our study suggest that studying human interaction directly through analysis of text message data is not only feasible, but also may be successfully undertaken with minimal biases regarding sample selection and text message selection among those who are engaged in research and engaged in text messaging outside of the study context. However, biases may occur depending on the type of platform (iPhone versus Android) used by participants for texting.

KEYWORDS: Text Messaging, Communication, Recruitment Methods

Data Sharing Statement: Due to the potentially sensitive nature of the data, we cannot share raw data from this project.

Collecting Text Messages from College Students:
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In the current methodological study, we introduce a novel design for collecting private text messaging data in a college student sample, evaluate potential selection biases in both participant and text messaging data, and describe relative trade-offs that underlie the procedure. The study is motivated by the changing nature of social behavior which increasingly involves computer-mediated communication, particularly among older adolescents and young adults (Anderson & Jiang, 2018). Although the study of computer-mediated communication has skyrocketed (Zhang & Leung, 2015), most research has examined open (e.g., Twitter) or networked (e.g., Facebook) platforms rather than more closed and personal platforms (e.g., text messaging; Manžuch, 2017). The relative lack of attention to text messaging analyses is not surprising given the many challenges that these data present (Underwood, Rosen, More, Ehrenreich & Gentsch, 2012), including rapidly changing approaches for capturing text message data in order to keep pace with technological updates to different cell phone operating systems (e.g., iPhones and Androids). However, the omission of studies focused on private text messaging neglects what may be a particularly salient form of online social interaction that occurs outside of a large public eye.

That text messaging is a popular form of social behavior, growing in salience with adolescent development, is undeniable. In the United States (US), nearly 100% of young adults today own a cell phone, with 94% owning smartphones (Smith & Anderson, 2018). Moreover, 45% of US teens say they are online “almost constantly” (Anderson & Jiang 2018) and 53% text on any given day, sending an average of 55 text messages per day (Rideout, 2016). Although texting platforms vary, in the US between 2014-2015 (when our data were collected), 88% of teens reported using text messaging (e.g., iMessage or SMS texting) to connect with their friends at least occasionally (with 55% doing so daily; Lenhart, Smith, Anderson, Duggan & Perrin, 2015). In contrast, 42% of US teens reported using other messaging apps, with only 14% reporting using these apps every day. Moreover, the limited literature on the content of these text messages suggests that older adolescents use text messaging as a platform to discuss a variety of topics important to their lives, including relationships, finances, school, risky behavior, and much more (Fletcher, Benito-Gomez, & Blair, 2018). Whether the mechanisms of existing theories regarding social development equally capture online as offline social interaction, both in form and in relation to adaptive functioning, however, remains to be seen. To better understand the structure and content of social interactions via text messaging, we need methods that successfully recruit participants into studies that directly examine text messaging threads.

Methods for Collecting Text Messaging and Mobile Aided Data

Leading the field in the study of text messaging in adolescents, Underwood and colleagues provided Blackberry phones to high school students, which enabled them to capture the content of private text messages over the span of years (Ehrenreich, Underwood & Ackerman, 2014; Underwood & Ehrenreich, 2017; Underwood, Ehrenreich, More, Solis, & Brinkley, 2015; Underwood, Rosen, More, Ehrenreich & Gentsch, 2012). This work has demonstrated that, although most text messaging content is positive or neutral, specific types of negative and deviant text messaging content relate to adolescent problem behaviors and substance use. For example, text messaging about antisocial behavior predicts increases in rule breaking across the 9th grade year. These findings have clear implications for social development in that they highlight the important role of private text message communication in maintaining and escalating youths' deviant peer affiliations. Although other researchers have examined a variety of public platforms for online social interaction and the great potential for social media to transform peer relations (e.g., Nesi, Choukas-Bradley & Prinstein, 2018a, 2018b), the work by Underwood and our group (Jensen & Hussong, 2019; Jensen, Hussong, Haston & Scales, 2018) remain the only studies that directly examine private text messaging, particularly as related to offline behavior.

However, other researchers have added to our understanding of methods for collecting text message data by studying what predicts participation in mobile technology aided studies more generally. Synthesizing this work, Wenz, Jackle and Couper (2019) describe three factors that may predict willingness to participate in such studies. These include respondent characteristics (e.g., device familiarity, physical limitations in using technology, type of internet access, mobile device specifications such as storage capacity, and time constraints), respondent data concerns (e.g., privacy and security concerns, prior study cooperativeness, and time in panels for a longitudinal design) and task characteristics (e.g., download and installation of app required, active versus passive data collection, upload of data required, technical demands, and privacy concerns). Studies evaluating this model identify varying respondent factors related to hypothetical willingness to participate (as actual participation rates are rarely assessed), with higher rates among people with more technological sophistication (more phone use, better technical skills); with lower privacy, security and trust concerns; with more familiarity with the research team (through prior waves of participation); and from certain demographic groups (those with more education, women, younger participants in adult samples; Ochoa & Revilla, 2018; Revilla, Couper & Ochoa, 2019). Hypothetical participation rates also vary significantly based on task characteristics including time and technical demands as well as perceived risks to privacy (Ochoa & Revilla, 2018; Revilla et al., 2019; Wenz et al., 2019).

The design evaluated in the current study was informed by many of the barriers to participation reported in these and other studies (e.g., Lind, Byrne, Wicks, Smidt, & Allen, 2018). First, we targeted individuals more likely to participate as a population of interest (i.e., college students who are younger, more technically skilled, and with more education than their older, non-college participating counterparts). Second, the design built on a two-session parent study that participants first completed before recruitment into the text messaging study, increasing familiarity with the research team. Third, the task was brief and immediate (reducing time constraints), occurred on their own phones (with which they were familiar as opposed to researcher-provided phones), included the downloading of text messages in the prior two weeks (instead of future messages) so participants knew what information was shared with the research team (potentially reducing privacy concerns and increasing respondent control). An added advantage of this approach is that reactance (participants changing their behavior because they know it is being monitored) was reduced. Fourth, to further reduce privacy concerns, we conducted downloads with the respondent present at all times, used computers to conduct downloads that had banker (privacy) screens, developed software to download text messages without them appearing on the screen for researchers to view, and replaced all identifying phone numbers with relationship codes for added confidentiality (e.g. mother's 919-919-9191 number was replaced by the relationship code for mothers=1). We also explained to participants that their text data would never be uploaded to a server or stored on a device with a live internet connection at any time, only IRB-approved researchers engaged in analysis would view the text messages, and participants could request that we destroy their data at any time.

Identifying Sources of Bias

We evaluated this method of collecting text messages in terms of selection biases in the participant sample (i.e., factors associated with actual participation), procedural biases in the participant sample (i.e., factors related to failed data capture due to technological and procedural issues), and selection biases in the sample of text messages (i.e., based on self-reported reasons for texting). Moreover, we conducted this study as an adjunct to a larger investigation of substance use in college students in 2015. This is a potentially informative recruitment pool because inclusion criteria involved prior alcohol use thus increasing potential engagement in illegal or deviant behaviors which may relate to privacy concerns regarding participation in a text messaging study.

We posited that participation in the study would primarily be related to potential privacy concerns motivated by the desire to (a) conceal deviant or illegal behavior (i.e., externalizing symptoms and substance use), (b) present well to others (i.e., social desirability and self-reports of dishonest reporting), (c) avoid potential risks (including those to privacy) in those high in anxiety or distress, (d) protect others in the social network who engage in deviant behavior, (e) decrease social vulnerability for members of ethnic minority groups (for whom there is a history of distrust of researchers; Corbie-Smith, Thomas, & George, 2002; Fisher & Wallace, 2000), and (f) to be less impulsive (resulting in wanting more time to consider the decision to participate). Biases in these factors would also limit generalizability of the sample in studying substance use, the target behavior of the parent study and a social behavior of significant interest to understanding adaptive functioning in young adulthood. Moreover, these measures are aligned with potential reasons why participants might have privacy concerns with regard to participating in the study and may provide insight into how those privacy concerns could translate into biases in the study of social behaviors that may be particularly relevant during young adulthood. In addition, to evaluate bias in the content of text messages, we examined whether self-reported reasons for texting (including feeling pressure, to facilitate substance use behaviors, to seek support, to engage in social comparison, and to be social) were related to study participation or procedural bias.

The Current Study

In the current study, we evaluated a design for collecting text message data in a college student sample by examining selection bias in the participant sample (i.e., factors associated with actual participation), procedural bias in the participant sample (i.e., factors related to failed data capture due to technological and procedural issues), and selection bias in the sample of text messages (i.e., based on self-reported reasons for texting). Specifically, we examined (1) rates and reasons for refusal to participate in a text messaging data collection study, (2) rates and reasons for unsuccessful data capture, (3) selection and procedural bias in those who chose versus refused to participate in the study, and (4) selection bias in the sample of text messaging behaviors of those who chose versus refused to participate in the study based on self-report surveys.

Method

PARENT STUDY Participants

We recruited participants from a parent study (the REAL-U study) through email invitations sent to 9,000 undergraduate students randomly sampled from all enrolled students who were aged 18-23, with oversampling for males (60%) and African Americans (14%). Students were recruited from a single four-year university. To participate in the study, students had to report alcohol use in the past year. An additional 57 people contacted us directly asking to participate and 5 people were dropped from the pool because they served as RAs in the study, resulting in a recruitment pool of 9,052. Of these, 17% completed the pre-screen survey with 1,141 (75% of those screened *before sample size targets were met*) qualifying for participation. A total of 854 students completed the first visit and 840 completed both visits (see Figure 1). Overall, the REAL-U sample was highly comparable to the student body, though more ethnically diverse (by design; see Table 1 for descriptive statistics).

Procedures

REAL-U participants completed two lab-based visits separated by two weeks. Participants gave informed consent at the beginning of the first lab visit. In 1½ hour sessions, they completed online surveys and received $20 (for session 1) and a $25 (for session 2). Participants were invited to participate in the text study immediately after the second lab visit if they had an Android phone or an iPhone with them. They completed a separate consent procedure for this study. They were informed that to participate they would present their own smartphone to the RA, who would connect it to a secure, non-networked computer using a standard USB cord. Students' text data were then downloaded using secure, for-pay software (MOBILedit Forensic Express; https://www.mobiledit.com/forensic-express) that allowed us to selectively download only text message data (no other applications) that were exchanged over the previous two weeks. Downloads occurred behind a partition and on a computer-screen obscured by a privacy screen. RAs were unable to see text messages during downloads. Downloads included all text-based messages (both SMS and iMessage formats) for all sent and received text messages during the last two weeks along with a time stamp and phone numbers for each text. No image files were extracted.

Although we had informed consent from our participants to collect their text messages, we did not obtain consent from their networks of text message communicants. Prior research has noted that “[p]ioneering researchers studying online communication have argued that electronic communication can be observed without permission in some contexts because the information need not be uniquely identifiable, unless the individual has chosen to make his or her online user name their actual names” (Underwood et al., 2012). Indeed, our procedures go one step further to remove phone numbers and names to whom and from whom participants receive messages. Consistent with North Carolina law (N.C. Gen. Stat. Ann. § 15A-287; Rasmussen, Komperda, & Baldino, 2012) our IRB chose to waive consent for these communicants, consistent with past studies of youth text message content (Underwood et al., 2012). To remove identifying names and phone numbers, but retain interaction threads, we asked participant to provide phone numbers for their mother, father, romantic partner, and up to three friends. These phone numbers were then entered into a computer program we developed that immediately processed the downloaded text messages, replacing phone numbers with a relationship identifier (i.e., mother, father) or a random identifier (i.e., person1, person2) for phone numbers of other contacts not identified on the survey. The sheet containing the phone numbers was destroyed. The resulting text messages included columns for relationship identifiers (which replaced and thus removed phone numbers), time stamps, and message content. This permitted us to retain text threads, identify who in relation to the participant was part of that thread, and discard phone numbers or other identifiers that were not part of text message content (and thus reduce the identifiability of the data).

Participants competed for one of four cash drawings of $100 each if they gave consent to participate in the text messaging study. These procedures were approved by the REAL-U Institutional Review Board (IRB#14-0360).

Measures

We used measures from the REAL-U study battery to evaluate recruitment, selection, and procedural bias. Students reported their *date of birth* (from which we calculated age), *gender (0=female; 1=male), whether they were part of a Greek organization on campus (0=no; 1=yes), race/ethnicity (0=European American; 1=Ethnic/Racial Minority), class standing at the university (first year, sophomore, junior or senior)*, and *parent education* (scored as the highest level of education completed by any parent). They also completed scales assessing *social desirability* (SDS-17; Stöber, 2001). This scale includes 17 items (e.g., “I always admit my mistakes openly and face the potential negative consequences”) rated as true (=1) or false (=0; Cronbach’s α=.70), which we averaged to form a scale score for analysis. (See Table 1 for other scale descriptives.)

We measured distress using three subscales from the Mini Mood and Anxiety Symptom Questionnaire (Casillas & Clark, 2000) indexing *anxiety (10 items;* α=.83*), depression (8 items;* α=.85*), and general distress (8 items;* α=.90*)*. Participants rated items (e.g., how much have you experienced “feeling tension or high-strung” in the past 12 months) using a 5-point response scale (ranging from not at all to the most possible) and we formed subscales by averaging items.

We measured deviance in the social network with two scales indexing peer substance use (combining Ennett et al., 2006 and Johnston, O’Malley, Bachman & Schulenberg 2013) and parental alcohol-related consequences (using the MAST, Crews & Sher, 1992). Items on the peer use scale asked participants to report how many of their friends used each of nine different substances (9 items such as “marijuana or hashish”; α=.84) using a 5-point response scale ranging from none (=0) to all (=4). For parent alcohol-related consequences, participants rated whether each parent had experienced 13 consequences using a yes (=1) / no (=0) response scale (α=.75 for fathers and .78 for mothers). We formed subscales by averaging items and assessed the parent alcohol-related consequences by taking the maxing score for either parent's averaged score.

We measured low impulsivity with the Urgency Premeditation Planning Sensation Seeking Impulsivity Scale-Revised (UPPS-R, Whiteside & Lynman, 2001) which separately assessed positive urgency (impulsivity around positive emotion; 14 items such as "when overjoyed, I can't stop myself from going overboard"; α=.93) and negative urgency (impulsivity around negative emotion; 12 items such as "I have trouble controlling my impulses"; α=.88). Participants rated items on a 4-point response scale ranging from strongly agree (=1) to disagree strongly (=4) and a mean of items formed subscale scores.

Finally, we assessed deviant behavior using measures of externalizing symptoms and drinking. Using a modified timeline follow back procedure (Sobell & Sobell, 1992), participants reported whether they used alcohol, cigarettes or other drugs on each of the past 10-days (a window that overlaps with their text messaging). A daily substance use score indicated whether use of any substance occurred on a given day (=1) or not (=0). Participants also reported how often in the past year they had experienced externalizing symptoms with 8 items from the Monitoring the Future study (Johnston et al., 2013; e.g., "started physical fighters at work or school"). The five-point response scale ranged from not at all (=0) to 5 or more times (=4); items were averaged to form scale scores (α=.73).

We also included a measure of *frequency of communication* via social media and text messaging. Nine items from the Electronic Interaction Scale for Time (Nesi & Prinstein, 2015) asked how much time on a typical day students spent engaging in various types of communication with parents and friends separately (face-to-face, text messaging, private social media, public social media, and phone calls/FaceTime/Skype). Response options ranged from 0 ("I don't use this") to 6 ("9 or more hours a day"). Items are reported in Table 4.

To capture experiences or potential content of text messages, participants in the REAL-U study completed items adapted from the *mobile maintenance expectations and entrapment* scale (Hall & Byam, 2012) assessing pressure felt by students to be in constant contact or to reply immediately to peers and parent texts (assessed separately). Participants rated 16-items (e.g., "I feel pressured to text or post online to tell this person what I am doing") about parents (α=.95) and peers (α=.94), respectively, on a 5-point scale from 0 (*not at all true*) to 4 (*extremely true*). A mean of these items formed scale scores for analyses.

Finally, we developed items to examine reasons that participants use text messaging, including subscales assessing the frequency with which students *seek parent support* ("To get help, advice, or sympathy from your parents"; 2 items; α=.85), *peer support* ("To talk about things that are hard to talk about in person"; 6 items; α=.89), *engage in social comparison* ("To see what others think about how I look"; 5 items; α=.79), *facilitate their substance use* ("to find parties", 14 items; α=.87), and *engage in general social interaction* ("To feel less lonely"; 7 items; α=.81) via text messaging. Participants rated all items on a 5-point scale from 0 (*not at all true*) to 4 (*extremely true*) and a mean of items within scale formed scores for analyses. Exploratory factor analyses with items in each subscale confirmed that all items loaded significantly on a single factor and that all items loaded at .35 or higher.

Results

Rates and Reasons for Refusal to Participate

Of the 854 REAL-U study participants, we offered participation in the text study to those who participated in visit 2 in person (*n*=14 lost to attrition; *n*=15 completed visit 2 remotely), had time after visit 2 for the brief recruitment for the text study (*n*=4 excluded), and received the full recruitment protocol (*n*=2 excluded for participation prior to a baseline protocol change and 13 errors in executing the protocol). Of the remaining 806 students offered participation in the text study, 779 met eligibility criteria of having an Android or iPhone with them at the time of recruitment (96.7% of those offered participation) and 528 consented to participate in the text study (67.8% of those offered and eligible to participate). Reasons for refusing consent included privacy concerns (19% of those invited to participate); time constraints (5%); not being motivated by the incentive, not using text messaging, or primarily texting in a non-English language (1%); and disinterest (5%). Thus, we attempted to download text messages from a sample of 528 college students.

Rates and Reasons for Unsuccessful Data Capture

One goal of the text study was to determine feasibility of downloading two weeks of text message data from students' personal phones. This procedure required many adjustments over the course of the study as the software platform and iOS updates rolled out. Moreover, with later updates, the software required downloading drivers onto personal Android devices. Because we were uncomfortable downloading software from a private company onto these devices, we did not perform downloads when required – resulting in fewer successful downloads for Android phones. As a result, text message downloads were sometimes not successful primarily because we did not download additional software or because system updates interfered with software performance.

We successfully downloaded text messages from 267 of 528 consented participants, representing a 50.6% capture rate of participants' text messages which yielded 569,172 texts over the 14 preceding days. As expected, phone type was highly related to whether data were successfully downloaded. We classified phone type as Android (n = 117), iPhone 4 (n = 46), iPhone 5 (n = 218), or iPhone 6 (n = 121); for 26 participants data for phone type was not recorded. Rates of successful downloads were lowest for Android phones (3.42%) followed by iPhone 4 (32.61%), unclassified phone types (34.62%), iPhone 6 (69.42%) and iPhone 5 (71.10%) devices. In general, we were more successful in downloading texts from updated, recently released iPhones. Because this factor may confound comparisons regarding selection biases, we controlled for type of phone (iPhone5.0 or 6.0=1 versus others=0) in subsequent analyses as a covariate and also performed ad hoc analyses to explore potential biases related to phone type.

Evaluating Potential Selection and Procedural Bias in the Participant Sample

In Table 1, we report characteristics of the recruitment sample (where available), the REAL-U sample (who participated in the parent study, n = 840), the eligible sample who had phones with them when offered participation in the text study (n = 779), the sample of those who consented to participate in the text study (n = 528), and the final text sample participants (n = 267). To determine selection bias in the sample, we first conducted a series of regression models (ordinary least squares for continuous outcomes and logistic for dichotomous outcomes comparing European American to other students for race/ethnicity differences) to determine whether those who consented to be in the study (n = 528) differed from those who were invited and eligible to be in the study but did not consent (n = 251). Controlling for type of phone, we found no differences on the 17 variables reported in Table 3 between those who consented to be in the study and those who were eligible but did not consent to be in the study.

Second, we evaluated procedural bias in the participant sample by conducting a series of regression models to evaluate differences between students whose data we did (n = 267) versus did not (n = 261) successfully capture from among those who consented to be in the study (reflecting a failed capture bias). Out of 17 comparisons among variables reported in Table 3, we found that those with successful data capture reported lower levels of peer tolerance of their substance use as compared to those without successful data capture (b = -.26; t = -2.02, p = .04). After correcting for alpha inflation using a Bonferroni correction, no differences were found.

Additional comparisons evaluated a combined selection and procedural bias in the sample by comparing students in the REAL-U sample who were (n = 267) versus were not (n = 587) included in the text sample. After controlling for phone type, these samples did not differ on any variables reported in Table 3. We also informally compared the text message sample to the undergraduate student body from which the sample was drawn (see Table 1). We found no differences on demographic indicators, though, like the parent sample, the text message sample was more ethnically diverse (by design) and less evenly distributed across matriculation status.

Evaluating Potential Selection Bias in the Text Message Sample

We conducted a second set of analyses to evaluate representativeness of text messages by comparing the self-reported text messaging experiences (variables reported in Table 4) of all eligible REAL-U study participants (n = 779), the sample of text study consenters (n = 528), and the final text sample participants (n = 267). Items assessing text message experiences were administered late in the assessment battery and, likely for this reason, we had some non-response (available n per sub-sample across items reported in Table 4). In a series of logistic regression analyses (see Table 4), controlling for type of phone once again, we found that consenters differed from eligible non-consenters only on 1 of 16 comparisons; consenters reported less face-to-face interaction time with peers (b = -.59; t = -2.46, p = .01) than non-consenters. In addition, those with successful data capture reported more frequent interaction with friends on private social media outlets that include text messaging (b = .32; $t = 2.46$, $p = .01$) and parents on public social media (b = .16; $t = 2.36$, $p = .02$). They also reported more frequently using texting for friend support (b = 26; $t = 2.65$, $p = .008$) and experienced more pressure to respond to friend texts (b = .12; $t = 2.65$, $p = .008$). Finally, compared to those not in the text sample, those in the text sample reported more frequent use of private social media with friends (b = .33; $t = 2.58$, $p = .01$), of public social media with parents (b = .16; $t = 2.26$, $p = .02$), of texting with friends for support (b = .26; $t = 2.69$, $p = .007$), and of texting for social engagement more generally (b = .16; $t = 1{,}96$, $p = .05$). Differences in extent of texting behavior across the two groups is likely due to those not in the text sample being less likely to have a smartphone or to carry one with them regularly (and thus to have one with them at the time of the study), an eligibility requirement for the study. However, after performing a Bonferroni correction for alpha inflation, no differences were found across any group comparisons.

Comparing Android and iPhone Users

Given the significant differences in data capture based on type of phone, and because various study designs may require the use of one platform over another, we compared Android and iPhone users who consented to be in the study (regardless of whether their text messaging data was successfully captured) on all self-report measures of behavior and text messaging through a series of t-tests (see Table 2). We saw no differences in age or parent education in this college sample, though iPhone users were less likely to endorse racial or ethnic minority identities. Those owning Androids were more likely to be racial/ethnic minority (62%) than White (38%) whereas those owning iPhones were more likely to be White (59%) than racial/ethnic minority (41%). However, within race/ethnicity, more students owned iPhones

(69% of racial/ethnic minority students and 83% of White students) than Android phones (31% of racial/ethnic minority students versus 17% of White students).

Where behaviors differed on other variables, iPhone users had lower social desirability and more embeddedness in drinking culture (i.e., greater peer use, more frequent drinking, and more involvement in Greek life) as compared to Android phone users. In addition, they reported more frequent face-to-face interaction with friends, private and public texting, and use of text messaging to engage in social comparison than Android phone users. Thus, for both deviant and more normative social behaviors, if iPhone and Android phone users differed, iPhone users reported higher rates of engagement. However, no differences were found on measures of distress or impulsivity or in self-reported reasons for and experiences of text messaging. After correcting for repeated testing using a Bonferroni correcting, only three effects remained. Compared to Android phone users, iPhone users were less likely to identify as racial/ethnic minority and more likely to interact with friends via public social media and use texting to engage in social comparison.

Given these differences, we re-estimated potential selection biases by comparing those who contributed data to the text message study (n=267) with all others from the REAL-U study who did not contribute data but were part of the recruitment sample (n=587) on all variables in Tables 3 and 4 (far right-hand column) but excluding phone type as a control. Differences were fewer than those noted for phone type in the consented sample, but, not surprisingly, when found, mirrored those for phone type. We saw that those in the text sample were more likely to be women and had lower rates of social desirability but higher rates of dishonest reporting in substance use; these differences reflected small effects (all r-square $< 1\%$) and became non-significant with Bonferroni correction for alpha inflation (indeed, all $p>.01$). No differences in race/ethnicity were found. Similar small effects that became non-significant with alpha correction included greater social media interactions in text study participants (as indicated by more texting with friends and parents) and more social engagement as a reason for texting. However, other differences that were maintained after alpha correction showed that those in the text messaging study were more likely to report interacting with friends through other forms of private and public social media and using text messaging more often for friend support and social comparison. These differences may in part reflect phone type as well as whether participant had a smartphone and engaged in texting in general.

Description of Text Message Data Base

On average, these participants exchanged 2,132 total texts (1,241 received and 891 sent) with a range of 3-10,792 texts exchanged over the 2-week study period (or an average of 152 texts exchanged per day). The quantity of texts exchanged fluctuated over the course of the day in a pattern consistent with more texting during waking hours (Figure 2). Participants also texted with a range of partners. Among text sample participants with complete data on texting partners (n=255), 96.9% identified a mother as a texting partner, 88.6% identified a father, 50.6% identified a romantic partner, and 100% identified at least one friend. (The relationship identity of other texting partners was not assessed.) Of those who identified a mother, they exchanged on average 87.8 texts over the two-week period (range 0-1,012; M = 6.3 texts per day). Of those who identified a father, they exchanged on average 28.4 texts over the two-week period (range 0-501; M = 2.0 texts per day). Of those who identified a romantic partner, they exchanged on average 783.4 texts over the two-week period (range 0-5,478; M = 56.0 texts per day). And, of those who identified at least one close friend, they exchanged on average 279.6 texts with their first-nominated friend over the two-week period (range 0-3178; M = 20.0 texts per day). The average participant exchanged texts with 39 unique communication partners over the 2-week study period (range=1-104 unique communication partners).

Discussion

Our findings indicate that the analysis of text message data is not only feasible but also may be successfully undertaken with minimal selection biases regarding sample and text message selection, though the platform (phone type) on which data capture occurs may be a significant factor in selection bias. Moreover, the results demonstrate the challenges of collecting text message data, particularly the notable barrier of data capture. Despite the low rate of data capture (particularly for Android phone users), we found little evidence of overall selection bias in either participants or text message data once controlling for phone type. Because so few teams have collected this type of data, understanding the pros and cons of the current method is an important contribution to this emerging field as we develop novel ways to study a dominant platform for social behavior in which youth increasing engage with development.

Although students reported privacy concerns as a primary reason for refusal, participants resembled those in the broader sampling frame across factors that may relate to privacy concerns, though were more likely to have phones and engage in text messaging and social media exchanges. A more reliable indicator of whether students successfully participated in our study was the type of phone they owned, as this was related to procedural bias. This highlights a significant challenge in this methodology, namely, maintaining effective, current technological programs to extract text messages from participants' phones within a quickly changing software (and hardware) environment.

Overall, participation rates using the current method compared favorably with those reported in the literature. As summarized by Revilla et al. (2019), rates of participant reported (hypothetical) willingness to engage in a GPS capture task include 8% (in a Czech study; Biler, Senk & Winkeroon, 2013), 26% (in a Dutch study; Toepel & Lugtig, 2014); and 30% (in a French study; Armoogum & Roux & Pham, 2013). Rates of actual participation, not surprisingly, are lower than hypothetical willingness rates, with 58% being willing and 20-33% actually participating (at a later wave) in a US study (Crawford, McClain, Young & Nelson 2013) and 37% being willing with 30% actually participating in a Dutch study (Scherpenzeel and Das, 2011). Rates are even lower for other tasks, including a passive browser tracking task with 31% being willing and 14% actually participating in a Dutch Study (deReuver & Bouwman, 2015) and 3.6% being willing and 2.1% installing the tracking software in a US study (Van Duivenvoorden & Dillon, 2015). Against these rates, our 67.8% (or 528 of 779 invited to participate) participation rate suggests that our task design and recruitment procedures yield relatively higher participation rates than in other study designs.

As noted, rates of successful downloads were lowest for Android phones (3.42%). Probing the differences in Android and iPhone users revealed either no differences or that, at the time of data collection, iPhone users reported greater engagement in social behavior (drinking culture, offline and online social interaction) than Android phone users. This may have implications for inclusion criteria and desirable data capture methods in further studies. However, this was less biasing for a US sample than it might have been for other samples. In December 2015, Apple iOS made up 52% and Android OS made up 46% of the mobile market share in the United States (Global Stats, 2019a); this differs from what has been reported for world markets (Apple iOS 19% and Android 66%; Global Stats, 2019b). Over time, US teens have shown an increasingly strong preference for iPhones over Android phones (Leswing, 2018).

Of greater concern were notable racial/ethnic differences in iPhone versus Android phone users that translated into differences in capture rates. Reflecting the larger market around this time (Statista, 2013), Android phones users were more likely to identify as a racial/ethnic minority than White and iPhone users were more likely to identify as White than as a racial/ethnic minority. Importantly for interpreting this difference, however, is that all students were more likely to have iPhones than Androids (83% of white students and 69% of racial/ethnic minority students). For this reason, our final text sample (56.8% White students) did not notably differ in racial composition from the REAL-U study or recruitment sample (55.7% white students). Further analysis showed that racial/ethnic minority participants from the REAL-U study did not differ in rates of consenting to participate in the text message study. However, other factors related to how phones were used (for engaging with friends and social comparison) were higher in iPhone than Android phone users and thus an awareness of choosing platforms for texting as related to social behaviors of interest is needed in future work.

Other researchers have avoided such problems by providing individuals with a phone dedicated to participant use for the duration of the study. This approach clearly provides greater stability to combat technological issues with data capture and to assure that those with older or less expensive phones are not systematically excluded. However, providing participants with phones as they enter the study also has disadvantages. For example, participants may change their text messaging behaviors when they know that they will be monitored. In addition, participants may have a long-standing phone number and platform and only use a study-provided phone for some of their online behaviors. Moreover, prior studies that have provided phones used a full-time staff person to manage phone issues, making such designs more time intensive and expensive (Underwood et al., 2012). In our design, participants were asked to provide text messages over the two weeks prior to the moment of data capture – allowing us to observe naturally occurring, uncensored communication patterns. However, with continuing changes to text messaging apps, new technologies for data capture are needed. One potential exciting approach under development by Allen and colleagues' effortless assessment of risk states tool (Lind et al., 2018).

Consistent with this advantage of our method, we found no meaningful differences between those in the text message sample versus the parent study in the selection indicators examined, including reasons for texting. Although not a direct comparison of text message content, these findings provide indirect evidence that text message content may not vary substantially between participants and non-participants. Indeed, a review of select de-identified text messages reveals that a variety of sensitive topics were discussed including the exchange of financial information, sexually explicit messages, and emotionally laden discussions. Further evidence that text messages collected in the study are typical in pattern to what we expect in college students is also apparent in the descriptive data. For example, students were less likely to text during sleeping hours and more likely to text their romantic partners, close friends, and then parents. However, they were also quite likely to text with communication partners outside of these roles – reflecting the wider online social circle in which they participate. Indeed, students differed from one another on the scope of their social circle, with the number of text partners ranging from 1 to 104.

In sum, the current method has several advantages including lower reactivity to data collection, limited sample and text message selection bias, low cost, and low time investment. Disadvantages include challenges in successful data capture due in part to ethical concerns. For example, we chose not to install required drivers for data extraction (on Androids only) routinely. In addition, we did not download pictures, images, or emojis to limit exposure of identifiable data collected from those not directly participating in the study. Although emojis were less common when we collected these data (Kaye, Malone, & Wall, 2017), this would be a significant concern with text message data today.

This highlights the significant issue of ethical and legal concerns related to collecting these types of data (Meter, Ehrenreich, Carker, Flynn, E., & Underwood, 2019). Although such issues are increasingly challenging to negotiate, they are worthy of our attention. The contribution of the current study, thus is not in proposing a singular approach to data capture but in identifying a design in which to embed emerging data capture methods.

Other study limitations are that the data come from a single college sample, all of whom reported prior alcohol use (for purposes of inclusion in the parent study). In our sample and at the time of data collection, text messaging was the preferred method of private text-based communication; given this, we believe our findings will generalize to other private messaging platforms if they align with participants' preferred platforms for texting. We have several reasons to believe that selection bias is minimal regarding study participation and potential reasons for non-participation related to privacy concerns (e.g., participants did not differ from the university student body on sociodemographic variables except where oversampling occurred and participants in the original study were not informed of this study prior to completing the original study and we had very little attrition). Nonetheless, we realize that our comparisons are not exhaustive.

Despite these limitations, like others we believe these data are unique and offer an opportunity to address questions with novel insights into social development. For example, Jensen, Hussong, Haston, & Scales (2019) showed that college youth texted more frequently with mothers than fathers and communicate primarily about checking in around youth behavior and well-being. Although the frequency of texting with parents was unrelated to well-being, youth who struggle most with internalizing symptoms were more likely to receive needed support via text messaging (based on coding of text messages adapted form observational paradigms) than were their peers. These findings suggest that support provision via text messaging is an aspect of parenting youth into young adulthood that is important to better understand. Moreover, Jensen and Hussong (2019) introduced an alcohol talk index based on semantic analysis that identified the extent of alcohol-related words (broadly construed) in text messages. Their findings showed that each alcohol-talk word was associated with a 22-23% increase in the likelihood of drinking on that day after (controlling for overall word counts). People who used more alcohol talk were more likely to drink in general, with a 14% increase in the number of drinking days for each additional texted indicator of alcohol talk. These findings hint at the possible analytic frameworks that may be used to derive meaningful indicators of communication and behavior from text data that relate to offline behavior.

Given the ubiquitous use of text messaging and social media communication, this form of social interaction is clearly a common part of young adult life. Furthermore, the study of these interactions provides a direct window into the social worlds of young adults in a way that is not hindered by the limitations of self-report and short-term (often lab-based) observational data. This is perhaps the most significant contribution of studies of online social behavior, particularly that which involves private messaging. Without these data, we do not yet know whether existing theories about the mechanisms that underlie social behavior, both in terms of factors that lead to social behavior and the implications of social behavior for adaptation, are the same for online and offline interactions or whether there is a fundamental shift in not just the social behaviors in which youth are engaging but also in how those behaviors impact ontogeny more broadly (Nesi, Choukas-Bradley & Prinstein, 2018a, 2018b). Toward this end, we believe that the methods used here can be applied beyond college student populations, with attention to factors described by Wenz et al. (2019) as a guide to how to adapt the procedure for different settings and populations. We believe that we are only beginning to scratch the surface of what we can learn using such methods and what we can contribute through a science aimed at understanding social development where it occurs.

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Table 1. Sample Characteristics

		Recruitment Pool	REAL-U Visit 2 Sample	Eligible Sample	Consented Sample	Text Message Sample
Total N		9052	840	779	528	267
%	Male Gender**	60.0	46.0	45.89	44.21	40.8
	Greek	--	16.0	15.92	15.0	17.6
	Race					
	American Indian or Alaska Native	0.38	0.48	0.52	0.76	.38
	Asian	8.7	10.87	10.57	9.14	7.58
	Pacific Islander	.1	0	0	0.00	0
	Black/African-American**	14.2	21.39	22.16	24.76	21.97
	White/Caucasian	60.0	55.68	55.03	59.81	56.82
	Latino/Hispanic	6.7	5.26	6.57	5.52	6.82
	Two or More Races	4.9	6.33	5.15	6.46	6.44
	University Classification					
	First-Year Undergraduate	25.54	28.69	29.01	29.36	31.46
	Sophomore	23.29	20.61	21.18	19.51	17.98
	Junior	25.31	20.02	19.13	20.08	17.98
	Senior	25.83	29.04	29.40	29.55	29.59
	Other	0	1.64	0.90	1.14	2.25
Mn (SD)	Externalizing Symptoms		0.08 (0.19)	0.08 (0.19)	0.07 (0.17)	0.08 (0.19)
	Num. of Drinking Days in Past 10	--	7.33 (12.12)	7.26 (11.77)	6.96 (11.39)	7.12 (10.01)
	Social Desirability	--	0.48 (0.19)	0.49 (0.19)	0.49 (0.19)	0.46 (0.19)
	Accuracy of Reporting		2.79 (0.37)	2.79 (0.38)	2.82 (0.33)	2.83 (0.32)
	Anxiety	--	0.50 (0.52)	0.50 (0.53)	0.49 (0.54)	0.50 (.57)
	Depression	--	1.16 (0.86)	1.15 (0.85)	1.13 (0.86)	1.12 (.88)
	General Distress	--	1.49 (0.74)	1.47 (0.73)	1.46 (0.72)	1.49 (.72)
	Peer Use	--	1.34 (0.58)	1.35 (0.58)	1.29 (0.57)	1.34 (0.55)
	Parents' Alcohol Consequences	--	0.22 (0.16)	0.22 (0.16)	0.21 (0.15)	0.22 (0.15)
	Age	19.83	19.91 (1.38)	19.90 (1.38)	19.91 (1.38)	19.87 (1.40)
	Parent Education	--	4.74 (1.30)	4.74 (1.31)	4.73 (1.32)	4.70 (1.38)
	Negative Urgency	--	2.85 (0.52)	2.86 (0.52)	2.88 (0.51)	2.85 (.53)
	Positive Urgency	--	3.32 (0.55)	3.33 (0.55)	3.35 (0.53)	3.32 (.54)

** Oversampled by design in drawing recruitment sample from undergraduate student body. Due to missing data, sample sizes ranged over outcome (803-840 for REAL-U Visit 2 Sample; 774-779 for Eligible Sample; 505-528 for Consented Sample; and 258-267 for Text Message Sample.

Table 2. iPhone versus Android Phone Users

	iPhone Users (n=364) MN	Android (n=114) MN	T-Test	P-Value
Deviant Behavior				
Externalizing Symptoms	.07	.06	1.04	.30
Past 10-day Substance Use	8.03	5.22	2.27	.02
Social Approval				
Social Desirability	.47	.53	-2.96	.003
Self-reported honesty of substance use reporting	2.82	2.80	.52	.60
Distress				
Anxiety	.48	.49	-.29	.77
Depression	1.46	1.47	-.10	.92
General Distress	1.10	1.19	-1.00	.32
Network Deviance				
+Greek Affiliation	31%	24%	8.66	.01
Peer Use	1.33	1.14	3.14	.002
Parent MAST	.21	.22	-.71	.48
Social Vulnerability				
+Race/Ethnic Minority	41%	62%	16.54	.001
Age	19.9	20.1	-1.25	.21
+Women	58%	51%	1.51	.22
Parent Education	4.743	4.77	-.26	.79
Low Impulsivity				
Negative Urgency	2.86	2.94	-1.45	.15
Positive Urgency	3.35	3.39	-.81	.42
Text Messaging Indicators				
*talking to friends in person (face to face)? Only include time you are talking for fun or social reasons, NOT just time you are sitting together in class	2.79	2.52	2.09	.04
*talking to friends through phone calls, FaceTime and Skype (NOT including texting)	1.01	.86	1.62	.11
*interacting with your friends through texting (NOT including phone calls)?	2.53	2.24	2.02	.04
*interacting with your friends through our private social media like SnapChat, private messaging on Facebook or emailing	1.83	1.73	.84	.40
*interacting with your friends through public social media like posting on FaceBook, Instagram, Twitter, Pinterest, or Tumblr	1.66	1.29	3.12	.002
*talking to your parents through phone calls, FaceTime and Skype (NOT including texting)	1.07	1.08	-.13	.89

*interacting with your parents through texting (NOT including phone calls)?	1.23	1.13	1.25	.21
*interacting with your parents through our private social media like SnapChat, private messaging on Facebook or emailing	.48	.38	1.42	.16
*interacting with your parents through public social media like posting on FaceBook, Instagram, Twitter, Pinterest, or Tumblr	.46	.44	.30	.77
Feeling pressure from friend about texting	.40	.33	1.22	.22
Feeling pressure from parent about texting	.78	.78	.03	.98
Texting to facilitate substance use	.39	.31	1.88	.06
Friend support through texting	1.27	1.16	1.14	.25
Social comparison through texting	.72	.48	3.38	.001
Parent support through texting	.99	.80	1.84	.07
Social engagement through texting	1.68	1.65	.38	.71

+Indicates chi-square results and percent iphone users (otherwise t-tests and means are reported).

Table 3. Results of Regression Analyses for Recruitment, Capture, and Selection Bias for Respondent Characteristics

	Recruitment Bias		Capture Bias		Selection Bias	
	b	t-Value/ Wald's χ^2	b	t-Value/ Wald's χ^2	b	t-Value/ Wald's χ^2
Deviant Behavior						
Externalizing Symptoms	0.03	0.69	0.01	0.56	0.01	0.62
Past 10-day substance use	-2.75	-1.17	-2.18	-1.78	-2.25	-1.75
Social Approval						
Social Desirability	0.04	0.99	-0.03	-1.48	-0.03	-1.26
Self-reported honesty of substance use reporting	0.16	2.11*	0.02	0.28	0.04	0.89
Distress						
Anxiety	0.17	1.65	0.03	0.50	0.04	0.78
Depression	0.16	0.94	0.09	0.97	0.10	1.12
General Distress	-0.08	-0.58	0.11	1.44	0.10	1.28
Network Deviance						
+Greek Affiliation	0.25	3.25*	0.01	0.00	0.03	0.06
Peer Use	-0.10	-0.87	0.01	0.07	0.01	0.07
Parent MAST	-0.03	-1.06	0.01	0.45	0.01	0.25
Social Vulnerability						
+Race/Ethnic Minority	0.30	2.36	0.10	0.24	0.18	0.74
Younger	0.03	0.10	0.03	0.22	0.03	0.24
+Women	0.12	0.37	0.30	2.04	0.30	2.12
Lower parent education	0.14	0.56	0.08	0.56	0.10	0.77
Low Impulsivity						
Negative Urgency	-0.08	-0.79	0.03	0.64	0.03	0.55
Positive Urgency	-0.01	-0.08	-0.02	-0.37	-0.02	-0.29

Note: Recruitment bias analyses compare those offered participation who refused (n=251) versus consented (n=528) to participate; capture bias analyses compare those consented to participate whose data were (n=261) versus were not (n=267) successfully downloaded; and selection bias analyses compare those who had successfully downloaded data (n=267) to all other parent study (REAL-U visit 2) participants (n=573). Note * indicates significant at $p<.05$ but not at Bonferroni corrected, $p<.003$ (for 16 repeated tests per bias analysis). +Indicates logistic regression results (otherwise OLS regression results are reported).

Table 4. Descriptive Statistics and Results of Regression Analyses for Recruitment, Capture, and Selection Bias for Self-Reported Text and Social Media Interactions

		SAMPLE DESRIPTIVES				RESULTS OF REGRESSION MODELS					
		REAL-U Sample	Eligible Sample	Consented Sample	Text Message Sample	Recruitment Bias		Capture Bias		Selection Bias	
	Total Sample n (Range of Observed n across variables)	854 (792-804)	779 (740-749)	528 (501-505)	267 (253-257)	b	t-val	b	t-val	b	t-val
Mn	*talking to friends in person (face to face)? Only include time you are talking for fun or social reasons, NOT just time you are sitting together in class	2.72	2.74 (1.19	2.74 (1.19)	2.83 (1.20)	-0.59	-2.47	0.17	1.35	0.11	0.91
	*talking to friends through phone calls, FaceTime and Skype (NOT including texting)	0.98	0.99 (0.89)	0.97 (0.90)	1.03 (0.94)	-0.14	-0.76	0.08	0.86	0.07	0.74
	*interacting with your friends through texting (NOT including phone calls)?	2.43	2.46 (1.39)	2.45 (1.36)	2.60 (1.34)	-0.31	-1.09	0.20	1.39	0.19	1.28
	*interacting with your friends through our private social media like SnapChat, private messaging on Facebook or emailing	1.76	1.77 (1.21)	1.81 (1.21)	1.95 (1.24)	-.01	-.03	0.32	2.46	0.33	2.58
	*interacting with your friends through public social media like posting on FaceBook, Instagram, Twitter, Pinterest, or Tumblr	1.54	1.56 (1.13)	1.56 (1.10)	1.71 (1.11)	-0.43	-1.92	0.19	1.59	.017	1.40
	*talking to your parents through phone calls, FaceTime and Skype (NOT including texting)	1.06	1.07 (0.69)	1.07 (0.69)	1.08 (0.66)	-0.05	-0.39	0.02	0.25	0.02	0.25
	*interacting with your parents through texting (NOT including phone calls)?	1.19	1.20 (0.73)	1.20 (0.69)	1.25 (0.66)	-0.16	-1.11	0.06	0.87	0.05	0.63
	*interacting with your parents through our private social media like SnapChat, private messaging on Facebook or emailing	0.46	0.46 (0.71)	0.46 (0.67)	0.54 (0.74)	0.06	0.42	0.14	1.94	0.15	1.93
	*interacting with your parents through public social media like posting on FaceBook, Instagram, Twitter, Pinterest, or Tumblr	0.44	0.44 (0.67)	0.46 (0.63)	0.52 (0.67)	0.02	0.15	0.16	2.36	0.16	2.26
	Feeling pressure from friend about texting	0.41	0.41 (0.58)	0.38 (0.54)	0.43 (0.58)	-0.06	-0.54	0.12	2.02	0.11	1.71
	Feeling pressure from parent about texting	0.79	0.79	0.77	0.79	-0.29	-1.68	0.03	0.33	0.01	0.11

		(0.86)	(0.85)	(0.85)						
Texting to facilitate substance use	0.37	0.37 (0.41)	0.36 (0.40)	0.41 (0.46)	-0.10	-1.19	0.07	1.54	0.06	1.28
Friend support through texting	1.22	1.22 (0.91)	1.24 (0.90)	1.35 (0.94)	0.09	0.50	0.25	2.65	0.26	2.69
Social comparison through texting	0.64	0.65 (0.65)	0.66 (0.66)	0.75 (0.75)	-0.01	-0.02	0.09	1.26	0.09	1.31
Parent support through texting	0.92	0.93 (1.00)	0.94 (0.99)	0.99 (1.05)	-0.06	-0.31	-0.01	-0.08	-0.01	-0.06
Social engagement through texting	1.63	1.65 (0.77)	1.67 (0.76)	1.74 (0.79)	0.13	0.84	0.15	1.79	0.16	1.96
*Construct assessed by single item on social interaction scale. Other entries reflect scale scores.										

Differences were fewer than those noted for phone type in the consented sample, but, not surprisingly, when found mirrored those for phone type. We saw that those in the text sample were more likely to be women and had lower rates of social desirability but higher rates of dishonest reporting in substance use; these differences reflected small effects (all r-square < 1%) and became non-significant with Bonferroni correction for alpha inflation (indeed, all p>.01). Similar small effects that became non-significant with alpha correction included greater social media interactions in text study participants (as indicated by more texting with friends and parents) and more social engagement as a reason for texting. However, other differences that were maintained after alpha correction showed that those in the text messaging study were more likely to report interacting with friends through other forms of private and public social media and using text messaging more often for friend support and social comparison. These differences may in part reflect phone type as well as whether participant had a smartphone and engaged in texting in general.

Figure 1. Recruitment of Text Message Sample

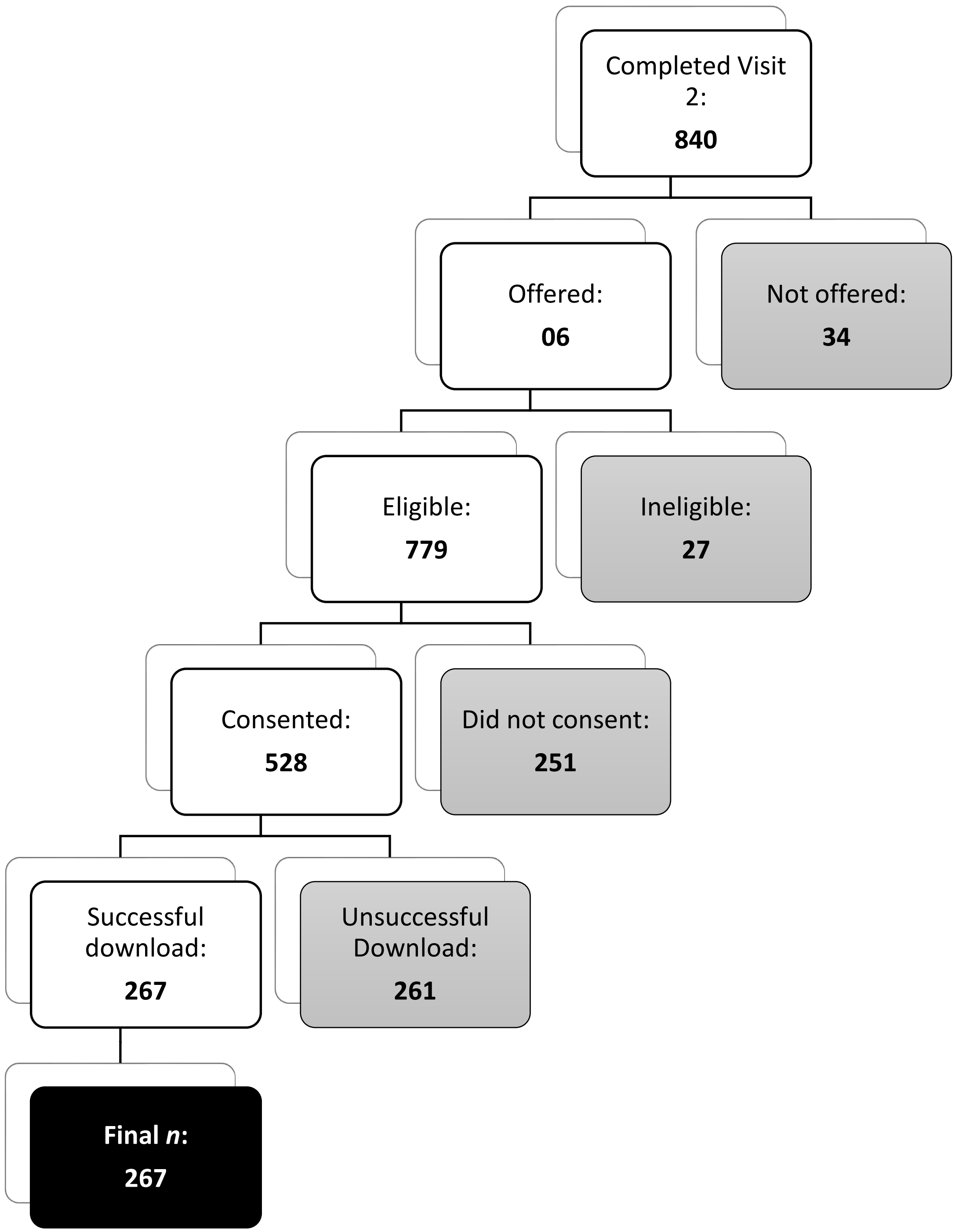

Figure 2. College Students' Text Message Exchanges over The Day