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Sociability as a disposition describes a tendency to affiliate with others (vs. be alone). Yet, we know relatively little about how much social behavior people engage in during a typical day. One challenge to documenting social behavior tendencies is the broad number of channels over which socializing can occur, both in-person and through digital media. To examine individual differences in everyday social behavior patterns, here we used smartphone-based mobile sensing methods (MSMs) in four studies (total $N = 926$) to collect real-world data about young adults' social behaviors across four communication channels: conversations, phone calls, text messages, and use of messaging and social media applications. To examine individual differences, we first focused on establishing between-person variability in daily social behavior, examining stability of and relationships among daily sensed social behavior tendencies. To explore factors that may explain the observed individual differences in sensed social behavior, we then expanded our focus to include other time estimates (e.g., times of the day, days of the week) and personality traits. In doing so, we present the first large-scale descriptive portrait of behavioral sociability patterns, characterizing the degree to which young adults engaged in social behaviors and mapping these behaviors onto self-reported personality dispositions. Our discussion focuses on how the observed sociability patterns compare to previous research on young adults' social behavior. We conclude by pointing to areas for future research aimed at understanding sociability using mobile sensing and other naturalistic observation methods for the assessment of social behavior.

Keywords: mobile sensing, smartphones, social behavior, Big Five personality traits, naturalistic observation

Supplemental materials: http://dx.doi.org/10.1037/pspp0000245.supp

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How many conversations do you have in a day? How long do they typically last? How many phone calls do you typically make or receive? What about text messages? And how often do you use messaging (e.g., Whatsapp) or social media (e.g., Facebook, Instagram) apps? If you are like most people, you will find it difficult to answer these questions about your social behaviors. When asked to report on such quantified aspects of their behavioral patterns (e.g., the frequency or duration of a behavior), most people are able to do little more than provide a rough estimate (Schwarz, 2012). Our failure to recall such details about our behavioral patterns might not be surprising to us as social scientists. But if we are to understand the mechanisms by which social behavior exerts its impact on so many consequential areas of life (e.g., physical and mental well-being), we are going to need a better understanding of how sociability plays out in the context of people's everyday lives.

Decades of research have pointed to the value of sociability (the preference for affiliating with others vs. being alone; Cheek & Buss, 1981) in predicting a diverse array of well-being outcomes, ranging from stress (Cohen & Wills, 1985), affect and life satisfaction (e.g., Chancellor, Layous, Margolis, & Lyubomirsky, 2017; Emmons & Diener, 1986; Sandstrom & Dunn, 2014; Siedlecki, Salthouse, Oishi, & Jeswani, 2014), to physiological markers of health (Yang, Boen, Gerken, Schorpp, & Harris, 2016). But until recently, social scientists have had to measure sociability dispositions by relying on technology equivalent to the set of questions with which we opened this article. For example, researchers might use survey questions that ask people to report on their (1) sociability self-views or (2) momentary sociability levels. To assess sociability self-views, researchers might use a set of questions designed to measure levels of Extraversion from the widely used Big Five personality trait model (John & Srivastava, 1999), asking people about the extent to which they are generally talkative, outgoing, and sociable versus shy, introverted, and quiet. To assess momentary sociability, researchers might use a set of repeated experience sampling questions designed to measure instances of sociable behavior in daily life, asking people about the extent to which they have been sociable recently (e.g., during an interaction, during the past hour; Breil et al., 2019), or about the quality or quantity of their recent social interactions (e.g., Wilson, Harris, & Vazire, 2015). Such questions obviously capture self-perceptions of sociability, but not the objective amount of social behavior a person tends to engage in over time.

According to the U.S. Department of Labor (2018), Americans aged 15 to 34, have reported spending an average of .71 to .97 hours per day "socializing and communicating," and .11 to .18 hours on "telephone calls, mail, and email" during a typical day. Yet, we know surprisingly little in terms of basic descriptive details about individual differences in socializing behavior, such as how much time people actually spend socializing in-person and through their devices, how many interactions they have, and when they tend to do so during a typical day (e.g., in the mornings, evenings) or week (e.g., on weekdays vs. weekends). A major challenge to documenting social behavior tendencies is the broad number of channels through which socializing can occur; people can engage in social behavior in many different ways that can be difficult to observe or recall, both in-person and through digital media (e.g., smartphones). It is little wonder then, that most existing approaches to measuring sociability do not account for the many ways people socialize with others across channels and over time. Instead, technological limitations have required researchers to summarize what we know to be a complex, dynamic, multifaceted suite of behaviors in terms of a few basic self-reported survey questions.

The present research aims to address the gap in our understanding of how sociability manifests behaviorally in daily life by adopting cutting-edge mobile sensing methods (MSMs) to track, describe, and examine individual differences in people's everyday social behavior patterns. In doing so, we aimed to address the calls made over the past decade for more descriptive research about important everyday behaviors (e.g., Baumeister, Vohs, & Funder, 2007; Cooper, 2016; Furr, 2009) by examining the behavioral manifestation of dispositional sociability across four communication channels: conversations, phone calls, text messages, and application use. Specifically, we report findings from four studies that used MSMs to measure the social behaviors of young adults as they went about their daily lives. By sampling from the microphone sensors and phone system logs embedded in their smartphones over several weeks, we were able to obtain sensed behavioral assessments of dispositional sociability, pointing to the promise of using MSMs for passive behavioral assessments in social science research. To contribute to a much-needed mapping of the "behavioral terrain" (Funder, 2009) for sociability, we describe social behavior tendencies at different times and explore the extent to which sensed behavioral tendencies relate to self-reported personality traits.

To provide an analysis of individual differences in young adults' naturally occurring social behaviors, we began our research by focusing on behavioral tendencies at the daily level, establishing the extent to which the sensed social behaviors showed (a) between-person variability, (b) stability from day-to-day, and (c) relationships among the daily socializing tendencies. We then expanded our analyses to provide a descriptive account of (d) young adults' tendencies to engage in conversation, calling, texting, and app use at different times (e.g., during a typical day, at different times of the day) and (e) the relationship between the socializing tendencies and self-reported personality traits. Before we describe the present research in greater detail, we introduce MSMs as a new form of naturalistic observation for psychological research on sociability and review the few past studies that have examined the social behavior of young adults using naturalistic observation methods.

Studying Social Behavior in Daily Life Using Mobile Sensors

One reason for the paucity of basic descriptive information on social behavior tendencies is the methodological challenges associated with monitoring behavioral patterns in real-time, over long periods of time. Researchers interested in behavioral patterns in daily life have had to rely on intensive longitudinal assessment methods that include active and/or passive tracking to obtain estimates of social behavior (e.g., ambulatory assessment, experience sampling; Bolger, Davis, & Rafaeli, 2003; Mehl & Conner, 2012).

Mobile sensing is a new form of passive naturalistic observation of daily life that capitalizes on recent advances in sensor technologies to obtain ecologically valid measurements of behavior (e.g., Eagle & Pentland, 2006). Of the various digital media devices that come equipped with mobile sensors that can measure objective behavioral information (e.g., computers, wearables, smart home appliances), smartphones stand out as being the mobile device with the greatest potential to revolutionize how behavior is measured in the social sciences (e.g., Harari et al., 2016; Miller, 2012; Raento, Oulasvirta, & Eagle, 2009).

Smartphones—with their onboard mobile sensors and system logs—already record precisely who we interact with, when we interact, what we say, what platforms we choose for our interactions, and where we are when our interactions occur (see Harari, Müller, Aung, & Rentfrow, 2017 for a review). As such, smartphone-based MSMs promise to provide researchers with an ecologically valid and unobtrusive behavioral tracking tool that can measure behavioral patterns in real time (via sensors and system logs; Lane et al., 2010). Moreover, behavioral data from smartphones can also be combined with in-the-moment experience sampling reports (e.g., Rachuri et al., 2010; Wang et al., 2014), making them enormously powerful as a new methodological tool for behavioral observation (Gosling & Mason, 2015). To date, however, most mobile sensing studies have been designed to make technical contributions that test and evaluate the technology being developed; few studies have focused on evaluating the behavioral measures obtained from smartphone data to establish the viability of using sensing applications to provide assessments of behavioral dispositions.

Conversation Behaviors From Microphone Sensors

Studies examining conversation behavior using naturalistic observation have typically relied on microphone sensors to measure instances of conversational behavior (e.g., Mehl, Gosling, & Pennebaker, 2006; Mehl & Pennebaker, 2003; Schmid Mast, Gatica-Perez, Frauendorfer, Nguyen, & Choudhury, 2015; Wang et al., 2014). In the daily life context, pioneering studies of real-world conversations used the Electronically Activated Recorder (EAR) to assess conversation behaviors by relying on passive microphone sampling to obtain acoustic records of a person's daily life. The acoustic files are then coded by raters to obtain dispositional estimates of social behavior, by assessing the amount of time people spend engaged in various social behaviors (e.g., talking in person, talking on the phone, time spent alone; Mehl, Pennebaker, Crow, Dabbs, & Price, 2001; Mehl & Pennebaker, 2003). These studies have provided initial estimates of the typical rates and stability of daily conversation behavior, finding that young adults spent about a third of their waking hours engaged in conversation (24% to 27% of the assessments; Mehl et al., 2001) and that conversation behaviors showed moderate to high stability over time (average test–retest $r = .54$ across a 4-week period; Mehl & Pennebaker, 2003).

Other studies have used microphone sensors to measure instances of conversational behavior in the context of daily life by relying on more automated methods for inferring social behavior from microphone data (e.g., Lu et al., 2012; Schmid Mast et al., 2015). Such studies use smartphone-based MSMs to measure the frequency and duration of in-person conversations (but not the content of conversations) by applying classifiers to the microphone data to infer social behaviors from audio files (Lu et al., 2012). Many of these studies have focused on technical issues that demonstrate the viability and validity of inferring social behavior from mobile sensor data. A few studies have also used such conversation inferences to examine substantive questions about sociability patterns among young adults over time (Harari et al., 2017; Wang et al., 2014).

Taken together, previous studies made important methodological inroads into measuring conversation behavior *in situ* but were mostly conducted with moderate sample sizes (*N*s < 100). Moreover, the studies were not focused on describing sociability in particular and thus did not provide much detail by way of descriptive information about individual differences in the social behaviors measured. For example, the extent to which people varied in their daily conversation behaviors between and within persons remains unknown. So, these studies established the viability of recording behaviors related to sociability, but they did not provide the level of detail or breadth of behaviors needed to obtain a continuous behavioral estimate of dispositional tendencies in social behavior. Thus, what is missing from the literature on conversation behaviors is a large-scale descriptive understanding of the rates of conversation (e.g., how many conversations, how much time is spent in conversation) in which people engage during a typical day and at different units of time (e.g., different times of the day and week).

Calling, Texting, and App Use Behaviors From Phone System Logs

Few empirical studies report basic descriptive statistics about rates of calling and texting behavior (i.e., SMS/MMS messages) based on naturalistic observation. Those that do have relied on telecommunication company server logs or MSMs to obtain estimates of calling and texting behaviors. For example, Boase and Ling (2013) used server log data from 426 subscribers of a Norwegian telecommunications company to study calling and texting rates. The Norwegian subscribers exchanged an average of 2.38 phone calls per day and exchanged 3.95 text messages per day. In studies using MSMs to collect data about calling and texting behaviors, researchers have found that people were on average involved in 4 calls per day and that calls on average lasted about 104 seconds (Stachl et al., 2017), suggesting that sample characteristics may influence observed rates of calling and texting behavior. Boase and Ling (2013) also found that the self-reported estimates of phone use frequency correlated only moderately with actual observational records of phone use measured from server logs, pointing to the need for more objective measures of phone-based social behavior.

Beyond calling and texting behaviors, smartphones increasingly mediate other forms of social behavior via third-party applications, such as messaging apps (e.g., Whatsapp) and social media apps (e.g., Facebook, Instagram). A few studies have investigated these types of app-mediated social behaviors, providing initial estimates of the rate with which people use them. For example, Montag et al. (2015) conducted a large study investigating rates of use for the popular messaging app, WhatsApp, over a period of four weeks, finding that people used WhatsApp for about 32 minutes a day and that this rate accounted for approximately 20% of all smartphone use on average. In a more recent and broader examination of app-mediated social behaviors, Stachl et al. (2017) used MSMs to collect application-use rates over a period of 60 days, finding that people on average used social media apps (e.g., Facebook, Instagram, Snapchat, Twitter, Weibo) 7 times per day with a mean duration of 51 seconds per app usage session. In their sample, communication apps (e.g., WhatsApp, Mail, Contacts, Dialer, SMS/MMS) were used about 38 times per day with a mean duration of 31 seconds per session.

Purpose of the Study

The purpose of this study was to provide the first large-scale descriptive account of young adults' socializing tendencies as measured in the natural stream of everyday life. Basic descriptive accounts of social behavior tendencies are needed to serve as the starting point for characterizing sociability patterns as they manifest outside the laboratory; these patterns can be combined with subsequent deductive studies that examine additional psychological phenomena associated with sociability (e.g., well-being; Cooper, 2016; Rozin, 2001).

The broad goals of the present study are twofold. First, we aimed to examine individual differences in sensed social behavior estimates obtained using MSMs. We focused on the sensed conversation, calling, and texting behaviors at the daily level to examine the extent of between-person variability in the daily assessments (*To what degree do young adults vary among one another in their daily social behaviors?*), mean level consistency across the daily assessments (*How stable are young adults' daily social behaviors?*), and relationships among the daily behavioral tendencies (*How do tendencies to engage in different forms of social behaviors relate to one another?*). An assessment of individual differences in sensed sociability behaviors is needed to facilitate comparisons between traditional methods (e.g., self-reports) and new MSMs as a behavioral observation approach to measuring dispositional sociability.

Second, we aimed to examine possible factors that may be driving the individual differences in social behavior (e.g., time, personality traits). To do so, we expanded the focus of our analysis to different time periods (e.g., mornings, afternoons, evenings, nights; weekdays, weekends), examining the between-person averages of the within-person means for each of the sensed social behaviors (*How much social behavior do young adults engage in during a typical day, across times of day, and across days of the week?*). We also explored the relationship between the sensed social behavior tendencies and self-reported personality traits (*How do the behavioral tendencies map onto the Big Five traits?*).

We undertake both goals in the context of measuring sensed social behaviors in four samples of young adults, using four different mobile sensing applications that sampled the microphone sensors and phone system logs on participants' smartphones. We focused on young adults' tendencies to engage in conversation, phone call, text message, and app use behaviors, capturing the amount (frequency, and duration or length) of these sensed social behaviors on a continuous basis. In focusing on behavioral tendencies, we adopt the dispositional view of sociability (Buss & Craik, 1980), using repeated assessments to capture the tendency for individuals to engage in social behaviors over time. We have shared our sensed sociability data and analytic scripts on the Open Science Framework at our project page to contribute to the descriptive foundation for research on behavioral sociability patterns (https://osf.io/p9rz3/).

Ethics Approval

This article reports on data from four studies. In each study, participants were explicitly informed about the purpose of the data collection and consented to using the mobile sensing apps prior to participation. Our studies were approved by the appropriate ethics committees at each respective institution: the Sample 1 (S1) study was approved by the Committee for Protection of Human Subjects at Dartmouth College under CPHS No. Study21858; the Sample 2 (S2) study was approved by Cambridge Psychology Research Ethics Committee at the University of Cambridge under Protocol No. PRE.2015.102; the Sample 3 (S3) study was approved by the Ethics Committee of Ludwig-Maximilians-Universität München Study No. 15_c_2015; the Sample 4 (S4) study approved by the Office of Research Support and Compliance at The University of Texas at Austin under Protocol No. 2012–07-0064.

In addition, we incorporated the following study design features in all four of our studies to protect participants' privacy while using the apps (see Beierle et al., 2018 for a through description of such considerations): (a) users consented to install the app and track their data, (b) users could opt-out at any point during the data collection period, (c) data were associated with random identifiers, (d) data were anonymized, (e) the app utilized the permission system, and (f) the data were securely transferred from the apps to our servers using SSL encryption.

Method

Participants and Procedure

In light of the novelty of using MSMs in psychological research, we started with two studies using smaller samples, that were designed to establish the overall viability of using these methods. We conducted two intensive, small-scale longitudinal studies (S1 and S2) to establish the viability and reliability of using MSMs as a naturalistic observation approach to collecting behavioral data. However, these studies were too costly (in S1 we gave Participants Android phones to use throughout the study duration) and labor-intensive (in S2 we conducted a two-phase study with several different sources of data collection) to scale up to a large sample. Therefore, after establishing the viability of collecting behavioral data using MSMs, we augmented the smaller studies with data from two larger studies (S3 and S4) designed to yield reliable point estimates regarding daily behavior (e.g., base rates of everyday social behavior, correlations between sensed social behaviors and self-reported personality traits). As larger-scale studies, these studies were inevitably less intensive than the S1 and S2 studies; we conducted studies in which participants downloaded our app onto their own phones (S3 included 30 days of data collection; S4 included 14 days of data collection). Details about the study design and sensed social behaviors for the four samples presented in this article are provided in Table 1.

The study design features shared across all four samples included the following: (1) participants were mostly young adult college students, (2) participants used a smartphone sensing application as a self-tracking tool that collected measures of social behavior, (3) participants could self-track using passive sensing (permitting the app to collect sensor data from the phone), (4) participants completed a personality measure that assessed the Big

Table 1
Overview of the Mobile Sensing Datasets

Dataset	*N*	Demographic information	Smartphone device	Study duration	Compensation	Sensing app	Conversation behaviors	Calling behaviors	Texting behaviors	App use behaviors
Sample 1	48	Age: $M = 22.81$, $SD = 2.35$ Sex: 77.08% male	100% Android	66 days	Prize lottery	StudentLife	CONVO FREQ CONVO DUR			
Sample 2	25	Age: $M = 19.39$, $SD = 2.11$ Sex: 57.14% male	100% Android	14 days	Money and feedback	MyLifeLogger		CALL IN FREQ CALL IN DUR CALL OUT FREQ CALL OUT DUR	TEXT IN FREQ TEXT IN LEN TEXT OUT FREQ TEXT OUT LEN	
Sample 3	137	Age: $M = 23.59$, $SD = 4.71$ Sex: 36.50% male	100% Android	14–30 days	Money, feedback, or course credit	PhoneStudy		CALL IN FREQ CALL IN DUR CALL OUT FREQ CALL OUT DUR	TEXT IN FREQ TEXT IN LEN TEXT OUT FREQ TEXT OUT LEN	MSG APP FREQ MSG APP DUR SOCMED APP FREQ SOCMED APP DUR
Sample 4[a]	775	Age: $M = 18.94$, $SD = 2.22$ Sex: 39.65% male	20% Android 80% iOS	14 days	Course credit and feedback	CampusLife	CONVO FREQ CONVO DUR	CALL IN FREQ CALL IN DUR CALL OUT FREQ CALL OUT DUR	TEXT IN FREQ TEXT IN LEN TEXT OUT FREQ TEXT OUT LEN	

Note. The sensed social behavior variables are denoted as follows: CONVO FREQ = conversation frequency; CONVO DUR = conversation duration; CALL IN FREQ = call incoming frequency; CALL IN DUR = call incoming duration; CALL OUT FREQ = call outgoing frequency; CALL OUT DUR = call outgoing duration; TEXT IN FREQ = text incoming frequency; TEXT IN LEN = text incoming length; TEXT OUT FREQ = text outgoing frequency; TEXT OUT LEN = text outgoing length; MSG APP FREQ = messaging app frequency; MSG APP DUR = messaging app duration; SOCMED APP FREQ = social media app frequency; SOCMED APP DUR = social media app duration.
[a] In Sample 4, the CampusLife app sensed conversation behaviors for both Android and iOS users ($N = 775$) but sensed only calling and texting behaviors for the subset of Android users ($N = 152$).

Five personality traits, and (5) participants completed a broader battery of survey measures (e.g., demographics, well-being measures) that are not reported here.

Next, we describe the main differences that distinguish the four samples, which included the sample sizes, study durations, recruitment strategies, use of different incentives, and use of different smartphone-sensing applications for data collection.

S1. Participants in S1 were students of a northeastern university in the United States who were enrolled in a computer science course about mobile app programming ($N = 48$). S1 consisted of a 10-week wave of data collection, for a total of 66 possible self-tracking days ($M = 49.92$ days, $SD = 12.52$ days). In S1, participants self-tracked their psychological experiences (via experience sampling surveys) and behaviors (via smartphone data) as part of a class assignment for 10 weeks of an academic term. Participants also took a battery of survey assessments at the beginning and end of the study (for full details about the study design, see Wang et al., 2014 or the publicly available data at studentlife.cs.dartmouth.edu).

Participation was voluntary, and the main incentive was the ability to use the anonymized data for a class assignment. Participants were given Android phones to use for the duration of an academic term with the StudentLife app preinstalled on the device (for full study details, see Wang et al., 2014). The StudentLife app measured two behavioral inferences from the microphone sensor that we focus on here: the frequency and duration of conversations.

S2. Participants in S2 were students in their first year of college at a university in the United Kingdom who were recruited for a study on student well-being and adjustment to university life (total $N = 118$). S2 consisted of two 2-week phases of data collection (Phase 1 and Phase 2) that were 3 months apart. Because of technical problems during the data-collection process for Phase 1, participants used two different sensing applications during the study—the Easy M app during Phase 1 and the MyLifeLogger app during Phase 2. The technical problems with the app used during Phase 1 compromised the quality of the sensing data collected, so here we focus only on the subset of participants who used the MyLifeLogger app during Phase 2 of the study ($N = 28$). The participants in Phase 2 had a total of 14 possible self-tracking days ($M = 13.96$ days, $SD = .20$ days).

In S2, participants were recruited by advertising the study at a freshman orientation fair, through undergraduate advisers, undergraduate tutors, student unions, and by posting fliers within various departments and on freshman Facebook groups. In addition to personal feedback, participants received £10 (approximately $14 dollars) for completing Phase 1 and up to £25 (approximately $36 dollars) for completing Phase 2. Compensation was higher for Phase 2 to incentivize participation during the final examination period. Participants also took a battery of survey measures at the beginning and end of each phase. The MyLifeLogger app measured 8 behavioral inferences from the phone system logs that we focus on here: frequency and duration of incoming and outgoing phone calls, as well as frequency and length of incoming and outgoing text messages.

S3. Participants in S3 were mostly students and employees at a southern German university who were recruited via social media, forums, blackboards, flyers, and mailing lists ($N = 137$). S3 consisted of an 8-week wave of data collection, for a total of 60 possible self-tracking days. In this study we used data from Day 2 to Day 31, resulting in 30 days of phone usage for all participants. Participants tracked their behaviors (via smartphone data) in exchange for €30 and individual personality feedback. Instead of money, students could also get course credit for their participation. Furthermore, participants took a battery of survey assessments in the lab at the beginning of the study (for full details about the study design, see Stachl et al., 2017). In addition to calling and texting behaviors, S3 included collection of app-mediated social behaviors. These app use behaviors were computed differently from the app use estimates reported in Stachl et al. (2017); here we separated the original "communication" and "social" app categories into different behavioral categories. Specifically, we focused on two app use behaviors for the present study: frequency and duration of messaging app use, and frequency and duration of social media app use.

S4. Participants in S4 were students of a southwestern university in the United States who were enrolled in an online introductory psychology course (data from two semester cohorts were included here, for a total possible $N = 1{,}734$). S4 consisted of a 2-week wave of data collection, for a total of 14 possible self-tracking days. Participants could self-track their psychological experiences (via experience sampling surveys) and behaviors (via smartphone data) as part of a class assignment for two weeks during an academic semester. Participants could choose to use e-mail (via questions presented using Qualtrics software) or a smartphone sensing application (called CampusLife, which is based on the StudentLife sensing software; Wang et al., 2014) as the self-tracking tool for the class assignment. For the purposes of this article, we focus on the subset of the participants who used the smartphone application, which collected sensed behavioral data about their daily social behaviors. We collapsed the samples across the two semesters to increase our sample size and ability to detect effects between the sensed social behaviors and personality variables ($N = 775$; 45% of the total possible sample). Participants also completed a battery of psychological surveys in exchange for personal feedback about their responses.

In S4, participants used the CampusLife application, which was designed to run on both Android and iOS phones. Because of sampling constraints imposed by the iOS system, the social behavior data collected by the app differed between Android and iOS phones. Specifically, the Android version of the CampusLife app measured 10 behavioral inferences from the microphone and phone-system logs: duration and frequency of conversations, frequency of incoming and outgoing phone calls, duration of incoming and outgoing phone calls, frequency of incoming and outgoing text messages, and length of incoming and outgoing text messages. In contrast, the iOS version of the CampusLife app was able to measure only two behavioral inferences from the microphone sensor: the frequency and duration of conversations. This difference in the sampling constraints of the operating systems (Android vs. iOS) led to different subsample sizes for the sensed social behavior estimates: conversation behaviors ($N = 709$; $M = 6.42$ days of app use), calling and texting behaviors ($N = 152$; $M = 9.27$ days of app use).

Primary data from two (of four) studies reported in this article have been previously published elsewhere. Specifically, the data from S1 were made publicly available in 2014 as part of the StudentLife study (Wang et al., 2014; https://studentlife.cs.dartmouth.edu). The StudentLife dataset has been used in several research studies examining the sensed behavioral patterns associated with academic performance and well-being among college students (e.g., Harari, Gosling, Wang, Chen, Chen, & Campbell, 2017; Saeb, Lattie, Schueller, Kording, & Mohr, 2016; Wang, Harari, Hao, Zhou, & Campbell, 2015). The present research substantively differs from the previously published research using the data from S1 in its focus on between person individual differences in conversation behaviors. In addition, the data from S3 were used in a past study examining whether Big Five personality traits predicted smartphone application use (Stachl et al., 2017). The present research differs from the past work by focusing on between person individual differences in use of messaging and social media applications.

Measures

Personality traits were measured in S1, S2, and S4 using the 44-item Big Five Inventory (John & Srivastava, 1999). In S3, personality traits were measured using the Big Five Structure Inventory (BFSI; Arendasy, 2009). The BFSI measures the Big Five personality dimensions at both the factor and facet level via 300 short items.

Sensed Social Behaviors From Smartphone Data

Inferring conversation behaviors from microphone sensors. Conversation was measured in S1 and S4. The audio classifier measuring conversation was developed in prior work (Lane et al., 2012; Rabbi, Ali, Choudhury, & Berke, 2011), where it achieved 84% to 94% accuracy at classifying microphone data into audio-based inferences (i.e., silence, noise, voices). The microphone sensor on participants' smartphones was sampled every third minute (on for 1 min, off for 2 min) and an audio classifier was applied to infer users' duration of time spent around other voices (vs. silence or noise) and the frequency of separate instances of conversation (Wang et al., 2014). When conversation (i.e., voices) was detected, the classifier continued monitoring the duration until the conversation was over. The content of conversations was never recorded. Instead, the application saved the audio inferences as a "0" for silence, "1" for noise, "2" for voices, and "3" for unknown. We used these audio inferences to aggregate the data into duration of time spent proximal to human speech (either in conversation or around conversation) for each hour of each day in the data collection period. This behavioral estimate captured a unique aspect of social behavior—the general tendency to affiliate with others as indexed by the amount of time participants spend around conversation and around separate instances of conversation.[1]

Inferring call and text message behaviors from phone system logs. Call and text message behaviors were measured in S2, S3, and S4. The call and text message logs used to measure interaction behaviors are naturally recorded as part of the phone's

[1] The ambient conversation estimates are particularly useful for detecting whether the participant is socially isolated (not around voices) vs. surrounded by other people (near or engaged in conversation). Note that the ambient conversation inferences do not distinguish between participants' being around conversation or actually in conversation. The inferences may also mistakenly infer that a participant is engaged in conversation when they are watching TV alone or sitting in a lecture. Thus, these inferences may overestimate or underestimate aspects of in-person conversation.

system logs. These logs include a record of the phone number, timestamp, duration, and direction (incoming vs. outgoing; ignoring missed calls) associated with each phone call and text message interaction. These logs were sampled each time a participant used the app (i.e., when responding to a survey notification). The phone numbers of interaction partners and content of calls and text messages were never recorded by the apps. Instead, the apps saved a hashed-identifier for interaction partners, along with the direction (incoming, outgoing), duration (of calls), and length (of text messages) of the interaction. We used these phone-log features to aggregate the data into frequency and duration of calling and text messaging for each hour of each day in the data collection period. These interaction estimates capture a more direct aspect of social behavior - the tendency to initiate, respond to, and spend time in calls and text messages with others.

Inferring app use behaviors from phone system logs. App use behaviors were measured in S3. The phone logs used to measure app-mediated social behavior are naturally recorded as part of the phone's system logs. Depending on the version of the Android operating system running on the phone, these logs were accessed by the app by directly retrieving all currently running apps on a phone. These logs recorded when (via timestamps) and where (via GPS measurements) apps were opened. We used the timestamped logs to aggregate the data into frequency and duration of use for messaging apps (e.g., Whatsapp, Facebook Messenger) and social media apps (e.g., Facebook, Instagram, Snapchat).[2] The frequency of app use was computed by summing the number of times a given app was opened. The duration of app use was computed by measuring the time between subsequent active user behaviors in the logs (e.g., time between a WhatsApp event and a "Screen Off" event), which made the estimates prone to the influence of outliers (e.g., because of very long usage breaks) so we calculated app durations using a robust approach to computing means (Huber, 1981). These interaction estimates captured another channel by which social behavior occurs today—the tendency to use messaging and social media apps.

Data Processing Steps to Obtain Sensed Social Behavior Tendencies

Several processing steps were required to prepare the smartphone data for analysis. The aims of our data processing steps were to compute valid estimates of the amount of social behavior participants engaged in each day (24-hr time period), at four different time-of-day periods (TOD; morning, afternoon, evening, and night), and at two different times of the week (TOW; weekdays, weekends).[3,4] Overall, our data processing steps followed this general order for each sensed social behavior, per person: (1) estimating the amount of social behavior engaged in (frequency, duration, or length) by summing up the observations within each day and for different times of the day based on timestamps associated with the behavioral records collected by the sensing app and (2) aggregating the data to compute a within-person average estimate that represents an individual's behavioral tendency across (a) days, to obtain a daily social behavior tendency estimate, (b) times of the day, to obtain four TOD tendency estimates per social behavior, and (c) weekdays and weekends, to obtain two TOW tendency estimates per social behavior. In the following text, we describe these data-processing steps in more detail within the context of each sensed social behavior estimated from the microphone and phone log data.

Estimating conversation tendencies. The conversation behavior estimates were based on features that were extracted from continuous measurements of microphone sensor data. Because of the continuous sampling rate of the apps, we could expect users to have up to 24 hr of microphone sensor data on any given day of data collection. So, prior to computing the conversation tendency estimates, we had to clean the data to ensure that a sufficient amount of microphone data had been recorded for the time period.[5]

Daily estimates. To estimate the daily level conversation tendencies, we wanted to ensure the behavioral estimates were representative estimates of the participants' conversation behavior for each day. To that end, we created a threshold for the minimum number of hours of sensor data needed per day (>14 hours, or over 60% of the day) for the data to be retained in the analyses. This threshold was used in the data-cleaning process to identify and remove any days with an insufficient amount of hourly data per participant. The daily estimates were then computed on the retained data by (1) summing across the 24 hours in each day to obtain the conversation estimate per day for each participant, (2) dropping any participants who had only 1 day of data, and (3) averaging across days within persons to obtain for each participant an estimate of their typical daily conversation rates (duration and frequency).[6]

Time of day estimates. To estimate the TOD-level conversation tendencies, we used a similar approach to ensure the TOD estimates were representative of the 6-hour time periods they represented. We created a threshold for the minimum number of hours of sensor data needed per TOD period for the data to be retained in the analyses (≥ to 3 hours, or over 50% of the period). This threshold was used in the data-cleaning process to identify and remove any TOD periods per day with an insufficient amount of hourly data per participant. The TOD estimates were then computed on the retained data by (1) summing across the 6 hour within each TOD period to obtain the four estimates per day for each participant and (2) averaging across days within persons to obtain for each participant an estimate of their typical conversation rates for mornings, afternoons, evenings, and nights.

Time of week estimates. To estimate the TOW-level conversation tendencies, we used the daily estimates described above, averaging across weekdays and weekend days within persons to

[2] The full list of apps that were included in the messaging and social media use categories are provided in the online supplemental material (see Table S1).

[3] We operationalized the time of day categories into 6-hr periods as follows: morning (6:00 a.m. to 11:59 a.m.), afternoon (12:00 p.m. to 5:59 p.m.), evening (6:00 p.m. to 11:59 p.m.), night (12:00 a.m. to 5:59 a.m.).

[4] We operationalized the weekday vs. weekend categories as follows: weekdays (Mondays through Fridays), weekends (Saturdays and Sundays).

[5] An insufficient amount of data in a day could be a result of a participant: (1) having their phone run out of battery, (2) quitting or closing out the app, or (3) uninstalling the app altogether. To collect microphone data, the app had to remain open in the background. If the app was closed out, the app could only resume data collection when the participant re-opened it, which could lead to insufficient amounts of data collected for a given hour or day.

[6] In S1, no participants were dropped. In S4, 59 participants with 1 day of data were dropped, bringing the final sample size to 716.

obtain for each participant an estimate of their typical weekday and weekend conversation rates.

Estimating calling, texting, and app use tendencies. The call, text, and app use behavior estimates were based on features extracted from phone logs from Android phones that included timestamped logs indicating when participants engaged in these behaviors. For the estimates from S3, a series of additional processing steps were applied to the data to exclude duplicate entries which were logged for the calling and texting data.[7]

Daily estimates. The daily tendencies were computed by (1) summing across the 24 hours within each day to obtain the calling, texting, and app use estimates per day for each participant and (2) averaging across days within persons to obtain for each participant an estimate of their typical daily rate of calling (frequency and duration of incoming and outgoing calls), texting (frequency and duration of incoming and outgoing text messages), and app use (frequency and duration of using messaging and social media apps).

Time of day estimates. To estimate the TOD-level tendencies for calling, texting, and app use, we (1) summed across the 6 hour within each TOD period to obtain the four estimates per day for each participant and (2) averaged across days within persons to obtain for each participant an estimate of their typical morning, afternoon, evening, and night rates of calling, texting, and app use.

Time of week estimates. To estimate the TOW-level tendencies for calling, texting, and app use, we used the daily estimates described above averaging across weekdays and weekend days within persons to obtain for each participant an estimate of their typical weekday and weekend rates of calling, texting, and app use.

Analytic Strategy

We conducted two sets of analyses in line with our two broad aims (1) to provide a large-scale descriptive assessment of individual differences in social behavior and (2) to examine possible factors that may be driving the individual differences in sensed social behavior (e.g., time, personality traits). All our statistical analyses were conducted using R Version 3.4.1. The R scripts needed to reproduce our analyses are available on our project's OSF page at https://osf.io/p9rz3/.

Our first set of analyses were focused on the behavioral estimates at the daily level. We began by describing the extent to which people varied between persons for each of the sensed social behaviors by computing intraclass coefficient (ICC)1 estimates. We then estimated the stability of the sensed social behaviors across days by computing ICC (3, *k*) estimates. Next, we aggregated the daily social behavior estimates to obtain within-person means as a measure of behavioral tendencies. We then examined the relationships among the daily sensed social behavior tendencies by computing correlations and principal components analyses (PCA) of the daily social behavior tendencies. Given that the viability of obtaining stable measures of individual differences in social behavior from MSMs is unknown, we evaluated the variability, stability, and relationships among the daily sensed social behaviors in all four samples (S1 through S4).

In our second set of analyses, we expanded our descriptive focus to individual differences in more fine-grained (time-of-day tendencies) and broader (time-of-week tendencies) behavioral tendencies. We conducted these additional analyses on the data from S3 and S4 (due to their larger sample sizes). Specifically, we examined the rates of conversation, calling, texting, and app use tendencies to provide a descriptive account of the average amount of social behavior in which young adults engaged during a typical day, at different times of the day, and at different times of the week. As a final exploratory step, we also examined the extent to which behavioral dispositions were related to personality traits by correlating the sensed social behavior tendencies for the different time periods with self-reported Big Five traits. This analysis contributed to our understanding of the validity of both subjectively reported sociability and more objectively measured sensed social behaviors by showing the extent to which they converged with one another. The findings also contributed to our understanding of the behavioral manifestations of the Big Five personality traits, by pointing to fine-grained and broader behavioral patterns that were associated with the personality reports.

Results

Examining Individual Differences in Daily Social Behavior

To examine individual differences in the daily social behavior estimates, we computed a series of intraclass correlation coefficients within each sample for each sensed social behavior to estimate (1) the between-person variability in the daily level assessments by calculating the ICC1 (an unconditional multilevel model that estimates the proportion of the total variance that can be explained by individuals; Bliese, 2016; Shrout & Fleiss, 1979) and (2) the stability of the individual sensed social behaviors over time (i.e., across days) by calculating the ICC (3, *k*, a two-way mixed effects model that estimates consistency [vs. absolute agreement] of multiple measurements; Koo & Li, 2016). The results of both sets of analyses are presented in Table 2.

Variability in the daily social behaviors. We computed ICC1 estimates for each of the sensed social behaviors across four samples to determine how much of the total observed variance in the social behavior data was due to between-person factors (individuals; vs. within-person factors and error). The variance attributable to between-person factors was highest for daily app use frequency behaviors in S3 (70% for messaging app frequency and 67% for social media app frequency). Across samples, the between-person variance estimates were also quite high for in-person conversation behaviors (e.g., 52% to 55% for conversation behaviors in S4, and 30% to 35% in S1), and for the various text messaging behaviors (e.g., 43% to 57% for texting behaviors in S4, 30% to 39% in S2, and 11% to 19% in S3, respectively). Compared to these social behaviors, the variance attributable to

[7] Specifically, we identified duplicate texting events (events where the timestamps, length, conversation partner etc. were identical) and excluded them from the analyses. For repeated call events, we handled the duplicate duration values by replacing them with an imputed mean that was the average of all remaining unique call durations (at the within person level) for incoming and outgoing calls respectively. We took this approach to estimating the call durations to prevent the mean estimates from being affected by the duplicate rows.

Table 2
Variability and Stability of Daily Social Behaviors

ICC estimates	CONVO FREQ	CONVO DUR	CALL IN FREQ	CALL IN DUR	CALL OUT FREQ	CALL OUT DUR	TEXT IN FREQ	TEXT IN LEN	TEXT OUT FREQ	TEXT OUT LEN	MSG APP FREQ	MSG APP DUR	SOCMED APP FREQ	SOCMED APP DUR
Sample 1														
Between-person variance	.30 [.22, .40]	.35 [.27, .46]												
Mean consistency	.97 [.95, .98]	.97 [.96, .98]												
Sample 2														
Between-person variance			.11 [.05, .23]	.11 [.04, .22]	.20 [.11, .35]	.15 [.07, .28]	.39 [.26, .57]	.30 [.19, .48]	.35 [.23, .53]	.33 [.21, .51]				
Mean consistency			.68 [.46, .84]	.67 [.44, .83]	.81 [.68, .90]	.75 [.58, .87]	.92 [.86, .96]	.88 [.80, .94]	.90 [.84, .95]	.89 [.82, .95]				
Sample 3														
Between-person variance			.16 [.12, .22]	.20 [.16, .27]	.33 [.27, .39]	.37 [.32, .44]	.17 [.14, .22]	.11 [.09, .15]	.19 [.15, .24]	.14 [.11, .19]	.70 [.65, .75]	.51 [.45, .57]	.67 [.60, .73]	.62 [.56, .68]
Mean consistency			.85 [.81, .89]	.88 [.85, .92]	.94 [.92, .95]	.95 [.93, .96]	.87 [.83, .90]	.80 [.74, .84]	.88 [.84, .91]	.83 [.79, .87]	.99 [.98, .99]	.97 [.96, .98]	.98 [.98, .99]	.98 [.97, .98]
Sample 4														
Between-person variance	.55 [.52, .57]	.52 [.50, .55]	.30 [.25, .35]	.42 [.37, .48]	.32 [.27, .38]	.26 [.22, .32]	.52 [.46, .58]	.43 [.37, .49]	.57 [.51, .63]	.45 [.40, .52]				
Mean consistency	.97 [.97, .97]	.97 [.96, .97]	.92 [.90, .94]	.95 [.94, .96]	.93 [.91, .94]	.90 [.88, .92]	.97 [.96, .97]	.96 [.95, .97]	.97 [.97, .98]	.96 [.95, .97]				

Note. The variability and reliability estimates were computed using the intraclass correlation coefficient (ICC) package in R. The between-person variance represents the ICC1 estimate, the percentage of variation in the observed daily social behaviors that can be explained by individual factors. The mean consistency represents the ICC(3,*k*) estimate, the average individual stability of the daily social behavior assessments across days. CONVO FREQ = conversation frequency; CONVO DUR = conversation duration; CALL IN FREQ = call incoming frequency; CALL IN DUR = call incoming duration; CALL OUT FREQ = call outgoing frequency; CALL OUT DUR = call outgoing duration; TEXT IN FREQ = text incoming frequency; TEXT IN LEN = text incoming length; TEXT OUT FREQ = text outgoing frequency; TEXT OUT LEN = text outgoing length; MSG APP FREQ = messaging app frequency; MSG APP DUR = messaging app duration; SOCMED APP FREQ = social media app frequency; SOCMED APP DUR = social media app duration.

between-person factors was lower for the calling behaviors (e.g., 26% to 42% for calling behaviors in S4, 11% to 20% in S2, and 16% to 37% in S3, respectively). Overall, the between-person variance estimates observed suggest that the daily level social behaviors may be explained by measures of individual characteristics (e.g., personality traits).

Stability in the daily social behaviors. Next, we computed the ICC (3, *k*) estimates to examine stability in the day-to-day social behaviors, revealing the extent to which the sensed social behavior estimates were consistent across the daily measurements. We used consistency estimates (instead of absolute agreement) because we expected the sensed social behaviors to vary somewhat across days, and not be perfectly equal from day-to-day. Across samples, the consistency estimates for the daily social behaviors across days were high (see Table 2). Overall, the estimates were highest for app use (.97 to .99 in S3), followed by conversation (e.g., .97 and .97 in S1 and S4), texting (e.g., .96 to .97 in S4), and calling behaviors (e.g., .90 to .95 in S4). The observed consistency estimates suggest that the mean amount of daily social behavior an individual engages in is quite stable across days, providing support for the idea that individual differences in sociability can be systematically measured using social behavior estimates from MSMs.

Having established that a sizable portion of the variance in daily social behavior is attributable to individual factors and that individuals show stable mean levels of social behavior from day-to-day, we turned our focus to examining interindividual relationships among the daily behavioral tendencies.

Relationships Among Daily Social Behavior Tendencies

To examine interindividual relationships among the daily social behaviors, we aggregated the daily level sensed social behavior estimates within individuals, across days, to obtain a single daily average tendency estimate for each social behavior per person. This aggregation process resulted in a single within person mean estimate for each sensed social behavior: 2 daily social behavior estimates in S1, 8 daily social behavior estimates in S2, 12 daily social behavior estimates in S3, and 10 daily social behavior estimates in S4 (see Table 3 for the list of the 14 different daily social behavior tendencies studied and which sample they were included in). In doing so, we aimed to explore the extent to which tendencies to engage in one type of social behavior (e.g., conversations) might be associated with tendencies to engage in another type of social behavior (e.g., text messaging). First, we examined the relationships among daily conversation, calling, texting, and app use tendencies by computing Spearman correlations between the daily social behavior measures.[8] Table 3 presents the correlations between the daily social behavior tendencies and their 95% confidence intervals. Second, we examined the underlying dimensional structure of the daily social behavior tendencies by conducting a series of principal components analyses within each sample.

[8] We used Spearman (instead of Pearson) correlations for all of our correlational analyses because the social behavior variables showed high kurtosis values and we did not want outliers in the data to influence the correlation estimates. Spearman correlations are preferable for variables with heavy-tailed distributions or that include outliers (de Winter, Gosling, & Potter, 2016), which was the case in our datasets.

Table 3
Correlations Between Daily Social Behavior Tendencies

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
							Sample 1							
1. CONVO FREQ	—	[.54, .83]												
2. CONVO DUR	**.72 (.000)**	—												
							Sample 2							
3. CALL IN FREQ			—	[.41, .85]	[.57, .90]	[.19, .78]	[.25, .83]	[.12, .78]	[.06, .76]	[−.04, .71]				
4. CALL IN DUR			**.69** (.000)	—	[.04, .70]	[.28, .81]	[−.02, .72]	[−.06, .70]	[−.16, .64]	[−.13, .66]				
5. CALL OUT FREQ			**.79** (.000)	**.42** (.034)	—	[.42, .86]	[.45, .89]	[.31, .85]	[.41, .88]	[.27, .83]				
6. CALL OUT DUR			**.55** (.005)	**.61** (.001)	**.70** (.000)	—	[.20, .81]	[.26, .83]	[.14, .79]	[.12, .78]				
7. TEXT IN FREQ			**.62** (.003)	.41 (.062)	**.74** (.000)	**.58** (.006)	—	[.71, .94]	[.90, .98]	[.81, .96]				
8. TEXT IN LEN			**.53** (.014)	.39 (.084)	**.66** (.001)	**.62** (.003)	**.87** (.000)	—	[.56, .90]	[.50, .89]				
9. TEXT OUT FREQ			**.48** (.027)	.30 (.194)	**.72** (.000)	**.54** (.011)	**.96** (.000)	**.79** (.000)	—	[.90, .98]				
10. TEXT OUT LEN			.40 (.074)	.32 (.154)	**.63** (.002)	**.53** (.014)	**.92** (.000)	**.75** (.000)	**.95** (.000)	—				
							Sample 3							
3. CALL IN FREQ			—	[.91, .95]	[.85, .92]	[.76, .87]	[.22, .51]	[.17, .47]	[.09, .41]	[.03, .36]	[−.14, .20]	[−.28, .05]	[−.15, .19]	[−.15, .18]
4. CALL IN DUR			**.94** (.000)	—	[.76, .87]	[.74, .86]	[.14, .44]	[.10, .41]	[.05, .37]	[.00, .33]	[−.11, .22]	[−.26, .07]	[−.17, .17]	[−.18, .15]
5. CALL OUT FREQ			**.89** (.000)	**.83** (.000)	—	[.90, .95]	[.19, .49]	[.17, .47]	[.07, .39]	[.02, .34]	[−.13, .2]	[−.28, .05]	[−.17, .16]	[−.19, .15]
6. CALL OUT DUR			**.83** (.000)	**.81** (.000)	**.93** (.000)	—	[.15, .46]	[.12, .43]	[.05, .37]	[.01, .33]	[−.13, .21]	[−.27, .06]	[−.21, .13]	[−.21, .13]
7. TEXT IN FREQ			**.37** (.000)	**.30** (.000)	**.35** (.000)	**.31** (.000)	—	[.96, .98]	[.73, .85]	[.65, .80]	[−.18, .15]	[−.25, .08]	[−.19, .14]	[−.18, .15]
8. TEXT IN LEN			**.33** (.000)	**.26** (.002)	**.33** (.000)	**.28** (.001)	**.97** (.000)	—	[.66, .81]	[.59, .77]	[−.17, .17]	[−.24, .09]	[−.20, .14]	[−.19, .15]
9. TEXT OUT FREQ			**.26** (.003)	**.21** (.013)	**.24** (.005)	**.22** (.010)	**.80** (.000)	**.74** (.000)	—	[.94, .97]	[−.26, .08]	[−.21, .13]	[−.31, .01]	[−.30, .03]
10. TEXT OUT LEN			**.20** (.019)	**.17** (.049)	**.19** (.028)	**.17** (.043)	**.74** (.000)	**.69** (.000)	**.95** (.000)	—	[−.29, .04]	[−.20, .13]	[−.34, −.02]	[−.33, −.01]
11. MSG APP FREQ			.03 (.726)	.05 (.533)	.03 (.686)	.04 (.630)	−.02 (.850)	.00 (.986)	−.09 (.276)	−.13 (.141)	—	[.69, .83]	[.14, .44]	[.14, .44]
12. MSG APP DUR			−.12 (.153)	−.10 (.243)	−.12 (.153)	−.11 (.214)	−.09 (.308)	−.07 (.384)	−.04 (.625)	−.03 (.691)	**.77** (.000)	—	[−.05, .28]	[.03, .35]
13. SOCMED APP FREQ			.02 (.799)	.00 (.994)	.00 (.962)	−.04 (.646)	−.02 (.778)	−.03 (.724)	−.15 (.071)	**−.19** (.030)	**.30** (.000)	.12 (.157)	—	[.94, .97]
14. SOCMED APP DUR			.01 (.880)	−.01 (.874)	−.02 (.791)	−.04 (.626)	−.02 (.855)	−.02 (.805)	−.14 (.100)	**−.17** (.042)	**.30** (.000)	**.20** (.020)	**.96** (.000)	—
							Sample 4							
1. CONVO FREQ	—	[.91, .93]	[.26, .54]	[.22, .50]	[.19, .48]	[.02, .34]	[.16, .45]	[.14, .44]	[.08, .39]	[.06, .37]				
2. CONVO DUR	**.92** (.000)	—	[.19, .48]	[.15, .44]	[.13, .43]	[−.01, .31]	[.13, .43]	[.13, .43]	[.08, .39]	[.03, .35]				
3. CALL IN FREQ	**.41** (.000)	**.34** (.000)	—	[.80, .89]	[.55, .74]	[.37, .61]	[.33, .58]	[.37, .61]	[.24, .52]	[.25, .52]				
4. CALL IN DUR	**.37** (.000)	**.30** (.000)	**.85** (.000)	—	[.49, .70]	[.38, .62]	[.29, .55]	[.32, .57]	[.19, .47]	[.21, .49]				
5. CALL OUT FREQ	**.34** (.000)	**.29** (.000)	**.65** (.000)	**.60** (.000)	—	[.77, .87]	[.30, .56]	[.26, .53]	[.19, .47]	[.17, .45]				
6. CALL OUT DUR	**.18** (.027)	**.15** (.068)	**.50** (.000)	**.51** (.000)	**.83** (.000)	—	[.22, .50]	[.20, .48]	[.15, .44]	[.14, .44]				
7. TEXT IN FREQ	**.31** (.000)	**.29** (.000)	**.46** (.000)	**.43** (.000)	**.43** (.000)	**.36** (.000)	—	[.78, .88]	[.65, .80]	[.56, .74]				
8. TEXT IN LEN	**.30** (.000)	**.29** (.000)	**.50** (.000)	**.45** (.000)	**.40** (.000)	**.35** (.000)	**.84** (.000)	—	[.45, .67]	[.52, .72]				
9. TEXT OUT FREQ	**.24** (.003)	**.24** (.004)	**.39** (.000)	**.34** (.000)	**.34** (.000)	**.30** (.000)	**.73** (.000)	**.57** (.000)	—	[.86, .92]				
10. TEXT OUT LEN	**.22** (.007)	**.19** (.020)	**.40** (.000)	**.36** (.000)	**.32** (.000)	**.30** (.000)	**.66** (.000)	**.63** (.000)	**.90** (.000)	—				

Note. Spearman correlation coefficients are presented below the diagonal, and 95% confidence intervals are above the diagonal. Exact p values are presented in parentheses alongside the correlation coefficients. p values are adjusted for multiple tests using the BH adjustment in R to control for the false discovery rate (Benjamini & Hochberg, 1995). Values in bold are significant at $p < .05$. CONVO FREQ = conversation frequency; CONVO DUR = conversation duration; CALL IN FREQ = call incoming frequency; CALL IN DUR = call incoming duration; CALL OUT FREQ = call outgoing frequency; CALL OUT DUR = call outgoing duration; TEXT IN FREQ = text incoming frequency; TEXT IN LEN = text incoming length; TEXT OUT FREQ = text outgoing frequency; TEXT OUT LEN = text outgoing length; MSG APP FREQ = messaging app frequency; MSG APP DUR = messaging app duration; SOCMED APP FREQ = social media app frequency; SOCMED APP DUR = social media app duration.

Table 4
Principal Components Analyses of Daily Social Behavior Tendencies

Variable	Component 1 loadings	Component 2 loadings	Component 3 loadings	Component 4 loadings
Sample 1	Conversation behaviors			
1. CONVO FREQ	**.92**	—	—	—
2. CONVO DUR	**.92**	—	—	—
% of variance explained	*.84*	—	—	—
Sample 2		Calling & texting behaviors		
3. CALL IN FREQ	—	**.83**	—	—
4. CALL IN DUR	—	**.68**	—	—
5. CALL OUT FREQ	—	**.75**	—	—
6. CALL OUT DUR	—	**.74**	—	—
7. TEXT IN FREQ	—	**.84**	—	—
8. TEXT IN LEN	—	**.93**	—	—
9. TEXT OUT FREQ	—	**.88**	—	—
10. TEXT OUT LEN	—	**.89**	—	—
% of variance explained	—	*.67*	—	—
Sample 3		Calling behaviors	Texting behaviors	App behaviors
3. CALL IN FREQ	—	**.85**	.11	.00
4. CALL IN DUR	—	**.80**	−.18	−.02
5. CALL OUT FREQ	—	**.84**	.14	.01
6. CALL OUT DUR	—	**.85**	−.04	−.01
7. TEXT IN FREQ	—	.08	**.92**	.02
8. TEXT IN LEN	—	.06	**.92**	.04
9. TEXT OUT FREQ	—	−.03	**.97**	−.03
10. TEXT OUT LEN	—	−.06	**.94**	−.03
11. MSG APP FREQ	—	.05	−.08	**.84**
12. MSG APP DUR	—	−.03	−.13	**.64**
13. SOCMEDIA APP FREQ	—	.00	.07	**.81**
14. SOCMEDIA APP DUR	—	−.06	.09	**.79**
% of variance explained	—	*.24*	*.31*	*.20*
Sample 4	Conversation behaviors	Calling behaviors	Texting behaviors	
1. CONVO FREQ	**.96**	.03	−.00	—
2. CONVO DUR	**.97**	−.03	−.00	—
3. CALL IN FREQ	.18	**.68**	.18	—
4. CALL IN DUR	−.05	**.82**	.00	—
5. CALL OUT FREQ	.16	**.75**	−.03	—
6. CALL OUT DUR	−.13	**.89**	−.02	—
7. TEXT IN FREQ	−.01	.08	**.88**	—
8. TEXT IN LEN	.09	−.06	**.81**	—
9. TEXT OUT FREQ	−.04	.06	**.87**	—
10. TEXT OUT LEN	−.04	−.07	**.90**	—
% of variance explained	*.20*	*.26*	*.31*	—

Note. Factor loadings greater than or equal to .40 are listed in boldface type. For each sample, the proportion of variance in the items explained by each factor is listed in italic type. The component correlations in Sample 3 were as follows: calling behaviors and texting behaviors (r = .42), calling behaviors and app behaviors (r = −.03), texting behaviors and app behaviors (r = −.01). The component correlations in Sample 4 were as follows: conversation behaviors and calling behaviors (r = .15), conversation behaviors and texting behaviors (r = .23), calling behaviors and texting behaviors (r = .40). CONVO FREQ = conversation frequency; CONVO DUR = conversation duration; CALL IN FREQ = call incoming frequency; CALL IN DUR = call incoming duration; CALL OUT FREQ = call outgoing frequency; CALL OUT DUR = call outgoing duration; TEXT IN FREQ = text incoming frequency; TEXT IN LEN = text incoming length; TEXT OUT FREQ = text outgoing frequency; TEXT OUT LEN = text outgoing length; MSG APP FREQ = messaging app frequency; MSG APP DUR = messaging app duration; SOCMED APP FREQ = social media app frequency; SOCMED APP DUR = social media app duration.

Table 4 presents the factor-loading matrices for the solutions within each sample.

Correlations among daily social behavior tendencies. In three of the four samples, the daily social behavior tendencies were all positively correlated with one another: in S1 r = .72 for the conversation behaviors, in S2 r's ranged from .30 to .96 for the calling and texting behaviors, and in S4 r's ranged from .15 to .92 for the conversation, calling, and texting behaviors. The exception to this pattern of positive correlational findings was observed for the relationships between daily calling, texting, and app use behavior tendencies in S3 (rs ranged from −.19 to .97). In particular, the correlations in S3 suggest that many of the daily calling and texting tendencies were positively correlated; however, there were no relationships (and in a few instances negative relationships) between the calling and texting tendencies and app use tendencies. For example, the daily length of outgoing text messages was negatively correlated with the frequency and duration of using social media apps (*r*s equaled −.19 and −.17, respectively), suggesting that individuals who used social media apps more frequently sent shorter text messages. More broadly, the general pattern of positive correlations among the individual sensed social behaviors suggests that these behaviors may be part of a broader construct, presumably one reflecting behavioral sociability.

Generally, and as to be expected, the strongest correlations among the sensed social behavior tendencies were observed between the same forms of social behavior (e.g., calling behaviors with other calling behaviors). For example, the frequency and duration of daily ambient conversations were highly correlated (S1 $r = .72$, S4 $r = .92$). The frequency and duration of incoming calls (S2 $r = .69$, S3 $r = .94$, S4 $r = .85$) and outgoing calls (S2 $r = .70$, S3 $r = .93$, S4 $r = .83$) were also highly correlated with one another. Similarly, the frequency and length of incoming text messages (S2 $r = .87$, S3 $r = .97$, S4 $r = .84$) and outgoing text messages (S2 $r = .95$, S3 $r = .95$, S4 $r = .90$) were highly correlated with one another. So were the frequency and duration of messaging app use (S4 $r = .77$) and social media app use (S4 $r = .96$). These high correlations indicate strong relationships among the conceptually similar forms of social behaviors.

Principal components analyses of daily social behavior tendencies. To examine the potential broader structure underlying the daily social behavior tendencies, we computed PCAs on the sensed social behavior variables within each sample. Given that the majority of the correlations between the daily social behaviors were positive, we used oblique (oblimin) rotation to allow the dimensions to correlate with one another. To determine the number of components to retain, we used multiple criteria: the scree plots, parallel analysis, and the interpretability of the resulting solutions (Zwick & Velicer, 1986).

In S1, these criteria pointed to a one-component solution that accounted for 84% of the total variance in conversation behaviors. This component reflected the conversation duration and conversation frequency estimates; these behaviors tapped into a tendency to affiliate with others and being around people talking in face-to-face contexts, so the dimension was labeled "Conversation Behavior."

In S2, we observed a one-component solution that accounted for 67% of the variance in calling and texting behaviors. This component included the frequency and duration of incoming and outgoing calls, as well as the frequency and length of incoming and outgoing text messages; these behaviors tapped into using the phone to both talk and text with others, so the dimension was labeled "Calling and Texting Behavior". However, these phone-based interactions separated into their own respective components in S3 and S4.

In S3, we observed a three-component solution that accounted for 75% of the variance in calling, texting, and app use behaviors. The first component included the frequency and duration of incoming and outgoing calls; these behaviors tapped into the specific tendency to talk with others on the phone, so the dimension was labeled "Calling Behavior". A second component included the frequency and length of incoming and outgoing text messages; these behaviors tapped into the specific tendency to interact with others via text message, so the dimension was labeled "Texting Behavior". Finally, a third component emerged that reflected the frequency and duration of app use; these behaviors tapped into the tendency to use messaging and social media apps, presumably to interact with others, so the dimension was called "App Use Behaviors".

In S4, a three-component solution that accounted for 76% of the variance in conversation, calling, and texting behaviors respectively. The first component reflected conversation behaviors, the second component reflected calling behaviors, and the third component reflected texting behaviors.

Overall, the large proportions of variance explained by these solutions indicates the components in each sample capture much of the individual variation in daily social behavior tendencies. Moreover, the correlations between the three components in S3 (*r*s = −.01 to .38) and S4 (*r*s = .23 to .42) suggest that the dimensions were related to one another, but still sufficiently distinct to reflect different aspects of a person's daily social behavior tendencies. It is worth noting that, in line with the observed relationships in the correlations between daily social behaviors, in Sample3, the app behavior component shows no relationship with the texting and calling behaviors (*r*s = −.01 and .01), while the texting and calling behaviors were positively related ($r = .38$). Having demonstrated the conceptual relationships between sensed social behavior tendencies at the daily level, we returned to our analysis of the individual social behaviors to examine the rates of behavioral sociability expressed by young adults in their daily lives.

Examining Rates of Behavioral Sociability

We then wrapped up our descriptiv analyses of the behavioral tendencies by examining the average amount of social behavior the typical young adult in our samples engaged in. Because of the larger sample sizes of S3 and S4 (S3 and S4 are several times larger than S1 and S2), we undertake the base rate (and subsequent correlational) analyses solely on the data from S3 and S4. We examined the sociability rates at different units of time to describe how much conversation, calling, texting, and app behavior a typical young adult engaged in during a typical day, at different times of the day (TOD; morning, afternoon, evening, night), and at different days of the week (DOW; e.g., Monday, Tuesday) and times of the week (weekdays vs. weekends). The descriptive statistics for the daily tendencies are presented in Table 5.

To facilitate comparisons across the sensed social behavior tendencies at different units of time, the descriptive patterns for different times of the day, days of the week, and times of the week are plotted alongside one another in Figure 1 (the table presenting the descriptive statistics for each of these units of time can be found in Tables S2 and S3 in the online supplemental material). In the following text, we describe the average social behavior tendencies we observed for each unit of time.

Typical daily tendencies. To obtain the social behavior estimates for a typical day, we computed the between-persons average of the daily behavioral tendencies (within-person averages) for each sensed social behavior.

The conversation behavior estimates revealed that on average, the young adults in S4 were around conversation for approximately 15% of their waking hours ($M = 145.85$ min) and showed

Table 5
Base Rates of Young Adults' Daily Social Behavior Tendencies

	Conversation behaviors		Calling behaviors				Texting behaviors				App use behaviors			
Descriptive statistics	CONVO FREQ	CONVO DUR	CALL IN FREQ	CALL IN DUR	CALL OUT FREQ	CALL OUT DUR	TEXT IN FREQ	TEXT IN LEN	TEXT OUT FREQ	TEXT OUT LEN	MSG APP FREQ	MSG APP DUR	SOCMED APP FREQ	SOCMEDAPP DUR
Sample 3														
M_{AVG}			.52	2.57	1.20	4.11	1.32	94.56	.73	56.00	27.40	14.01	6.59	5.40
SD_{AVG}			.66	4.80	1.57	6.89	1.76	98.02	1.46	114.23	23.32	11.40	10.23	8.07
Min			0	0	0	0	0	0	0	0	.53	0	0	0
Med			.30	.86	.63	.98	.70	62.80	.23	23.60	20.63	11.21	2.90	1.57
Max			4.37	40.68	8.10	45.42	10.10	537.37	10.80	881.03	118.10	56.55	67.13	39.31
Skew			2.32	4.40	2.02	2.76	2.95	2.18	4.08	4.92	1.97	1.24	2.78	2.14
Kurtosis			8.14	28.05	4.44	9.96	9.35	5.42	20.02	29.13	4.15	1.39	10.21	4.89
Sample 4														
M_{AVG}	18.89	145.85	1.05	4.92	1.56	6.59	18.45	216.11	13.51	133.82				
SD_{AVG}	11.05	109.43	1.08	13.77	1.75	12.55	21.68	171.59	18.35	136.89				
Min	0	0	0	0	0	0	0	0	0	0				
Med	17.33	123.30	.72	1.44	.91	2.65	10.81	189.34	8.16	95.71				
Max	81.17	605.52	4.73	139.89	11.42	97.49	113.91	1319.20	94.11	696.79				
Skew	.75	1.12	1.43	7.23	2.04	4.42	2.16	2.06	2.40	1.35				
Kurtosis	1.19	1.30	1.57	61.91	6.05	23.74	5.13	9.80	5.98	1.62				

Note. Data presented for Sample 3 (N = 137 for calling, texting, and app use behaviors) and Sample 4 (N = 709 for conversation behaviors; N = 152 for calling and texting behaviors). Conversation, call, and app use duration estimates are in minutes. Text message length is in characters. CONVO FREQ = conversation frequency; CONVO DUR = conversation duration; CALL IN FREQ = call incoming frequency; CALL IN DUR = call incoming duration; CALL OUT FREQ = call outgoing frequency; CALL OUT DUR = call outgoing duration; TEXT IN FREQ = text incoming frequency; TEXT IN LEN = text incoming length; TEXT OUT FREQ = text outgoing frequency; TEXT OUT LEN = text outgoing length; MSG APP FREQ = messaging app frequency; MSG APP DUR = messaging app duration; SOCMED APP FREQ = social media app frequency; SOCMED APP DUR = social media app duration; Min = minimum; Med = median; Max = maximum.

Table 6
Correlations Between Daily Social Behavior Tendencies and Self-Reported Big Five Traits

Variable	Extraversion			Agreeableness			Conscientiousness			Neuroticism			Openness		
	r	[95% CI]	*p*	*r*	[95% CI]	*p*	*r*	[95% CI]	*p*	*r*	[95% CI]	*p*	*r*	[95% CI]	*p*
Sample 3															
CALL IN FREQ	.12	[−.05, .28]	.152	.00	[−017, .17]	1.00	−.07	[−.24, .10]	.402	−.06	[−.22, .11]	.522	.01	[−.16, .18]	.908
CALL IN DUR	.03	[−.14, .20]	.737	−.02	[−.19, .15]	.819	−.07	[−.24, .10]	.411	.01	[−.15, .18]	.870	−.02	[−.19, .15]	.804
CALL OUT FREQ	**.19**	[.02, .34]	.029	−.01	[−.18, .15]	.873	−.10	[−.27, .06]	.224	−.08	[−.25, .08]	.326	−.01	[−.18, .16]	.890
CALL OUT DUR	.09	[−.08, .25]	.303	−.02	[−.19, .15]	.832	−.06	[−.22, .11]	.499	−.10	[−.26, .07]	.244	−.03	[−.20, .14]	.710
TEXT IN FREQ	**.20**	[.03, .35]	.020	.01	[−.15, .18]	.866	−.10	[−.26, .07]	.245	.06	[−.11, .23]	.463	.15	[−.01, .31]	.074
TEXT IN LEN	**.21**	[.04, .36]	.014	.03	[−.14, .20]	.735	−.10	[−.26, .07]	.252	.07	[−.10, .23]	.432	.14	[−.03, .30]	.112
TEXT OUT FREQ	**.18**	[.01, .33]	.040	.01	[−.15, .18]	.872	−.05	[−.22, .12]	.544	.04	[−.12, .21]	.613	.16	[−.01, .32]	.061
TEXT OUT LEN	.14	[−.03, .30]	.101	.05	[−.12, .21]	.601	−.02	[−.18, .15]	.851	.08	[−.09, .24]	.374	.16	[.00, .32]	.056
MSG APP FREQ	**.24**	[.07, .39]	.006	.05	[−.12, .21]	.579	−.03	[−.19, .14]	.747	.08	[−.09, .24]	.378	.02	[−.15, .19]	.830
MSG APP DUR	**.20**	[.03, .35]	.021	.11	[−.06, .27]	.200	.02	[−.15, .19]	.800	.05	[−.12, .21]	.597	.03	[−.13, .20]	.693
SOCMEDIA APP FREQ	.11	[−.06, .27]	.191	.05	[−.12, .21]	.575	.07	[−.10, .24]	.396	.00	[−.17, .17]	.980	−.08	[−.25, .08]	.324
SOCMEDIA APP DUR	.13	[−.04, .29]	.131	.06	[−.11, .22]	.500	.08	[−.09, .24]	.375	−.01	[−.18, .16]	.885	−.04	[−.20, .13]	.655
Sample 4															
CONVO FREQ	**.19**	[.11, .27]	.000	−.02	[−.10, .06]	.662	.04	[−.04, .12]	.328	.01	[−.07, .09]	.863	.00	[−.08, .08]	.959
CONVO DUR	**.18**	[.10, .26]	.000	−.01	[−.09, .07]	.837	.05	[−.04, .13]	.276	.02	[−.06, .10]	.681	.01	[−.07, .09]	.854
CALL IN FREQ	**.32**	[.15, .48]	.000	.13	[−.05, .31]	.153	.12	[−.07, .29]	.212	**−.19**	[−.36, −.01]	.036	**.19**	[.01, .36]	.035
CALL IN DUR	**.33**	[.16, .49]	.000	.16	[−.02, .34]	.076	.13	[−.06, .30]	.175	−.11	[−.29, .07]	.229	**.19**	[.01, .36]	.040
CALL OUT FREQ	**.38**	[.22, .53]	.000	.03	[−.15, .21]	.747	.17	[−.01, .34]	.067	−.18	[−.35, .00]	.048	**.19**	[.01, .36]	.039
CALL OUT DUR	**.26**	[.09, .43]	.004	−.10	[−.28, .08]	.290	.10	[−.09, .27]	.301	−.05	[−.23, .13]	.604	.18	[.00, .35]	.054
TEXT IN FREQ	**.31**	[.14, .47]	.001	**.18**	[.00, .35]	.050	.17	[−.02, .34]	.075	**−.18**	[−.35, .00]	.050	**.25**	[.08, .42]	.006
TEXT IN LEN	**.29**	[.12, .45]	.001	**.19**	[.01, .36]	.039	.11	[−.07, .28]	.246	**−.22**	[−.39, −.04]	.015	**.26**	[.08, .42]	.004
TEXT OUT FREQ	**.27**	[.09, .43]	.003	.08	[−.10, .26]	.373	.14	[−.05, .31]	.139	**−.21**	[−.37, −.03]	.025	**.24**	[.06, .40]	.009
TEXT OUT LEN	**.24**	[.06, .40]	.009	.12	[−.06, .30]	.196	.04	[−.15, .22]	.704	**−.20**	[−.37, −.02]	.029	**.25**	[.08, .42]	.006

Note. Data presented for Sample 3 ($N = 137$ for calling, texting, and app use behaviors) and Sample 4 only ($N = 709$ for conversation behaviors; $N = 152$ for calling and texting behaviors). Correlation coefficients are presented alongside their 95% confidence intervals (CIs) and exact *p* values. In Sample 3, the emotional stability dimension of the Big Five Structure Inventory was reverse coded to reflect neuroticism. CONVO FREQ = conversation frequency; CONVO DUR = conversation duration; CALL IN FREQ = call incoming frequency; CALL IN DUR = call incoming duration; CALL OUT FREQ = call outgoing frequency; CALL OUT DUR = call outgoing duration; TEXT IN FREQ = text incoming frequency; TEXT IN LEN = text incoming length; TEXT OUT FREQ = text outgoing frequency; TEXT OUT LEN = text outgoing length; MSG APP FREQ = messaging app frequency; MSG APP DUR = messaging app duration; SOCMED APP FREQ = social media app frequency; SOCMED APP DUR = social media app duration. Correlational estimates with $p < .05$ are listed in boldface type.

19 instances of conversation during a typical day.[9] The estimates also revealed individual variability between persons in the amount of conversation across days as shown by the standard deviations (see the second row of Table 5). The standard deviations for daily conversation duration and daily average conversation frequency were $SD = 109.43$ min and $SD = 11.05$ conversations, respectively.

The calling behavior estimates revealed that on average, the young adults received about 1 call per day (S3 $M = .52$ calls; S4 $M = 1.05$ calls) lasting for around 5 minutes or less (S3 $M = 2.57$ min; S4 $M = 4.92$ min), and made about 2 calls (S3 $M = 1.20$; S4 $M = 1.56$ calls) lasting around 5 to 10 minutes (S3 $M = 4.11$ min; S4 $M = 6.59$ min). The mean estimates also revealed some variability between persons in the frequency of incoming (S3 $SD = .66$; S4 $SD = 1.08$) and outgoing (S3 $SD = 1.57$; S4 $SD = 1.75$) phone calls during a typical day, indicating that young adults varied in the number of calls they made in a typical day. The duration of incoming (S3 $SD = 4.80$; S4 $SD = 13.77$ min) and outgoing (S3 $SD = 6.89$; S4 $SD = 12.55$ min) calls during a typical day also showed some variability.

Similarly, the typical texting behavior estimates across S3 and S4 were quite different, with participants in S4 texting at much higher rates than participants in S3. In S3, the texting estimates revealed that on average, the participants received 1.32 texts of a total of 94.56 characters in length and sent 0.73 texts of 56.00 characters in length during a typical day. In comparison, the texting estimates in S4 revealed that on average, participants received 18.45 texts of 216.11 characters in length and sent 13.51 texts of 133.82 characters in length during a typical day. The texting estimates also showed variability between persons in the frequency of incoming (S3 $SD = 1.76$; S4 $SD = 21.68$) and outgoing (S3 $SD = 1.46$; S4 $SD = 18.35$) texts, and in the character length of incoming (S3 $SD = 98.02$; S4 $SD = 171.59$) and outgoing texts (S3 $SD = 114.23$; S4 $SD = 136.89$).

The typical app use estimates in S3 revealed that on average, the participants used messaging apps 27.40 times for 14.01 min and used social media apps 6.59 times for 5.40 min during a typical day. The typical app use patterns also showed individual variability between persons in both the frequency ($SD = 23.32$) and duration ($SD = 11.40$) of messaging app use, and the frequency ($SD = 10.23$) and duration ($SD = 8.07$) of social media app use.

Typical time of day and day of week tendencies. To obtain the social behavior estimates for a typical time of day, we computed the between-persons average for each of the time-of-day social behavior tendencies (within-person averages for mornings, afternoons, evenings, and nights). As shown in the left panel of Figure 1, we observed that the typical young adult in our samples

[9] To obtain an estimate for the number of waking hours per day, we assumed that a typical day in which a person gets 8 hours of sleep would include 16 waking hours (i.e., 960 minutes).

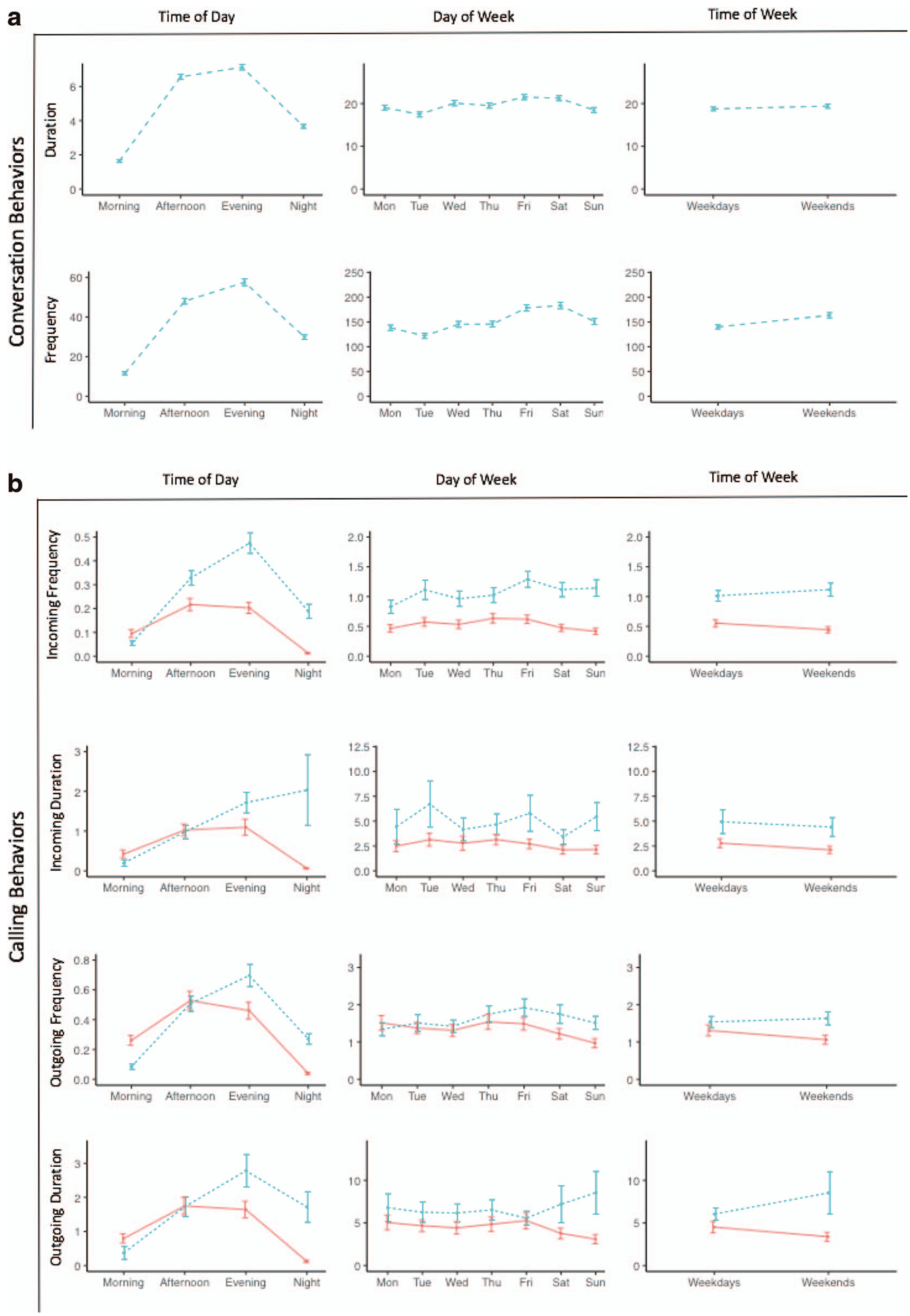

Figure 1. (a) Base rates of young adults' conversation behavior tendencies over time in Sample 4 (dotted line). (b) Base rates of young adults' calling behavior tendencies over time in Sample 3 (solid line) and Sample 4 (dotted line). (c) Base rates of young adults' texting behavior tendencies over time in Sample 3 (solid line) and Sample 4 (dotted line). (d) Base rates of young adults' app usage behavior tendencies over time in Sample 3 (solid line). See the online article for the color version of this figure.

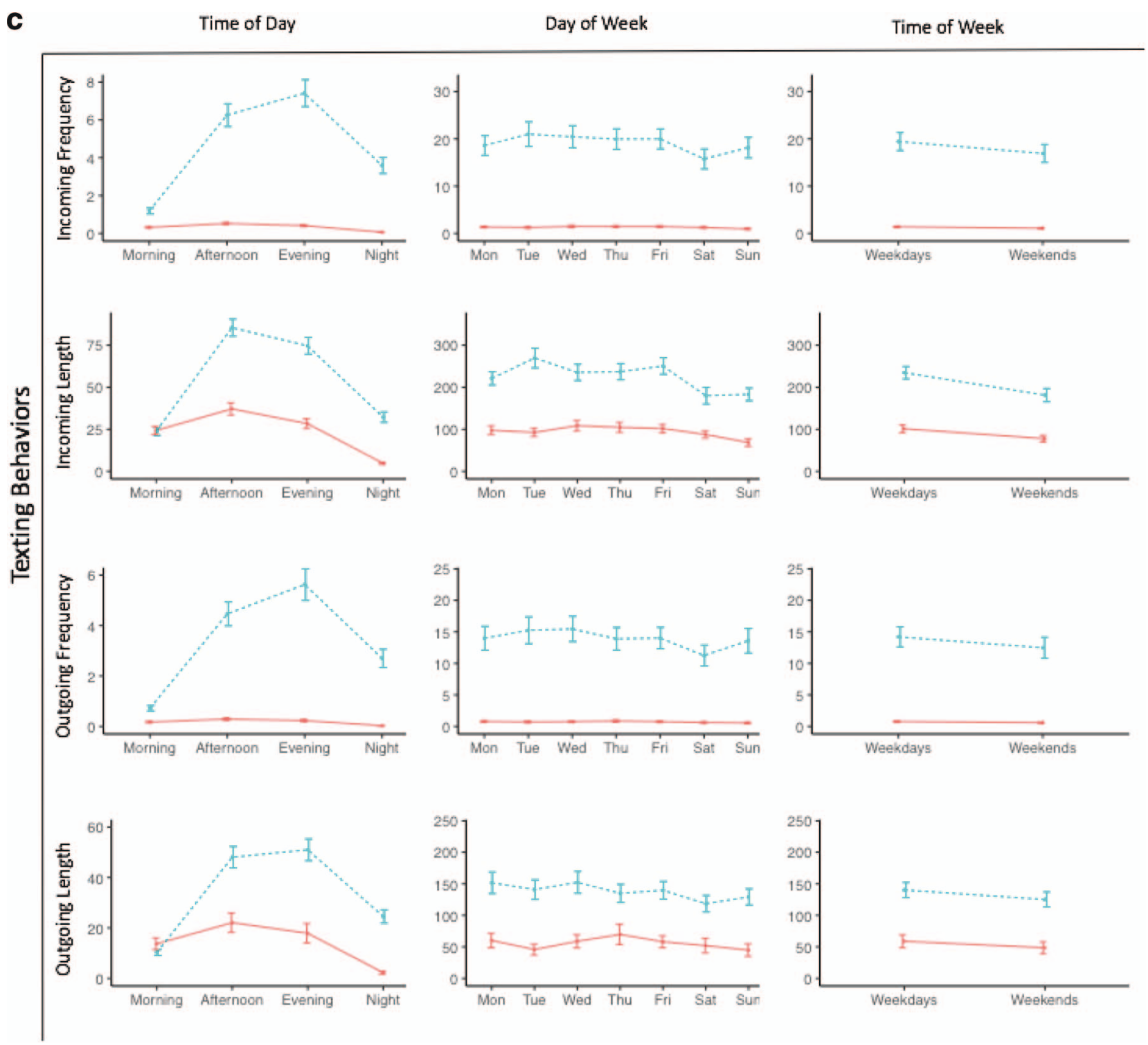

Figure 1. *(continued)*

tended to engage in more conversation, calling, texting, and app use behavior in the afternoons and evenings, compared to the mornings and nights. For example, in S4 the conversation behavior estimates revealed that on average, participants tended to engage in approximately 7 conversations for 48 to 58 min during the afternoons and evenings, compared to approximately 2–4 conversations for 12 to 30 min during the mornings and nights.

To obtain the social behavior estimates for a typical time of the week, we computed the between-persons average for each of the weekday (Monday through Friday) and weekend (Saturday through Sunday) sensed social behavior tendencies. As shown in the middle and right panels of Figure 2, we did not observe many mean-level differences between the typical amount of social behavior the participants in our samples tended to engage in on different days of the week, as well as on weekdays compared to weekends.

Behavioral Sociability and Self-Reported Personality Traits

To examine the extent to which these new measures of behavioral sociability tendencies map on to standard self-reported measures of personality traits, we computed Spearman correlations between the conversations, calling, texting, and app use tendencies and participants' self-reported Big Five trait ratings (i.e., extraversion, agreeableness, conscientiousness, neuroticism, and openness). We expected to find stronger correlations between the behavioral tendencies and extraversion, the trait theoretically related to social behaviors, than between the behavioral tendencies and the other Big Five personality traits. Theoretically, such findings would support the validity of self-reported personality measures (in this case, extraversion ratings) as predictors of domain-relevant behavior (everyday rates of conversation, calling, texting, and app use). Table 6 and Table 7, and Supplemental Table S9 present the correlational estimates, associated 95% confidence intervals, and exact *p* values for the correlational analyses conducted in S3 and S4.

Given the exploratory nature of this set of multivariate correlational analyses, we used randomization and replicability tests developed by Sherman and colleagues (e.g., Sherman & Funder, 2009; Sherman & Serfass, 2015; Sherman & Wood, 2014) to

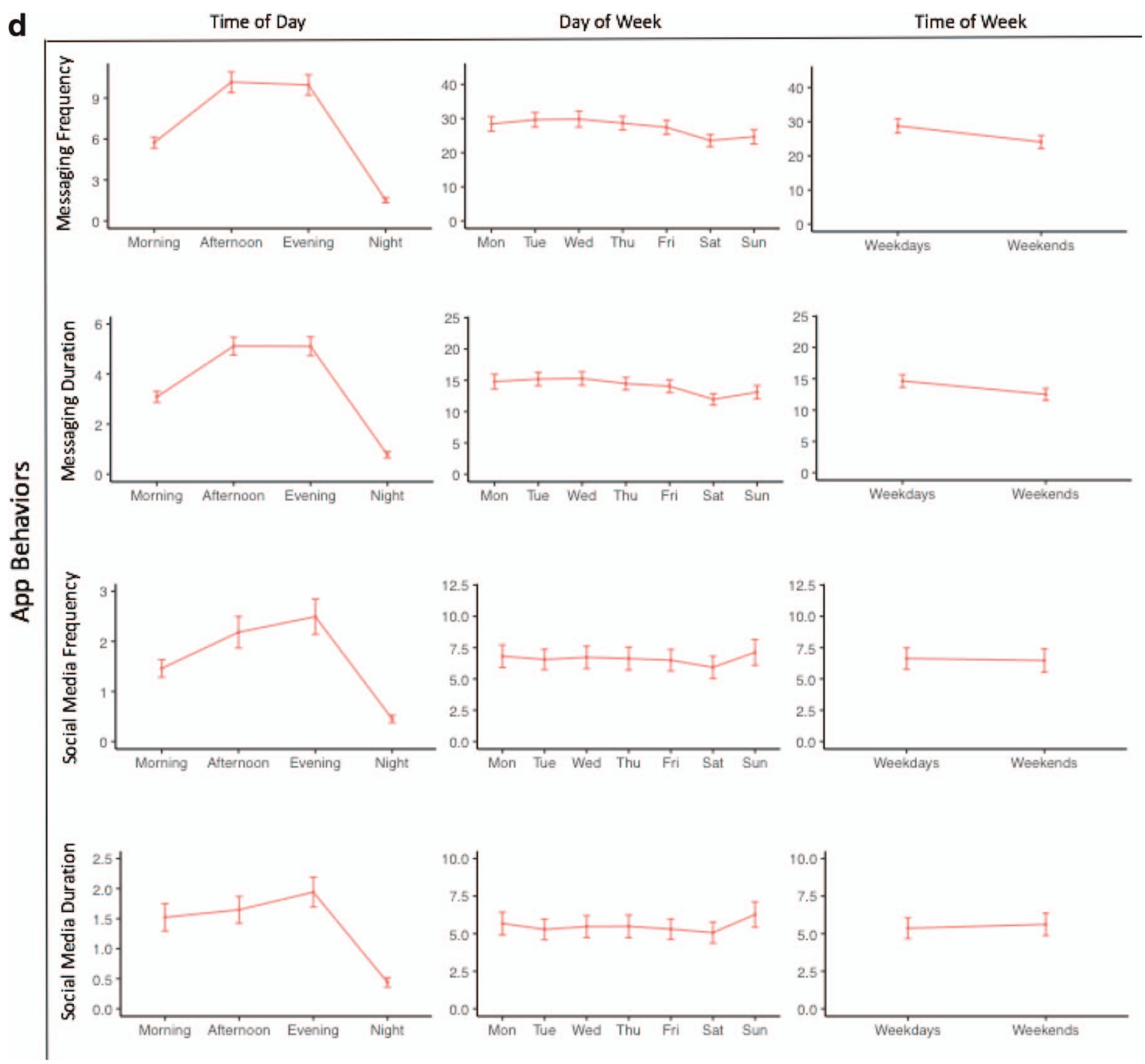

Figure 1. (continued)

evaluate our findings, focusing our interpretation and discussion of the findings on those that were found to be beyond chance and replicable. For a more thorough explanation of our motivation for using these tests in evaluating our exploratory multivariate analyses and interpreting our findings, we point interested readers to our online supplemental material, where we have included additional text describing these analytic techniques and the table of results from the randomization and replicability tests (see Tables S4 through S8 and Table S10 in the online supplemental material).

Correlations between sensed social behavior tendencies and Extraversion. Overall, the pattern of correlations observed in S3 and S4 suggest that the behavioral sociability tendencies measured using MSMs do map on to self-reported Extraversion.

In S3, the results from the randomization tests indicated that the correlations observed in between Extraversion and texting behaviors (observed r = .17, expected r = .07), and app use behaviors (observed r = .16, expected r = .07) had a greater average absolute value and showed more significant associations (15 significant for texting behavior, 1.4 expected; 12 significant for app use behavior, 1.4 expected) than would be expected by chance (see Table S4 in the online supplemental material for details). For example, we found that participants reporting higher extraversion received more (r = .20) and longer (r = .21) incoming text messages per day and used messaging apps more frequently (r = .24) and for longer durations (r = .20) per day, compared with participants lower in extraversion (see Table 7). However, the replicability analyses suggest that overall patterns of correlations between Extraversion and the texting and app behaviors were not replicable (see Table S10 in the online supplemental material), so we do not interpret the more fine-grained estimates further here, but we point interested readers to Table S9 in the online supplemental material for the full correlation matrix.

In S4, the correlations between Extraversion and conversation (observed r = .17, expected r = .04), calling (observed r = .18, expected r = .08), and texting behaviors (observed r = .17, expected r = .08) also had a greater average absolute r value and showed more significant associations (14 significant for conversation, .70 expected; 13 significant for calling, 1.4 expected; 12

Table 7
Correlations Between Time of the Day/Week Social Behavior Tendencies and Self-Reported Big Five Traits (Sample 4)

	Extraversion			Agreeableness			Conscientiousness			Neuroticism			Openness		
Variable	*r*	[95% CI]	*p*	*r*	[95% CI]	*p*	*r*	[95% CI]	*p*	*r*	[95% CI]	*p*	*r*	[95% CI]	*p*
CONVO FREQ															
Morning	**.16**	[.08, .24]	.000	0	[−.08, .08]	.985	.07	[−.01, .15]	.088	.01	[−.07, .09]	.803	−.05	[−.13, .03]	.248
Afternoon	**.18**	[.10, .26]	.000	.01	[−.07, .09]	.820	.06	[−.03, .14]	.186	.03	[−.05, .11]	.511	.02	[−.07, .10]	.712
Evening	**.19**	[.11, .27]	.000	.01	[−.07, .09]	.764	.03	[−.05, .11]	.470	−.04	[−.12, .04]	.340	−.02	[−.10, .07]	.704
Night	**.16**	[.08, .24]	.000	−.06	[−.14, .02]	.140	−.01	[−.10, .07]	.722	−.01	[−.09, .08]	.866	.01	[−.07, .10]	.741
Weekday	**.20**	[.12, .27]	.000	−.01	[−.09, .07]	.864	.05	[−.03, .13]	.220	.01	[−.08, .09]	.883	.00	[−.09, .08]	.937
Weekend	**.18**	[.10, .26]	.000	−.04	[−.12, .05]	.389	.00	[−.08, .09]	.946	−.02	[−.10, .07]	.671	.01	[−.07, .10]	.755
CONVO DUR															
Morning	**.14**	[.06, .22]	.001	−.03	[−.12, .05]	.412	.07	[−.01, .15]	.097	.02	[−.06, .10]	.607	−.03	[−.11, .05]	.435
Afternoon	**.15**	[.07, .23]	.000	−.01	[−.09, .07]	.865	.07	[−.01, .15]	.105	.05	[−.04, .13]	.280	.02	[−.06, .10]	.581
Evening	**.19**	[.11, .27]	.000	.04	[−.04, .12]	.316	.05	[−.04, .13]	.262	−.05	[−.13, .03]	.210	−.01	[−.09, .07]	.815
Night	**.18**	[.10, .26]	.000	−.04	[−.12, .04]	.315	.00	[−.08, .09]	.929	−.01	[−.09, .07]	.834	−.01	[−.10, .07]	.726
Weekday	**.17**	[.09, .25]	.000	−.02	[−.10, .07]	.717	.05	[−.03, .13]	.234	.03	[−.05, .11]	.487	.00	[−.08, .08]	.988
Weekend	**.20**	[.11, .28]	.000	.00	[−.09, .08]	.963	.02	[−.07, .10]	.708	−.03	[−.12, .05]	.445	.00	[−.08, .09]	.970
CALL IN FREQ															
Morning	.10	[−.08, .28]	.282	.09	[−.10, .26]	.356	−.05	[−.23, .13]	.565	−.03	[−.21, .15]	.762	−.04	[−.22, .14]	.683
Afternoon	**.20**	[.02, .37]	.028	.15	[−.03, .32]	.105	.08	[−.10, .26]	.376	−.13	[−.31, .05]	.149	**.29**	[.12, .45]	.001
Evening	**.31**	[.13, .46]	.001	.04	[−.14, .22]	.688	.14	[−.04, .31]	.137	−.16	[−.33, .02]	.080	.14	[−.04, .32]	.124
Night	**.27**	[.09, .43]	.003	.11	[−.08, .28]	.251	.14	[−.04, .31]	.131	**−.19**	[−.36, −.01]	.039	.06	[−.12, .24]	.514
Weekday	**.26**	[.08, .42]	.005	.11	[−.07, .29]	.217	.12	[−.06, .29]	.204	−.14	[−.32, .04]	.125	**.18**	[.00, .35]	.049
Weekend	**.35**	[.18, .50]	.000	.17	[−.02, .34]	.074	.13	[−.06, .30]	.169	**−.26**	[−.42, −.08]	.006	.14	[−.04, .32]	.122
CALL IN DUR															
Morning	.11	[−.07, .29]	.227	.09	[−.09, .27]	.332	−.03	[−.21, .16]	.774	−.03	[−.21, .15]	.766	−.01	[−.19, .17]	.936
Afternoon	.16	[−.02, .34]	.076	.13	[−.06, .30]	.174	.08	[−.11, .25]	.416	−.07	[−.25, .11]	.456	**.27**	[.09, .43]	.003
Evening	**.33**	[.16, .48]	.000	.10	[−.09, .27]	.302	.15	[−.03, .33]	.097	−.12	[−.30, .06]	.191	.16	[−.02, .33]	.085
Night	**.28**	[.10, .44]	.002	.11	[−.07, .29]	.230	.15	[−.04, .32]	.118	−.15	[−.32, .04]	.115	.08	[−.1, .26]	.368
Weekday	**.31**	[.14, .47]	.001	.15	[−.03, .33]	.099	.12	[−.07, .29]	.209	−.07	[−.25, .12]	.472	**.19**	[.01, .36]	.038
Weekend	**.32**	[.14, .47]	.001	.17	[−.02, .34]	.078	.17	[−.01, .35]	.062	**−.20**	[−.37, −.02]	.030	.12	[−.06, .30]	.193
CALL OUT FREQ															
Morning	**.23**	[.05, .40]	.011	.12	[−.06, .29]	.198	.15	[−.03, .32]	.101	−.18	[−.35, .00]	.056	.10	[−.08, .28]	.290
Afternoon	**.28**	[.11, .44]	.002	.08	[−.10, .26]	.396	**.18**	[.00, .35]	.046	−.16	[−.33, .02]	.079	**.22**	[.04, .39]	.018
Evening	**.44**	[.28, .58]	.000	.00	[−.18, .19]	.960	.13	[−.05, .31]	.149	**−.18**	[−.35, .00]	.049	**.22**	[.04, .39]	.015
Night	**.29**	[.11, .45]	.002	.02	[−.16, .20]	.836	.17	[−.02, .34]	.073	−.14	[−.31, .04]	.138	.02	[−.16, .20]	.796
Weekday	**.35**	[.18, .50]	.000	.01	[−.17, .20]	.878	.14	[−.04, .31]	.132	−.14	[−.31, .04]	.132	**.21**	[.03, .38]	.021
Weekend	**.38**	[.22, .53]	.000	.09	[−.09, .27]	.321	**.22**	[.04, .39]	.019	**−.23**	[−.39, −.05]	.014	.17	[−.01, .34]	.067
CALL OUT DUR															
Morning	**.22**	[.04, .39]	.015	.13	[−.06, .30]	.171	.15	[−.03, .33]	.100	−.17	[−.34, .01]	.065	.12	[−.07, .29]	.213
Afternoon	**.20**	[.02, .37]	.033	.01	[−.17, .19]	.920	.12	[−.07, .29]	.217	−.02	[−.20, .16]	.832	**.22**	[.04, .39]	.015
Evening	**.36**	[.20, .51]	.000	−.07	[−.24, .12]	.478	.11	[−.07, .29]	.228	−.11	[−.28, .08]	.249	**.20**	[.02, .36]	.034
Night	**.26**	[.09, .43]	.004	.00	[−.18, .18]	.989	.17	[−.01, .34]	.060	−.06	[−.24, .12]	.488	.07	[−.11, .25]	.427
Weekday	**.26**	[.08, .42]	.005	−.09	[−.27, .09]	.342	.06	[−.12, .24]	.511	−.02	[−.20, .16]	.795	**.22**	[.04, .39]	.018
Weekend	**.31**	[.14, .47]	.001	−.02	[−.20, .17]	.859	**.21**	[.03, .38]	.025	−.12	[−.30, .07]	.205	**.18**	[.00, .35]	.050
TEXT IN FREQ															
Morning	**.30**	[.13, .46]	.001	.06	[−.12, .24]	.521	**.19**	[.01, .36]	.040	**−.23**	[−.39, −.05]	.014	.16	[−.03, .33]	.094
Afternoon	**.35**	[.18, .50]	.000	.18	[.00, .35]	.052	.18	[.00, .35]	.054	**−.20**	[−.37, −.02]	.028	**.21**	[.03, .38]	.021
Evening	**.24**	[.06, .40]	.009	.17	[−.01, .34]	.066	.08	[−.10, .26]	.382	−.14	[−.31, .04]	.131	**.21**	[.03, .38]	.021
Night	**.30**	[.12, .45]	.001	**.21**	[.03, .38]	.020	**.21**	[.03, .38]	.024	**−.21**	[−.38, −.03]	.023	**.24**	[.06, .40]	.010
Weekday	**.31**	[.13, .46]	.001	.18	[.00, .35]	.053	.15	[−.03, .33]	.101	−.17	[−.34, .01]	.069	**.27**	[.09, .43]	.003
Weekend	**.23**	[.05, .40]	.012	**.18**	[.00, .36]	.048	.16	[−.03, .33]	.097	**−.21**	[−.38, −.03]	.025	**.18**	[.00, .35]	.050
TEXT IN LEN															
Morning	**.25**	[.07, .41]	.006	.07	[−.12, .25]	.474	.14	[−.05, .31]	.140	−.15	[−.33, .03]	.096	**.18**	[.00, .35]	.047
Afternoon	**.32**	[.14, .47]	.001	.17	[−.01, .34]	.060	.08	[−.10, .26]	.368	**−.19**	[−.36, −.01]	.036	**.21**	[.03, .37]	.026
Evening	**.26**	[.08, .42]	.004	**.22**	[.04, .38]	.019	.08	[−.10, .26]	.375	**−.26**	[−.42, −.08]	.005	**.29**	[.12, .45]	.001

(*table continues*)

Table 7 (*continued*)

	Extraversion			Agreeableness			Conscientiousness			Neuroticism			Openness		
Variable	*r*	[95% CI]	*p*	*r*	[95% CI]	*p*	*r*	[95% CI]	*p*	*r*	[95% CI]	*p*	*r*	[95% CI]	*p*
Night	**.27**	[.09, .43]	.004	.16	[−.02, .33]	.084	.14	[−.05, .31]	.139	**−.20**	[−.37, −.02]	.031	**.20**	[.02, .37]	.029
Weekday	**.29**	[.12, .45]	.001	.16	[−.02, .33]	.080	.09	[−.10, .26]	.354	**−.19**	[−.36, −.01]	.036	**.27**	[.10, .43]	.003
Weekend	**.22**	[.03, .38]	.021	**.21**	[.02, .37]	.028	.17	[−.01, .34]	.065	**−.25**	[−.41, −.07]	.007	.18	[.00, .35]	.052
TEXT OUT FREQ															
Morning	**.35**	[.18, .50]	.000	.04	[−.14, .22]	.630	.17	[−.01, .34]	.071	**−.24**	[−.41, −.07]	.008	.12	[−.06, .30]	.183
Afternoon	**.31**	[.13, .46]	.001	.05	[−.13, .23]	.589	.14	[−.04, .32]	.121	**−.21**	[−.37, −.02]	.026	**.22**	[.04, .38]	.019
Evening	**.20**	[.02, .37]	.027	.07	[−.11, .25]	.443	.06	[−.12, .24]	.527	−.17	[−.34, .01]	.072	**.22**	[.04, .39]	.016
Night	**.26**	[.08, .42]	.005	.14	[−.05, .31]	.145	**.19**	[.01, .36]	.039	**−.24**	[−.40, −.06]	.009	**.22**	[.04, .39]	.016
Weekday	**.28**	[.10, .44]	.003	.08	[−.11, .26]	.404	.13	[−.05, .30]	.163	**−.19**	[−.36, −.01]	.043	**.26**	[.08, .42]	.005
Weekend	**.20**	[.02, .37]	.029	.09	[−.09, .27]	.316	.15	[−.03, .33]	.102	**−.25**	[−.41, −.07]	.007	**.15**	[−.03, .33]	.104
TEXT OUT LEN															
Morning	**.34**	[.17, .49]	.000	.06	[−.12, .24]	.518	.11	[−.07, .28]	.242	**−.26**	[−.42, −.08]	.005	.18	[.00, .35]	.052
Afternoon	**.26**	[.08, .42]	.005	.07	[−.12, .24]	.484	.04	[−.14, .22]	.644	**−.19**	[−.36, −.01]	.038	**.25**	[.07, .41]	.007
Evening	**.21**	[.03, .38]	.025	.11	[−.07, .29]	.220	−.01	[−.19, .17]	.930	**−.20**	[−.37, −.02]	.032	**.23**	[.05, .39]	.013
Night	**.20**	[.02, .36]	.034	.12	[−.07, .29]	.207	.13	[−.05, .30]	.169	**−.21**	[−.38, −.03]	.023	.16	[−.03, .33]	.094
Weekday	**.21**	[.03, .38]	.021	.1	[−.09, .27]	.301	.03	[−.16, .21]	.777	**−.18**	[−.35, .00]	.051	**.24**	[.07, .41]	.008
Weekend	**.23**	[.04, .39]	.015	.14	[−.04, .32]	.126	.11	[−.07, .29]	.241	**−.25**	[−.41, −.07]	.008	.17	[−.02, .34]	.073

Note. $N = 709$ for conversation behaviors; $N = 152$ for calling and texting behaviors. Correlation coefficients are presented alongside their 95% confidence intervals (CIs) and exact p values. CONVO FREQ = conversation frequency; CONVO DUR = conversation duration; CALL IN FREQ = call incoming frequency; CALL IN DUR = call incoming duration; CALL OUT FREQ = call outgoing frequency; CALL OUT DUR = call outgoing duration; TEXT IN FREQ = text incoming frequency; TEXT IN LEN = text incoming length; TEXT OUT FREQ = text outgoing frequency; TEXT OUT LEN = text outgoing length. Correlational estimates with $p < .05$ are listed in boldface type.

significant for texting, 1.4 expected) than would be expected by chance (Supplemental Table S4). Moreover, the replicability analyses suggest that the overall pattern of correlations between Extraversion and the conversation ($\alpha = .50$) and calling behaviors ($\alpha = .66$), in particular, were replicable (see Table S10 in the online supplemental material). Specifically, these correlational findings suggest that participants reporting higher trait-level Extraversion engaged in more frequent and longer conversations (rs = .19 and .18) per day, more frequent and longer calls (rs = .26 to .38), and more frequent and lengthier text messages per day (rs = .24 to .31), compared to participants lower in Extraversion (see Table 7). The correlational analyses with the more fine-grained behavioral dispositions by time of day and day of week show that self-reported Extraversion was positively correlated with nearly all of the behavioral sociability tendencies in S4 (see Table 7).

Correlations between sensed social behavior tendencies and other Big Five traits. We also correlated the behavioral sociability tendencies with participant's Agreeableness, Conscientiousness, Neuroticism, and Openness ratings. We generally expected the relationships between these traits and the behavioral dispositions to be lower than those observed between the behaviors and self-reported Extraversion.

In S3, the results from the randomization tests indicated that none of the correlations observed between the remaining Big Five traits and the behavioral sociability dispositions had a greater average absolute value or more significant associations than would be expected by chance. Moreover, the replicability tests also indicated that the pattern of correlational findings were not replicable, so we do not interpret them further here (see Table S4–S10 in the online supplemental material for details).

In S4, the results from the randomization tests indicated that the correlations observed between Openness and calling (observed r = .17, expected $r = .08$) and texting behaviors (observed $r = .20$, expected $r = .07$) had a greater average absolute r value and showed more significant associations than would be expected by chance (12 significant for calling, 1.6 expected; 20 significant for texting, 1.4 expected; see Table S8 in the online supplemental material). However, the replicability analyses suggest that the overall pattern of correlations between Openness and calling behaviors ($\alpha = .62$) in S4 were replicable, whereas the texting patterns were not replicable so we do not interpret those further here (see Table S10 in the online supplemental material).

With regard to calling behaviors, we found that participants who reported higher Openness tended to receive more incoming calls ($r = .19$), had longer duration of time spent on incoming calls ($r = .19$), and made more outgoing calls ($r = .19$) per day, compared to participants low in openness (see Table 7). At a more fine-grained level, the correlational findings suggest that participants who reported higher Openness tended to engage in more calling behavior during the afternoons (rs = .22 to .29), evenings (rs = .20 to 22), and weekdays (rs = .18 to .22) in particular, compared to participants lower in openness (see Table 7).

Discussion

The purpose of this study was to provide the first large-scale descriptive study characterizing the real-world social behaviors of young adults as they go about their daily lives. In doing so, we also aimed to provide the first assessment of individual differences in smartphone-based measures of social behavior. To address these aims, we examined individual differences in the sensed social behavior tendencies of four cohorts of young adults, focusing on their rates of conversation, calling, texting, and app use behavior. These social behaviors were assessed using different mobile sensing applications that collected data from participants' smartphones via their microphones and phone system logs. The results indicated that young adults' day-to-day social behaviors show both substantial between-person variability and stability over time, with estimates varying across the different communication channels considered. The results also suggest the daily social behavior tendencies were related to one another, providing insight into the behavioral expression of sociability. Finally, the results provide a descriptive portrait of the quantity of social behavior in which young adults engage during a typical day, across different times of day, and times of the week; and how these sensed social behavior tendencies were related to their self-reported Big Five personality traits. Taken together, the study establishes the robustness of mobile sensing as a naturalistic observation method for studying individual differences in behavioral sociability as it occurs in the context of daily life.

Individual Differences in Young Adults' Daily Social Behavior

Variability in daily social behaviors. Our results showed a substantial degree of between-person variability in the daily social behavior patterns of young adults. The ICC1 estimates revealed that anywhere from 11% (for incoming call duration tendencies) up to 70% (for daily frequency of messaging app use) of the variability in the daily socializing estimates was due to unique characteristics of the individual. These findings are important because they suggest that people can be distinguished based on their sensed everyday socializing patterns.

Although young adults' individual characteristics may explain some of the variation in their daily social behaviors, a substantial amount of variability in the sensed social behaviors over time remains to be explained. Variability in social behavior rates could be related to several contextual factors (e.g., situational cues; Rauthmann, Sherman, & Funder, 2015), such as where a person is (e.g., being at home or work), who they are with (e.g., alone, with a significant other, with friends), and the mood or mental state of the person at the time of the interaction. Moreover, such variability in socializing patterns may be related to important momentary well-being outcomes, such as a person's satisfaction with their social life, sense of loneliness, mood, or happiness.

Stability of daily social behaviors. The stability estimates for participants' day-to-day social behaviors were high for all sensed social behaviors ICC(3,*k*) estimates ranging from .68 to .99 depending on the behavior), suggesting that mean levels of engagement in conversation, calling, texting, and app use were quite consistent from day-to-day. We also observed some differences in the stability estimates when comparing across behaviors and samples, suggesting that certain behaviors may be more consistent than others (e.g., app use and texting behaviors compared with calling behaviors) or that sample characteristics may be influencing the consistency in behaviors from day-to-day.

Relationships among daily social behavior tendencies. The correlational analyses among the daily social behavior tendencies examined the extent to which the sensed social behavior estimates were related to one another and their underlying dimensional structure. The results indicated that the daily socializing tendencies for conversation, calling, and texting behaviors were all positively related to one another. But these same sensed social behavior tendencies also showed no relationship (or in some instances a negative relationship) to daily app use tendencies (e.g., daily texting frequency and messaging app frequency were negatively correlated). Overall, our findings suggest that sensed social behavior estimates tapped into broader constructs of sociability-relevant behavior. In particular, the smartphone-based measures captured four dimensions of social behavior: conversation behavior (frequency and duration), calling behavior (incoming frequency and duration, outgoing frequency and duration), texting behavior (incoming frequency and length, outgoing frequency and length), and app use behavior (frequency and duration of messaging and social media app use).

A Snapshot of Young Adults' Behavioral Sociability Tendencies

Our descriptive findings provide the first large-scale study of the naturally occurring social behaviors of young adults measured unobtrusively and *in situ* as they go about their daily lives. Such descriptive findings can provide a foundation for theories about the factors underlying social behavior and for understanding the mechanisms by which sociability impacts people's stress, well-being, and health.

At the daily level, the base rates observed here for conversation behaviors differ from the rates of conversation reported in past research using the EAR, which found that a cohort of young adults spent approximately 32% of their waking hours talking to others (Mehl & Pennebaker, 2003). Such discrepancies in daily conversation behavior base rates could be due to several factors, including differences in: the forms of daily social behavior young adults engage in (e.g., texting and social media apps becoming more popular during the past 15 years), sampling rates used (continuous vs. periodic sampling of ambient sound), how conversation behavior was recorded (automated classification of voices vs. human rated coding of audio files), and operationalization of the social behavior estimates (automated classifications of frequencies and durations vs. the human-coded percent of audio files with conversation behaviors in them). Moreover, other research has found higher rates of talking with others among cohorts of cancer patients (47% of waking hours) and healthy working adults (40% of waking hours; Milek et al., 2018), suggesting that rates of daily conversation behavior may generally vary depending on the demographic or psychological characteristics of the sample.

The base rates observed here for calling and texting behaviors also differ from those published in past research. Our estimates are both lower and higher than those reported in past research (2.38 phone calls per day, 3.95 text messages per day; Boase & Ling, 2013). We suspect there are two main reasons why we observed these differences in calling and texting rates. First, our base rates may differ because of the proliferation of new social media platforms (e.g., Instagram, Snapchat). Such platforms permit smartphone-based socializing to occur through various channels, which may have led to decreases in how much young adults use phone calls to socialize. Second, our base rates may differ from those obtained by Boase and Ling (2013) because they did not focus on young adults in particular and because differences in phone plan subscriptions across countries (United States vs. Norway) may affect how much people use phone calls or text messages to socialize with others. Thus, to get a full picture of the amount of social behavior young adults engage in during a typical day, future studies using naturalistic observation methods should examine rates of social behavior occurring across platforms simultaneously (e.g., in-person and via different social media apps) and devices (e.g., computers, smartphones, tablets) and possibly query people about their phone plans (e.g., whether they have restricted text messaging rates) to obtain comprehensive estimates of sociability across various digital media platforms. However, it will always be difficult to obtain absolute estimates of daily social behavior because of the rapid changes in communication technology and general cross-country differences in communication preferences and technologies available.

We also found evidence for interindividual differences in young adults' daily social behavior tendencies. Some young adults showed behavioral tendencies that suggest they were often alone or interacted with very few people on most days, while other young adults seemed to interact with dozens of people on most days. Variability in socializing patterns is to be expected, but the ability to pinpoint exactly how much an individual does (or does not) socialize in a given day is unprecedented. For example, one person had a daily average of zero instances of conversation sensed during the study, while another person had a daily average of 82 instances of conversation. These individual differences in the daily sensed social behavior rates are underscored by the standard deviations, and the wide range in the minimum, median, and maximum values observed for the daily behavioral tendencies. Substantial degrees of variability were also observed for calling behaviors, with some people making zero calls on average per day, whereas another person made an average of 11 calls per day.

Mapping Everyday Behavioral Sociability Tendencies to Self-Reported Personality Traits

Do extraverts engage in greater amounts of conversation, calling, texting, and app behavior, than introverts do? Overall, our results suggest that they do, providing support for the validity of self-reported sociability at the trait level. Specifically, participants who reported higher levels of Extraversion also showed higher daily social behavior tendencies at the daily level (in S3: more outgoing calls, incoming texts, and messaging app use; in S4: more in-person conversations, calls, and texts). Calling behaviors were also associated with Openness, suggesting that these social behaviors may also be driven by other personality factors or motivations.

The correlational results have broader theoretical implications for our understanding of the Big Five and the factors that underlie everyday social behavior. Specifically, our results provide initial insight into the personality traits that may be driving the observed rates of behavioral sociability. As expected, we found that Extraversion was associated with higher daily rates of conversation, calling, texting, and app use behavior. But we also found Openness was associated with calling behaviors. Specifically, our findings suggest that young adults who were higher in Openness engaged in more calling behavior (received more incoming calls, made more outgoing calls) per day, compared to those low in openness.

Our findings also add to past research linking personality traits to calling and texting tendencies. Several studies have examined the associations between self-reported Big Five traits and phone log data captured from sensing apps. Our findings conceptually replicate past studies that found relationships between Extraversion and greater rates of calling and texting behavior (Montag et al., 2014). However, we observed a different pattern of results among the relationships between openness with calling and texting behaviors, compared to past research. The discrepancies across the studies may be due to several factors including the use of different sampling methods (phone log data vs. self-reports), different units of analysis (ways of operationally defining texting behavior), and levels of aggregation. Moreover, the studies have been conducted in samples with different characteristics (e.g., countries, phone subscription plans), which may lead to discrepancies due to cultural differences in how people use different communication channels. More research is needed using larger and more representative samples, to establish the relationship between behavioral sociability dispositions and personality traits before a robust mapping of the relationship between social behaviors and Big Five traits is attained.

Limitations

The current study had several limitations that need to be addressed in future research. The first concerns the characteristics of our young adult samples. Given that the young adults in our study were college students, it is likely that some of the base rate estimates were influenced by factors specific to the college experience. For example, college students probably have fewer constraints (e.g., classes) in the evenings and more reasons to engage in social behavior during a typical day (e.g., to socialize with friends, organize study sessions, communicate with parents), compared to a typical working adult. Moreover, the reliance on young adults enrolled in college may lead to observed patterns of daily sociability that do not generalize to young adults from non-Western, educated, industrialized, rich, and democratic (WEIRD) societies (Henrich, Heine, & Norenzayan, 2010) nor to other demographic groups within WEIRD societies. For example, we expect that young adults from different socioeconomic backgrounds and countries would show different daily social behavior patterns (e.g., depending on whether they are in college, due to different access to communication technologies, different phone plan subscriptions). In addition, our analyses of calling, texting, and app use behaviors in S3 and S4 could be conducted only with participants who used Android phones because iOS does not permit collection of phone-based interactions from third-party apps at the time of this writing. These sample sizes may influence the reliability of the point estimates reported in this research. Thus, the descriptive findings presented here should be replicated in other studies, with diverse samples, and with larger sample sizes to see how the sociability tendencies compare with those observed in other groups of young adults.

The second limitation is that the sensors, while objective, may incorrectly infer certain micro behaviors. For example, when inferring conversation behavior from the microphone sensor, it is possible that the audio classifier mistakenly underestimates the sociability of the participant by failing to capture conversation when the device is stored in the participant's bag, or overestimates the sociability of the participant by mistakenly inferring that the participant is engaged in conversation when they are watching TV alone or sitting in a lecture. Moreover, the audio classifier picked up on voices as a way to infer conversation and the phone logs measured calling and texting behaviors, but we did not measure other sociability behaviors and so may incorrectly infer that someone is not socializing when they are talking with others via social media (e.g., Facebook, Instagram) and messaging applications (e.g., Facebook Messenger, Whatsapp, FaceTime, Skype). At present, there are some technical limitations inherent to the current generation of devices, such as the inability to monitor the microphone sensor for conversation while the participant is using the microphone to make a phone or video call. Such limitations are likely to be overcome in future iterations of mobile sensing software. However, it is likely that new technical challenges will arise given that such technologies are changing so rapidly.

Future Directions for Sensing Research on Social Behavior

The conversation and phone-based social behaviors measured in the present study are distinct from prior measures of social behavior. Most notably, the sensed social behaviors captured using smartphone apps are unique in their assessment of aspects of everyday social behavior that are difficult to report on—namely, the duration and frequency of conversations, and frequency and duration/length of interactions via phone calls and text messages. Thus, the sensed social behaviors measured here present a new window into the quantity of social behavior participants are exposed to and engage in during their day-to-day lives.

A next step for future research is to examine how the stability of smartphone-based behavioral measures changes at different levels of aggregation. For example, past research has demonstrated higher stability estimates at higher levels of aggregation (e.g., Brown & Moskowitz, 1998; Epstein, 1979), so it may be that weekly or monthly estimates of social behavior would be more reliable than those observed here at the daily level. Thus, additional research is needed to determine the set of best practices for creating behavioral measures from mobile sensing data that are psychometrically on par with traditional methods (e.g., surveys, experience sampling). Such findings will be instrumental in identifying the optimal levels of aggregation for mobile sensing data in studies designed to predict psychological characteristics (e.g., mental health) from passively sensed behavioral data.

It seems likely that these sensed social behaviors are correlated with other forms of social behavior occurring within communication channels (e.g., active vs. passive use of social media) and via other mediums (e.g., social media use on laptops or tablets). For example, past research has found that Extraversion is associated with more frequent Facebook-related behaviors (e.g., having more friends, posting more frequently; Gosling, Augustine, Vazire, Holtzman, & Gaddis, 2011). However, it is possible that this is not the case for all forms of social behavior. How do conversation, calling, and texting behaviors relate to specific types of within-platform social media use (e.g., posting vs. browsing a newsfeed on Facebook or Instagram) or Bluetooth-based measures of face-to-face interaction? Additional research is needed to further examine the relationships between these sensed social behavior tendencies and other forms of social behavior.

Moreover, how do self-reports of these behaviors match onto the observed reality? Do people overestimate or underestimate the amount of social behavior they engage in on a daily basis? One previous study that also used observation methods examined such questions using server logs from a telecommunication company and showed that people tend to overestimate the amount of phone-based interaction they engage in (Kobayashi & Boase, 2012). Considering the well-known difficulties associated with recalling and reporting on durations and frequencies of behavior (Schwarz, 2012), it seems likely that subjective measures of everyday social behavior will diverge from more objective estimates derived from smartphones.

What might be driving individual differences in daily social behaviors? A next step for future research in this area would be to examine other psychosocial characteristics and situational factors that predict these behavioral differences. Do people with certain demographic and psychological characteristics use one mode of communication more than the others? Do people use one mode of communication more than others in certain contexts based on situational cues (e.g., being at home, work, a café) and characteristics (e.g., being in a work-related vs. dating-related situation; Rauthmann et al., 2015)?

Additional research is needed to further examine the psychological significance of the sensed social behavior rates observed here. For instance, how does the quantity of daily social behavior relate to everyday psychological states (e.g., stress, mood) and mental health outcomes (e.g., depression, anxiety)? Do young adults who spend more time around conversation on a daily basis report more satisfaction with their social lives? Are they less lonely than other young adults who spend more time in solitude? It is possible that some young adults may be around others in conversation a great deal of their waking hours, but still feel ‘alone’ or lonely psychologically. Prior research using the Sample 1 dataset has provided an initial look into the well-being related correlates of these conversation estimates (Wang et al., 2014). For instance, higher daily average conversation behaviors were associated with reports of psychological flourishing at the start of the academic term and were also associated with lower levels of perceived stress at the end of the term. Interestingly, conversation behaviors were not associated with young adults’ self-reported loneliness. However, the sample size in the study was too small ($N = 48$) to obtain generalizable between-person effects due to low statistical power. Clearly, more research is needed in this domain to identify the situational factors and well-being outcomes associated with young adults’ daily social behaviors. Such research will pave the way for behavior change interventions that passively track sociability patterns and provide just-in-time interventions that promote positive well-being (e.g., Aung, Matthews, & Choudhury, 2017).

The sensed social behaviors measured in this study also did not capture other important aspects of social behavior. In fact, a key component of social behavior is missing active contributions to conversations. In particular, the conversation estimates did not capture whether the participant was actually speaking with the people around them, it simply reveals how much time they spent around conversation, or how many separate instances of conversation they were around. Researchers specifically interested in a person’s contributions to conversations should consider using other classifiers for microphone sensor data that are designed to capture turn-taking and identify speakers in conversation (e.g., Wyatt, Choudhury, Bilmes, & Kitts, 2011), other forms of mobile sensing to capture nonverbal social behaviors during interactions (e.g., eye gaze; for a review see Schmid Mast et al., 2015), or other acoustic observation methods like the EAR that are designed to capture the content of conversations and ambient sound more generally (Mehl et al., 2001).

The qualitative characteristics of the social interactions are another important aspect of social behavior not captured by behaviors measured in our study. More specifically, the smartphone-based behavioral estimates do not capture qualitative aspects such as the kinds of people that are around the participant (e.g., friends, family, strangers), the content of interactions (e.g., language use), or context (e.g., location, situational characteristics) in which the interaction occurred. In the context of smartphone-based MSMs, it is possible to measure these more qualitative aspects of social life by incorporating self-reported experience sampling surveys in the study design, by collecting other forms of sensor data (e.g., GPS data to measure location), and by adopting more complex automated methods (e.g., classifiers that identify speaking rates during conversation).

Finally, the exploratory personality findings also point to new kinds of research questions that can be generated from descriptive data about real-world behavioral patterns. For example, why might people who are more extraverted and open-minded engage in more calling behavior? One possible explanation for the observed pattern of findings could be that the plasticity (vs. stability) theorized to underly both Extraversion and Openness (e.g., DeYoung, Peterson, & Higgins, 2002) is playing a role in the use of digital media platforms for socializing with others. More specifically, people who are high on the plasticity factors of Extraversion and Openness may be more interested in using such platforms for communicating with others. However, we do not know the extent to which the observed associations generalize to other forms of social behavior. Thus, additional research examining the motivations to use different types of social media (e.g., online forums) and communication channels (e.g., face-to-face conversations, calls, texts, social media messages) could provide some insight into why these traits were associated with phone-based social behaviors.

Conclusion

Descriptive research mapping real-world behaviors to psychological characteristics has been scarce in the social-personality psychological literature (Baumeister et al., 2007; Cooper, 2016; Funder, 2009; Furr, 2009). To understand how daily behavior is played out in the context of people's everyday lives, we demonstrated the viability of using MSMs to obtain basic descriptive details about how much people tend to socialize and when they tend to do so. In doing so, we provided the first evaluation of individual differences in sensed social behaviors, establishing the viability, stability, validity and utility of using sensing for capturing everyday behavior as it naturally occurs. By capitalizing on the sensing capabilities of digital media devices that people naturally use and carry as they go about their days, we can finally start to understand the basic behavioral contours that define people's day-to-day lives (Harari et al., 2016). As MSMs become a standard part of research in the social sciences, we anticipate the advent of large-scale naturalistic observation studies mapping behavior to psychological characteristics (e.g., personality traits, attitudes, values) and consequential life outcomes (e.g., mental health, physical health), as well as real-time interventions that promote well-being through positive behavior change. This new era of behavioral research will yield promising new theoretical and empirical directions for research that is grounded in passively sensed, observable, real-world behavior.

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