Loneliness and social interaction dynamics: An ambulatory assessment study in a student population

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Abstract

Loneliness is the feeling associated with a perceived lack of qualitative and quantitative aspects of social relationships. Loneliness is thus evidently intertwined with individuals' social behaviors in day-to-day life. Yet, little is known about the bidirectional pathways between loneliness and social interactions in daily life. In this exploratory study, we thus investigate (a) how loneliness predicts the frequency and duration of social interactions and (b) how frequency and duration of social interactions predict changes in loneliness. We examine these questions using fine-grained ambulatory-assessed smartphone-sensor data of students' social behavior covering 10 weeks ($N_{\text{participants}} = 45$, $N_{\text{observations}} = 74,645$). Before (T1) and after (T2) the ambulatory assessment phase, participants completed the UCLA loneliness scale, covering subscales on intimate, relational, and collective loneliness. Using multistate survival models, we show that T1 loneliness subscales are not significantly associated with differences in social interaction frequency and duration—only relational loneliness predicted shorter social interaction encounters. In predicting changes in loneliness subscales (T1-T2), only the mean duration of social interactions was negatively associated with collective loneliness. Thus, effects of loneliness on the structure of social interactions may be small or limited to specific forms of loneliness.

Keywords: loneliness; social interaction; longitudinal; ambulatory assessment; social sensors

Introduction

Most students are faced with a myriad of challenging tasks such as forming and maintaining stable social relationships, making career choices, coping with academic pressures and navigating through the increasingly complex digital world (Buote et al., 2007; Stadtfeld et al., 2019; Thomas et al., 2020). It thus comes as no surprise that students are the population group with the highest levels of loneliness (Nicolaisen & Thorsen, 2014).

The feeling of loneliness arises when individuals experience a discrepancy between the desired and actual quantity or quality of social interactions (Peplau & Perlman, 1982). As loneliness is a subjective evaluation, it is different from the objective state of being alone (Peplau & Perlman, 1982). Prolonged feelings of loneliness can have serious consequences for mental and physical health: Loneliness is associated with numerous mental and physical illnesses, which contributes to a lower life expectancy (S. Cacioppo et al., 2015; Holt-Lunstad et al., 2015). The feeling of loneliness is by definition intertwined with our experience of social relationships. Existing research suggests that broader measures of social relationships, such as the quality of friendship and the number of friends one has, are relevant for the development of loneliness (Schwartz-Mette et al., 2020). Yet, much less is known about the day-to-day social experiences that are related to loneliness, such as social interactions (van Roekel et al., 2016).

Social interactions constitute the smallest building blocks of long-term social relationships. Every form of social relationships is started and maintained through digital or face-to-face social interactions. Besides being important for the formation of stable social relationships, and thus trait loneliness (Schwartz-Mette et al., 2020), social interactions and the feeling of loneliness are more directly intertwined: Loneliness can be the result of the subjective

evaluation of the fit between expected and the actual number of social interactions (De Jong Gierveld et al., 2016; Peplau & Perlman, 1982), but loneliness can also affect how individuals engage in social interactions (Qualter et al., 2015). On the level of day-to-day social interactions two mechanisms of how loneliness affect social interactions have been proposed: On the one hand, loneliness could result in a motivation to reconnect, and thus predict more or longer social interactions, but on the other hand, loneliness could result in withdrawal, and thus predict fewer or shorter interactions (Qualter et al., 2015). As a consequence of such behavioral tendencies, individuals who do not frequently interact with others may fail to build stable social relationships and thus become lonelier over time (Schwartz-Mette et al., 2020).

To date, little is known about how loneliness and social interactions in daily life mutually affect each other. In the present exploratory study, we thus tease apart the bidirectional association between day-to-day social interactions and loneliness by investigating (a) how loneliness predicts the frequency and duration of social interactions (Research Question [RQ]1) and (b) how the frequency and duration of social interactions predict changes in loneliness (RQ2). We explore these questions using smartphone-based sensor data, providing a complete overview of all social interactions that participants had in a period covering 10 weeks.

The Bidirectional Relationship Between Loneliness and Social Interactions

The loneliness model by Cacioppo and Hawkley suggests that when basic human needs of social contact are thwarted, individuals start to feel lonely as a result of this threat (J. T. Cacioppo et al., 2006; J. T. Cacioppo & Hawkley, 2009; Hawkley & Cacioppo, 2010). Do lonely individuals respond to this threat by seeking out *more* social interactions to reduce this negative feeling of loneliness, or do they *withdraw* from social interactions because they are

lonely, resulting in fewer social interactions? According to the Reaffiliation Motive Model (RAM-model) of loneliness, which is an expansion of Cacioppo's loneliness model, people who experience loneliness become motivated to re-connect in order to alleviate the negative experience, hence, they regulate their behavior in order to achieve that goal (Qualter et al., 2015). Part of this regulation entails initial withdrawal from interactions, as this allows people to assess their environment, to become more focused on social cues, and use those cues to reconnect. Thus, on the one hand, after initial withdrawal, the feeling of loneliness can motivate individuals to seek others in order to reduce the feeling of loneliness, thereby increasing interactions (J. T. Cacioppo et al., 2006; Qualter et al., 2015). Yet, for some people this process of re-connection goes awry. Hypervigilance for negative social information can affirm feelings of loneliness and result in further social withdrawal, to protect oneself from future rejection (J. T. Cacioppo et al., 2006; Qualter et al., 2015). Thus, on the other hand, loneliness may result in withdrawn behavior, thereby decreasing social interactions, especially for those who experience high levels of prolonged loneliness (Goossens, 2018; Qualter et al., 2015). In line with this notion, some empirical evidence suggests that individuals high in loneliness are more likely to withdraw and avoid others than non-lonely individuals (Nurmi et al., 1997; Watson & Nesdale, 2012). Furthermore, loneliness is associated with fewer reports of social interactions in females, in terms of time spent in interaction and number of interactions (Wheeler et al., 1983), fewer self-reported social interactions with close others but not with acquaintances (Lee & Ko, 2017), and to more self-reported time spent alone on weekdays for females (Hawkley et al., 2003).

Thus, based on existing findings, it is unclear whether loneliness mainly results in increases in interactions, or in withdrawal from interactions. Moreover, as existing findings are primarily based on participants' self-reports, effects may be overestimated because of common method biases (Podsakoff et al., 2003). The present multi-method study is set out to

investigate if loneliness predicts social interactions measured with automatically sensed social interaction data and if, in turn, these structural aspects of social interactions predict changes in self-reported loneliness. Interactions can be defined as “reciprocal influence of individuals upon on another’s actions when in one another’s immediate physical presence” (Goffman, 1956; p. 18). In the present study, we use automatically recorded conversations as indicators of interactions, thereby, we are sure that there is exchange between people, and that these people are in each other’s immediate physical presence. We differentiate between joining interactions and leaving social interactions, as these are two different social processes (Hoffman et al., 2019). Differentiating between joining and leaving social interactions could provide new insights into, for example, whether loneliness is more associated with the initiating of social interactions (i.e., joining process, or the frequency of interactions) or with leaving interactions once they are established (leaving process, or the duration of interactions). To date, these two aspects of the structure of social interactions have not been examined in relation to loneliness. Thus, our first research question (RQ1) states: Is loneliness is associated with (a) the frequency with which individuals join social interactions (i.e., interaction frequency) and (b) the frequency with which individuals leave social interactions (i.e., interaction duration)?

So far, studies have only assessed how loneliness measured prior to social interaction assessment predicted the (self-reported) quantity of social interactions at a later point in time (e.g., Wheeler et al., 1983). However, little is known about how the social interactions experienced in daily life are associated with *changes* in loneliness, using a longitudinal study design. In line with the RAM model, more frequent social interactions or social interactions that are longer in duration may reduce feelings of loneliness, as they may signal a sense of reconnection. At the same time, in line with the loneliness model by Cacioppo and colleagues (2006; 2009; 2010), cognitive biases may cause lonely individuals to interpret their

interactions negatively, and as such lonely individuals may not benefit from having many or long interactions – in contrast, this may even be a risk continued loneliness for those individuals who interpret their social environment negatively. Indeed, studies employing a momentary assessment design indicated that being company reduced state loneliness for some but not all adolescents (Van Roekel et al., 2014). It remains unclear whether the frequency or duration of interactions will reduce feelings of loneliness. In an exploratory analysis, we therefore examine a second Research Question 2 (RQ2): Are characteristics of day-to-day social interactions (i.e., frequency and duration) associated with changes in loneliness?

Types of Loneliness

Researchers have differentiated between different types of loneliness (S. Cacioppo et al., 2015; Luhmann et al., 2016). Some individuals feel lonely because they seek a close and intimate attachment (S. Cacioppo et al., 2015). Other sources of loneliness can come from a feeling of lacking social relationships and a lacking of belonging in different social networks such as family networks, friendship networks, or classroom networks (relational loneliness; Maes et al., 2019). A third type of loneliness comes from a feeling of lacking connections to similar others in society (S. Cacioppo et al., 2015). In this study, we differentiate between these three types of loneliness (intimate, relational, and collective loneliness) that correspond to different compartments in social and attentional spaces: Intimate loneliness corresponds with an individual's personal space that is made up of around five individuals; relational loneliness relates to a relational space of around 15 to 50 individuals, and collective loneliness corresponds to a societal space of 150 to 1500 individuals (S. Cacioppo et al., 2015; Dunbar, 2014). It is possible that the structural aspects of social interactions may contribute to some types of loneliness more strongly than to others. For instance, a higher number of interactions may be most important to create a sense of belonging in close

networks, and thus be most strongly related to relational loneliness, and a higher interaction duration may signal higher quality, and thus be most important for intimate loneliness. In this study, we therefore explore whether the association between loneliness and the structure of social interactions differs between different types of loneliness.

The Present Study

To investigate our research questions, we use data from a student population in which loneliness was measured before (T1) and after (T2) a 10-week ambulatory assessment phase (Wang et al., 2014).

During the ambulatory assessment phase, the smartphones of students measured when the students were in a social interaction ($N_{obs} = 74,645$). Ambulatory assessment methods, in which participants are observed in their day-to-day life, provide excellent opportunities to study the dynamics of individual behavior on a moment-to-moment basis in real-life situations (Trull & Ebner-Priemer, 2014). This study design is unique in three ways, allowing to gain new insights into the interplay between the structure of social interactions and feelings of loneliness. First, the combination of traditional survey methods (assessing loneliness) with state-of-the-art passive sensing technologies (measuring social interactions) provides a multi-methods setting, where common-method biases are eliminated (Goossens & Beyers, 2002). When assessing social interactions in daily life through the smartphone, passive sensor methods offer various advantages over widely used retrospective questionnaires in terms of temporal granularity and measurement biases (Elmer et al., 2019; Myin-Germeys et al., 2009). In addition, data from other smartphone sensors can be used to understand social interaction dynamics as we demonstrate with data on student's smartphone usage and their short-term effect on the presence of social interactions. Second, the longitudinal study design, with loneliness measures before and after the ambulatory assessment phase, makes it possible to investigate short-term changes in loneliness and how

characteristics of the structure of social interactions, captured during the ambulatory assessment phase, are predictive of such changes. Examining which factors contribute to changes in loneliness may provide more insights into what causes loneliness, which is crucial for interventionists (Heinrich & Gullone, 2006). Third, the fine-grained longitudinal data on participants' social interactions allow investigating social interaction dynamics in much detail. More specifically, the use of fine-grained time-stamped ambulatory assessment data on social interactions further allows us to make a unique differentiation: the joining and leaving of a social interaction. Research in the past, that predominantly relied on self-reports of social interactions, only examined interaction frequency. Taken together, in this study we explore relationships between interaction frequency and duration and (changes in) loneliness in a student sample, using novel measurement and analysis methods. To test the robustness of our findings, we report additional analyses including effects of smartphone usage, extraversion, and the overall level of loneliness on social interaction dynamics. All data and analyses scripts can be accessed at https://osf.io/c94vs/?view_only=5d7307a0a15449e79447d534c09be2c7 [will be deanonymized after peer-review]

Materials & Methods

Participants

Forty-eight students of a computer science program participated in the Dartmouth StudentLife study (Wang et al., 2014). The data of this study is publicly available (studentlife.cs.dartmouth.edu). Unfortunately, no information about participants' gender and age was made available in the dataset. The data owners were also not willing to share this information upon request. However, in the data-introduction paper, Wang et al. (2014) report that the sample was predominantly male (38 participants, 79%). Most students were undergraduate students (63%). Most participants identified as either Caucasian (N = 23, 48%)

or Asian ($N = 23$, 48%). Two participants (4%) identified as African-American. The data collection was approved by the Institutional Review Board at Dartmouth College.

Participants were recruited through a computer science class at Dartmouth College in 2013.

All 75 participants of the class were invited. Sixty participants agreed to participate in the study. Twelve students decided to drop the class ($N = 5$) or the study participation ($N = 7$).

The remaining 48 students participated in the ambulatory assessment part. Of those, 45 participants filled out the T1 loneliness survey. Our analyses on predicting social interaction dynamics from loneliness (RQ1), thus will be carried out with the sample of 45 participants.

Of those 45 participants, 36 filled out the T2 loneliness survey. For our analyses on predicting loneliness change (RQ2), we will use only those 36 participants that filled out the T1 and T2 survey.

Procedure

The study consisted of online surveys and a 10-week ambulatory assessment phase covering the entire duration of one university term at Dartmouth (United States). Students were incentivized with two price draws at the end of week three and six, to win technical devices such as smartphones.

During the online surveys that were administered before (T1) and after (T2) the ambulatory assessment phase, participants reported on various mental health dimensions (e.g., perceived stress, depressive symptoms, loneliness) and Big Five personality traits (John & Srivastava, 1999)

During the ambulatory assessment phase, participants were asked to carry a smartphone with the StudentLife sensing app. Students that did not have a smartphone were offered to use a Nexus 4s smartphone during the study. Each student received a one-to-one tutorial what the application does and how to use it. The StudentLife app had two purposes: (1) Prompting participants with experience sampling questionnaires and (2) passively sensing participants

behavior. Participants received on average eight experience sampling surveys a day about studying behavior, sleeping behavior and mood. These experience sampling data were not used in this study because participants did not fill them out regularly. The StudentLife sensing app measured participants' physical movement through GPS and accelerometer sensors (for more details see Wang et al., 2014). Relevant for this study is the automated classification of conversation data through the smartphone's microphone, which provides information about the start and the end time of participants' conversation periods. From this data, the number of interactions and their duration can be derived.

Measures

Social Interactions. Using the input from the smartphone's microphone, a machine learning algorithm was applied to classify the audio signal into periods in which participants were part of a conversation. The algorithm ran locally on the smartphone, so that no audio data had to be transmitted to the researchers. The algorithm was shown to validly detect social interactions in prior studies (Lane et al., 2011; Rabbi et al., 2011). For instance, Lane et al. (2011) showed that the algorithm "overestimates true social interaction by 14%" (p. 7). Conversation information during lectures and class meetings were removed from the dataset (Wang et al., 2014).

Loneliness. Loneliness and its three subscales (intimate, relational, and collective loneliness) was measured with the Revised UCLA Loneliness Scale (Russell, 1996). The scale consists of 20 items assessing how often the participant felt the way described in the item. Subscales for intimate, relational, and collective loneliness were calculated in line with Luhmann et al. (2016). Intimate loneliness was measured with 3 items such as "there are people I feel close to" ($\alpha = .87$), relational loneliness with 3 items such as "x" ($\alpha = .67$), and collective loneliness with 3 items such as "I have a lot in common with the people around me" ($\alpha = .78$). Cronbach's α for the entire scale (omitting the subscales), as used in

sensitivity analyses, was .93. The average loneliness score at T1 was 1.96 (SD = 0.58). The change in loneliness was computed as the difference between the T1 and T2 measurement ($\Delta L = L_{T2} - L_{T1}$).

Control variables.

Extraversion. Prior to the ambulatory assessment phase, participants responded to the Big Five Inventory (John & Srivastava, 1999) which assesses the Big Five personality traits. The Extraversion subscale consists of eight items such as “I see myself as someone who is talkative”, measured on a five-point scale ranging from “Disagree strongly” (1) to “Agree strongly” (5). The average of these items constitutes the Extraversion score, which in this sample was on average 2.98 (SD = 0.72).

Smartphone usage. During the ambulatory assessment phase, the smartphone also collected data on its usage (i.e., when the screen was unlocked). To assess the association between short-term phone usage and the frequency and duration of social interactions, we coded a dummy variable as 1 when the participant was using the smartphone within the last hour prior to the start of a social interaction event, and 0 otherwise. On average participants were using their smartphone in 74.5% (SD = 10.4%) within the hour prior to the start of a social interaction event.

Analytical Strategy

RQ1. Is loneliness is associated with (a) the frequency with which individuals join social interactions (i.e., interaction frequency) and (b) the frequency with which individuals leave social interactions (i.e., interaction duration)? To model the effects of loneliness on the dynamics of social interactions, we use multistate models (Stoolmiller & Snyder, 2006). Using state-of-the-art multistate models (Stoolmiller & Snyder, 2006) allows us to make prediction of individuals’ social interactions dynamics based on their past social

behavior, temporal dynamics (e.g., fluctuations in the structure of interactions governed by the time of the day), and their level of loneliness. Multistate models are frequently applied in medical sciences, where the timing of multiple types of events are of interest. For instance, Putter et al. (2007) use multistate models to model the transition events of patients between healthy, ill, and death states. In such applications, it is assumed that individual can transition back-and-forth between healthy and ill states. Similarly, in our social interaction data participants transition between “alone” and “interaction” states as illustrated in the data excerpt shown in Table 1. Table 1 shows the first six observations for the individual with id = 1. The start and end columns indicate from when to when that individual was in a particular state (see state column).

Table 1 here

Multistate models are based on Cox’s proportional hazard model (Cox, 1972) which estimate how independent variables are associated with the probability of observing a single type of event at a particular point in time (e.g., social interaction event, illness event). Put simply, the dependent variable of the analysis is the time until an event/transition is observed (see last column in in Table 1). Extending the proportional hazard model to a multistate model, state transition events (i.e., from alone to interaction and from interaction to alone) are modeled instead of a single type of event. The state transition from alone to interaction is informative about the (joining) frequency of interactions and the state transition from interaction to alone informs us about the duration of social interactions. Multistate models also take into account that observations are nested within individuals by estimating robust standard errors (Putter et al., 2007).

To test RQ1, we add the three loneliness subscales measured at T1 as predictors of transitions from the alone to the interaction state (frequency) and from the interaction to the alone state (duration). Further covariates, controlling for general social interaction dynamics, consist of dummy variables for the time of the day (night, morning, afternoon, evening), whether or not the interaction took place on a weekend (dummy variable with 0 = weekday, 1 = weekend), window variables capturing the number of social interactions in the past two and twenty-four hours, and the mean duration of social interactions in the past two hours. These variables account for tendencies of interactions to occur more frequently during the daytime (than at night) and for the influence of previous interactions. With these variables we can control for fluctuations in interaction patterns that be due to situational factors (e.g., conversation phases might be more frequently interrupted due to where people place their sensing smartphone, interactions happen more frequently during certain times of the day). For example, the covariate entailing the number of interactions within the past two hours captures a tendency of individuals to repeatedly interact within a short (i.e., 2h) time window. This can for instance be because the smartphone is placed somewhere where there are frequent signal interruptions (e.g., in a backpack) or because the person had many short interactions within the given time window (e.g., because they were attending a social mixer). This variable thus captures some unobserved heterogeneity between situations. Such time and window-control variables are commonly used when modelling interaction dynamics (Hoffman et al., 2019; Stadtfeld & Block, 2017).

We further control for the effect of short-term effects of student's smartphone usage on social interactions by including a variable in the model that captures whether or not the student had been using the smartphone in the previous hour (value = 1) or not (value = 0).

It is important to note that we did not compute the “time in state” for the overnight observation, hence these the time gaps between the last measure in the evening and the first measure in the morning are not part of the analyses.

We further conducted a post-hoc power analysis to examine the statistical power of this multistate analysis. The power analysis showed that with $\alpha = .05$, $1 - \beta = .80$, $N_{individuals} = 45$ and a total of $n \geq 72,000$ interaction observations, effect sizes of Cohen’s $d = .50$ (medium effect size, corresponding to a Person correlation of $r = .24$) can be detected. For details on the power analysis see Figure S2 in the Supplementary Materials or the respective R-script on [OSF](#).

RQ2. Are characteristics of day-to-day social interactions (i.e., frequency and duration) associated with changes in loneliness? Because the sample of students who participated in the T1 and T2 survey was rather small ($N = 36$), inferential statistical analyses would not have enough statistical power to detect significant differences. In a power analysis, with $\alpha = .05$ (type I error) and $\beta = .20$ (type II error), a sample size of $N = 36$ could only detect correlations above $r = .45$ (Hulley et al., 2013). However, just because sample size is small and the design of this study is underpowered, does not mean that descriptive statistical analyses cannot provide insights into the nature of the phenomena (Siebert & Siebert, 2009). By relying on a measure of within-person change from L1 to L2 loneliness, the variability in scores due to between-person variability is reduced (i.e., there is less noise in the data). As a result of the decreased noise, not as many datapoints are needed to detect meaningful statistical associations (Tambling & Anderson, 2014). Furthermore, statistical techniques such as bootstrapping can aid in making correlation estimates of analyses with small sample sizes more reliable (Tambling & Anderson, 2014). By resampling data from an observed distribution, bootstrapping methods allow researchers to draw more accurate inferences about population parameters (Efron & Tibshirani, 1986).

Instead of inferential statistical analyses (such as regression models), we thus explore associations between changes in loneliness and characteristics of social interactions with scatterplots and discuss the size and confidence intervals of bootstrapped correlation coefficients.

For this we compute changes in the three types of loneliness (intimate, relational, collective) from before (T1) to after (T2) the ambulatory assessment phase ($\Delta L = L_{T2} - L_{T1}$). Variables characterizing social interaction dynamics consist of (a) the number of social interactions measured during the ambulatory assessment phase, and (b) the mean duration of these social interactions. These measures of social interaction characteristics have been shown to be important predictors of loneliness and related mental health measures (Elmer et al., 2020; Wheeler et al., 1983).

Sensitivity Analyses. As controlling for the other subscales may affect the outcomes, we repeated the analyses for RQ1 with separate analyses for each scale. In addition, we repeated the analyses for both research questions using the average across all 20 items of the UCLA loneliness scale, thus treating loneliness as a unidimensional scale.

Results

Descriptives

Social Interactions. In total 74,645 interactions were recorded. Participants were classified to be part of a social interaction on average 1512.62 times ($SD = 541.26$) and on average 27.28 times per day ($SD = 14.50$). On average, interactions lasted for 10.02 minutes ($SD = 14.46$). The average time between two interactions was 45.50 minutes ($SD = 259.07$).

Loneliness Change. Table 2 shows the mean and SD values of T1 and T2 loneliness as well as loneliness change. An increase in loneliness between T1 and T2 was observed for 67% of the individuals in intimate loneliness, 83% in relational loneliness, and 69% in

collective loneliness. Hence, although the average across all individuals in loneliness change was close to zero, it seems that for most individuals, loneliness got slightly higher, and for only a few loneliness got a lot lower. For details, see the descriptive Figure S1 in the Supplementary Materials.

Table 2 here

RQ1. Is loneliness is associated with (a) the frequency with which individuals join social interactions (i.e., interaction frequency) and (b) the frequency with which individuals leave social interactions (i.e., interaction duration)?

Table 3 shows the results of the multistate analysis. The 2nd to 4th columns in Table 3 show the estimates for the transitions from the alone state to the interaction state (i.e., the effect of interaction frequency). Although all estimates with regards to loneliness were negative, indicating a lower tendency of individuals with higher loneliness scores to move from an alone state to an interaction state, none of the three loneliness subscales measured at T1 were significantly associated with the rate of joining social interactions. Other variables in the model, however, were important predictor variables: Students were more likely to engage in social interactions during the day, if they were in more interactions in the past 2h and 24h, and if they were in longer interactions within the past 2h. Students that were on the smartphone prior to the social interaction were less likely to engage in social interactions. Columns 5 through 7 in Table 3 show the estimates for the transitions from the interaction state to the alone state (i.e., the leaving rates, or the interaction duration). In this sub-model,

only relational loneliness measured at T1 was significantly associated with the rate of leaving social interactions. The effect of $\beta = 0.099$ suggests that individuals with one unit higher in relational loneliness at T1, were $\exp(\beta) = 1.10$ times more likely to leave social interactions than those with a one-unit lower value in relational loneliness. In other words, those individuals at the high end of the relational loneliness scale (value = 4) are 35% ($\exp(3 * \beta) = 1.33$) more likely to leave an interaction than an individual at the low end of the scale (value = 1), thus, the duration of their interactions was shorter. With regards to the covariates, students did leave social interactions more likely on weekends, less likely during the day, and less likely if they had longer interactions within the past 2h. Also, those who had more interactions within the past 2h were slightly more likely to leave social interactions. Being on the phone prior to the start of the social interaction was associated with a lower likelihood to leave social interactions.

Table 3 here

RQ2. Are characteristics of day-to-day social interactions (i.e., frequency and duration) associated with changes in loneliness?

Figure 1 here

shows the bivariate scatterplots between all variable combinations and a fitted line. Most noteworthy is the association between the mean duration of social interactions and change in collective loneliness. This association was estimated to be $r(34) = -.30, 95\%CI [-.02; -.61]$ in a bootstrapped correlation analysis (with 10,000 samples), indicating that having longer social interactions is associated with a decrease in collective loneliness. None of the other bivariate associations relating to our research question reached significance, and most were close to zero. There was a trend for an association between relational loneliness ($r(34) = -.13, 95\%CI [-.58; .29]$) and intimate loneliness ($r(34) = -.10, 95\%CI [-.42; .20]$) and the frequency of interactions, but the effects were relatively small and did not reach significance. All correlation coefficients and associated 95% Confidence Intervals are reported in Table 6 of the Supplementary Materials.

 Figure 1 here

Sensitivity Analyses

We performed several sensitivity analyses. First, we examined whether we would replicate results when we examined all loneliness subscales separately, rather than in a single analysis where they controlled for each other. Second, we repeated both RQ1 and RQ2 for loneliness as a unidimensional construct by averaging a loneliness score across all 20 items of the UCLA loneliness scale. Third, we additionally controlled for the role of extraversion in modeling social interaction dynamics (RQ1). The size and significance level of the research-question related effects remained robust against these alternative model specifications (see also section Sensitivity Analyses and Tables S1 to S4 in the Supplementary Materials).

Discussion

Students are a major risk group for loneliness. Despite decades of research on student populations (e.g., Qualter et al., 2009), little has been done on investigating the bidirectional relationship between social interactions and loneliness in student populations. Using data from a longitudinal ambulatory assessment study design, we disentangle this bidirectional association and investigated (a) how types loneliness (intimate, relational, collective) predict the frequency and duration of interactions and (b) how this structure of social interactions is associated with changes in the three types of loneliness. For this, we used a multi-method combination of novel, automatically sensed social interaction data and longitudinal survey methods.

Our analyses provide no suggestion that intimate and collective loneliness predict the frequency or duration of social interactions (RQ1). Relational loneliness was associated with leaving social interactions more frequently, but not with joining them more frequently. In other words, we found evidence that relational loneliness is related to shorter social interactions, but not necessarily to the frequency of interactions. This pattern was confirmed in a sensitivity analysis.

Due to the small sample size, we investigated changes in loneliness (RQ2) only with descriptive analysis methods in an exploratory analysis. Hence, the findings on RQ2 need to be interpreted with caution, as the statistical power for these analyses was low and only descriptive bivariate associations were tested. Using bootstrapping correlation methods, we observed that an increase in collective loneliness was associated with shorter social interactions during the ambulatory assessment phase, but not with the frequency of interactions. There was no evidence that intimate or relational loneliness were associated with the duration or frequency of interactions.

When only looking at the findings regarding the frequency of interactions, we found little evidence to suggest that the frequency of interactions is related to loneliness. Loneliness neither predicted the frequency of interactions, nor was the frequency of interactions significantly associated with changes in loneliness.

When only looking at the findings regarding the duration of interactions, we did show that the duration of interactions was significantly related to initial levels of relational loneliness, and that changes in collective loneliness were descriptively associated to lower duration of interactions. A possible explanation for this finding is that the duration of interaction may be related to the quality of those interactions, as people may be less likely to leave social interactions that they perceive to be pleasurable compared to social interactions that they perceive to be unpleasurable. Indeed, earlier research provided some indication that the evaluation of the quality of interactions was important for loneliness (Jones et al., 1983; Zakahi, 1986). Moreover, when it comes to broader relationship measures, although both the quantity and quality of friendship relations are related to loneliness, the effect of the quality of friendship relations is more important than the quantity (Sun et al., 2019).

Earlier research using self-reported interactions suggested that loneliness is associated with less time spent in interactions (Lee & Ko, 2017; Wheeler et al., 1983). In the present study, we cannot confirm this notion. Only for relational loneliness we found suggestions that it may be related to fewer interactions. This could indicate that especially people who are relationally lonely are more withdrawn from social interactions (Watson & Nesdale, 2012).

Relational loneliness reflects a feeling that one does not belong to a peer group. Many interactions in students' lives take part in group settings (Elmer & Stadtfeld, 2020). Thus, it is likely that especially those students who feel a lack of belonging are likely to leave such interactions more quickly. As earlier studies did not differentiate between different types of loneliness, it is not clear whether their results were also mainly driven by students

experiencing relational loneliness. Yet, in a sensitivity analysis we also examined loneliness as a unidimensional construct, comparable to previous studies. Here, we did not find significant associations with loneliness. Thus, the differences could also reflect a difference between self-reported and automatically detected interactions, showing the value of using different measures to examine such questions. Moreover, earlier research indicated that especially the fit between the expected and actual number of social contacts is relevant for the development of loneliness (De Jong Gierveld et al., 2016; Peplau & Perlman, 1982).

Possibly, loneliness is not related to the absolute number of social interactions one has, but to the discrepancy between the desired and actual number of social interactions. Future research could examine this possibility by taking the expectations for interaction frequency and duration into account.

Interestingly, when exploring the association between interactions and changes in loneliness (RQ2), we only found a significant relation for collective loneliness. Collective loneliness reflects deficits in the collective space, the personal space consisting of others that share your social identity (S. Cacioppo et al., 2015). Early adulthood is characterized by consolidation of one's identity, which partly happens through social interactions (Madsen & Collins, 2018). Those who have shorter interactions may be less likely to discover others whom they share a social identity with, thereby resulting in increased feelings of collective loneliness. Yet, as this study was explorative in its nature and the sample size was small, future research should be conducted to confirm these ideas.

Although it is possible that the duration of interactions is related to specific subtypes of loneliness, we should acknowledge that we found no significant effects when examining loneliness as a unidimensional construct, and that overall, effects in the present study were small. This lack of significant effects was surprising, as based on the RAM-model (Qualter et al., 2015) and the Loneliness Model (Hawkley & Cacioppo, 2010), we expected that those

who experience higher levels of loneliness are less likely to engage in social interactions, and may also be more likely to withdraw from social interactions. Possibly, the initial withdrawal from interactions in response to the experience of loneliness as described in the RAM model is only relevant at the level of individual interactions. That is, the process of initial withdrawal may be especially relevant for state loneliness, and may not be translated to associations between trait loneliness and patterns of social interactions over a longer period of time (van Roekel, Verhagen, et al., 2016). As this is the first study to explore the association between different forms of loneliness and social interactions measured with automatic detection methods, future research should explore whether the effects for relational and collective loneliness found in this study reflect true effects or not. Preferably, such studies would employ a larger sample.

Indeed, the size of the sample was one of the main limitations of the present study, which limited our options to examine our second research question, regarding the association between change in loneliness and the structure of interactions. A strength of the present study is that, despite the limited number of participants, we were able to capture the social behavior of those individuals was on a very fine-grained level by using ambulatory assessment sensor technologies leading to a lot of observations and sufficiently high statistical power to detect medium effect sizes. Studies with small sample sizes but intensive longitudinal design strategies (i.e., many observations per individual – such as in our study) are becoming increasingly common because of their usefulness for hypotheses generation and idiographic analyses (Zuidersma et al., 2020). Nevertheless, future studies should include larger samples when aiming to predict person-level outcomes such as loneliness.

A second limitation of this study is that we examined a very specific population of individuals (i.e., male-majority computer science students). Hence, we cannot generalize our findings to other groups of populations. Future studies should further examine the interplay

between social interaction dynamics and loneliness in larger and more diverse populations. It would furthermore be relevant to investigate this interplay in specific populations, such as individuals with depressive symptoms, as social, affective, and depression dynamics are highly intertwined (Elmer, 2020; van Winkel et al., 2017).

A further limitation is that we did not measure the qualitative aspects of social interactions, which would have allowed us to explore some of the potential explanations for our findings as discussed above. Finally, it would have been interesting to examine changes in loneliness over a longer period. Although sufficient variability in changes in loneliness were observed (see Figure S1 in the Supplementary Materials), developments in loneliness may be more visible in the longer term. Yet, as little research has been done on the shorter-term changes in loneliness (i.e., over multiple-weeks) and its predictors, the study also provided novel information. Future studies should aim at further investigating the changes in loneliness over (a) shorter timespans, such as Mote et al. (2020) on a moment-to-moment basis, and (b) over longer timespans than ten weeks (this study), to draw better inference about the bidirectional interplay between interaction quantities and loneliness. Ambulatory assessment methods using automated social interaction sensor technologies in combination with experience sampling methods hold great potential in the investigation of short-term (weekly, daily, momentary) loneliness and social interaction dynamics. Future studies, could furthermore incorporate the increasingly important role of online social interactions (Achterhof et al., 2021) into the study of loneliness and social interaction dynamics.

Despite these limitations, this article contributes to research on loneliness by making substantive and methodological advancements. Our exploratory analyses indicate that social interaction dynamics and are more intertwined through subtypes of loneliness rather than through the loneliness total score. On a methodological level, this article demonstrates how the richness of sensor data extracted from individual's smartphones can be used to draw

conclusions about the interrelations between social interaction dynamics, smartphone usage, and loneliness in a longitudinal setting. For this, we use multistate survival models that are common in medical sciences, but have not yet been used on ambulatory assessment data.

Conclusion

Taken together, our explorative study suggests that loneliness may be more strongly related to the duration of interactions than to the frequency of interactions. Moreover, we showed that the duration of social interactions may be more relevant for relational and collective loneliness than for intimate loneliness. Whether these effects reflect true associations between specific subtypes of loneliness and characteristic of interactions or not remains a topic for future research. This study advances knowledge on loneliness with a unique longitudinal, multi-method study design and exemplifies how sensor data can be used in loneliness research.

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Table 1. *Exemplary data excerpt.*

id	state	start	end	time in state [in s]
1	alone	27.03.13 07:17:45	27.03.13 07:25:16	451
1	interaction	27.03.13 07:25:16	27.03.13 07:49:53	1477
1	alone	27.03.13 07:49:53	27.03.13 07:50:33	40
1	interaction	27.03.13 07:50:33	27.03.13 07:51:34	61
1	alone	27.03.13 07:51:34	27.03.13 08:03:06	692
1	interaction	27.03.13 08:03:06	27.03.13 08:04:26	80

Table 2. *Mean and Standard Deviation of loneliness variables at T1, T2 and their change.*

	Type of loneliness	Mean	SD
T1	Collective	1.76	0.66
	Relational	1.54	0.61
	Intimate	2.27	0.71
T2	Collective	1.82	0.74
	Relational	1.63	0.71
	Intimate	2.27	0.65
Change (T2-T1)	Collective	0.06	0.46
	Relational	0.07	0.43
	Intimate	-0.06	0.55

Table 3. *Estimates of the multistate model for transitions interaction to alone states and alone to interaction states.*

	alone to interaction			interaction to alone		
	Est.	SE	p-value	Est.	SE	p-value
Weekend (ref. weekday)	0.164	0.100	.102	0.078	**	0.027 .004
Morning (ref. night)	1.352 ***	0.106	<.001	-0.324 ***	0.043	<.001
Afternoon	1.289 ***	0.100	<.001	-0.213 ***	0.027	<.001
Evening	0.949 ***	0.097	<.001	-0.187 ***	0.031	<.001
Mean duration of interaction in past 2h [in min]	0.012 ***	0.002	<.001	-0.024 ***	0.001	<.001
Number of interactions in past 24h	0.012 ***	0.003	<.001	<.001	0.001	.701
Number of interactions in past 2h	0.088 ***	0.008	<.001	0.011 *	0.005	.027
phone used within last hour (ref. Not used)	-0.457 ***	0.064	<.001	-0.116 ***	0.022	<.001
Intimate loneliness T1	-0.019	0.095	.844	-0.044	0.049	.366
Relational loneliness T1	0.001	0.078	.987	0.099 **	0.036	.006
Collective loneliness T1	-0.060	0.088	.490	0.009	0.046	.848

Note. $N_{\text{observations}} = 74,645$ corresponding to $N_{\text{transitions}} = 132,372$ of $N_{\text{individuals}} =$

45. Cox and Snell pseudo- $R^2 = 18.9$. * p (two-sided) $< .05$, ** $p < .01$, *** $p < .001$, SE =

Standard Error.

Figure 1. Scatterplots (each point is one individual's observation) and fitted bivariate associations (line) of loneliness and social interaction variables.