CARNEGIE MELLON UNIVERSITY

THESIS

Understanding the Effect of Everyday Social Interactions on Well-Being

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Abstract

Humans are social creatures in nature. Through interactions, we form and maintain relationships, which provide benefits to our physical and mental well-being. However, not all interactions are beneficial as they inevitably involve both positive and negative experiences. Research has shown that while positive interactions (those that are pleasant and enjoyable) are associated with better well-being, negative interactions (containing conflicts or poor treatment) can bring more harm. However, literature has not extensively examine what contributes to a positive and negative interaction, other than partner type and social support behaviors. Therefore, this thesis studies the factors that make an interaction positive or negative and whether they have any impact on one's well-being.

This thesis approaches this by examining the effect of interaction details, i.e., what happens in a social interaction such as who is involved, what joint activities are done, where the interaction occurs, whether there are exchanges of support behaviors, and etc. Specifically, **the thesis queries how these interaction details affect the positive or negative experience of the interaction and well-being**. Using Ecological Momentary Assessments, I conducted three separate longitudinal studies with a total of over 800 local and national participants. The data showed that interactions that involve close partners or contain joint activities and exchanges of support are rated more positively than their counterparts. More importantly, these interaction details have both direct and indirect impact on well-being. For example, interactions where people provide or receive support have direct associations with better well-being at the end of the day. Interactions that involve close ties and doing joint activities have indirect associations with better well-being by contributing to more positive interactions. In addition, the studies show that the interaction details do not explain the negative interactions.

This theoretical contribution, i.e., what happens in a social interaction can impact well-being, has both practical and technical implications. One benefit is its potential to lead to actionable recommendations for people who are willing to make changes to their social lives for a more thriving life. In addition, examining interaction details provides a tangible way to measure aspects of one's social life that matter for well-being. The thesis explores the possibility of using sensors embedded in mobile phones to automatically predict occurrences of social interactions and what happens in them. While the prediction performance did not work as well as hoped, it performed better than change, suggesting that there is useful information in the mobile sensed data to predict the medium of an interaction, whether it involves a close tie, and what activity is done. Based on the prediction results, the work discusses barriers and challenges to practical deployment of such systems in the near-term.

In summary, this work contributes: 1) theoretical understanding of how interaction details affect the experience of the interactions and well-being; 2) practical and actionable recommendations on changes one can make to their social lives for better well-being; and 3) technical implications on how to use mobile sensors to passively measure one's social life and what to measure.

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Chapter 1

Introduction

People are social in nature and have the need to interact and build relationships with others on a daily basis. From the moment when we wake up, myriads of interactions occur throughout the day. Some of the interactions are short and minor, e.g., chatting with a bus driver or making a small talk with a neighbor, while others are more memorable, such as having a family dinner or celebrating a best friend's birthday. The collection of all these interactions form the fabrics of one's daily life and help us live fulfilling and prosperous lives [8]. However, recent research has found that not all interactions bring benefits. While literature has found that positive interactions, i.e., those that are enjoyable and pleasant, have positive associations with well-being, it also found evidence that negative interactions (ones that contain conflict or poor treatment for any form) can do harm to one's well-being [50, 27, 127]. This separation between positive and negative interactions prompts the questions of what makes an interaction positive or negative.

This thesis addresses this question through the lens of what happens in a social interaction (or details of a social interaction), e.g., who is involved in the interaction, what happens during the interaction, which medium the interaction occurs, where the interaction happens and etc. These interaction details, as small units of a social interaction, can provide useful and interpretable insights into what type of interactions provide positive and negative experiences. Another benefit to studying interaction details is that they are mostly aspects of an interaction that people can have control over. Therefore, an understanding of these interaction details may lead to clear and actionable recommendations for better interactions and well-being.

While there is much value in studying interaction details, existing studies have only closely examined the effects of 2 types of interaction details on the experience outcome, i.e., how positive and negative, of the interactions, i.e., interaction partners [26, 125, 46] and support gestures [136, 6]. Considering the diversity of one's daily interactions, there are many other details unexplored in existing work, such as location and length. Therefore, the current thesis, by conceptualizing interaction details as building blocks of a social interaction, explores how a broad set of interaction details may influence the subjective experience of the interaction.

The thesis further probes whether interaction details can have downstream effects on one's well-being by influencing the experience of the interactions. While the question of how subjective experiences of social interactions impact well-being is not new in the realm of social psychology, not many studies have focused on the role of interaction details on well-being, by affecting how people experience the interactions (shown in Figure 2.1). In addition, most existing work has separately examined the effects of positive interactions and negative interactions on well-being [88]. The thesis will concurrently account for the effects of both positive and negative interactions on well-being. Different from existing work on the topic that measures well-being and social interactions only once or twice throughout the study [127], the current thesis examines the effects of positive and negative interactions on well-being at a fine-grained daily level. This method provides deeper insights in terms of how social interactions that happen during the day may affect well-being at the end of the day.

To answer the above questions, I conducted 3 studies in which short surveys were administered multiple times a day to query people's current or recent interactions, specifically interaction details and subjective experience of the interactions. These survey responses are used to examine whether social interactions have an effect on one's well-being, which was measured at the end of each day using survey questions on multiple dimensions of well-being. A summary table of the results can be found in Table 8.1. Three groups of findings were uncovered.

First, results show that positive experiences of a social interaction (i.e., how pleasant and enjoyable it is) can be better explained by what happens in a social interaction, compared to negative interactions (i.e., whether it contains conflicts or poor treatments). Specifically, exchanges of support (both emotional and tangible), interaction length, and presence of close ties are critical to a positive interaction. Surprisingly, the effect of interaction modality on positive interactions is unsubstantial, compared to presence of close tie and exchanges of support.

Our analyses further showed that days with more positive interactions are associated with lower stress, loneliness, and depression and higher level of thriving. The opposite was true for negative interactions — days with more negative interactions are associated with higher stress, loneliness, depression and lower thriving. While positive interactions from the previous day have an effect on well-being of the current day, this was not observed for negative interactions.

We also found evidence that what happens in social interactions can indirectly influence one's well-being by affecting how positive and negative one's interactions are. Structural equation models suggest that longer interactions, interactions with close ties, interaction activity, exchanges of support can all benefit one's well-being by creating more positive interaction experiences. Moreover, emotional support and doing sedentary fun activities (e.g., playing games together or watching TV together) are associated with better well-being by reducing the negative experiences of negative interactions. Phrased differently, subjective experiences of interactions mediate the effects of interactions details on well-being.

In addition to contributing to the theoretical understanding of social interactions, this thesis has practical contributions in that the theoretical insights can lead to actionable recommendations that can help people live a more thriving life. Moreover, the thesis contributes to the technical sensing community as it takes a step towards a larger vision where interactions can be automatically quantified based on sensor data. I envision a future where social interactions could be measured similar to how physical activities can be measured using physical sensors. This concept of a "social fitbit" can passively quantify one's social interactions and what type of interactions they are. Along this vision, part of the thesis explored the possibility of automatically detecting what happens in a social interaction using machine learning and mobile sensors. While the performance of the effort is less than ideal, there are valuable lessons that may be beneficial to future researchers who have similar aspirations.

1.1 Thesis Overview

The thesis document is structured as follows:

Chapter 2 offers a background review of what has been done in the domain of positive and negative social interactions and well-being and lays the foundation for the theoretical portion of the thesis work. The chapter also reviews existing applications of mobile sensing in well-being and social aspects.

Chapter 3 describes in detail study designs of three studies I conducted. Table 3.1 summarizes the differences and similarities between the studies.

Chapter 4 addresses the question of what makes a social interaction positive or negative. Specifically, I examined the details of interactions to understand what are the "ingredients" to a positive and negative interaction.

Chapter 5 focuses on disentangling the effects that positive and negative interactions have on one's well-being.

Chapter 6 dives deeper in the relationship between interaction details, experience outcomes of social interactions, and well-being. It aims to answer the question if the subjective experiences have a mediation effect between what happens in an interaction and well-being.

Chapter 7 shows exploration work in using machine learning and mobile sensing to predict details of one's social interactions. While the prediction results are not ideal, the results can shed light on how future work can improve the performance by setting up the surveys differently and using more wearable sensors that stay with the user.

Chapter 8 & 9 offer high-level discussion and conclusions of the thesis.

1.2 Thesis Impact

The current thesis addresses the question of what makes an interaction positive or negative and how these factors affect well-being. The thesis differs from existing studies in that it looks at low-level building blocks of a social interaction, i.e., what happens during the interaction, to understand how they affect the interaction outcome and, in turn, have potential downstream influence on well-being. By using longitudinal self-reports of social interactions at the level of an individual interaction, the work demonstrates that a single interaction can have a larger impact on, not only the subjective experience of the interaction, but also one's well-being. This contributes to our theoretical understanding of how social interactions impact well-being.

At a practical level, these theoretical findings have the potential to lead to actionable recommendations for people who are willing to make changes to their social lives for a more thriving life. In addition, the thesis contributes to the technical field as it provides quantifiable components of social interactions that have direct and indirect impact on well-being. These components can be sensed using commonplace sensors, such as those in smartphones. Chapter 7 demonstrates the possibility of mining for social interaction details (at a single interaction level) in sensor data using machine learning algorithms. This has the potential to capture one's social lives at a fine scale, which can not only help future researchers better study people's social interactions but also assist users in understanding their own social lives.

Chapter 2

Social Interactions and Well-Being

Social interactions are common in people's daily lives and they take on various forms, from chatting with a friend over coffee, having a small talk with a barista, to hanging out with a sibling in a bowling alley. Given its variety in appearance, it is critical to formally define what a social interaction is. According to Reis and Wheeler [123]:

> *By social interaction, we refer to all situations involving two or more people in which the behavior of each person is in response to the behavior of the other. Conversation is not necessary, although in practice most interaction involves talk.*

In literature, social interactions have also been referred to as *social exchange* [50], *social activity* [106, 37, 22], *social contact* [42, 22], or *social participation* [42]. In this thesis, I use *social interactions* for consistency.

Social interactions have attracted researchers for decades for its consistent benefits to one's physical and psychological health. Numeral studies have found that interactions are associated with better psychological well-being, such as higher level of happiness, positive affect and life satisfaction, and lower level of stress and depression [15, 147, 110, 132, 37]. This positive effect has been shown to be consistent at various stages of one's adult life [69]. For example, Ishii-Kuntz found that quality of social interaction measured by satisfaction with family life and friendship are positively related to well-being of adults in all age groups. The benefits of social interactions also extend to physical health. Marital social interactions have been found to be associated with subclinical cardiovascular disease in healthy middle-aged adults [72]. Interactions with family members and spouses are correlated with lower ambulatory blood pressure [65]. There is also some evidence that suggests having an active social life in late life protects against dementia and Alzheimer's disease [57].

As more research is done on this topic, researchers started to find evidence that not all interactions bring benefits to people. Instead, while positive interactions have positive associations with well-being, negative interactions can also do harm to one's well-being [50, 27, 136]. This separation of positive and negative interactions lays the foundation of the current thesis. Next, I will provide an overview of existing literature on positive and negative interactions, which I will refer to as experience of an interaction.

2.1 Subjective Experience of Interactions

While the majority of the literature on social interactions has focused on the benefits of social interactions, a rising group of works has found that negative interactions can have a deleterious impact on mental health. In senior citizens, Rook found that negative social outcomes were more consistently and more strongly related to well-being than were positive social outcomes [127]. In a young adult sample, social conflicts are significantly correlated with affect and quality of life when the conflict is with a specific person or with people in respondents' life [1]. These studies call for closer looks at how both positive and negative interactions influence one's well-being.

Relationship between different interaction experiences

What is the relationship between positive and negative interactions? Contrary to most people's belief, positive and negative social interactions are not two sides of the same coin. Instead, research has found that positive and negative social interactions are only weakly correlated and may be distinct dimensions. In a review paper by Lincoln [88], the author mentioned that among a small number of papers that measure both concepts separately, only a few of them found a strong relationship between positive and negative interactions. In other words, the same interaction can contain both positive and negative components. In addition, structural equation modeling also indicates that positive and negative social interactions constitute empirically distinct constructs. Therefore, in my thesis, I measured positive and negative experiences of interactions separately, using questions from the DABS (Diary of Ambulatory Behavioral States) by Kamarck and colleague [75]. DABS evaluates the two concepts using 4 Likert-scale questions. Two items assess the positive aspects of interactions (i.e., "agreeable interaction" and "pleasant interaction") and two items evaluate the negative aspects (i.e., "someone in conflict with you" and "someone treated you badly"). These measures have been shown to associate with a number of important psycho-social indicators and outcomes, such as perceived social support [76], hostility [161], and marital quality [71].

Interaction details and interaction experiences

Given that a social interaction could lead to multiple outcomes, what determines whether an interaction will be positive or negative? A natural place to examine is the details of the interactions, e.g., who is involved, what is done, how it occurs and so on. There are 3 benefits to studying the interaction details. First, they are building blocks of a social interaction and can be considered as the smallest, while meaningful, unit of analysis. The interaction details are also observable. Participants can easily identify and report these details, without confusion. From the perspective of potential interventions, understanding the role of different interaction details can directly lead to clear and actionable recommendation items for people.

Literature has examined some key details to an interaction that influence experience. First and foremost is who is involved in the interaction. Social interactions with family and friends have been found to be one of most pleasant experiences [125]. Such interactions are also more likely to boost one's feeling of autonomy and relatedness, both of which are positively associated with pleasant social interactions [46]. There's also evidence indicating interactions with strong ties, in general, are associated with how meaningful the interaction is [90]. Interestingly, there have not been many studies that have separately examined how partners involved in a social interaction influences negative outcomes of the interaction.

Another important element is whether there is an exchange of social support during the interaction. In fact, supportive behaviors are considered so important to a pleasant interaction that many papers use words "supportive interactions" and "positive interactions" interchangeably in their work [136, 6, 170]. Given its importance, it is surprising that there is very little work that has empirically confirmed that presence of social support behaviors in an interaction are positively associated with pleasantness of the interaction. The current thesis will empirically examine how social support behaviors that occur in interactions influence the experience of the interaction.

The quantity of the interaction has also been a focus of study. There are two ways to quantify interaction – length and interaction count. When trying to understand what contributes to a positive or negative interaction, interaction length is more appropriate as it is a measure of the interaction itself, rather than a more global measure of interaction frequency. However, there have been very few studies that demonstrate length of an interaction can influence the experience outcome. Interestingly, previously designed surveys of social interaction have a built-in check for length of the interaction. For example, Rochester Interaction Records [123] requests participants to only record interactions that are longer than 10 minutes. Part of the reason for this design is because the survey is designed to "incorporate the more meaningful social events that occur in one's life, and we believe (supported by pilot data) that, for the most part, very brief social contacts rarely meet this criterion. (p. 287)" [123]. This provides some evidence that length of the interaction can account for how positive the interaction is. In the current thesis, I will empirically test this hypothesis.

How the interactions are carried out can also have an impact on the experience outcome of the interactions. Some studies suggest that being face-to-face provides better quality communication, such as less disruption and more efficiency at task solving, compared to mediated communication (mostly computer-mediated communication) [107, 19]. However, others show that computer-mediated and phone-mediated communication can be as rich and deep as face-to-face ones [9, 36]. A more recent by Litt and colleagues found that the medium of the interactions has no association with the meaningfulness of the interaction [90]. While these studies have inconsistent findings, there is evidence that suggests the importance of interaction medium on the outcome of social interactions.

Beyond the elements mentioned above, the current thesis also tests how activity (what is done during a social interaction) and location (where the interaction occurs) contribute to the experience of the interaction. Activity is inspired by Litt and colleague's work [90], where they found that five of the six most frequently-reported activities done in a social interaction are positively associated with how meaningful the social interaction is. These five activities are talking, eating, celebrating, work/study session, and doing physical exercise. While previous studies have examined how doing shared activities contribute to one's general well-being, the finding by Litt and colleagues provides evidence that the activities done during an interaction can have almost an immediate influence on the experience outcome of the interaction.

The location of a social interactions provides context to the type of activities involved and defines appropriate behaviors [63, 60, 20]. For example, different locations serve different functions for self-managing people's depression conditions – home is a common and comfortable place for many to connect with a significant other while busy public places allow them to engage with work in the presence of other people [20]. In addition, locations are subject to social norms for appropriate behaviors [63]. Places like restaurants and bowling alleys encourage people to stay and socialize, while other places, like classroom and libraries, discourage social interactions. Although locations can constrain the types of social interactions that happen, it is not well studied in the context of social interactions. The current thesis includes the type of locations (i.e., public, private) as a potential factor for experience outcome of social interactions.

TABLE 2.1: A list of interaction details that characterizes interactions that may have an impact on the experience of the interaction.

Interaction Detail	Empirical Support
Interaction length	[123]
Types of partners	[125, 46, 90]
Types of activity	[90]
Location type	[111, 53]
Interaction medium	[51, 107, 19]
Support behaviors	[90, 6, 170, 136]

Summary

In summary, the current thesis will examine how details of a social interaction, i.e., who is involved, what medium the interaction is carried out, where the interaction takes place, what activity is done during the interaction, and presence of support behaviors. Different from previous studies, like [90, 105], the current thesis uses experience sampling method to collect participants' social interaction details and their experience of the interaction multiple times throughout the day. This allows our study to test findings from these previous studies from a different angle – rather than using people's recall of a recent social interaction or general social interaction experience, ecological momentary assessment repeatedly samples subjects' current behaviors and experiences in subjects' natural environments [140].

Research Question 1: What makes an interaction positive or negative?

This thesis focuses on the specific details of a social interaction for multiple reasons. One, these are building blocks of a social interaction. If a social interaction is a recipe, each of the interaction details is an ingredient to the recipe. Similar to how varying the ingredients affects the outcome of the recipe, interactions involving different building blocks may influence the outcome of the interaction. Another reason for studying the interaction details is that, as building blocks, these details are observable. As this thesis is a part of a larger vision where social interaction can be automatically measured and quantified by a sensor, the factors that influence the outcome of a social interaction, ideally, need to be observable by a sensor. In contrast to other factors of social interaction outcome, e.g., autonomy, which is difficult for a sensor to pick up, these interaction details provide physical traces. For example, an interaction with a family member can be sensed using various sensors, e.g., a camera to recognize facial features or an audio recorder to detect unique voice features of the speaker. Furthermore, these chosen interaction details are, mostly, under one's control. One can choose to interact with a certain friend over a colleague or determine whether they would like to go out for a meal or just sit and chat. If there is significant association between the experience outcome and the interaction details, one could make adjustments to the type of interactions they have to optimize their interaction experience. By focusing on these interaction details, the insights may lead to clear and actionable recommendation items for people.

Knowing what contributes to positive and negative interactions, the next question is do they all affect well-being in a similar way?

2.2 Effect of Subjective Experience of Interactions on Well-Being

The reason why researchers have been studying subjective experiences of interactions is because of its influence on one's well-being, which is consistent across all age ranges [15, 147, 110, 132, 37, 69, 50, 27, 136]. In these studies, the well-being measures researchers have used are mostly depression, life satisfaction, and stress. The following section provides a brief review for each type of well-being measure.

Depression - Majority of the studies on social interactions and depression found similar high-level results [26, 105, 1]. Positive and supportive interactions are negatively associated with depression [1] while negative interactions with conflicts are positively associated with depression [1]. Okun and Keith found similar results in both younger (28 to 59) and older (60 to 92 years old) sample [105]. In addition, they found that positive social exchanges had stronger net effects on depressive symptoms than negative social exchanges.

Positive Well-Being - Work on the effect of positive and negative social interactions on positive aspects of well-being is significantly less, compared to those on negative well-being, such as depression. Among the work that has studied positive well-being, some looked at quality of life [1] and found that supportive interactions are positively associated with life quality while conflictive interactions contribute negatively to it. Similar findings were reported when positive well-being is measured by either life satisfaction [26] or a composite of measures, including meaning in life and life satisfaction [147].

Stress - Existing work conceptualizes the effect of social interactions and stress in two ways. One is that positive social interactions serves as a stress-buffer for other well-being measures, e.g., depression [88]. Another way of conceptualizing social interactions is that negative social interactions function as a stressor, bringing negative impact to one's well-being [141]. Therefore, there are not many studies that directly examines the effect of positive and negative social interactions on perceived stress. However, evidence drawn from social relationships work suggests that having positive social ties is generally negatively associated with perceived stress and having negative or ambivalent social interactions is positively associated with stress [159, 59, 95]. Therefore, I hypothesize that social interactions, as a macro sample of a relationship, will have similar association with stress, i.e., positive social interactions are negatively associated with stress and negative social interactions will positively contribute to perceived stress. However, as positive social interactions have a buffering effect while negative social interactions have a direct effect on stress, the effect that positive social interactions have on stress may be less than than of negative social interactions.

Loneliness - A variable that is hardly studied in the realm of positive and negative social interactions is loneliness. Similar to perceived stress, literature has suggested that a lack of positive social relationships have a significant impact on one's sense of loneliness [113] and social conflicts contribute to one's feeling of loneliness [21]. As social relationships are built through interactions, I hypothesize that similar results will be observed, i.e., positive social interactions will have positive association with loneliness and negative social interactions will have a negative association.

One gap in these existing work is that very few work has concurrently examined the effect of both negative and positive interactions on well-being. This is partially due to the belief that positive and negative interactions are two ends of the same dimension. As many work has found that this is not the case (see review paper [88]), it is of interest to understand how positive and negative interactions can interactively impact well-being. More intriguingly, some initial work has found evidence for 2 different models [88, 68]. One is a domain-specific model, which states that only positive interactions affect positive well-being and only negative interactions affect negative well-being. Another is an additive or direct effects model that suggests that both positive and negative social interactions can have additive effects on both positive and negative well-being. This motivates the current work to include both positive and negative aspects of well-being:

Research Question 2: How do both positive and negative interactions affect one's well-being, specifically, depression, loneliness, stress, and positive well-being?

While all these measures quantify one's various aspects of well-being, the effect that social interactions can have on these different well-being measures may differ. Below are some of my exploratory hypotheses. For example, stress is typically a result of what stressors one experiences at that time. As negative interactions can be considered as a type of stressor, they may have observable impact on one's perceived stress. Depressive symptoms, on the other hand, are not as directly associated with stressors as one's perceived stress does. Therefore, the effect that negative interactions have on one's depressive symptoms may be less than that on one's perceived stress. Loneliness, which is a (perceived) state of solitude and being alone [157], is more directly associated with the presence and lack of meaningful social interactions. Therefore, positive interactions may have an impact on loneliness, possibly more so than on stress and depression, which are less caused by lack of social ties and social interactions.

2.3 Mediating Effect of Interactions Details on Well-Being Through Subjective Experience

An area unexplored in the literature is whether one's subjective experience of a social interaction, i.e., positive and negative interactions, can mediate the effect of interaction details on well-being. As there is evidence in existing literature on the potential effect that interaction details can have on its outcome and the experience of social interactions can impact well-being, I hypothesize that the interaction details can have either a direct or indirect effect on well-being, by influencing how positive and negative a social interaction is. That is, the subjective experience of social interactions may mediate the effect that interaction details have on well-being.

Research Question 3: Does subjective experience of social interactions mediate any effect between social interaction details and well-being?

More specifically, positive interactions may mediate the effect between interaction details and loneliness, due to the definition of loneliness mentioned above (perceived state of solitude and being alone). In other words, interaction details that have significant associations with positive interactions are likely to have an indirect association with loneliness. In addition, since loneliness is directly associated with lack of company, interactions that involve close ties may directly and negatively relate to loneliness. For stress, since negative interactions are a source of stress [141], interaction details that promote or hinder negative interaction are likely to also indirectly impact perceived stress.

Figure 2.1 visually presents the three research questions of the thesis.

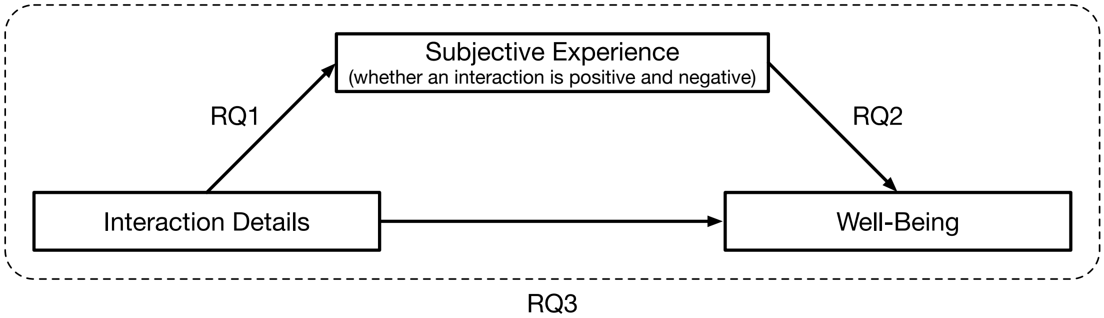

FIGURE 2.1: A visual representation of the three research questions of the thesis. **RQ1:** What details of a social interaction make an interaction positive or negative? **RQ2:** How do positive and negative interactions affect one's well-being, specifically, depression, loneliness, stress, and positive well-being? **RQ3:** Does subjective experience of social interactions mediate any effect between social interaction details and well-being?

2.4 Mobile Sensing of Social Interactions

A main difficulty with studying social interactions is data collection. As social interactions happen throughout the day, a continuous and comprehensive report of one's interactions is almost impossible to obtain as it requires participants to be constantly aware of their interactions and report them immediately as they happen. Due to this difficulty, Most existing studies on social interactions use daily self reports that ask participants to recall interactions they have at the end of each day or the previous day. However, this method can be prone to errors as studies have shown that human memory can be biased by current mood and affect [121]. Participants are also more likely to report positive interactions or interactions with strong ties than negative interactions or interactions with weak ties [58]. This poses two issues on studying social interactions. First, negative interactions and interactions with weak ties are more likely to be under-reported, both of which can have a strong effect on one's affect [132, 136]. In addition, there is a high cost on participants as they have to actively remember to report their interactions and need to carry special equipment or surveys to fill out throughout the day. These constraints substantively limit the quantity and quality of data collection.

To address these issues, the current thesis takes a step towards using mobile phones as passive sensors to collect people's interaction data. I will utilize machine learning algorithms to test the possibility of recognizing one's social interactions and their details from the sensor data collected on the phone. Ideally, a good machine learning algorithm will be able to alleviate the bias issue of self report and also lessens the burden on the participants to complete numerous surveys in a day.

This mobile sensing method is gaining popularity among the research community as it is more common for people to carry phones with them throughout the day – a survey done by Pew Research Center in 2015 showed that nine in ten respondents reported that they "frequently" carry their phone with them [119]. Beyond its growing presence, these phones have many sensors embedded, e.g., accelerometer, GPS, microphone, light sensor and etc. They can provide various types of data related to the user. Many studies have demonstrated the potentials of mobile phones in studying human behaviors.

2.4.1 Mobile Sensing and Well-Being

Mobile phones have been used as a passive data collection device in many recent studies [164, 83, 94]. They provide richer and more temporally fine-grained details on human behavior than traditional self-report methods. For example, phones can non-intrusively collect users' screen interactions and action logs around the clock [85, 24]. They can also continuously detect devices and people physically close to them [49]. These details can inform researchers about the users' psychological and social state.

Multiple work has examined the possibility of using mobile sensed data to predict one's well-being. Accelerometer data, smartphone usage patterns (e.g., the time and length of smartphone usage or recharge events) and environmental observations (e.g., prolonged silence and darkness) are fruitful in detecting sleep patterns as in [25, 98]. Saeb and colleagues also found that phone usage duration and frequency are both positively correlated with depressive symptoms [131]. A separate study showed that sensed speech, i.e., fraction of time human speech was present, is highly correlated with depressive symptoms [116]. A decrease in outgoing messages is associated with depressive symptoms in people with bipolar disorders [11]. Beyond depressive symptoms, studies have also applied this methodology on predicting stress and mood. Bogomolov and colleagues demonstrated that weather conditions sensed by mobile phone sensors (data pertaining to transitory properties of the environment) and the personality traits (obtained from participants one time) can predict one's stress level at 72% accuracy [17]. Mood prediction using multiple data sources, e.g., microphone, accelerometer, location, messages, and calls, has shown to be successful and accurate in multiple studies [91, 117, 139, 92]. This group of work shows the potential of using mobile phones to predict well-being.

2.4.2 Mobile Sensing and Social Behaviors

One of the earliest uses of sensors to learn about one's social behaviors was by Eagle and Pentland in 2006 [47]. With proximity sensors, i.e., Bluetooth sensors, in mobile phones, they demonstrate the possibility to infer friendship networks and the type of a relationship between two people as workplace colleagues, outside friends, and people within a user's circle of friends with 90% accuracy. Following their work, more and more research has started to explore how to use data sensed from mobile phones to learn about one's social activities.A few other work has also explored the possibility of using embedded sensors in mobile phones to predict loneliness (or social isolation) and social support [87, 45]. For example, Doryab and colleagues used both smartphones and Fitbit® data to predict loneliness [45]. With their machine learning pipeline, they achieved an accuracy of 80.2% in detecting the binary level of loneliness and an 88.4% accuracy in detecting change in the loneliness level. Their data also suggest that students with low loneliness, in comparison to students with high levels of loneliness, spent less time outside of campus during evening hours on weekends and less time in places for social events in the evening on weekdays. Ghosh and Singh showed initial success in using social features from call and text message logs to predict social support scores [61]. With phone features that indicate social activity, tie strength, relationship maintenance, and temporal rhythms, their predictive score and the actual social support score are moderately to highly correlated (0.68). Among all features used, total call duration and call frequency with strong ties are highly associated with one's social support. Min and researchers utilized call and text message logs from mobile phones to classify contacts to family, work, and social by extracting features such as communication intensity, regularity, and medium [99].

All the studies mentioned above demonstrate that it is practical and highly valuable to use mobile sensing to study one's social and mental well-being. However, the prediction outcomes in these studies are the status of one's social network or social trait rather than details of an interaction episode. This is also commonly seen in the next set of work that predicts the 4 aspects of social interactions.

Occurrence of social interactions

As the majority of mobile sensing work on social activities focuses on predicting one's general social status or trait, there is very little work that examines prediction of a single social interaction. A relevant work uses location type, physical activity, time of day, and weekday to predict whether a person is in company or alone [52]. In its exploratory analyses, the paper found that place types are highly correlated with being alone or in company. For examples, bars and nightclubs are frequently visited with a company while gyms and post offices are more likely to be visited alone. In the in-field user study, the paper showed over 90% accuracy in predicting whether a person is in company or alone using place type from 1 hour before the ground-truth label, time of day, and weekday as features. While this work focuses on interactions that occur physically together, we will broaden the prediction of social interactions to include both in-person and mediated interactions as social interactions, as defined previously, can occur in both settings. To be able to capture all types of interactions are important if the goal is to use the resulting algorithm in future studies.

Interaction medium

The current work differs from existing studies in 3 ways: 1) the goal of the current paper is to predict occurrences and details of social interactions at the moment rather than one's social status or trait; 2) the current work adapts a broader definition of social interactions to include beyond the most commonly seen face-to-face conversation-based interactions; and 3) our data collection happened in-the-wild, rather than in a controlled setting. Participants carried and used their phone as they regularly would without set constraints on how they should place their phone, e.g, on the body or in a pocket.

The current work is not the first in using mobile sensing to detect social interactions. However, existing work in the area of social interactions mainly focuses on predicting presence of interaction or tie strength. For example, detection of conversations (one type of social interaction) has been widely studied, using microphone [116, 165] and other additional wearable sensors, e.g., infrared sensor [28], accelerometer strapped around chest [97], and respiratory inductive plethysmograph [118]. Physical proximity is another measure that can be used to infer presence of social behaviors [3]. For instance, Bluetooth and Wi-Fi access point data are indicative of co-location between individuals and presence of interaction [13, 97]. Other than predicting occurrences of interactions, tie strength can be inferred using mobile sensed data Call and text message logs from mobile phones can classify contacts according to life facet (family, work, and social) [99]. Presence of relationships, friendship network structure, and relationship strength are also predictable outcomes using mobile sensed data [49, 48, 137].

To take a step beyond simply predicting the presence of interactions, the current thesis made attempts to predict interaction medium and interaction partner.

Chapter 3

Study Designs

To study the research questions outlined in Chapter 1, I conducted three studies from 2019 to 2020. This chapter will describe the setup of each study. As an overview, Table 3.1 highlights and similarities and differences between the three studies.

3.1 2019: Study 1 (Pilot)

The first study was conducted during the fall of 2019. It was five days long and took place at a local university. The study was approved by our university's Institutional Review Board, and participants were aware that they could leave the study at any point. This study was the first of the sequence and helped shape the design of the remaining two studies. Below, we will describe in detail the procedures of the study, variables of our interest, and our analysis methods.

3.1.1 Participants

We recruited a total of 35 participants (66% female) from our city using a local participant recruiting website.

Twenty-two of the 35 participants were students, and the remaining 13 participants held either part-time or full-time jobs, e.g., social workers, lawyers, and nurses. This is a sample of young adults: Thirteen participants were between 18-24; Fifteen between 25-30; six between 31-35; and one between 41-45. Because our survey delivery only worked on the Android OS, all recruited participants were Android phone users. All participants completed the full data collection.

3.1.2 Procedure

Participants visited our lab prior to the study to grant informed consent. With the participants' permission, we installed an app that collected usage data and delivered surveys to their phones. After completing the installation of the data collection app, participants filled out a name generator survey [96] that prompted them to list friends and family members with whom they enjoy spending time and discussing important matters. These initials were later used in an EMA survey question that asked about the communication partner, along with other general categorical choices, i.e., friend, family, colleague, acquaintance/stranger (more details on the EMA surveys in the section below). After this first session, they carried and used their phones as usual for the duration of the study and responded to the surveys when prompted. While participants did not start on the same date, all first initial sessions were scheduled between Wednesday to Friday so that the study spanned across the weekend for all participants.

On the 6th day, participants returned to the lab for an end-of-study session where they received compensation based on their rate of survey completion. During this session, participants were also asked to

		Study 1	**Study 2**	**Study 3**
Time		Fall 2019	Spring 2020	Summer 2020
Physical or Virtual Lab Sessions		Physical	Virtual	Virtual
Study Length		5 Days	6 Weeks	3 Weeks
# of EMA Surveys Per Day		24 Surveys	8 Surveys	8 Surveys
Sample Size		35	48	714
Sample Population		All local, Mostly students	Mostly local, mostly students	Across the US, various age ranges, various occupation
EMA Surveys	Interaction Details	Partner Medium Location Activity	Length Partner Medium Location Activity Supporting gestures	Length Partner Medium Location Activity Supporting gestures
	Experience Outcomes	Positive interaction Negative interaction	Positive interaction Negative interaction	Positive interaction Negative interaction
End-of-Day Surveys (Well-Being)		Loneliness (1 item) Depression Stress	Loneliness Depression Stress Thriving	Loneliness Depression Stress Thriving
Collected Mobile Sensing Data		Yes	Yes	No

TABLE 3.1: A high-level overview of the similarities and differences of the 3 studies conducted for the thesis.

walk through the survey responses from the last day of the study to check the accuracy of these semi-hour reports. For each survey response, participants briefly described what they were doing at the time of the survey and what interactions they had. Across the 524 survey responses we checked, only 4 were faulty responses entered by mistake. This suggests that our EMA survey responses were reliable.

3.1.3 EMA Surveys

During the study, participants received EMA surveys roughly every 30 minutes on their smartphones between 9:30 AM to 10:30 PM, asking them to report their current or recent social interactions. The survey-delivery window was designed to cover waking hours for the majority of the people (both student and non-student population). No survey was delivered early in the morning or late at night so that participants wouldn't be disturbed during their rest. 30-minutes intervals were chosen to maximize the quantity of the surveys while minimizing disruption to participants' daily lives. The surveys were not designed to capture all of participants' social interactions in a day. Instead, the survey responses are treated as representative of a person's social life in a day as these surveys are roughly evenly spaced throughout the day. In total, there were 24 surveys delivered to the participants in a day.

The surveys are delivered in a custom-built Android application. When a survey is prompted, the app generates a notification to notify the participants (Figure 3.1a). At the end of each day, they also received a separate survey assessing their well-being and social support. Participants were compensated on a daily rate of $10 on days where they completed 70% (or 17) of the interaction surveys and the end-of-day well-being survey. To help participants keep track of their progress, our survey application lists the completion

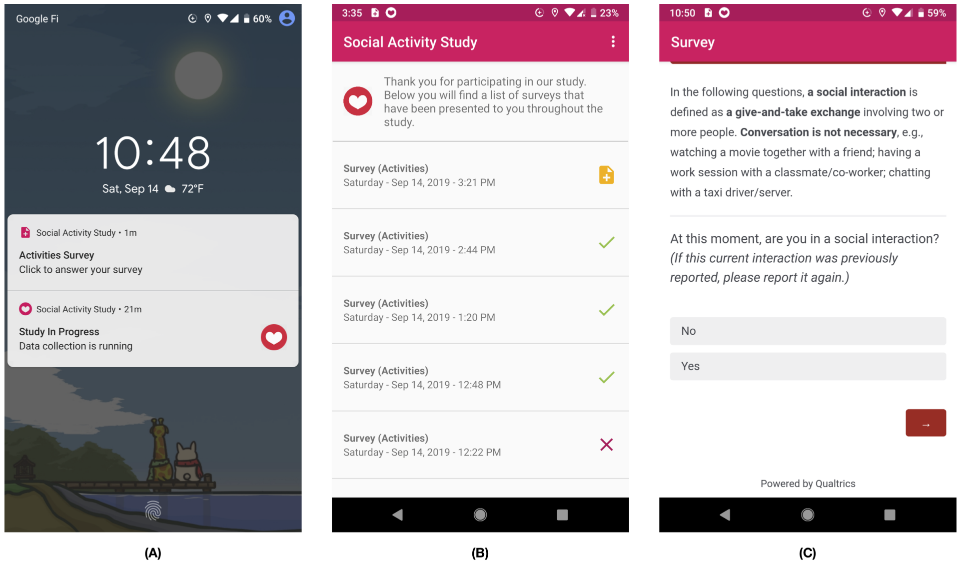

FIGURE 3.1: Our custom app that delivers survey items to participants. (A) Notification that prompts participants to respond to a survey, together with a notification that indicates ongoing data collecting in the background. (B) Overview of all surveys. Yellow icon signals a survey awaiting a response; green check means completed surveys; red cross is missed surveys. (C) Survey screen.

status of past surveys (Figure 3.1b).

These surveys first provide a definition of a social interaction, based on [123]. A social interaction is defined as a give-and-take exchange involving two or more people. Conversation is not necessary, e.g., watching a movie together with a friend; having a work session with a classmate/co-worker; chatting with a taxi driver/server. After the definition, the survey asks participants if they are currently having a social interaction (Figure 3.1c). If participants' response is no, the survey proceeds to ask if they have had any social interactions in the past 10 minutes. If the response to both questions are "no", the survey exits. If participants respond "yes" to either question, the survey continues to query the details of the interaction. This protocol was adapted from a work by Joseph and colleagues [72]. We limited the report of social interactions to the most recent 10 minutes to minimize the effect of memory bias. Since the EMA surveys are not meant to comprehensively capture all interactions, the 10-minutes limit does not affect how representative the reported interactions are of participants' daily social interactions.

Among the interaction details queried in the EMAs, they include: (1) who are involved in the interaction. Participants could select from a list of 3 identified friends and 1 identified family members, based on the name generator survey [96] from the pre-study session. If their social interactions did not involve these 4 people, they could select from 4 partner type options, i.e., a friend, a family member, a colleague, and/or an acquaintance/stranger. Participants are allowed to select multiple choices. For example, one can be interacting with friends and family at the same time; (2) how close they feel towards the interaction target(s) (on a 5-point Likert scale); (3) what medium the interaction occurs (phone, in-person, laptop, other); (4) location of the interaction (home/someone else's home, school/work, public, other); (5) interaction activity, i.e., a conversation, a meal (e.g., dinner, lunch, coffee), physical activity (e.g., running, hiking), sedentary entertainment (e.g., watching a movie, playing a board game), and active entertainment (e.g., shopping). Multiple choices are allowed; (6) subjective ratings of the interaction on 4

Category	Survey Question	Response Choice	% of Interactions (or Mean (SD))
Partner Type	Whom you have socialized with? (Individuals from Name Generator)	Friend 1 Friend 2 Friend 3 Family 1	20.42 13.05 6.72 7.53
	Whom you have socialized with? (Other)	Friend Family Colleague Other	35.88 10.84 19.97 14.85
	How close do you feel with the person you are socializing with?	1(Not at all) – 5(Extremely)	3.27(1.23)
Location	Where did the interaction occur?	Public Work/School Other Home/Other's home	22.08 32.11 1.71 44.10
Medium	What channel on which the social interaction take (took) place?	In person Via Phone Via Computer Other Channel	70.60 28.75 7.38 0.25
Activity	What activities are involved in the interaction?	Talking Work/Study session Sharing meal Celebrating Physical activity Sedentary entertainment Other active entertainment	80.48 14.20 9.28 2.41 2.96 9.58 3.81
Outcome	Is it an agreeable interaction? Is it a pleasant interaction?	NO!, No, no, yes, Yes, YES!	5.01 (0.89) 4.94 (0.98)
	Is someone in conflict with you? Is someone treating you badly?	NO!, No, no, yes, Yes, YES!	1.50 (0.88) 1.41 (0.77)

TABLE 3.2: Study 1: Descriptive statistics for the social activity variables collected in the EMA surveys, across all 35 participants.

separate five-point Likert scales, i.e., agreeable, pleasant, in conflict, being treated badly.

To measure experience of the interaction, we adapted a 4-item scale from two sub-scales of the Diary of Ambulatory Behavioral States (DABS), a multi-item scale that assesses key aspects of social interaction. The sub-scales are Positive Engagement, consisted of 2 questions (i.e., agreeable and pleasant) and Social Conflict, consisted of 2 questions (i.e., conflict and bad treatment). Both of these scales have been shown to represent relatively independent characteristics of daily social interactions [72], and are associated with a number of important psycho-social indicators and outcomes, such as perceived social support [76], perceived discrimination [153], hostility [161], and marital quality [71].

Table 3.2 summarizes the EMA variables. Column 2 and 3 list the wordings of the questions and the response choices. Column 4 shows, for categorical variables, the distribution of each choice as a percentage of the total number of reported social interactions. For numeric variables, column 4 displays the average and standard deviation of all collected responses.

All questions are multiple choice questions to make it easy for participants to quickly input their responses. The questions have an "Other" option that allows participants to input their own answer if the pre-defined choices do not fit.

3.1.4 Evening Surveys

The evening surveys were designed to assess participants' well-being at the end of the day. They were delivered at 8 PM and participants were asked to complete the survey before they went to bed. The questions include 1) one-item loneliness scale from the Brief Inventory of Thriving [149]; 2) Patient Health Questionnaire-2 for depression [79]; 3) four-item version of the Perceived Stress Scale [31] . These short-versions of assessments were chosen to minimize the time and attention burden of participants.

3.1.5 Smartphone Data Collection

For the duration of the study, the data collection software ran in the background to collect sensed data. The collected data was temporarily stored on the phone before they were uploaded to our secure private data server every 10 minutes when the phone was connected to WiFi. Below are the data collected on the phone in detail.

Time of Day and Day of Week

Time of day and day of week are context information that is readily available to any mobile device. While basic, past work has found that both provide critical information in inferring whether or not people are in the presence of company [52].

Physical Activity

Physical activity predicts one's current activity using Google's Activity Recognition API [2]. The data was based upon built-in accelerometers and was sampled once every 5 minutes. The returned results were still, walking, running, biking, in vehicle, and unknown.

Location

Location data query the phone's GPS sensor and contain rough estimates of the phone's longitude and latitude. The data was collected once every 3 minutes. Each reading contains an accuracy measure that Android calculates, which is the radius of 68% confidence. We only kept location data with an accuracy of 500, i.e., if you draw a circle centered at this location's latitude and longitude and with a radius of 500 meters, there is a 68% probability that the true location is inside the circle.

We ran DBSCAN, a clustering algorithm, on the raw location data. DBSCAN is a commonly used density-based algorithm that forms adjacent data points as a cluster while marking points that lie alone in low-density regions as outlier points. Used on location data, DBSCAN can form meaningful clusters while leaving out noisy location points that were generated due to low sensor accuracy or mistake. After forming location clusters, we were able to identify participants' home and work clusters, based on density of visit, similar to the method used by Hayashi and colleagues in [64]. For all of our participants, the top 2 most dense clusters are home and work. To further distinguish between the two, we looked at the time of the day and day of the week they visit those places. Home clusters are defined to be the cluster that people stay in at night while work is the one where people visit during weekdays and not on weekends. Using this method, we were able to identify participants' work and home clusters.

For the remaining clusters, we identified the type of the place using Yelp API [171]. As Yelp only contains public places, e.g., restaurants, cafes, bars, and parks, we marked locations that Yelp API returns a match as "public" locations, i.e., places that are not someone's home.

App Usage

Application usage data is collected via Android's Accessibility API. The data include the name of the app that participants were using and the corresponding timestamp. App usage data was triggered by participants' interaction event, e.g., tapping the screen or typing. The Accessibility API first traverses through the screen content and returns high-level nodes of the trigger point.

Screen Status

Screen status refers to participants turning the screen on or off. It is automatically logged whenever there is a change in screen status, i.e., on to off or vice versa.

Call and Message Log

Call and message logs are obtained using Android's native function calls. Call log contains incoming, outgoing, and missed calls and their duration. The call contact is encrypted to protect the identity of any third party. For message log, message contents were not stored in the database to protect participants' privacy. Rather, message contents were piped through a semantic analyses library, Linguistic Inquiry and Word Count [112]. Resulting category scores, timestamp of the message, and encrypted message receivers/senders were stored in the database. We also used Android's Accessibility APIs to capture messages from WhatsApp. As message logs, only linguistic category scores of WhatsApp messages were saved.

Inferred Conversation

Inferred conversation data were collected using an audio classifier developed in prior works []. In prior works, the classifier achieved 85% to 94% accuracy at classifying microphone input into audio inferences, specifically silence, noise, and voice. The data collection was done every 10 minutes. Input audio was recorded with 100-200 millisecond windows at a time for 1 minute and resulting inferences were 1 of 3 categories, i.e., silence, noise, and voice. If there is voice detected during the 1 minute period, another 3 minutes of recording will be taken. After the recorded audio was processed, the recording was deleted. No conversation content was collected at any point.

3.1.6 Ethics and Privacy

As the data collection involves a large amount of data from each participant, we took ethics, privacy, and data safety as the top priority.

All participants were enrolled voluntarily and were made aware of the full list of collected data prior to joining the study. During the study session, participants went through an informed-consent process and were encouraged to ask questions regarding the study and the data collection. Participants were also provided a walk-through of the data collection app and received a briefing about the purposes of the study. In addition, participants were informed that at any point of the study they could withdraw their participation and data collection.

The sensing software was built upon the PrivacyStreams library, a programming framework that makes it easy to access and process various types of sensitive personal data from Android phones in a uniform and privacy-friendly manner [86]. All data were encrypted, following the Advanced Encryption Standard that is established by the U.S. National Institute of Standards and Technology. All data were de-identified and were associated with random identifiers to protect the privacy of the participants. Collected data were transferred from the app to our password-protected server using secure-sockets-layer (SSL) encryption and were only accessible by researchers on the project team.

3.2 Early 2020: Study 2 (6-Week Local Sample)

The first study did not query a few interaction details that are of interest, i.e., interaction length and support behaviors. In addition, Study 1 is not long enough to capture more variances in the well-being measures. Therefore, we ran Study 2. The second study was 6 weeks long. The data collection spanned from March 2020 to June 2020. Study 2 followed the same study procedure as Study 1. However, the survey schedule and a few question items were edited. Below is the procedure of the study. I highlighted the changes that we made based on Study 1.

3.2.1 Participants

We recruited a total of 60 participants, 48 of whom completed the full data collection. The data analysis only includes the data of the 48 participants (58.29% female).

Participants were recruited from the same recruiting website. Before the study took place, coronavirus started to spread across the country. To adapt to the fast changing situation, we changed the first and last lab session to be virtual. Therefore, not all participants were physically located in our city during the study.

Thirty of the 48 participants were students. The remaining 15 participants had part-time or full-time jobs or were unemployed. In terms of age, twenty-two participants were between 18-24; Eighteen between 25-30; five between 31-35; and three between 41-45. Same as Study 1, all recruited participants were Android phone users. All participants completed the full data collection.

3.2.2 Procedure

While the overall steps of the study were the same as Study 1, some procedure details are different due to the pandemic.

Participants had a 30-minute video call with the experimenter to complete the first study session. All participants were informed of the details of the study and all the data that would be collected. After addressing questions from the participants, they grant us informed consent. With the participants' permission, we guided them to download and install our data-collection app (same app as Study 1). After completing the installation of the app, participants digitally filled out the name generator survey [96]. Different from Study 1, the name generator asked people to list 1 more friend and 1 more family member. We also separately asked participants to list their romantic partners by their initials (if they have one).

All of the initials were entered by the participants into the app so that the survey questions could refer to these initials in the EMA surveys. After this first session, participants carried and used their phones as usual for the duration of the study and responded to the surveys when prompted.

After 6 weeks, participants were scheduled for a second video call, in place of a physical end-of-study session. They received digital compensation based on their rate of survey completion. During this session, participants were also asked to walk through the survey responses from the last day of the study to check the accuracy of these semi-hour reports. For each survey response, participants briefly described what they were doing at the time of the survey and what interactions they had. Overall, most of the participants did not correct any of the entries.

3.2.3 EMA Surveys

The EMA survey schedule for Study 2 was different from that of study 1. For Study 2, participants received 8 EMA surveys on their smartphones between 9:00 AM to midnight. We reduced the amount of interaction surveys to accommodate for the fact that Study 2 was much longer than Study 1. The activity surveys were roughly 1-2 hours apart to get a sample of one's social interactions throughout the day. Participants were required to complete 6 EMA surveys in a day to receive the full payment.

Same as Study 1, the surveys were delivered in the Android data-collection application. The interface was the same as Figure 3.1. At the end of each day, they received a separate survey assessing their well-being and social support.

The survey items followed the same flow: the surveys first define a social interaction before asking participants if they are currently having a social interaction. If participants' response is no, the survey proceeds to ask if they have had any social interactions in the past 10 minutes. If the response to both questions are "no", the survey exits. If participants respond "yes" to either question, the survey continues to query the details of the interaction.

The interaction questions surveyed in Study 1 were all included in Study 2. They were: (1) who, (2) closeness, (3) interaction medium, (4) location, (5) interaction activity, and (6) 4 subjective ratings of the interaction, i.e., agreeable, pleasant, in conflict, being treated badly.

In addition to the questions above, we included a few additional questions that could also affect the experience of the interaction. These new questions were (1) length of the interactions and (2) specific supporting gestures that were adapted from DABS [75]. For the supporting gesture question, we asked 9 support gestures, chosen from DABS, as binary questions. An additional "None of the above" option was available if none of the behaviors happened during the interaction. The nine supporting gestures are:

- Discuss personal feelings
- Feel understood and appreciated
- Someone offer you helpful information
- Someone do you a favor
- Someone help you with an errand/task
- Someone expresses confidence in you
- Someone expresses care/concern for you
- Someone give you positive feedback
- You try to be helpful to someone

Table 3.3 summarized participants' responses.

3.2.4 Evening Surveys

Study 2 uses the same evening survey protocol as Study 1 with some survey changes. For loneliness, we used the four-item version of the UCLA Loneliness Scale [129]. To evaluate social support, we changed to 12-item Interpersonal Support Evaluation List [32]. The stress and depression surveys stayed the same. In addition, we added the Brief Inventory of Thriving as a measure of one's positive well-being [149].

3.2.5 Smartphone Data Collection

The smartphone data collected in Study 2 was identical to that of Study 1.

3.3 Mid 2020: Study 3 (3-week National Sample)

The third study was 3 weeks in length, spanning from June 31, 2020 to Sep 3, 2020. The study is very different from the previous 2 studies in both the sample and the data collection. Study 3 contains participants sampled across the United States. It does not have a smartphone data collection component. The data collection was only limited to survey responses. The details of Study 3 are outlined below.

3.3.1 Participants

A total of 1,083 participants were recruited through a recruiting company. Before participating in the study, participants completed an initial set of demographic questions on the recruiting company's portal about their gender, age, geographic location (both region area and zip code), current employment and living status. This information is used to balance the sample, i.e., roughly half of the participants self-identified as female and half as male and even location region distribution across the United States (regions are based on [89]).

The age and employment distribution of the population is shown in Figure 3.2. Because there was no collection of phone usage data, all participants with a smartphone could participate in the study. We set the smartphone constraint so that participants, after receiving the surveys, could complete them even if they are away from their computers and were, potentially, in an interaction.

3.3.2 Procedure

The study was 3 weeks long. People who were registered in the participation pool of the recruitment company and who were qualified for the study, i.e., living in the United States and of age 18 years or older, were prompted about the study. If they were interested to participate, they would click on a link that took them to the recruiting company's screener survey where they were given the full detail of the study, the compensation, and consent information for the study. If participants wished to continue, they would fill out the initial demographic questions and explicitly consent to participate in the study by checking a checkbox. These initial set of demographic questions were used to balance the sampled participants, based on gender, living situation (alone or with other), and geographic region.

After completing the initial screener, participants would visit a Qualtrics web page to complete a pre-study survey, hosted by the research team, where participants filled out a few additional demographic

Category	Survey Question	Response Choice	% of Interactions (or Mean (SD))
Length	How long has this interaction been going on?	< 10 min	21.84
		10-20 min	20.75
		20-60 min	28.88
		> 60 min	28.52
Partner Type	Whom you have socialized with? (Individuals from Name Generator)	Partner	28.79
		Friend 1	9.46
		Friend 2	6.66
		Friend 3	3.65
		Friend 4	4.34
		Family 1	12.40
		Family 2	14.83
	Whom you have socialized with? (Other)	Friend	15.14
		Family	19.28
		Colleague	11.51
		Other	10.06
	How close do you feel with the person you are socializing with?	1(Not at all) – 5(Extremely)	3.59(1.17)
Location	Where did the interaction occur?	Public	2.85
		Work/School	0.94
		In transit or vehicle	2.12
		Other	0.47
		Home/Other's home	93.63
Medium	What channel on which the social interaction take (took) place?	In person	54.98
		Via Phone	28.99
		Via Computer	23.40
		Other Channel	0.36
Activity	What activities are involved in the interaction?	Talking	76.29
		Work/Study session	15.76
		Sharing meal	13.76
		Celebrating	1.98
		Physical activity	3.23
		Sedentary entertainment	21.33
		Other active entertainment	1.94
Support Behavior	Did any of the following things happen?	Discuss personal feelings.	26.45
		Feel understood and appreciated.	18.90
		Someone express care/concern for you.	13.41
		Someone give you positive feedback.	12.09
		Someone express confidence in you.	6.64
		Someone offer your helpful information.	17.55
		Someone do you a favor.	8.64
		Someone help you with an errand/task,	10.13
		You try to be helpful to someone.	25.63
Outcome	Is it an agreeable interaction?	NO!, No, no, yes, Yes, YES!	4.84 (0.82)
	Is it a pleasant interaction?		4.78 (0.90)
	Is someone in conflict with you?	NO!, No, no, yes, Yes, YES!	1.73 (0.93)
	Is someone treating you badly?		1.64 (0.84)

TABLE 3.3: Study 2: Descriptive statistics for the variables collected in the EMA surveys, across all 48 participants. The last column shows, for categorical variables, occurrence frequency in reported interactions or, for numeric values, the mean and standard deviation.

questions, i.e., race and ethnicity and their household composition. These additional demographic questions were only used as control variables and participants were not screened with these questions. In addition, the pre-study survey included a series of personality, social connectedness, and well-being questionnaires that capture the baseline well-being of the participants. These surveys are: COVID Impact Scale [148], stress (using Perceived Stress Scale-10 [31]), anxiety (General Anxiety Scale [79]), loneliness (UCLA Loneliness Scale [130]), Depression (Center for Epidemiologic Studies Depression Scale), 10-item Big-Five Personality Questionnaire [120], Social Network Index [30], and Perceived Social Support [32]. As previous studies, participants completed a Name Generator survey that asked them to list the initials of 2 people they felt comfortable discussing important matters with and 3 more initials for people they enjoyed socializing with. Participants were only required to list 1 person. The remaining 4 people were optional.

The pre-study survey also asked participants for a phone number and an email address that would be used to deliver surveys. In addition, we asked a few preference questions that were used to set up the survey-sending schedule for each participant, such as their timezone, when they would like to receive their evening survey and the first EMA survey. This concludes the pre-study survey and the on-boarding process for the study. 838 participants completed the pre-study survey.

Once they completed the pre-study survey, they would start to receive personalized links for EMA surveys on their phone. The delivery of the links were through text messages, or email, or both. Same as Study 2, each participant would receive a total of 8 EMA surveys asking about their current or recent social interaction and one evening survey that assessed people's well-being close to the end of the day. For payment purposes, participants were required to complete 6 of the EMA surveys and the evening survey to receive full payment for the day. All participants were compensated for completing the surveys, based on their survey completion rate. The compensation was delivered weekly and was $10 for week 1, $25 for week 2, and $40 for week 3. A total of 714 participants completed at least 1 EMA survey and 1 end-of-day study on the same day. These participants' data were included in the analysis.

After 3 weeks, participants would receive an end-study survey. The survey was almost identical to the pre-study survey. We repeated the same questions on people's well-being, i.e., COVID Impact Scale, stress, anxiety, loneliness, and depression. In addition, we asked how their communication had changed

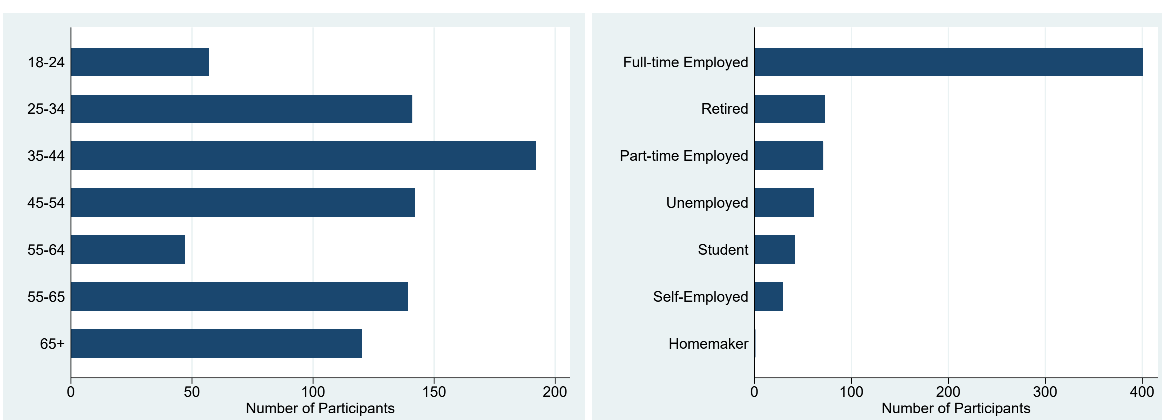

FIGURE 3.2: The age and employment distribution of Study 3. Compared to the first 2 studies, the population varied more in age and are no longer student-centric population.

with people in their lives and whether or not they have noticed any changes in the use of communication platforms, i.e., face-to-face, phone, video, email, messaging applications, and social media. All these questions were responded to on a 5-point Likert scale (decreased a lot, decreased a little, neither decreased nor increased, increased a little, and increased a lot). After submitting their post-study survey response, participants completed the full study.

3.3.3 EMA Surveys

EMA surveys were sent to participants throughout the pay, roughly 1-2 hours apart. The default hours were from 9 am - midnight but participants could customize the start hour, based on their schedule. The EMA survey items were similar to that of the previous studies. However, a few changes were made and some questions were added to better capture people's social interactions in the age of the pandemic.

The survey first defined a social interaction as "a give-and-take exchange involving two or more people. Social interactions can occur in any modality, including in-person, telephone, video call, text messages,, email, and social media as long as you and the interaction partner are responding to each other." The definition also made it clear that social interactions can include both work-related interactions and ones that are purely social. Following the definition, participants were asked:

- How many social interactions they had in the last hour. The options are None, 1, 2 or 3, and 4 or more.
- When the most recent social interaction ended using 5 choices, i.e., 0-10 minutes ago, 11-30 minutes ago, 31-60 minutes ago, 1-2 hours ago, and more than 2 hours ago.

If they selected that the most recent social interaction ended more than 2 hours ago, the survey skipped questions on reporting the details of the interaction and proceeded to questions on their mood, using the Short Form Positive Affect and Negative Affect Scale [156]. As PANAS over-represent high-activation positive affect, we added 2 more positive adjectives that represent low-activation positive affect, adapted from [160]. The two terms are "happy" and "relaxed". Participants rated on a scale of 0 to 10 the extent to which they were experiencing each emotion at the moment of responding to the survey. Table 3.4 shows the average of all positive word scores and the average of all negative word scores.

If the most recent social interaction ended less than 2 hours ago, participants were prompted to report the details of the interaction. This includes:

- A short text description of the interaction
- How long the interaction lasted: < 1 minute, 1-10 minutes, 10-20 minutes, 20-60 minutes, > 60 minutes;
- Who were involved: any of the Name Generator enlisted partners, or other. If other was selected, participants had the option to indicate the role of the person, i.e., child/grandchild, parent, other relative, friend, boss/employee/co-worker/school mate, acquaintance, group member (e.g., church), service professional, or stranger;
- How close they felt with the person they interacted the most on a 5-point scale from "not at all" to "extremely";
- How the interaction took place. The choices were in person, phone/voice call, video call (e.g., Zoom, Skype), text message, email, social media/social network site;

- Where the participant was during the interaction, i.e., their home, someone elseś home, work/school, other indoor public places (e.g., a store), other public places (e.g., a park), or other;
- Whether the goal of the interaction was to socialize;
- Whether the goal of the interaction was to accomplish a task;
- Activities that were done during the interaction, e.g., a conversation, a meal, a study/work session, physical activity, other active activities, e.g., shopping, sedentary entertainment, celebration, or other.
- Specific supporting gestures (rated on a scale of 0-10), i.e., someone share personal feelings with you, someone provide you useful information, someone did you a favor, someone helped you with an errand/task, someone expressed confidence in your, someone expressed concern/care for you, and someone gave you positive feedback, you shared personal feeling with someone, you offered someone positive feedback, you expressed care/concern for another, you offer help to someone, you felt understood and appreciated. These items were adapted from the DABS [64].
- Quality of the interaction, rated on a scale of 0 to 10. The items are conversation flowed easily; we shared common interests and values; this was a pleasant interaction; this was an agreeable interaction; someone treated me badly; this interaction contained conflict; and this is a meaningful interaction.

3.3.4 Evening Surveys

We used the same evening survey protocol as the previous 2 studies. Stress, depression, loneliness, and thriving were assessed using the same scale as Study 2. For social support, we switched to an eight-item emotional support scale from the NIH Toolbox [39]. The decision to change was motivated by the social distancing and stay-at-home orders that were ongoing during the study. As a result, some of the original support items, e.g., if I needed help in moving to a new house or apartment, I would have a hard time finding someone to help me, were no longer applicable. Therefore, we used the new scale to more accurately assess peopleś social support.

We also added a 2-item version of the General Anxiety Scale [80] as an additional measure of peopleś ill-being. Another addition to the evening survey is a list of positive and negative daily events as an objective measure of important (and/or unexpected) things that happened during the day. These items were designed to cover multiple aspects of people's lives, i.e., interpersonal, financial, health, and work. Some of the events were adapted from DABS. The full list of positive events are:

- Successful completion of important project at work or home.
- Intimate times with someone.
- Special activity with friends or family.
- Enjoyable chores (e.g., cooking, gardening, home repair).
- Excellent entertainment (e.g., TV show, movie)
- Enough free time
- Exercise

The negative events are:

- Unusually difficult or time-consuming chores/errands.

- Problem with money (e.g., check bounced, could not buy something).
- Failed to achieve an important goal or did poorly on an important project at work or home.
- Argument or disagreement.
- Lost money or something else you needed.
- Unexpected money or financial gain.
- New accident, illness or medical problem.
- Disappointing entertainment (e.g., TV show, movie, book).
- Too many things to do at home or work.

All these items were responded using binary options.

Category	Survey Question	Response Choice	% of Interactions (or Mean (SD))
Length	How long has this interaction last?	$<$ 1 min	15.25
		$<$ 10 min	32.41
		10-20 min	21.09
		20-60 min	9.73
		$>$ 60 min	21.52
Partner Type	Whom you have socialized with? (Individuals from Name Generator)	Person 1	38.06
		Person 2	17.00
		Person 3	9.13
		Person 4	6.62
		Person 5	5.92
	Whom you have socialized with? (Other)	Friend	5.42
		Family	21.25
		Colleague	4.68
		Other	10.13
	How close did you feel with the person you interacted with most?	1(Not at all) – 5(Extremely)	2.97(1.19)
Location	Where were you during the interaction?	Home	77.20
		Other's home	4.88
		Public-Indoor	5.55
		Public-Outdoor	3.13
		Work/School	6.65
		In transit or vehicle	2.12
		Other	0.47
Medium	How did the interaction take place?	In person	74.99
		Phone call	13.41
		Via Video	3.69
		Via Text	8.63
		Via Email	1.57
		Via Social Media	1.77
Activity	Were the following activities involved in the interaction?	Conversation(s)	81.26
		Work/Study session	4.40
		Sharing meal	18.93
		Celebrating	0.54
		Physical activity	4.15
		Sedentary entertainment	13.62
		Other active entertainment	6.80
		Other activity	9.21
Support Behavior	How much did the interaction involve the following?	Questions were on a scale 0(No) - 10(Yes).	
		• Someone shared personal feelings with you.	5.11 (3.81)
		• Someone expressed care/concern for you.	4.86 (3.80)
		• Someone gave you positive feedback.	5.12 (3.80)
		• Someone expressed confidence in you.	4.55 (3.76)
		• You shared personal feelings with someone.	5.12 (3.84)
		• You offered someone positive feedback.	5.31 (3.79)
		• You expressed care/concern for another.	5.43 (3.78)
		• You felt understood and appreciated.	6.36 (3.38)
		• Someone provided you helpful information.	4.93 (3.79)
		• Someone did you a favor.	3.49 (3.81)
		• Someone helped you with an errand/task.	3.48 (3.84)
		• You offered help to someone.	4.56 (3.95)
Outcome	How much did the interaction involve the following?	Questions were on a scale 0(No) - 10 (Yes)	
		• This was an agreeable interaction.	7.65 (2.92)
		• This was a pleasant interaction.	7.61 (2.93)
		• This interaction contained conflict	0.79 (2.17)
		• Someone treated me badly.	0.59 (1.86)

TABLE 3.4: Study 3: Descriptive statistics for the variables collected in the EMA surveys, across all 714 participants. The last column shows, for categorical variables, occurrence frequency in reported interactions or, for numeric values, the mean and standard deviation.

Chapter 4

Understanding What Makes a Social Interaction Positive / Negative

This chapter examines how interaction details (i.e., what happens during an interaction) affect people's subjective experience with the interaction (highlighted section in Figure 4.1).

All three studies show that interactions with close ties are associated with higher positive scores (i.e., they were more pleasant and more agreeable). Interactions involving joint activities, such as sharing a meal, watching TV, and playing games together, are rated more positively. In both Study 2 and 3 where social support exchange behaviors are measured, analyses showed that an interaction that involves exchange of either emotional or tangible support are rated more positively.

Negative interaction scores (i.e., whether there is conflict or bad treatment in the interactions), however, are less predicted by the interaction details. Less than 3% of variances are explained for negative interaction scores, compared to 10-30% for the positive score. This indicates that negative experiences during an interaction occur due to other factors and are more random in nature compared to positive interactions. Location and medium of interactions were less significantly associated with positive and negative interaction scores when partner and supporting gestures were controlled.

A summary of these findings can be found at the end of the document in Table 8.1

4.1 Method of Analysis

To understand how the details of a social interaction, such as tie strength of those involved and what activities are done, affect one's perceived outcome, i.e., positivity and negativity, we conducted multi-level regression analyses, treating the data we collected as panel data. Data from each study were analyzed separately.

Analyses were conducted using Stata. The data was converted to a panel data format using command **-xtset-**. To control for the effect of individual characteristics and to better focus on the effect of social

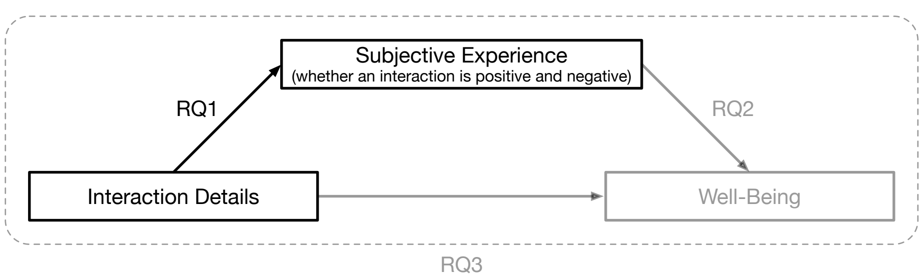

FIGURE 4.1: This chapter examines the first research question: What details of a social interaction make an interaction positive or negative?

interaction details on the subject experience, the analyses were done using fixed-effect linear regressions with Stata's command **-xtreg-**. Positive and negative interaction scores were entered into separate regression models as the dependent variable. The independent variables were introduced sequentially in groups to see how the addition of variables affects model fit and variance explained. The order of the added independent variable is (1) support behaviors, (2) partner type, (3) length, (4) activities, and (5) location and medium. This ordering is based upon the theoretical significance of the variables according to existing literature. Ordering the independent variables and entering them sequentially will help interpret the influence of the more important interaction details, i.e., support behaviors, partner type, and length. In addition, the addition of the less relevant variables at the end will help answer the question of whether these variables, i.e., activities, location, and medium, add anything to the experience outcome [29]. I will show each sub-model as well as the final model for each dependent variable. For all models, adjusted R-square value and BIC (Bayesian information criterion) are reported. Both measures reflect goodness of fit. For R-square, a higher value indicates a better model fit while for BIC, a lower value suggests a better fit. AIC is not reported here as it is similar to BIC values and is removed to avoid redundancy.

For each study, I will first describe the data we collected before diving in the regression results.

4.2 Study 1 (Pilot)

4.2.1 Sample Characteristics

The 35 participants completed a total of 3401 daily social interactions survey responses. On average, participants completed 101.48 (SD = 18.93) surveys, 84% of the semi-hour surveys delivered to them. Out of these responses, 58.60% of them reported either currently having a social interaction or had a social interaction in the past 10 minutes. Among these reported interactions, about 41.24% of the interactions occurred with a partner listed in the Name generator survey and 70.7% of the interactions were with a partner not from the Name generator survey. An overview of this can be found in Table 4.1.

Table 4.1 illustrates the distribution of different types of interactions. Most of the interactions happened at home or someone else's home (44.10%). School and work were the second most frequent spot for interaction (32.11%). Public places were the third (22.08%). Only 37 occurrences of interactions occurred in "Other" locations, with majority being in vehicles, such as cars. This motivated having "in vehicle" as a separate choice in the future studies.

Most of the interactions collected happened in person (70.60%). Approximately 28.75% of them were over the phone, with less than 7.5% mediated by computers. Only five interactions occurred in "other" media (they did not fit under the pre-given medium options). It is worth noting that among these 5 interactions, participants dutifully reported "minor" interactions, such as receiving a hand-written note from a colleague. This suggests that the surveys captured both long and memorable interaction as well as short and brief ones. Of all the social interactions, approximately two-thirds of them were spontaneous (65.28%). The majority of social interactions involved a conversation (80.48%). Working or studying together was the second most frequent activity (14.20%).

A pair-wise confusion matrix (Figure 4.2) shows the correlation between the details of the social interactions. For instance, interactions that include a close tie normally do not include a non-close tie (corr=-0.6). Interactions with close ties are positively correlated with home or other's home (corr=0.26)

Independent Variable (% of total reported interactions)	**Study 1**	**Study 2**	**Study 3**
Emotional support	na	42.00	85.61
Tangible support	na	40.44	77.06
Close tie	41.24	66.62	64.78
Not close tie	70.70	49.99	39.43
<1 minute long	na	na	14.92
<10 minute long	na	21.84	32.45
<20 minute long	na	20.75	21.18
<60 minute long	na	28.88	9.74
>60 minute long	na	28.52	21.71
A conversation	80.48	76.29	81.95
A study/work session	14.20	15.76	4.46
A meal	9.28	13.76	19.11
A celebration	2.41	1.98	0.53
Physical activity	2.96	3.23	4.09
Sedentary activity	9.58	21.33	13.63
Active entertainment	3.81	1.94	6.86
In person	70.60	54.98	75.15
Phone-mediated	28.75	28.99	14.26 (phone call)
Video	na	na	3.71
Text	na	na	8.79
Email	na	na	1.52
Social media	na	na	1.66
Computer-mediated	7.38	23.40	na
Home/Other's home	44.10	93.63	77.57 (home) 4.95 (other's home)
Public location	22.08	2.85	5.58 (indoor) 3.18 (outdoor)
In transit or vehicle	na	2.12	2.92
Other location	1.71	0.47	2.79
Work/School	32.11	0.94	6.62

TABLE 4.1: Percent of reported interactions that contain each type of interaction details for all three studies.

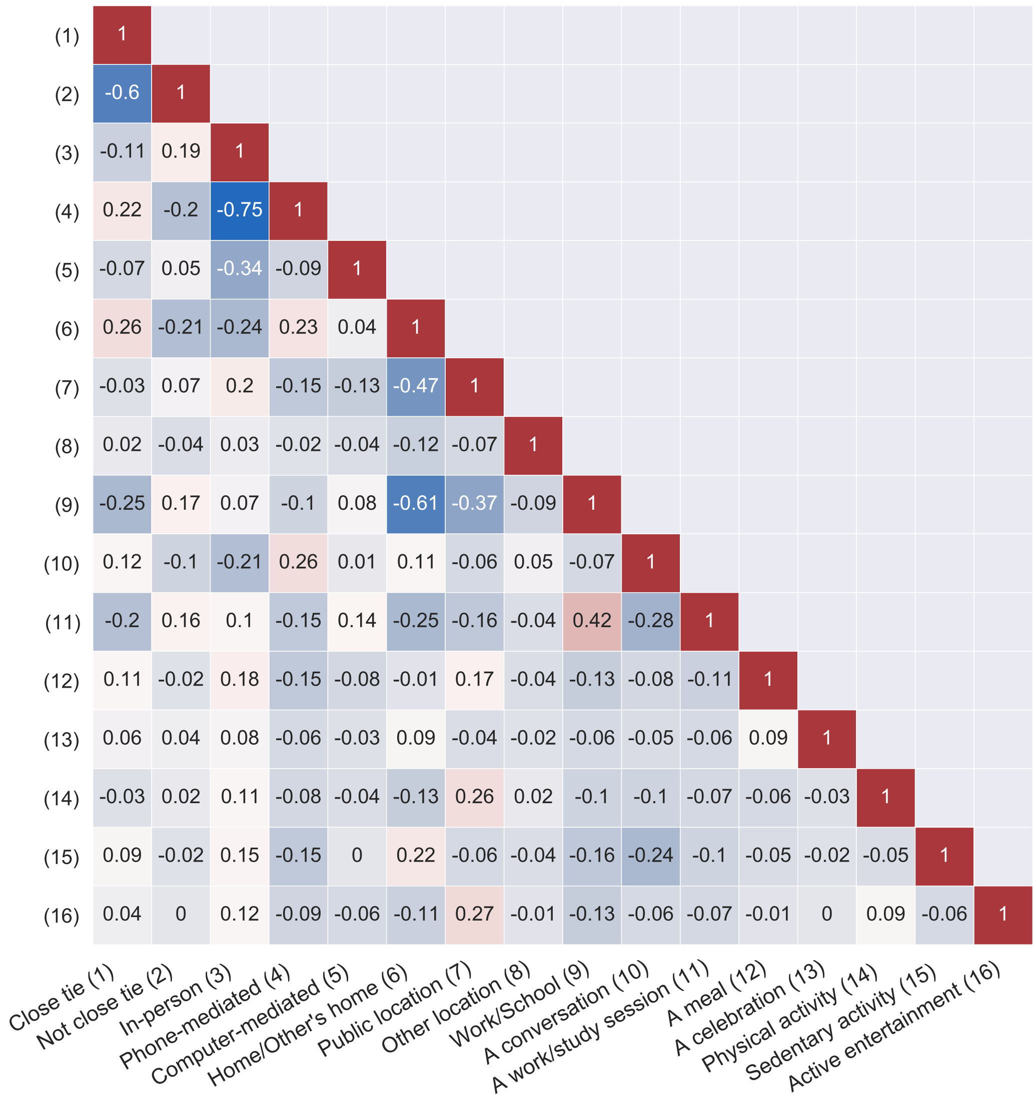

FIGURE 4.2: Study 1: Pair-wise correlation between the independent variables. * p<0.05. N=1993 observations.

and negatively associated with school and work (corr=-0.25). Not surprisingly, work and study sessions are likely to occur at work and school (corr=0.42).

In terms of the experience outcome variables, the reported interactions were highly agreeable and pleasant and low in conflict and bad treatment. This finding is consistent with previous works where more positive social interactions are observed than negative ones [27]. Following Joseph and colleagues' approach [72], responses to the two positive items were averaged to form a positive interaction score (α = .94). Responses to the two negative items, i.e., conflict and bad treatment, were averaged to generate a negative interaction score (α = .91). The positive and negative interaction scores were moderately correlated, Pearson's r = -.55, p < .001.

Study 1 Positivity	(1) Partner Type		(2) Activities		(3) Medium&Location	
	B	SE	B	SE	B	SE
Close tie	0.37***	0.04	0.29***	0.05	0.29***	0.05
Not close tie	0.05	0.05	0.02	0.05	0.05	0.05
A conversation			0.20***	0.05	0.21***	0.05
A study/work session			−0.03	0.05	0.01	0.06
A meal			0.27***	0.06	0.27***	0.06
A celebration			0.35**	0.11	0.34**	0.11
Physial activity			0.37***	0.10	0.39***	0.10
Sedentary activity			0.20***	0.06	0.21***	0.06
Active entertainment			0.18*	0.09	0.20*	0.09
In person					−0.15 *	0.07
Phone-mediate					−0.10	0.07
Computer-mediated					−0.25 **	0.08
(Home/Other's home omitted)						
Other location					−0.04	0.13
Public					−0.03	0.05
Work/School					−0.04	0.05
constant	4.78***	0.05	4.61***	0.07	4.75***	0.09
Adj. R-sqr	0.03		0.06		0.06	
DF	1956		1949		1943	
BIC	4330.00		4315.95		4350.73	

TABLE 4.2: Study 1: Fixed-effect regression models predicting positivity of an interaction. * p<0.05, ** p<0.01, *** p<0.001. N=1993 observations. Interactions with close ties and with joint activities are strong predictors of positive interactions.

4.2.2 Results

Results of the primary analyses are shown in Table 4.2 (positive interaction score) and Table 4.3 (negative interaction score). For positive interaction score, the adjusted R-square values (variance explained) increased roughly equally when partner type and activity variables were added. When all variables are included, the model explains about 6% of the variance in the positive interaction score. For the partner type variables, interactions with close ties (those listed in the name generator) were associated with higher positivity (b=0.29, p<0.001) while interactions with non-close ties did not show such a significant association. Interactions that include any of the joint activities, except for a work/study session, were rated more positively than interactions that don't involve these activities. For interaction media and location, in-person and computer-mediated were negatively associated with how positive an interaction is (in-person: b=-0.15, p=0.04; phone-mediated: b=-0.25, p=0.003). The location where an interaction took place were not significantly associated with the positive interaction score.

For negative interactions, the interaction detail variables do not explain any of the variances in the negative rating, based on the adjusted R-square value. While some of the variables are significant, e.g., interactions with non-close ties are positively associated with the negativity score, the significance are not very meaningful to interpret. Most of the interaction activity, media, and location variables were not significantly associated with how negative an interaction was.

Study 1 Negativity	(1) Partner Type B	 SE	(2) Activities B	 SE	(3) Medium&Location B	 SE
Close tie	−0.05	0.03	−0.04	0.04	−0.05	0.04
Not close tie	0.09*	0.04	0.09*	0.04	0.09*	0.04
A conversation			−0.08 *	0.04	−0.09 *	0.04
A study/work session			−0.01	0.04	−0.05	0.04
A meal			−0.02	0.05	0.00	0.05
A celebration			0.06	0.08	0.05	0.09
Physical activity			−0.11	0.08	−0.07	0.08
Sedentary activity			0.01	0.05	0.01	0.05
Active entertainment			−0.03	0.07	0.01	0.07
In person					0.09	0.06
Phone-mediate					0.09	0.05
Computer-mediated					0.11	0.07
(Home/Other's home omitted)						
Other location					0.05	0.10
Public					−0.08 *	0.04
Work/School					0.04	0.04
constant	1.42***	0.04	1.49***	0.05	1.41***	0.07
Adj. R-sqr	−0.01		−0.01		0.00	
DF	1956		1949		1943	
BIC	3307.60		3352.95		3384.45	

TABLE 4.3: Study 1: Fixed-effect regression models predicting negativity of an interaction. * p<0.05, ** p<0.01, *** p<0.001. N=1993 observations. Interaction details do not strongly predict negative interactions.

4.2.3 Exploratory Analyses

The model for positive score shows a significant negative association with in-person interactions. This seems counter-intuitive as much existing work has always considered in-person and face-to-face interactions to be better than mediated interactions in many aspects, such as richness in expression and information and helping people form positive impressions [146, 101, 104]. To further understand the negative association, I did exploratory analyses to test 2 hypotheses.

First, the effect of in-person interaction may differ depending on tie strength. For example, interactions with partners who are close, regardless of whether it is in person or not, may be rated similarly in terms of positivity, but interactions with less close ties may be less positive when done in-person. To test this hypothesis, I added an interaction term between close tie and in-person interaction and non-close tie and in-person interaction into the full regression models for positive score (model (3) in Table 4.2). Both interaction terms are not significant ($b_{closetie \times in-person}$=0.09, p=0.38; $b_{non-closetie \times in-person}$=0.08, p=0.43). While these two interaction terms are not significant, adding them to the model removed the significant effect of in-person interaction (b=-0.06, p=0.64). It is possible that the lack of interaction effect is due to the small sample size of Study 1.

The second hypothesis is related to the difference in nature between in-person and non-in-person interactions. In-person interactions occur only when people who are physically co-located. Therefore, compared to non-in-person interactions, they are more likely to happen incidentally and spontaneously, e.g., chatting with one's partner while going for a cup of water in the kitchen. However, non-in-person interactions, e.g., video chats or texts, require additional planning and effort – people need to actively initiate these interactions. Given the incidental nature of the in-person interactions, the experience of such interactions may be more varied and lower, in general, compared to the more deliberate non-in-person interactions. In Study 1, the EMA surveys included a question on planned vs. spontaneous nature of the interactions. Participants were asked whether the interaction they reported in the EMA surveys were planned or spontaneous. Therefore, I added the binary planned (vs. spontaneous) variable, as well as an interaction term between planned (vs. spontaneous) and in-person interaction, into the full regression models for positive interaction score. Again, neither terms were significant ($b_{spontaneous}$=0.00, p=0.97; $b_{spontaneous \times in-person}$=-0.07, p=0.51). However, the effect of in-person interaction on positive interaction score became non-significant when these two terms were introduced (b=-0.10, p=0.37).

Therefore, in Study 1, there is no conclusive evidence that tie strength and the spontaneous nature of in-person interactions can explain the negative association with the positive interaction score in Study 1. However, as sample size is a concern, I will repeat these exploratory analyses for the next two studies.

4.3 Study 2 (6-Week Local Sample)

4.3.1 Sample Characteristics

For the 48 participants whose data were included in the analysis, they completed a total of 10,758 EMA surveys. Table 4.1 shows a summary of the interaction details. Out of these responses, 41.75% reported either was currently having a social interaction or had a social interaction in the past 10 minutes. The duration of the reported interactions span roughly evenly from less than 10 minutes to over 60 minutes long. Among these recorded interactions, two-thirds (66.62%) of them occurred with a partner listed in the name generator survey. This number was higher, compared to Study 1. We suspect that the difference is due to stay-at-home orders that started to take place after March given the sample population was similar. 49.99% of interactions were with non-name generator partners.

Table 4.1 describes the distribution of people's interaction types. Almost all of the interactions happened at home or someone else's home (93.63%). Only 2.85% of interactions happened in public places and another 2.12% in transit. 21 occurrences of interactions occurred in "Other" locations. More than half of them were outside of one's house, such as in the backyard or on the street in front of the house. About half of the interactions collected happened in person (54.98%). Approximately 28.99% of them were over the phone and 23.40% were mediated by computers. The majority of social interactions involved talking (76.29%). Doing joint sedentary entertainment activities, e.g., watching TV, was the second most frequent activity (21.33%).

In Study 2, we added a question that asked participants to report occurrences of support behavior in the interactions. To reduce the number of support behavior variables entered in the regression model, a Principal Component Analysis is run to see if there are any key components that can capture the variances between the individual items. Participants' responses of all the support behavior items were used. PCA revealed 2 principal components that capture 45% of the variance. To better interpret the loading of each item on the components, varimax rotation is applied to the principal components (rotated components are shown in Table 4.4). The first component is correlated with emotional support behaviors while the second

Support Behavior	Comp1	Comp2
Discuss personal feelings.	0.46	
Feel understood and appreciated.	0.47	
Someone express care/concern for you.	0.45	
Someone give you positive feedback.	0.39	
Someone express confidence in you.	0.46	
Someone offer your helpful information.		0.46
Someone do you a favor.		0.51
Someone help you with an errand/task.		0.57
You try to be helpful to someone.		0.37
Explained Variance (%)	30.51	14.81

TABLE 4.4: Rotated principal components for the support behavior items. Values less than 0.25 were omitted for clarity. Component 1 represents emotional support behaviors and Component 2 is positively associated with tangible support behaviors.

represents tangible support items. Therefore, 2 separate support scores were calculated, i.e., emotional support and tangible support. The score is the sum of the number of behaviors participants reported in an interaction. For example, the emotional support score is 3 if participants reported that they discussed personal feelings with others, felt understood and appreciated, and someone expressed positive feedback. Both support scores were standardized for the analyses.

Figure 4.3 shows the pairwise correlation between the independent variables. Similar to Study 1, interactions that involve close ties are less likely to involve those that are not close (corr=-0.71). In addition, interactions with close ties are more likely to happen in-person (corr=0.31) and less likely to happen over computer (corr=-0.36). For non-close ties, on the other hand, interactions with them are more likely to take place over a computer (corr=0.28) and are more likely to be a work or study session (corr=0.28). Interactions where people share a meal are more likely to be in-person (corr=0.31). Emotional support and tangible support behaviors are positively associated (corr=0.31), suggesting that they are likely to co-occur in the same interaction.

In terms of the experience outcome variables, similar to Study 1, the reported interactions are highly agreeable and pleasant and low in conflict and bad treatment (all items ranged from 1 to 6). Responses to the two positive items, i.e., agreeableness and pleasantness, were averaged to form a positive interaction score (α = .904; the range for positive interaction score is still 1 to 6.). Responses to the two negative items, i.e., conflict and bad treatment, were averaged to generate a negative interaction score (α = .92; the range for negative interaction score is 1 to 6.). The correlation between the positive and negative interaction scores were moderate (Pearson's r = -.56, $p < .001$).

4.3.2 Results

The final fixed-effect regression model results for the outcome variables, i.e., positive interaction score and negative interaction score, are shown in Table 4.5 and Table 4.6.

For the positive interaction score (Table 4.5), introducing new variables to the model increases the amount of variance explained. But the increase plateaus after the introduction of activity variables. Variance explained by support behaviors was the largest – the adjusted R-square is 0.09. In comparison,

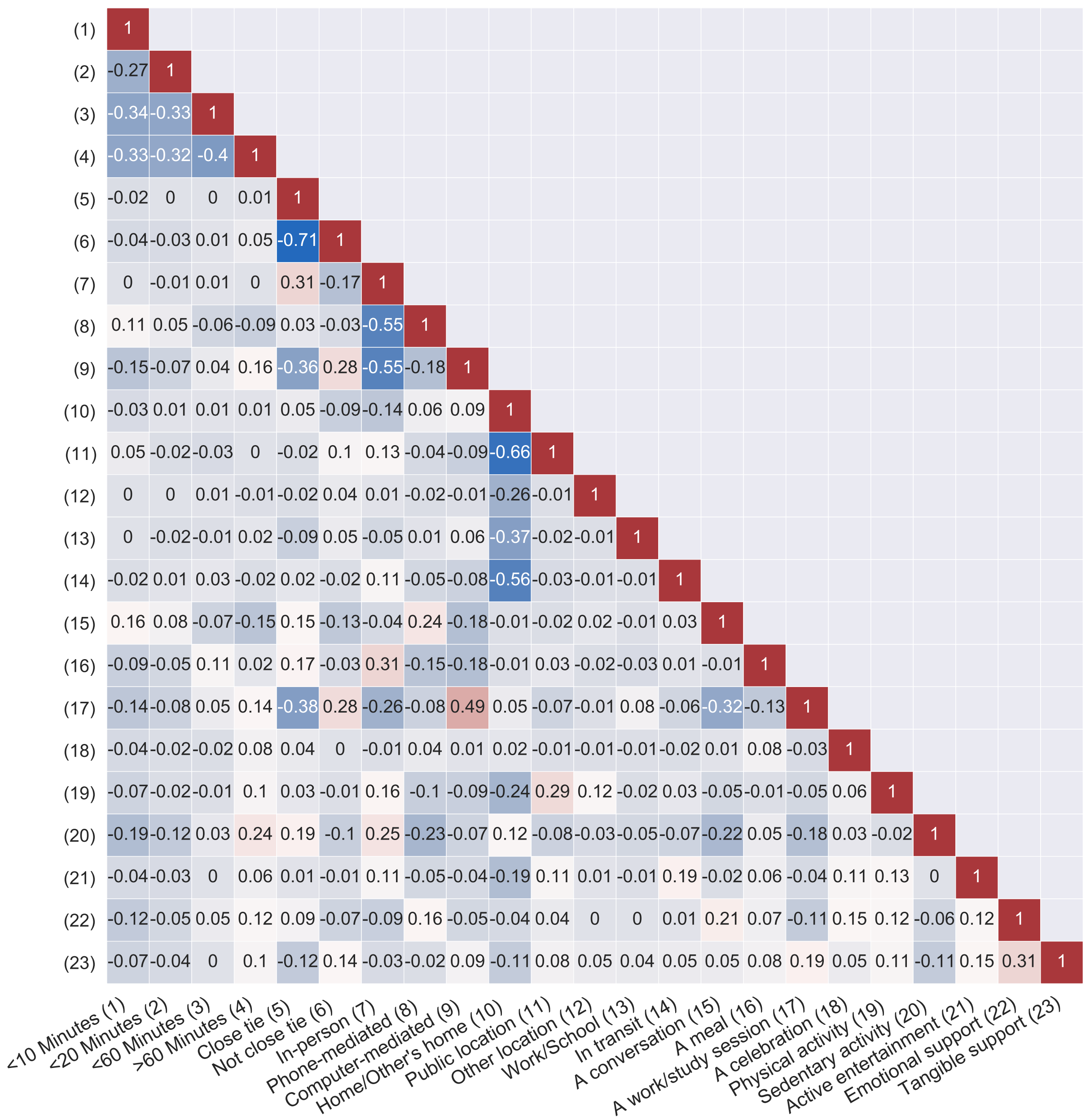

FIGURE 4.3: Study 2: Pair-wise correlation between the independent variables. * p<0.05. N=4491 observations.

Study 2 Positivity	(1) Support Gesture B	SE	(2) Partner Type B	SE	(3) Length B	SE	(4) Activity B	SE	(5) Medium&Location B	SE
Emotional support	0.24***	0.01	0.23***	0.01	0.22***	0.01	0.21***	0.01	0.21***	0.01
Tangible support	0.02*	0.01	0.03**	0.01	0.03**	0.01	0.05***	0.01	0.05***	0.01
Close tie			0.20***	0.03	0.20***	0.03	0.09**	0.03	0.11**	0.03
Not close tie			0.03	0.03	0.02	0.03	0.00	0.03	0.01	0.03
(<10min omitted)										
<20 min					0.12***	0.03	0.11***	0.03	0.11***	0.03
<60 min					0.10***	0.03	0.09**	0.03	0.09**	0.03
>60 min					0.11***	0.03	0.07*	0.03	0.08*	0.03
A conversation							0.04	0.03	0.04	0.03
A meal							0.04	0.03	0.07*	0.03
A study/work session							−0.16 ***	0.03	−0.14 ***	0.04
A celebration							0.30***	0.07	0.30***	0.07
Physial activity							0.05	0.06	0.06	0.06
Sedentary activity							0.21***	0.03	0.23***	0.03
Active entertainment							0.00	0.07	0.00	0.07
In person									−0.17 ***	0.04
Phone-mediate									−0.04	0.04
Computer-mediated									−0.12 **	0.04
(Home/Other's home omitted)										
In transit or vehicle									0.15*	0.07
Other location									0.24	0.14
Public									0.05	0.07
Work/School									0.00	0.11
constant	4.81***	0.01	4.66***	0.03	4.59***	0.04	4.62***	0.05	4.71***	0.06
Adj. R-sqr	0.09		0.10		0.11		0.13		0.13	
DF	4438		4436		4433		4426		4419	
BIC	8947.26		8902.73		8909.67		8843.99		8875.59	

TABLE 4.5: Study 2: Fixed-effect regression models predicting positivity of an interaction. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. N=4491 observations. Support behaviors, interactions with close ties, longer interactions, and interactions with most joint activities are are strong predictors of positive interactions.

location and medium variables have minimal effect on the variance.

Looking at specific variables, both support behaviors have a positive association with how positive people perceive the interaction to be. In terms of interaction partners, interactions with a close tie are reported more positively than those that are not with a close tie (b=0.11, p<0.001). Interactions with non-close ties have no significant effect on the positive score (b=0.01, p=0.80). For duration, interactions that are between 10 - 20 minutes long (b=0.11, p<0.001), between 20-60 minutes long (b=0.09, p=0.004), and longer than 1 hour (b=0.08, p=0.02) are more positively associated with the positive interaction score, compared to short interactions that are less than 10 minutes long. In terms of activities done during the social interaction, meal-sharing (b=0.07, p=0.02), celebrating (b=0.30, p<0.001), and doing sedentary activity, e.g., watching TV or playing a game, (b=0.23, p<0.001), are associated with more positively rated interactions. Being a part of a study/work session, on the other hand, is negatively associated with the positive interaction score (b=-0.14, p<0.001). For interaction medium, in-person interactions are negatively associated with positive interaction score (b=-0.17, p<0.001) and similar trend is observed for

Study 2 Negativity	(1) Support Gesture B	SE	(2) Partner Type B	SE	(3) Length B	SE	(4) Activity B	SE	(5) Medium&Location B	SE
Emotional support	−0.10 ***	0.01	−0.10 ***	0.01	−0.10 ***	0.01	−0.10 ***	0.01	−0.10 ***	0.01
Tangible support	−0.01	0.01	−0.01	0.01	−0.01	0.01	−0.01	0.01	−0.01	0.01
(<10min omitted)										
<20 min					−0.02	0.03	−0.01	0.03	0.00	0.03
<60 min					0.03	0.03	0.05	0.03	0.06*	0.03
>60 min					0.02	0.03	0.07*	0.03	0.07*	0.03
Close tie			0.02	0.03	0.02	0.03	0.04	0.03	0.03	0.03
Not close tie			0.04	0.03	0.04	0.03	0.05	0.03	0.05	0.03
A conversation							0.00	0.03	0.01	0.03
A meal							0.00	0.03	−0.04	0.03
A study/work session							−0.01	0.03	−0.01	0.03
A celebration							−0.12	0.06	−0.11	0.06
Physial activity							−0.16 **	0.05	−0.21 ***	0.05
Sedentary activity							−0.12 ***	0.03	−0.15 ***	0.03
Active entertainment							0.04	0.07	0.02	0.07
In person									0.06	0.04
Phone-mediate									−0.08 *	0.04
Computer-mediated									−0.02	0.04
(Home/Other's home omitted)										
In transit or vehicle									−0.12	0.07
Other location									−0.18	0.13
Public									0.05	0.06
Work/School									0.08	0.10
constant	1.68***	0.01	1.64***	0.03	1.64***	0.03	1.63***	0.04	1.63***	0.05
Adj. R-sqr	0.01		0.01		0.01		0.02		0.02	
DF	4438		4436		4433		4426		4419	
BIC	7929.64		7943.51		7965.38		7987.24		8013.06	

TABLE 4.6: Study 2: Fixed-effect regression models predicting negativity of an interaction. * p<0.05, ** p<0.01, *** p<0.001. N=4491 observations. Interaction details are poor predictors of negative interactions, based on Adjusted R-square value.

computer-mediated interactions (b=-0.12, p=0.01). The only location that has a significant association with positive score is interactions that take place in transit or vehicle (b=0.15, p=0.03). Compared to interactions that happen home or someone's home, these interactions are rated more positively.

For the negative interaction score (Table 4.6), only a minor amount of variances in the score is explained by the interaction details. This is similar to what is observed Study 1. Among all variables, only support gestures and activity variables increase the variance by 1%. Specifically, interactions that contain more emotional support are associated with lower negative interaction score (b=-0.10, p<0.001). Doing physical activities (b=-0.21, p<0.001) and sedentary activities (b=-0.15, p<0.001) are both negatively associated with the negative perception of the interaction.

4.3.3 Exploratory Analyses

As in Study 1, the model for positive score shows a significant negative association between in-person interactions and positive interactions. Therefore, I replicated the exploratory analyses from Study 1 to test

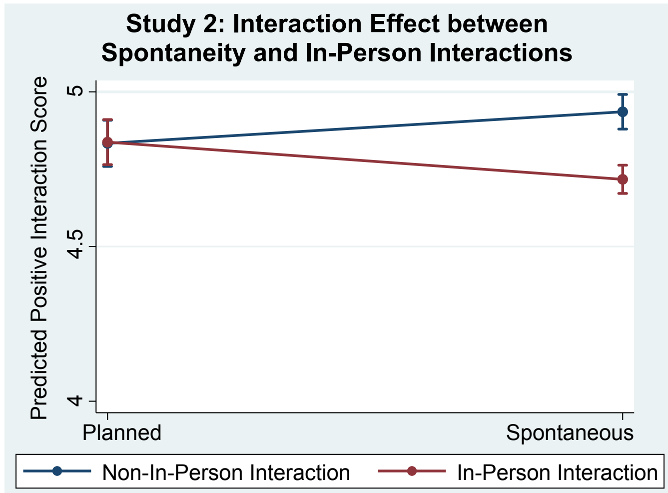

FIGURE 4.4: Interaction effect between whether an interaction is planned or spontaneous and is in-person, on positive interaction score. The spontaneous nature of in-person interactions may be one of the reasons for the negative association between in-person interaction and positive interaction scores. The error bars indicate 95% confidence interval.

whether tie strength and spontaneous nature of in-person interactions explain the negative associations between in-person interactions and positive interaction score.

First, when interaction terms between close tie and in-person interaction, and non-close tie and in-person interaction were added to the full regression model of positive interaction score (model (5) in Table 4.5), neither interaction terms are significant ($b_{closetie \times in-person}$=-0.06, p=0.39; $b_{non-closetie \times in-person}$=-0.02, p=0.76). While these two interaction terms are not significant, adding them to the model also removed the significant effect of in-person interaction (b=-0.12, p=0.16). Then to test the second hypothesis that the spontaneous nature of the in-person interactions may have contributed to the negative association between in-person interaction and positive interaction score, I added the binary planned (vs. spontaneous) variable, as well as an interaction term between planned (vs. spontaneous) and in-person interaction, into the full regression models for the positive interaction score. Both the spontaneity term and the interaction term are significant ($b_{spontaneous}$=0.10, p=0.01; $b_{spontaneous \times in-person}$=-0.22, p<0.001). Figure 4.4 shows that, for planned interactions, those that occur in-person (red lines) were rated similarly as those that are not in-person (blue lines). However, the perceived positivity decreases for spontaneous in-person interactions while it increases for spontaneous non-in-person interactions.

Therefore, in Study 2, while there is still no evidence for interaction effect of tie strength on negative association between in-person interactions and positive interaction score, there is a significant effect between spontaneity and in-person interactions. This indicates that spontaneity may play a role in explaining the negative association between in-person interactions and positive score.

4.4 Study 3 (3-Week National Sample)

4.4.1 Sample Characteristics

A total of 714 participants' data were included in the analyses for Study 3. These participants completed a total of 46,565 EMA surveys. Table 4.1 shows the summary of the interaction details. Out of these responses, 60.23% contained at least one social interaction in the past hour. The duration of the reported interactions was mostly less than 1 hour (78.48%). Among these interactions, two-thirds (64.31%) of them occurred with a partner listed in the name generator survey, comparable to the amount from Study 2 and higher than that of Study 1. Interestingly, participants listed the partners from the name generator in the order of how frequently they socialize together. For the first partner from the name generator, roughly 38% of the interactions involve these partners, compared to 5.92% for partner #5. In terms of who were listed in the name generator, 86.87% were a family member, 86.71% were friends; 58.58% were a spouse or a romantic partner; 3.58% were a housemate; 23.66% listed colleagues, acquaintances, and strangers.

Table 4.1 summarizes the frequency of each type of interaction. The vast majority of the interactions happened at home (77.20%) or at someone else's home (4.88%). This percentage was slightly lower compared to that of Study 2 but significantly higher than Study 1. The higher increase of interactions at home for Study 2 and 3 was probably a result of the pandemic and people following the stay-at-home order. While the slight decrease between Study 2 and Study 3 may be due to the relaxation of stay-at-home orders and businesses opening back up, it can also be a result of the difference in sample population (see Table 3.1 for time and sample differences between the studies). Corresponding to the decrease in home-based interactions, an increased amount of interactions happened in public (8.68%) compared to Study 2. There was also an increase in percentage of interactions that happen at work or school locations (6.65%). However, both values are still much lower compared to Study 1.

Around 75% of reported interactions happened in person (77.20%) and 13.41% occurred over phone calls (audio calls). Surprisingly, we did not observe a large amount of video-mediated interactions, e.g., over Zoom, FaceTime, and etc, in our data collection. Only 3.69% of the reported interactions occurred over video. This could be either because of the sample as people who were employed full-time are more likely to be in a video call (M=5.34%, SD=22.49%), compared to the overall sample. It is also possible that people are less likely to be responding to the surveys when they are in a video call or soon after.

Similar to the past two studies, the majority of social interactions involved a conversation (81.26%). There was a decrease in the amount of sedentary entertainment, e.g., watching TV, compared to Study 2 (13.62% vs. 21.33% from Study 2).

The difference between Study 1, Study 2 and Study 3 could be a result of multiple factors. First is time. Study 1 was done prior to the pandemic. While Study 2 was done at the very beginning of the pandemic, Study 3 was during the summer where people had more understanding and knowledge of the situation. In addition, Study 12 and 3 differ in sample. Both Study 1 and Study 2 were mostly local while Study 3 included a national sample across the United States. Relatedly, differences in demographics may have also contributed to the difference in data, e.g., age, employment, marital status and etc.

In Table 3.4, emotional support behaviors were separated from tangible ones. A Principal Component Analysis of all the support behavior items indicate 2 principal components that capture over 70% of the variance (rotated components are shown in Table 4.7). Component 1 is correlated with support items that are related to emotional support while component 2 with tangible support items. Interestingly,

Support behaviors	Comp1	Comp2
Someone shared personal feeling	0.3804	
Someone expressed concern.	0.3339	
Someone gave positive feedback	0.3119	
Someone expressed confidence.	0.2859	
You shared personal feeling	0.3812	
You offered positive feedback	0.3355	
You expressed care/concern	0.3789	
You felt understood	0.3206	
Someone provided helpful information		0.2652
Someone did you a favor		0.5964
Someone help with an errand/task		0.656
You offered help		0.2858
Explained Variance (%)	51.34	18.88

TABLE 4.7: Rotated principal components for the support behavior items. Values less than 0.25 were omitted for clarity. Component 1 represents emotional support behaviors and Component 2 is positively associated with tangible support behaviors.

the direction of the support behavior, i.e., whether it is provided or received, do not appear on the first 2 components. Therefore, 2 separate scales are created, i.e., emotional support and tangible support, respectively for items on Component 1 and Component 2. The scales measure how many of the queried support items are done in a social interaction (same as Study 2). For example, the tangible support score is 4 if a participant reports that an interaction contains "Someone provided you helpful information.", "Someone did you a favor.", "Someone helped you with an errand/task.", and "You offered help to someone.". The two support variables were standardized for the regression model.

Figure 4.5 shows the Pearson's correlation between pairs of independent variables. Interactions that were very brief (less than 1 minute long) were less likely to contain support exchanging behaviors. Same as the last two studies, interactions that involved a close tie did not normally involve a not close tie at the same time (corr=-0.78). Work/study sessions were likely to take place at work or school (corr=0.26) or were video-mediated (corr=0.22). Physical activities happened more often at outdoor public locations (corr=0.36). Emotional support and tangible support were highly correlated (corr=0.69).

In terms of the experience outcome variables, similar to the previous studies, the reported interactions are highly agreeable and pleasant and low in conflict and bad treatment. Responses to the two positive items, i.e., agreeableness and pleasantness, were averaged to form a positive interaction score (α = 0.95; final positive score ranges from 0 to 10). Responses to the two negative items, i.e., conflict and bad treatment, were averaged to generate a negative interaction score (α = 0.86; final negative score ranges from 0 to 10). The positive and negative interaction sores were only weakly correlated (Pearson's r = -0.24, $p < 0.001$).

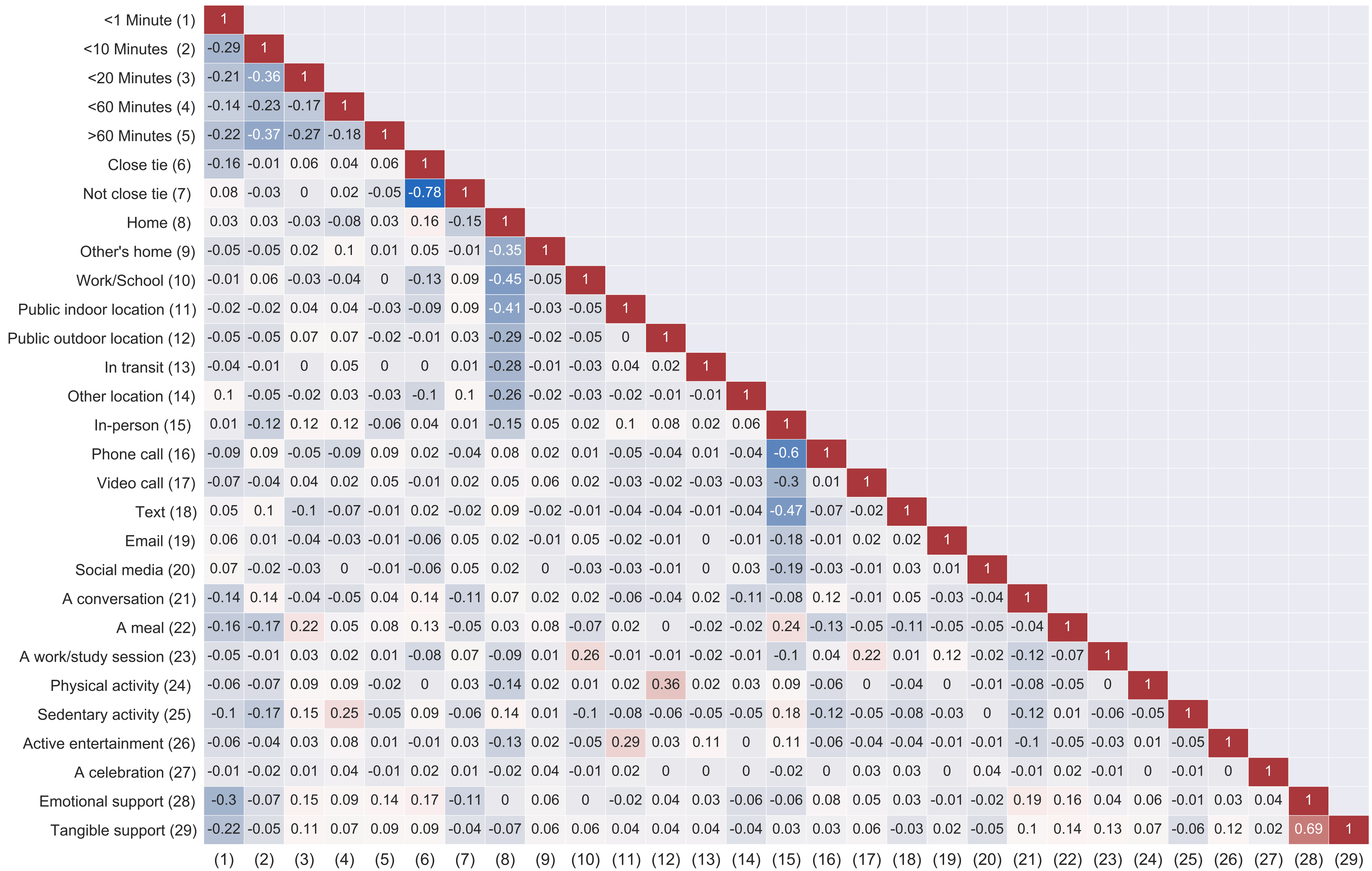

FIGURE 4.5: Study 3: Pair-wise correlation between the independent variables. N=31,946 observations.

4.4.2 Results

Table 4.8 and Table 4.9 show the results of the linear regressions.

For positive interaction score, the adjusted R-square increased consistently as more variables were introduced to the model. For the full model, a total of 28% of the total variances in the positive interaction score is explained by all the interaction detail variables. Similar to Study 2, the addition of support behavior variables increased the variances explained dramatically, from 0 to 0.21. Interaction length variables explained 4% of the total variances. This suggests the importance of these support behaviors in a positively perceived interaction. Including location and medium variables, as well as partner type and activity variables, only increased the variance of the model by 1%, indicating that these variables did not play a significant role in explaining a positive interaction.

More specifically, both emotional and tangible support behaviors were associated with more positive interactions, with the association to be larger for emotional support (b=1.04, p<0.001 for emotional support; b=0.23, p<0.001 for tangible support). Interactions with close ties (those from the name generator survey) are positively associated with positive interaction score (b=0.33, p<0.001). Interactions with non-close ties are negatively associated with the positive score (b=-0.09, p=0.01). Longer interactions (longer than 1 minute) have a higher association with how positive the interaction is. In terms of activities, all activities, except for study/work sessions and other active entertainment, are positively associated with the positive interaction score. Similar to Study 1 and 2, in-person interactions were negatively associated with how positive the interaction was (b=-0.30, p<0.001). Phone and voice calls show a similar trend (b=-0.30, p<0.001). Text-mediated interactions, compared to non-text-mediated interactions, were more positively rated (b=0.13, p=0.03). For the location of the interactions, home is negatively associated with the positive score (b=-0.22, p=0.003), as well as at other's home (b=-0.16, p=0.03). Interactions that occur at indoor public places were rated more positively (b=0.30, p<0.001). Places that people reported to be "other" were negatively associated with the positive score (b=-0.74, p<0.001).

The models for the negative interaction score, on the other hand, shows poorer fit for the data (adjusted R-square=-0.01 for the full model). A few variables the models suggest to have a significant association with the negative interaction score are: 1) emotional support behaviors are associated with a decrease in negative score (b=-0.17, p<0.001); 2) Interactions that involve the close ties are rated to be more negative (b=0.09, p=0.001); 3) length of the interaction–interactions that are less than 1 minute long were rated to be less negative (compared to those that are between 1-10 minutes long. Those that are between 10 to 20 minutes and 20 to 60 minutes were more negatively rated compared to those that were less than 10 minutes or longer than 60 minutes long; 4) both interactions that involve sharing a meal and sedentary entertainments were associated to be less negative (b=-0.08, p<0.001 for meal-sharing; b=-0.21, p<0.001 for sedentary entertainment); and 5) interactions that occur over phone calls are rated to be more negative (b=0.10, p=0.03).

4.4.3 Exploratory Analyses

As in the previous studies, the model for positive score shows a significant negative association between in-person interactions and positive interactions. Therefore, I replicated the exploratory analyses from Study 1 and Study 2 to test whether tie strength explains the negative associations between in-person interactions and positive interaction score. Spontaneity was not included in the current study. Therefore, I could not test the interaction effect of the spontaneous nature of in-person interactions.

Study 3 Positivity	(1) Support Behavior		(2) Partner Type		(3) Length		(4) Activity		(5) Medium&Location	
	B	SE	B	SE	B	SE	B	SE	B	SE
Emotional support	1.28***	0.02	1.20***	0.02	1.08***	0.02	1.03***	0.02	1.03***	0.02
Tangible support	0.26***	0.02	0.27***	0.02	0.24***	0.02	0.23***	0.02	0.22***	0.02
Close tie			0.60***	0.04	0.45***	0.04	0.35***	0.04	0.37***	0.04
Not close tie			0.02	0.04	−0.05	0.04	−0.06	0.04	−0.04	0.04
(<10min omitted)										
<1 min					−1.24 ***	0.04	−1.13 ***	0.04	−1.10 ***	0.04
<20 min					0.11***	0.03	0.04	0.03	0.07*	0.03
<60 min					0.10*	0.04	0.00	0.04	0.04	0.04
>60 min					0.06*	0.03	0.04	0.03	0.06*	0.03
A conversation							0.74***	0.03	0.72***	0.03
A meal							0.21***	0.03	0.25***	0.03
A study/work session							0.25***	0.05	0.18**	0.06
Physical activity							0.36***	0.05	0.36***	0.06
Sedentary entertainment							0.46***	0.04	0.51***	0.04
Active entertainment							0.15***	0.04	0.07	0.04
A celebration							0.49***	0.14	0.45**	0.14
In person									−0.34 ***	0.06
Phone call									−0.31 ***	0.06
Video									−0.09	0.07
Text									0.08	0.06
Email									−0.11	0.10
Social media									−0.24 *	0.10
Home									−0.22 ***	0.06
Other's home									−0.15 *	0.08
Work/School									0.04	0.07
Public (indoor)									0.28***	0.07
Public (outdoor)									0.01	0.08
In transit or vehicle									−0.15 *	0.07
Other location									−0.84 ***	0.08
constant	7.68***	0.01	7.28***	0.04	7.55***	0.04	6.87***	0.05	7.33***	0.09
Adj. R-sqr	0.21		0.22		0.26		0.27		0.28	
DF	31 338		31 247		31 239		31 232		31 219	
BIC	129 823.56		128 836.15		127 482.76		126 916.79		126 714.48	

TABLE 4.8: Study 3: Fixed-effect regression models predicting positivity of an interaction. * p<0.05, ** p<0.01, *** p<0.001. N=31,946 observations. Support behaviors, interactions with close ties, longer interactions, interactions with most joint activities, and in-person and call-based interactions are are strong predictors of positive interactions.

Study 3	(1)		(2)		(3)		(4)		(5)	
Negativitiy	Support Behavior		Partner Type		Length		Activity		Medium&Location	
	B	SE	B	SE	B	SE	B	SE	B	SE
Emotional support	−0.13 ***	0.01	−0.14 ***	0.01	−0.15 ***	0.01	−0.16 ***	0.01	−0.16 ***	0.01
Tangible support	0.00	0.01	0.00	0.01	0.00	0.01	−0.01	0.01	0.00	0.01
Close tie			0.09**	0.03	0.07*	0.03	0.07*	0.03	0.06	0.03
Not close tie			0.01	0.03	0.00	0.03	0.00	0.03	0.00	0.03
(<10min omitted)										
<1 min					−0.14 ***	0.03	−0.14 ***	0.03	−0.14 ***	0.03
<20 min					0.03	0.02	0.08**	0.02	0.08**	0.03
<60 min					0.02	0.03	0.10**	0.03	0.10**	0.03
>60 min					0.01	0.02	0.03	0.02	0.02	0.02
A conversation							0.02	0.02	0.01	0.02
A meal							−0.07 **	0.02	−0.08 ***	0.02
A study/work session							−0.07	0.04	−0.05	0.04
Physical activity							−0.04	0.04	−0.05	0.04
Sedentary entertainment							−0.21 ***	0.03	−0.23 ***	0.03
Active entertainment							−0.03	0.03	−0.01	0.03
A celebration							−0.04	0.10	−0.03	0.11
In person									0.11*	0.04
Phone call									0.12**	0.04
Video									−0.02	0.06
Text									0.03	0.04
Email									0.15*	0.07
Social media									−0.02	0.07
Home									0.03	0.05
Other's home									0.10	0.06
Work/School									−0.10	0.06
Public (indoor)									−0.11 *	0.05
Public (outdoor)									0.00	0.06
In transit or vehicle									0.00	0.06
Other location									−0.06	0.06
constant	0.69***	0.01	0.63***	0.03	0.66***	0.03	0.67***	0.04	0.58***	0.07
Adj. R-sqr	−0.02		−0.02		−0.02		−0.01		−0.01	
DF	31 338		31 247		31 239		31 232		31 219	
BIC	108 425.36		108 127.58		108 125.46		108 125.99		108 212.74	

TABLE 4.9: Study 3: Fixed-effect regression models predicting negativity of an interaction. * p<0.05, ** p<0.01, *** p<0.001. N=31,946 observations. Interaction details are poor predictors of negative interactions, based on Adjusted R-square value.

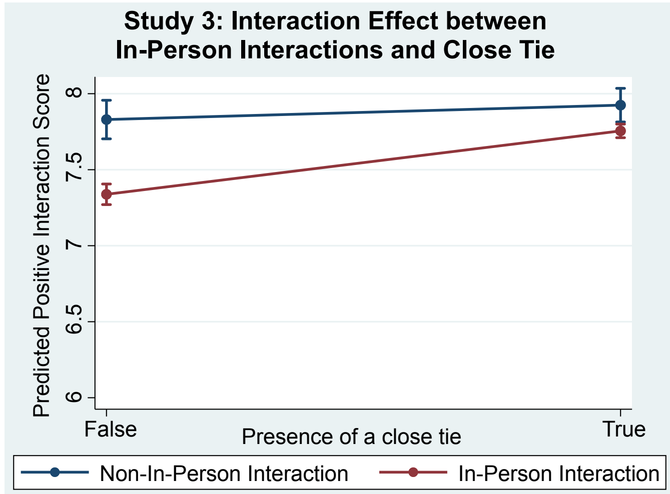

FIGURE 4.6: Interaction effect between whether an interaction is with a close/non-close tie and whether it is in-person. The interaction effect in the plot is significant, indicating that tie strength may be one of the reasons for the negative association between in-person interaction and positive interactions. The error bars indicate 95% confidence interval.

For positive interaction score, when interaction term between close tie and in-person interaction, and non-close tie and in-person interaction were added to the full regression model (model (5) in Table 4.8), the interaction terms between close tie and in-person interactions is significant ($b_{closetie \times in-person}$=-0.32, p<0.001) but the interaction term between non-close ties and in-person interactions is not ($b_{non-close \times in-person}$ = -0.06, p=0.51). Adding these interaction terms to the model removed the significant effect of in-person interaction (b=-0.13, p=0.19). Figure 4.6 shows that, when interacting with close ties, the positive score difference between in-person interactions (red line) and non-in-person interactions (blue line) is much smaller, compared to when interacting with non-close ties.

Therefore, in Study 3, there is evidence that interactions that do not involve close ties may explain the negative association between in-person interactions and positive interaction score since these interactions, when done in-person, are perceived to be much less positive.

4.5 Discussion

4.5.1 Summarizing Across All Studies

The three sets of statistical models, one for each study, examine if what happens during an interaction (e.g., who was involved, what was done) has a significant effect on how the interaction is perceived, in terms of how positive it is and how negative it is. I would like to highlight a few common trends that persist across all three studies.

Negative interactions are explained less consistently by what happens in the interaction, compared to positive interactions.

Compared to positive interactions, only a very small portion of the variance in the negativity of interactions was explained by the objective facts of the interaction. This is consistent across the three studies, suggesting that negative interactions, unlike positive interactions, cannot be predicted by only knowing who is involved, where it is, and what is done. This is also supported by participants' verbal description of their negative interactions. While a few of them did not involve a close partner (e.g., "I decided to complain to the phone about problem with restaurant ordering for my dinner"(P18601), "With with Hewlett-Packard they screwed up my computer and now they're not admitting that it was their fault."(P10773)), many of the interactions were with someone close, who normally they enjoy socializing with or discussing important matters with. For example, one participant wrote that a family member "yelled at me for not waking him up for his learning even though that is his responsibility, not mine." (P13203). Another wrote that "My son just [drove] me insane again today. His behaviors during this COVID are only getting worse. It makes me miserable to be with him" (P19644). Based on the written descriptions, many of these reported negative interactions were one-time incidents with someone who typically were enjoyable to be with. This supports our analyses that negative interactions were less predictive by the details of the interactions.

While the negative interactions were mostly incidental in nature, it is possible that there are more global variables that affect people's perceived negative interactions. For example, one's personality and attachment styles are associated with the amount of conflicts with peers [7] and the emotional outcome of interactions [74]. There is also some evidence that suggests negative interactions are associated with low self-esteem, low interpersonal trust, and other dysfunctional attitudes [82]. Social anxiety also plays a negative role in the quality of interactions [163]. In addition, one's current mood can also influence the perceived outcome of people's social interactions. For instance, negative affect is associated with arguing and conflicting [162].

It is also interesting to note that the different factors associated with positive and negative interactions may serve as a piece of evidence for the different nature of the two types of interactions. Many researchers have participated in the discussion of whether positive and negative are distinct in nature or two sides of the same coin [88]. More recent literature has adapted the view that the two types of events have very weak association [105, 88]. Our study seems to be in line with this view. First, we only found weak to moderate associations between participants' positive and negative interaction ratings. But more importantly, our models suggest that there are different underlying sources that are associated with a positive versus a negative interaction. Therefore, this work contributes an additional proof that positive and negative interactions are separate and distinct events.

While our result is consistent on this finding, it is also important to note that in our studies, the majority of the interactions reported were highly positive in nature and contain only rare instances of high negative interactions. This general bias towards positive interactions are commonly observed in other studies as well [126, 72]. However, this restriction in range for the negative interaction score may account for the small variance explained – if we do not observe enough instances of negative interactions, it is difficult to find commonalities across these instances reliably.

Exchange of support, both emotional and tangible, is an important ingredient to positive interactions.

Across all models, support behaviors, when added to the models, substantially increased the amount of variance explained for positive interactions, suggesting the critical role of these behaviors for a positive interaction. In addition, all models indicate that both emotional and tangible actions are positively associated with the positive interaction score.

Across the three models, the increase in positivity scores is larger for emotional support than for tangible support. This means that if an interaction has emotional support behaviors, people tend to rate it as more positive than if tangible support is involved. This seems in line with existing literature's perspective that emotional support is the more important type of support [14, 155, 108]. This may be due to the fact that tangible support behaviors can simultaneously signal emotional support, e.g., helping someone move (tangible support) suggests care (emotional support). This can lead to emotional support splitting some of the effect of tangible support on the outcome measures. This simultaneous occurrence of two support behaviors is supported by the moderate to high correlations observed in Study 2 and 3. Furthermore, tangible support can be unwarranted by the receiver, leading to negative effects on the outcome. For example, compared to emotional support, unwanted tangible support can call attention to recipients' incompetence, which can have negative impact to the recipient [55].

For negative interaction scores, interactions that include emotional support exchange were rated to be less negative than those that do not. This finding can be interpreted in two ways. One, receiving or providing emotional help makes an interaction less likely to develop conflicts. On the other hand, interactions that are less negative are more likely to result in an exchange of emotional help.

Interactions with close ties are more positively rated.

Across all three studies, models suggest that interactions involving close tie partners, as identified by the Name Generator survey, were more positively rated. While the who-type variables did not increase the variances explained as much as other factors, e.g., support behaviors, this result is highly consistent across the three studies.

Multiple factors may be at play. First, given the close ties were listed in all studies using the Name Generator, which asks people to think of people they enjoyed spending time with and discussed important matters with, these close ties are very likely to be high-quality relationships, as defined by Ross and colleagues in [128]. These relationships are characterized to have more positive aspects than negative ones overall. Therefore, given the positive quality of the relationships, people are more likely to have positive experiences when being with them. Looking beyond the nature of the relationships, we are more likely to share similar views and interests with those we enjoy spending time with and discuss important matters with [109, 100]. The shared similarities have been shown to predict multiple positive relational outcomes, such as more long-term relationships, more frequent communication, and stronger relationships [152, 138]. Another mechanism behind the positive association between closeness and positive social interactions is through self-disclosure. Disclosing information about self is a key component to relationship maintenance and can promote relationship quality and increase how close people feel with the interaction partner [145, 84]. People who are close together are also more likely to disclose information about themselves [38]. Interestingly, self-disclose can also produce a positive and rewarding feeling in the people involved [35, 73]. This may explain the positive association observed in the current study between close ties and positive interactions.

Longer interactions are rated more positively.

Interactions longer than 20 minutes are reported to be more positive and more meaningful compared to those that are shorter. In both Study 2 and 3, post-hoc pairwise tests show that interactions that are longer

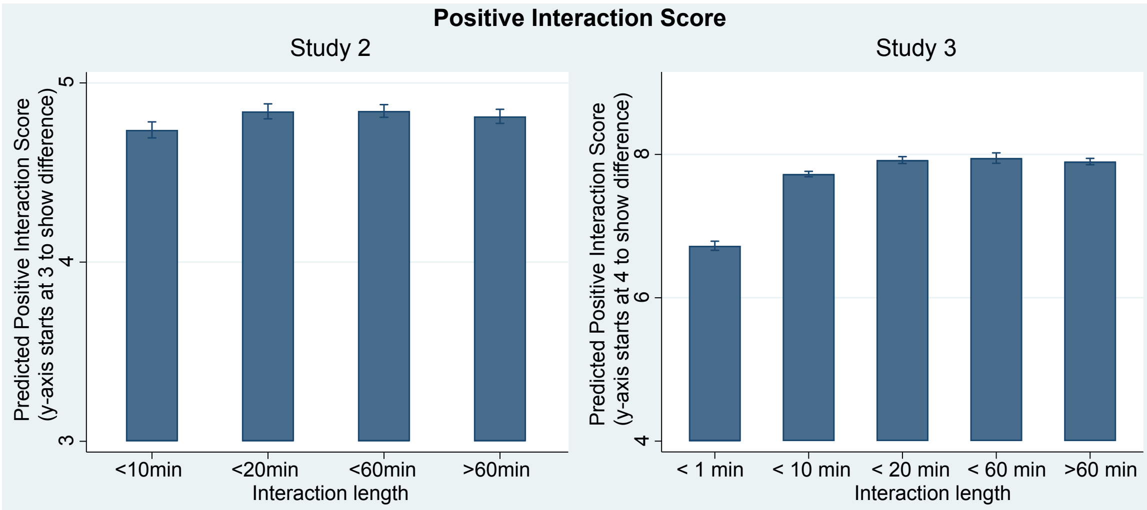

FIGURE 4.7: The predicted positive interaction score for interactions of various length. In both studies, pairwise tests showed significant differences between interactions that are more than 10 minutes long than those that are less. Error bar shows 95% confidence interval.

than 20 minutes are rated significantly more positively than interactions that are less than 20 minutes (Figure 4.7. This intuitively makes sense – people are more likely to continue with an interaction that they consider to be pleasant. People are more likely to end it short if the interaction is less positive. Furthermore, it is also possible that activities that are associated with high positive scores take longer to do. For example, based on the pair-wise correlations between independent variables (Figure 4.3 and Figure 4.5), in both studies, meal-sharing and sedentary activities are positively associated with interactions that are longer than 20 minutes. Both of these types of activities are also positively associated with the positive score. This indicates that longer interactions offer opportunities for people to engage in constructive joint activities, which can explain the higher ratings for longer interactions. Beyond joint activities, longer interactions also provide chances for people to exchange support. This can be observed by the positive correlation between long interaction lengths and the two types of support behaviors. Also, there are moderate negative associations between interactions that are less than 1 minute and both support behaviors in Study 3.

Where interactions occur and what medium interactions occur on do not contribute much to how the interactions turn out.

Across all three studies, location, together with medium, variables consistently explain very little of the variances of people's experiences with an interaction. This suggests that these two types of variables do not contribute much to how an interaction turns out. For location, the lack of consistent effects may be because each location type can support a wide range of interactions – people can have an argument at home but also heart-warming events at home as well. Similarly, people can have conflicts and arguments in public but they can also have fun activities together while being in public, e.g., eating dinner at a restaurant with a significant other or watching a movie together with best friends. I suspect that due to the mixed nature in the types of activities occurring in various places, location variables are less predictive of the interaction outcome.

Interaction medium, surprisingly, did not account for much variances in the experience of the interactions. A lot of existing work considers in-person interactions to be better due to its richness in information and its ability to facilitate relationship maintenance behaviors, such as self-disclosure [135, 146, 101, 104]. But in our studies, we observed that what platform an interaction occurs on does not contribute much to how an interaction turns out (in line with previous work by [90]). This is probably due to the fact the models include other interaction details that are correlated to the medium variables, and hence, shows reduced effect of the medium variables. For example, in Study 3, in-person interactions are positively correlated with meal-sharing, doing sedentary activities and work/study sessions are likely to occur as video calls. In Study 2, close ties are more likely to interact in-person while non-close ties are positively correlated with computer-mediated interactions. In addition, emotional support and phone-mediated interactions are positively associated as well. Therefore, the lack of effect of medium may be due to the control of these partner, activity, and support variables.

While medium variables do not explain much of the variances in the experience outcomes. It is still interesting to note that in-person interactions, across all three studies, are negatively (and significantly) associated with the perceived positivity of the interaction. In the exploratory analyses that followed the main analyses, I explored how tie strength and spontaneity may explain the negative associations.

In Study 3, there is a significant interaction effect of tie strength on positive scores such that in-person interactions are rated less positively if they do not involve a close tie. However, this difference diminishes (but still present) for interactions that involve a close tie. This interaction effect is not observed for the first 2 studies. The lack of result in Study 1 is likely to be due to small sample size and lack of power. For Study 2, it is possible that the insignificant interaction effect is because the name generator was only used to elicit close family members and friends while in Study 3 participants could enlist anyone whom they were close to. The broadened scope may have strengthened the interaction effect for Study 3. Regardless, the significance of the close-tie interaction term suggests that the experience outcome of interactions with a close tie are less prone to the influence of being in-person. As for why interactions that do not include a close tie are rated less positively, it may be similar to the main effect of interactions with close ties. Interactions that are not with a close tie are probably less likely to contain the same level of shared similarities among people in the interaction and less self-disclosure and other pro-relationship behaviors.

In Study 1 and 2, I also tested if the spontaneous nature of in-person interactions can explain the negative association between in-person interactions and positive interaction score. For Study 2, there is a significant interaction effect between spontaneity and in-person interaction on positive score. This suggests that in-person interaction, in particular the spontaneous ones, are rated much less positively compared to planned ones. This may be because spontaneous interactions are more likely to occur with co-located people and, hence, not necessarily close ties, which makes such interactions less likely to be as positive. In addition, people are less likely to plan interactions that they do not enjoy or they expect to be negative while people have less control over the outcome of spontaneous interactions.

Joint activities are associated with subjective experience of an interaction, but the specific type of activity matters less than the act of doing it together.

Across all three studies, almost all of the joint activities queried (except for study/work session and active entertainment) have positive associations with the reported positivity of the interaction. This means that the type of activity done in an interaction matters less than the fact that an activity is done together. This finding is unsurprising considering that doing shared activities provides opportunities for people to engage in relationship-building behaviors, e.g., self-disclosure, creating shared experiences, cultivating a sense of shared identity and goals.

Chapter 5

Effect of Subjective Experience of Interactions on Well-Being

The focus of this chapter is to understand how one's subjective experience of social interactions, i.e., how positive and negative interactions are, is associated with change in well-being at the end of the day (highlighted section in Figure 5.1).

A meta-analysis of the analyses from the three studies show that positive and negative interactions are better predictors of daily positive well-being, i.e., thriving, than negative well-being, i.e., stress, depressive symptoms, and loneliness. Despite this, days where people have more positive interactions are associated with decreased stress, loneliness, and depressive symptoms and increased thriving. Reverse is true for days where people have more negative interactions. In addition, the positive interactions that one has on the day before are significantly associated with decreased loneliness and increased thriving on the present day. This effect was not found for negative interactions from the day before. On a person-level, people who generally experience more positive interactions report lower stress, lower loneliness, and higher thriving. People who generally experience more negative interactions report higher stress, higher loneliness, and more severe depressive symptoms. A summary of these findings can be found at the end of the document in Table 8.1.

5.1 Method of Analysis

As well-being measures were collected once a day, we took the daily average of participants' positive and negative interaction scores (the independent variables). This means that the panel data contains 2 levels – participants (level 2) and day (level 1).

As in the first research question, analyses were done using Stata. Panel data format was setup using -xtset- command. Regression models were constructed using -xtmixed- command, separately for each well-being measure. xtmixed command allows for random within slope (see more explanation in the

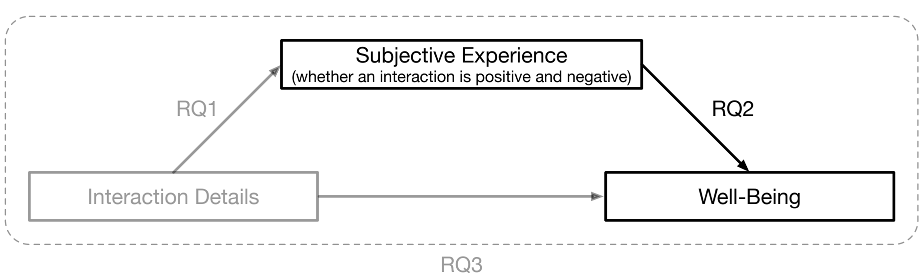

FIGURE 5.1: This chapter examines the second research question: How do positive and negative interactions affect one's well-being, specifically, depression, loneliness, stress, and positive well-being?

	Study 1			Study 2			Study 3	
	Instrument	Likert Choices (min/max score)	Mean (SD)	Instrument (Study 2& 3)	Likert Choices (min/max score)	Mean (SD)	Likert Choices (min/max score)	Mean (SD)
Stress	PSS-4	Strongly disagree - Strongly agree (0/16)	5.08 (3.62)	PSS-4	Never - Very often (0/16)	6.38 (3.29)	Strongly disagree - Strongly agree (0/16)	4.28 (3.69)
Loneliness	BIT (1)	Strongly disagree - Strongly agree (1/5)	1.96 (1.14)	UCLA Loneliness 4	Never - Always (4/16)	8.15 (2.88)	Strongly disagree - Strongly agree (4/20)	8.58 (3.84)
Depression	PHQ-2	Not at all - Extremely (0/8)	1.57 (1.80)	PHQ-2	Not at all - Extremely (0/8)	2.48 (2.01)	Not at all - Extremely (0/8)	1.44 (2.00)
Thriving	–	–	–	BIT-10	Strongly disagree - Strongly agree (0/50)	35.19 (8.66)	Strongly disagree - Strongly agree (10/50)	38.50 (9.03)

TABLE 5.1: Study 1-3: Instrument surveys used in each study for the 4 well-being constructs and their corresponding choices. The mean and standard deviations are also show for each study. Since for loneliness and stress the choices are different for each study, it is not meaningful to compare the mean and standard values across studies. Thriving was not measured in Study 1.

next paragraph), which xtreg does not. Each model also controls for personal characteristics, i.e., gender, relationship status, personality and/or age range. Since 3 studies were done, it would be interesting to compare the coefficients across studies. To make this possible, all independent and dependent variables were standardized (mean is 0 and standard deviation is 1) using the -std- command in Stata. As a measure of effect size, we report a pseudo-R-square value [78] as other measures cannot be obtained for hierarchical models with random slopes. Pseudo-R-sq compares the variance explained by the full model against a null (or restricted) model with only the dependent variable and level-1 random intercept. The pseudo-R-sq can be expressed as: $(V_{null} - V_{full})/V_{null}$. However, pseudo-R-sq cannot be determined exactly for models with random slopes. Readers should take these values as an approximation.

To separately examine day-level (within) and participant-level (between) effects, we followed the with-between random effect model outlined in [12]. The three subjective experience scores, i.e., positive interaction and negative interaction, are entered into the models in two forms: 1) demeaned by personal mean (within effect) and 2) person mean (between effect). This can be expressed as the following equation:

$$y_{it} = \mu + \beta_{within}(x_{it} - \overline{x_i}) + \beta_{between}\overline{x_i} + \beta_3 z_i + v_{i0} + v_{i1}(x_{it} - \overline{x_i}) + \varepsilon_{it0}$$

Here, y_{it} is the dependent well-being variable for participant i at time t. x_{it} stands for time-varying independent variables (level 1), e.g., positive interaction score, for participant i at time t. z_i denotes time-invariant variables (level 2), e.g., gender. β_{within} represents the average within effect of subjective experience of social interactions on well-being while $\beta_{between}$ represents the average between effect of subjective experience. β_3 represents the (between) effect of time-invariant variable z_i on well-being. v_{i0} is a random intercept and v_{i1} is a random effect for the within slope. Following Bell and colleague's suggestions, our models include the random effects to the within slopes (i.e., $v_i t \neq 0$) to produce more consistent coefficient estimates.

In addition to including day t's social interaction variables, I also included lagged day-level terms

	Stress	Loneliness	Depressive Symptoms
Stress	1		
Loneliness	0.43***	1	
Depressive Symptoms	0.76***	0.40***	1

TABLE 5.2: Study 1: Pair-wise Pearson's correlation between stress, loneliness, and depression. ***: p<0.001. N=107 observations.

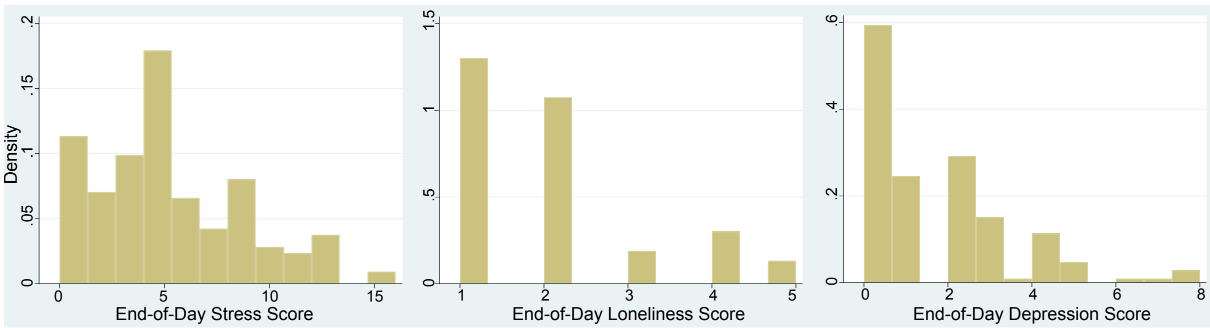

FIGURE 5.2: Study 1: The distribution of the 3 end-of-day well-being measures, i.e., stress, loneliness, and depression. N=107 observations.

from the day before $t-1$ to 1) examine how long the effect of subjective experience on well-being lasts and 2) control for any effect that social interactions on day $t-1$ may have on well-being at the end of day t.

For each study, I will first describe the well-being variables collected in each study before introducing the results of the regression models.

5.2 Study 1 (Pilot)

5.2.1 Well-Being: Sample Characteristics

The 35 participants completed a total of 159 end-of-day surveys, reporting their well-being, i.e., depression (PHQ-2), loneliness (1 item from BIT[149]), stress (PSS-4 [31]). For each scale, all items were summed to produce a final score, following the scoring instructions of the scales. Figures 5.2 shows the distribution of the 3 well-being scores. The mean of stress score is 5.08 (SD=3.62); of loneliness score is 1.96 (SD=1.14); of depression is 1.57 (SD=1.80) (see Table 5.1. The three well-being measures are moderately correlated (average Pearson's r=0.53; see Table 5.2). In particular, depression and stress were highly correlated (Pearson's r=0.76, p<0.001).

As the study was 5 days long, I plotted the average well-being scores across days of the week (Figure 5.3). While ANOVA tests did not show any significant difference between days of week for the three well-being scores, there is some interesting trend. For example, people reported higher level of stress on Wednesday, compared to the rest of the days (interestingly, Crisis Text Line, a text messaging-based crisis counseling hotline, has found that Wednesday is also the most anxiety-provoking day of the week [124]). In addition, people reported to be less lonely on Sundays than the rest of the week.

5.2.2 Results

The interaction and personal characteristics variables explained 8% of the variances in stress, 19% of variances in loneliness, and 9% of variances in depressive symptoms.

Personal Characteristics. Participants of age 25-30 years reported lower depression scores, compared to the younger population (b=-0.67, p=0.03). Participants with higher neuroticism score report higher levels of stress (b=0.43, p=0.006), loneliness (b=0.29, p=0.04) and depression (b=0.38, p=0.03).

Between-person differences. Participants who, on average, have more positive interactions reported greater loneliness (b=0.48, p=0.02). Participants who, on average, have more negative interactions also reported greater loneliness (b=0.64, p<0.001).

Within-person differences. The models did not show any significant effect of people's subject experience of social interactions on the end-of-day experience. Same is true for interactions of the day before.

5.3 Study 2 (6-Week Local Sample)

5.3.1 Well-Being: Sample Characteristics

The 48 participants completed a total of 1074 end-of-day surveys, which includes the well-being questions, e.g., depression (PHQ-2), loneliness (ULCA Loneliness Scale-4), stress (PSS-4), and thriving (BIT). Figure 5.4 shows the distribution of the well-being variables in the current participant sample. To visually see fluctuations of the well-being measures throughout the course of the study, Figure 5.5 shows the standardized well-being scores, averaged by date across the span of the data collection. When the same plot is done over the day of the study (instead of calendar dates), no general increase or decrease trend is observed. This suggests that common events that occur during the dates of the study influenced changes in well-being that are seen in Figure 5.5. Specifically, loneliness increased during the first part of the study and decreased since late May. This could be due to relaxed stay-at-home orders that started to occur throughout May, which allowed people to socialize (while socially distanced). This might have relieved people's sense of loneliness, leading to a downward trend. There is no clear trend in stress and depression.

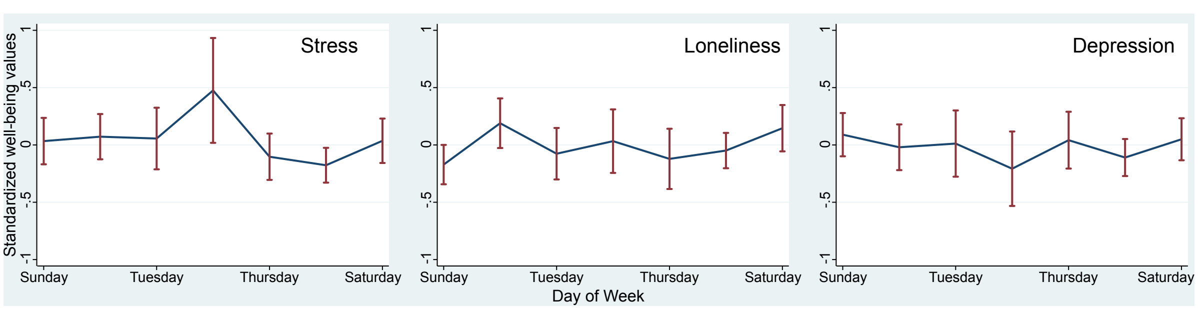

FIGURE 5.3: Study 1: The 3 end-of-day well-being measures averaged across days of the week. The y-axis are standardized well-being score for each measure. Error bars are 1 standard error.

	(1) Stress		(2) Loneliness		(3) Depressive Symptoms	
	B	SE	B	SE	B	SE
Day-Level (Within)						
Positive Interaction	0.00	0.06	−0.04	0.07	−0.03	0.05
Negative Interaction	0.01	0.04	−0.12	0.08	0.04	0.04
Positive Interaction (lagged)	−0.04	0.08	0.04	0.06	−0.05	0.08
Negative Interaction (lagged)	−0.06	0.05	−0.07	0.05	0.01	0.09
Person-Level (Between)						
Positive Interaction	0.15	0.17	0.43*	0.19	0.04	0.18
Negative Interaction	0.21	0.20	0.60**	0.18	0.07	0.20
Female	0.18	0.32	−0.09	0.25	0.07	0.29
Age (18-24 omitted)						
25-30	−0.45	0.29	0.11	0.22	−0.67 *	0.30
31-40	−0.18	0.42	0.32	0.44	0.04	0.41
41-50	0.65	0.63	0.66	0.52	0.33	0.73
In a romantic relationship	−0.01	0.30	−0.16	0.26	−0.27	0.30
Personality						
Extroversion	−0.10	0.16	−0.15	0.13	−0.22	0.16
Agreeable	0.05	0.17	0.01	0.17	−0.02	0.19
Conscientious	−0.04	0.17	0.06	0.17	−0.09	0.18
Neuroticism	0.43**	0.15	0.29*	0.14	0.38*	0.17
Openness	−0.16	0.16	0.09	0.16	0.02	0.16
constant	0.33	0.33	−0.09	0.22	0.49	0.30
Pseudo R-sqr	0.08		0.19		0.09	
DF			16			

TABLE 5.3: Study 1: Within-between random effect regression models predicting end-of-day stress, loneliness, and depression from the positivity and negativity of interactions that happen during the day and the day before. * p<0.05, ** p<0.01, *** p<0.001. N=107 observations.

5.3.2 Results

The interaction and personal characteristics variables explained 4% of the variances in stress, 7% of variances in loneliness, 8% of variances in depressive symptoms, and 20% of variances in thriving.

Personal Characteristics. As the last study, models of study 2 showed a positive association between neuroticism and stress (b=0.42, p<0.001), loneliness (b=0.40, p=0.002), depression (b=0.55, p<0.001), and thriving (b=-0.64, p<0.001). Openness is positively associated with thriving (b=0.15, p=0.04). Participants who are in a romantic relationship reported lower levels of loneliness compared to those who are not (b=-0.44, p=0.03). In addition, participants of age 41-50 reported higher levels of loneliness (b=0.83, p=0.002) and lower level of thriving (b=-1.02, p<0.001) than those of age 18-24 years old .

Between-person differences. Participants who, on average, have more positive interactions reported to be less lonely (b=-0.29, p=0.005) and have higher thriving level (b=0.20, p=0.03). No other between-person effect of social interactions on well-being was observed.

Within-person differences. Social interactions from the previous day do not have a significant effect on current day's end-of-day well-being measures. For interactions that happen during the day, days with more negative interactions are associated with decrease in stress (b=-0.09, p=0.002) and decrease in

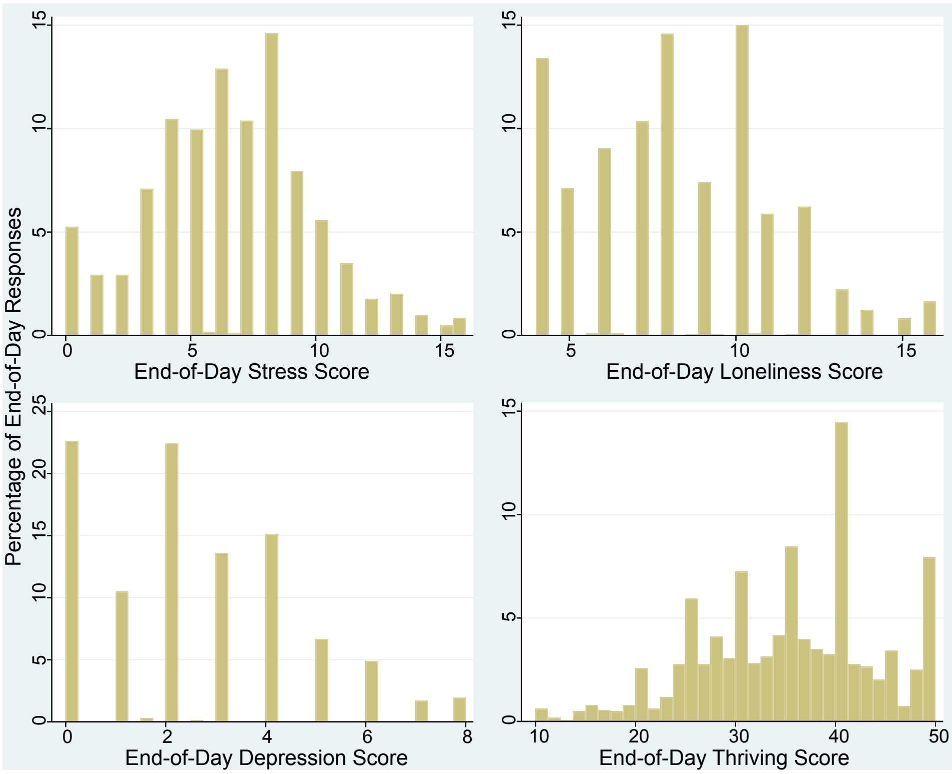

FIGURE 5.4: Study 2: The distribution of 4 end-of-day well-being measures, i.e., stress, loneliness, depression, and thriving. N=1074 observations.

depression (b=-0.10, p<0.001). On days with more positive interactions, participants reported a decrease in stress (b=-0.06, p=0.01), a decrease in loneliness (b=-0.05, p=0.008), a decrease in depression (b=-0.08, p=0.002), and an increase in thriving (b=0.04, p=0.02).

5.4 Study 3 (3-Week National Sample)

5.4.1 Well-Being: Sample Characteristics

The 714 participants contributed a total of 10,773 end-of-day survey responses. Figure 5.6 shows the distribution of the 3 well-being measures in the current participant sample. Note that for stress and loneliness, the question choices are different from that of Study 2. Therefore, direct comparisons of

	Stress	Loneliness	Depressive Symptoms	Thriving
Stress	1			
Loneliness	0.53	1		
Depressive Symptoms	0.72	0.53	1	
Thriving	−0.75	−0.52	−0.67	1

TABLE 5.4: Study 2: Pair-wise Pearson's correlation between stress, loneliness, depression, and thriving. ***: p<0.001. N=1074 observations.

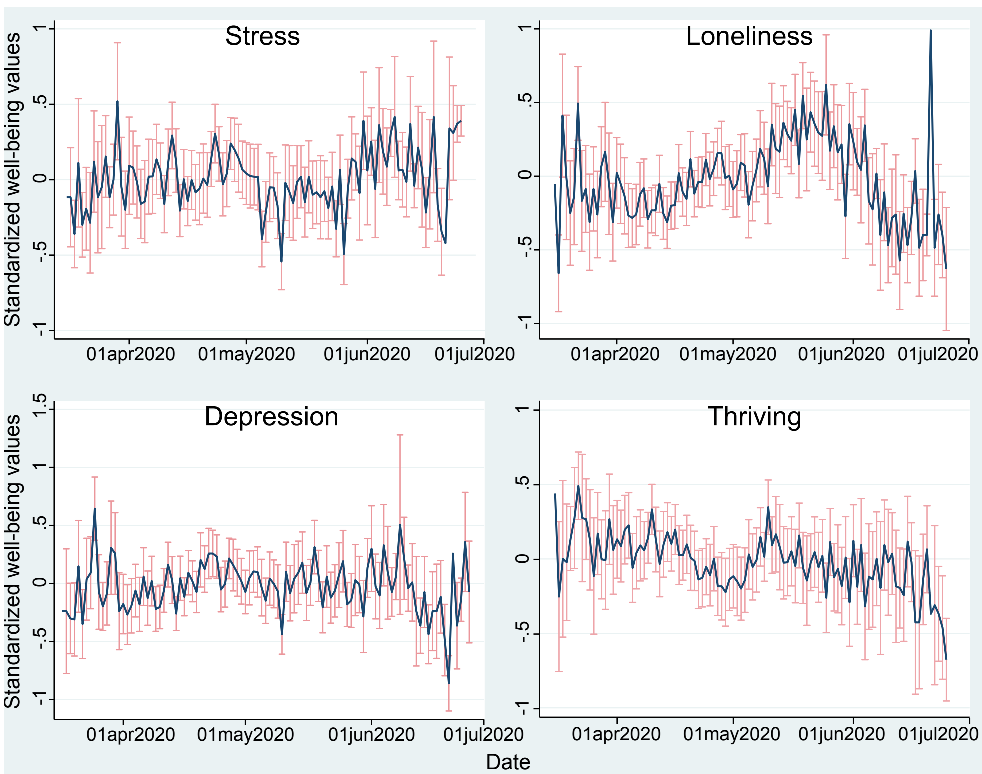

FIGURE 5.5: Study 2: The 4 end-of-day well-being measures averaged across calendar dates for the span of the data collection. The y-axis are standardized well-being score for each measure. Error bars are 1 standard error.

	(1) Stress		(2) Loneliness		(3) Depressive Symptoms		(4) Thriving	
	B	SE	B	SE	B	SE	B	SE
Day-Level (Within)								
Positive Interaction	−0.06 *	0.02	−0.05 **	0.02	−0.08 **	0.03	0.04*	0.02
Negative Interaction	−0.09 **	0.03	0.03	0.02	−0.10 ***	0.03	0.01	0.03
Positive Interaction (lagged)	−0.05	0.03	−0.03	0.02	−0.04	0.03	0.00	0.03
Negative Interaction (lagged)	0.02	0.03	−0.01	0.02	0.00	0.03	−0.02	0.02
Person-Level (Between)								
Positive Interaction	−0.13	0.10	−0.29 **	0.11	0.02	0.09	0.20*	0.09
Negative Interaction	0.13	0.11	0.13	0.11	0.20	0.10	−0.04	0.09
Female	0.24	0.17	−0.11	0.20	0.03	0.16	−0.12	0.15
Age (18-24 omitted)								
25-30	0.04	0.22	0.23	0.23	0.32	0.21	−0.43 *	0.19
31-40	−0.32	0.31	0.44	0.38	0.17	0.24	−0.04	0.24
41-50	0.17	0.24	0.83**	0.28	−0.04	0.22	−1.02 ***	0.20
In a romantic relationship	0.08	0.18	−0.43 *	0.20	−0.09	0.17	0.22	0.16
Personality								
Extroversion	0.12	0.10	0.11	0.10	0.18*	0.09	−0.09	0.08
Agreeable	−0.02	0.09	−0.02	0.11	−0.06	0.08	0.07	0.10
Conscientious	0.03	0.07	−0.10	0.09	0.12	0.08	−0.13	0.07
Neuroticism	0.42***	0.10	0.41**	0.13	0.54***	0.10	−0.64 ***	0.09
Openness	−0.08	0.09	0.17	0.15	−0.04	0.08	0.15*	0.07
constant	−0.21	0.15	0.02	0.19	−0.16	0.14	0.23	0.14
Pseudo R-sqr	0.04		0.07		0.08		0.20	
DF					16			

TABLE 5.5: Study 2: Within-between random effect regression models predicting end-of-day stress, loneliness, depression, and thriving from the positivity and negativity of interactions that happen during the day and the day before. * p<0.05, ** p<0.01, *** p<0.001. N=1074 observations.

these two measures between Study 2 and 3 are not meaningful (see Table 5.1). Figure 5.7 shows the changes of the three well-being measures across the duration of the data collection. As in the end of Study 2, there was still a gradual decline in the three measures over time, especially for loneliness and depression. The decrease accelerated at the very end of the data collection but this may be a result of fewer people remaining in the data collection and, hence, larger variation in the well-being reports. Thriving score, correspondingly, increased slowly for the duration of the study. The four well-being measures are moderately to strongly correlated (see Table 5.6). In particular, thriving and stress are highly and negatively correlated (Pearson's r=-0.78, p<0.001), as well as thriving and loneliness (Pearson's r=-0.69, p<0.001). A separate factor analysis was done with all variables, i.e., positive/negative interaction scores and the 3 well-being scales. It showed that positive and negative interaction scores are loaded on separate factors, suggesting that subjective experience of interactions differ in dimension from well-being.

5.4.2 Results

The interaction and personal characteristics variables explained 14% of the variances in stress, 14% of variances in loneliness, 18% of variances in depressive symptoms, and 25% of variances in thriving.

	Stress	Loneliness	Depressive Symptoms	Thriving
Stress	1			
Loneliness	0.68	1		
Depressive Symptoms	0.64	0.60	1	
Thriving	−0.78	−0.69	−0.56	1

TABLE 5.6: Study 3: Pair-wise Pearson's correlation between stress, loneliness, depression, and thriving. ***: p<0.001. N=7624 observations.

	(1) Stress		(2) Loneliness		(3) Depressive Symptoms		(4) Thriving	
	B	SE	B	SE	B	SE	B	SE
Day-Level (Within)								
Positive Interaction	−0.06 ***	0.01	−0.07 ***	0.01	−0.05 ***	0.01	0.05***	0.01
Negative Interaction	0.05***	0.01	0.03**	0.01	0.04***	0.01	−0.02 *	0.01
Positive Interaction (Lagged)	−0.01	0.01	−0.02 *	0.01	−0.01	0.01	0.01*	0.00
Negative Interaction (Lagged)	0.01	0.01	0.00	0.01	0.00	0.01	−0.01	0.01
Person-Level (Between)								
Positive Interaction	−0.23 ***	0.03	−0.28 ***	0.03	−0.07 *	0.03	0.23***	0.03
Negative Interaction	0.13***	0.03	0.14***	0.02	0.33***	0.03	−0.05	0.04
Female	0.02	0.06	−0.13 *	0.06	0.02	0.05	0.03	0.06
Age (18-24 omitted)								
25-34 25-34	−0.06	0.15	0.08	0.15	0.20	0.14	0.03	0.15
35-44	0.00	0.15	0.03	0.15	0.12	0.14	−0.11	0.15
45-54	−0.08	0.15	−0.08	0.16	−0.08	0.14	−0.14	0.15
55-64	−0.11	0.15	−0.06	0.15	−0.12	0.15	−0.12	0.15
65+	−0.26	0.16	−0.15	0.16	−0.21	0.14	0.04	0.15
Marital status (Married omitted)								
Never married	−0.02	0.07	0.02	0.07	−0.19 **	0.06	−0.08	0.08
separated	0.04	0.22	0.12	0.17	−0.01	0.17	0.09	0.17
divorced	0.16	0.10	0.32***	0.10	0.15	0.09	−0.24 *	0.10
widowed	0.27*	0.14	0.26*	0.13	0.05	0.14	−0.55 ***	0.14
Personality								
Extroversion	−0.07 *	0.03	−0.08 *	0.03	−0.03	0.03	0.09**	0.03
Agreeable	−0.04	0.03	−0.05	0.03	0.00	0.03	0.14***	0.04
Conscientious	−0.11 ***	0.03	−0.08 **	0.03	−0.10 **	0.03	0.15***	0.04
Neuroticism	0.25***	0.03	0.17***	0.03	0.20***	0.03	−0.23 ***	0.04
Openness	0.05	0.03	0.03	0.03	0.01	0.03	−0.07 *	0.03
constant	0.05	0.14	0.02	0.15	0.02	0.14	0.14	0.14
Pseudo R-sqr	0.14		0.14		0.18		0.26	
DF				21				

TABLE 5.7: Study 3: Within-between random effect regression models predicting end-of-day stress, loneliness, depression, and thriving from the positivity and negativity of interactions that happen during the day and the day before. * p<0.05, ** p<0.01, *** p<0.001. N=7624 observations.

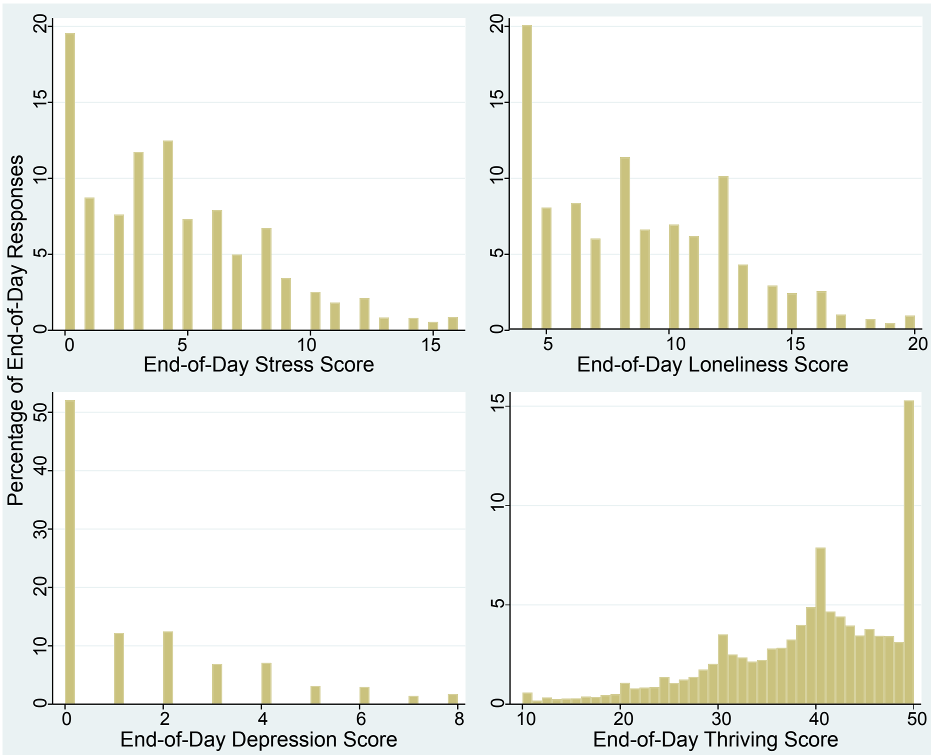

FIGURE 5.6: The distribution of 4 end-of-day well-being measures, i.e., stress, loneliness, depression, and thriving from Study 3. N=10,773 observations.

Personal Characteristics. Participants who were more extroverted reported lower stress (b=-0.07, p=0.03), lower loneliness (b=-0.08, p=0.01), and higher thriving (b=0.09, p=0.008). People who were more conscientious are associated with lower stress (b=-0.11, p=0.001), lower loneliness (b=-0.08, 0.01), lower depression (p=-0.10, p=0.002), and higher thriving (b=0.15, p<0.001). As Study 1 and 2, neuroticism is positively associated with stress (b=0.25, p<0.001), loneliness (b=0.17, p<0.001), depression (b=0.20, p<0.001), and thriving (b=-0.23, p<0.001).

Study 3 asked participants for their marital status. The analyses showed that people who were never married, compared to married people, reported lower depression (b=-0.19, p=0.004). Participants who were divorced reported higher levels of loneliness, compared to their married counterparts (b=0.32, p<0.001). They also reported less thriving (b=-0.24, p=0.02). Participants who were widowed were more stressed (b=0.27, p=0.04), more lonely (b=0.26, p=0.046), and less thriving (b=-0.55, p<0.001) than married participants. Study 3 models did not show any effect of age on well-being. Female participants, compared to male participants, reported lower levels of loneliness (b=0.13, p=0.02).

Between-person differences. Participants who, on average, have more positive interactions reported lower level of stress (b=-0.23, p<0.001), lower level of loneliness (b=-0.28, p<0.001), less severe depressive symptoms (b=-0.07, p=0.02), and more thriving (b=0.23, p<0.001). Participants who typically have more negative interactions are associated with higher stress (b=0.13, p<0.001), higher loneliness (b=0.14, p<0.001), and higher depression (b=0.33, p<0.001).

Within-person differences. Days where participants have more positive interactions are negatively associated with end-of-day stress (b=-0.06, p<0.001), loneliness (b=-0.07, p<0.001), depression (b=-0.05,

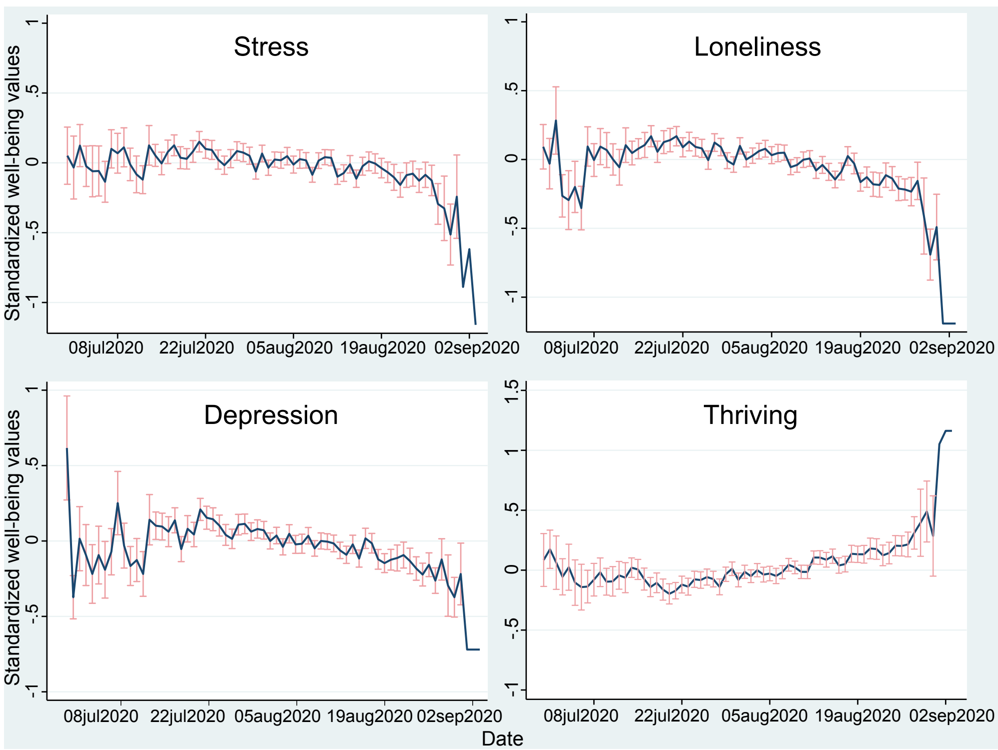

FIGURE 5.7: Study 3: The 4 end-of-day well-being measures averaged across calendar dates for the span of the data collection. The y-axis are standardized well-being score for each measure. Error bars are 1 standard error. The last three days only have data from 1 participant. Therefore, there is no error bar.

$p<0.001$), and thriving ($b=0.05$, $p<0.001$). On days where participants have more negative interactions, they also experienced higher stress ($b=0.05$, $p<0.001$), higher loneliness ($b=0.03$, $p=0.001$), higher depression ($b=0.04$, $p<0.001$), and lower thriving ($b=-0.02$, $p=0.01$).

Unlike the previous 2 studies, Study 3 models showed a significant effect of previous day interaction on current day well-being. Specifically, more positive interactions on the day before are negatively associated with loneliness ($b=-0.02$, $p=0.04$) and positively associated with thriving ($b=0.01$, $p=0.04$). There is no lagged effect of negative interactions from the previous day.

5.5 Meta Analysis

As some of the results between the three studies are not consistent, e.g., Study 3 indicated a significant association between positive interactions from previous day and loneliness but this is not observed in Study 1 and 2, I conducted a series of meta analyses to synthesize the results of the 3 studies. The meta analyses combine the coefficient estimates produced by the three studies, accounting for the standard error of each coefficient estimate and the sample size. This is possible because the regression models produced standardized coefficient estimates (since all variables were standardized, as mentioned in Section 5.1). Therefore, these coefficients can be used as effect–size indices for combining the 3 studies to examine the effect of subjective experience, e.g., positive interaction, on the well-being outcome, e.g., stress [77]. As all 3 studies were done using almost-identical methods, the subjective experience and well-being were measured in very similar fashion, and similar demographic measures were controlled in each regression model, meta analyses of the regression slopes are possible, according to the assumptions of synthesizing slopes from [10].

The goal of these meta analyses is to reach an unifying conclusion of how the subjective experience variables influence various well-being outcomes.

5.5.1 Methods

All meta analyses were done in Stata, using the -meta- command. The coefficient estimates and their corresponding standard errors, from the regression models in this chapter, were entered as inputs for the meta analysis. For each pairing of independent and dependent variable, a fixed-effects model meta analysis was conducted. For example, a meta analysis was run for the day-level (within effect) positive interaction variable and stress.

5.5.2 Results

Figure 5.8, figure 5.9, figure 5.10, and figure 5.11 show the results of the meta analyses. The blue square symbols represent the coefficient estimate from each study while the green diamonds are the synthesized regression coefficients, produced by the meta analysis. The horizontal stretch of the diamonds represent the 95% confidence interval of the coefficient. Test of θ indicates whether the synthesized coefficient is significantly different from zero. A significant test of θ means that the variable of interest has a significant non-zero, i.e., positive or negative, effect on the well-being variable.

Stress

On a day-level, positive interaction score has a significantly negative effect on stress (z=-7.76, p<0.001). Measures of heterogeneity show no heterogeneity between the studies (I^2 = 0%, H^2=0.67), indicating that this effect is consistent across the three studies. Negative interaction score has a positive effect on stress (z=3.35, p<0.001). However, the heterogeneity test shows that this effect is not consistent between studies (I^2 = 90.41%, H^2=10.43).

On a day-level, previous-day interaction measures show no significant effect on stress. Specifically, positive interaction score from the day before had no significant effect on stress (z=-1.39, p=0.16). The same holds for negative interaction scores from the previous day (z=1.15, p=0.25).

On a person-level, people with higher levels of positive interactions, on average, are associated with lower stress (z=-7.47, p<0.001). This is relatively consistent across the three studies (I^2 = 63.67%, H^2=2.75). People who experience higher levels of negative interactions, on average, are associated with higher levels of stress (z=4.48, p<0.001). This was consistently observed across all three studies (I^2 = 0%, H^2=0.08).

Loneliness

For loneliness, both measures of subjective experience have a significant effect on a day-level. Positive interaction score has a significantly negative effect (z=-8.78, p<0.001) on loneliness. No heterogeneity was observed between the studies (I^2 = 0%, H^2=0.65), suggesting that this effect is consistent across the three studies. Negative interaction score has a positive effect on loneliness (z=3.22, p<0.001). Heterogeneity test shows that this effect is fairly consistent between studies (I^2 = 44.33%, H^2=1.80).

In terms of the effect of the previous-day interaction variables, the meta analysis only showed a significant effect of positive interaction score from the previous day on today's end-of-day loneliness rating (z=-2.87, p<0.001). The heterogeneity test indicates that this effect is consistent for the 3 studies (I^2 = 0%, H^2=0.65). There is no significant effect of previous-day negative interaction on loneliness (z=-0.11, o=0.91).

On a person-level, people with higher levels of positive interactions, on average, are associated with lower loneliness (z=-8.70, p<0.001). However, this is not consistent across the three studies, especially Study 3 (I^2 = 85.80%, H^2=7.04). People who experience higher levels of negative interactions, on average, are associated with higher levels of loneliness (z=6.40, p<0.001). Yet, this is only moderately consistent across the three studies (I^2 = 67.42%, H^2=3.07).

Depression

For depression, the meta analyses showed significant day-level effects of subjective experience variables. Days where people have more positive social interactions are negatively associated with end-of-day depression (z=-6.16, p<0.001). Heterogeneity test showed that this result is consistent for the 3 studies (I^2 = 0%, H^2=0.55). Days where people have more negative interactions are positively associated with the depression score (z=2.78, p=0.01). However, this is not consistently observed in all studies based on the heterogeneity test (I^2 = 90.39%, H^2=10.40).

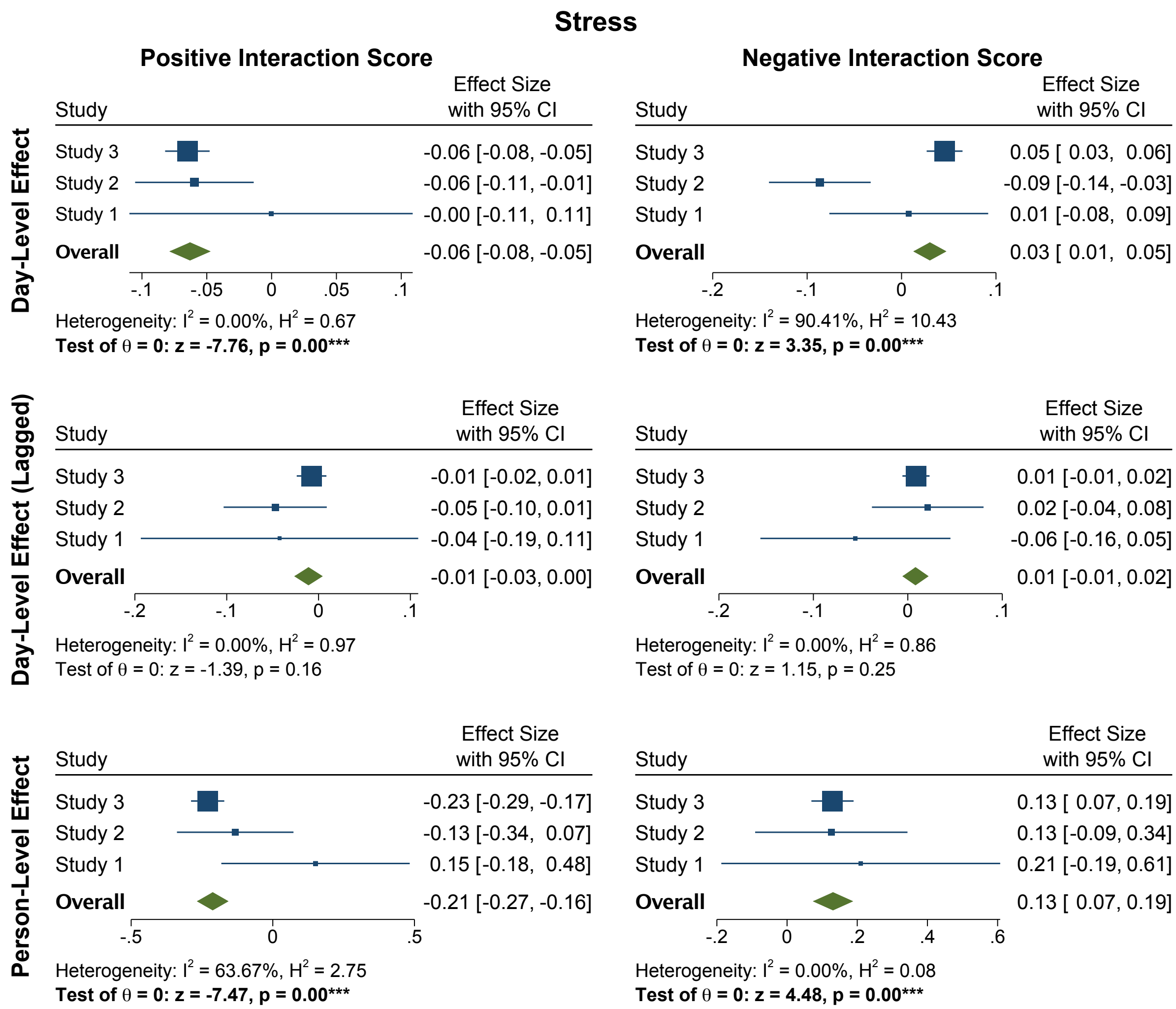

FIGURE 5.8: Depression: This figure visually shows the results to all meta analysis for the effect of subjective experience on **stress**. The 2 columns are the 2 measured subjective experience variables, i.e., positive and negative interaction scores. The 3 rows are for the 3 types of effect, i.e., day-level (within) effects, day-level (within) effects of the lagged variables, person-level (between) effects. The size of the square symbols represent the weight of the study. It is the largest for Study 3 due to large sample size and smallest for Study 1 due to its small sample size. A significant test of θ indicates that the effect of a variable is significant based on the meta analysis.

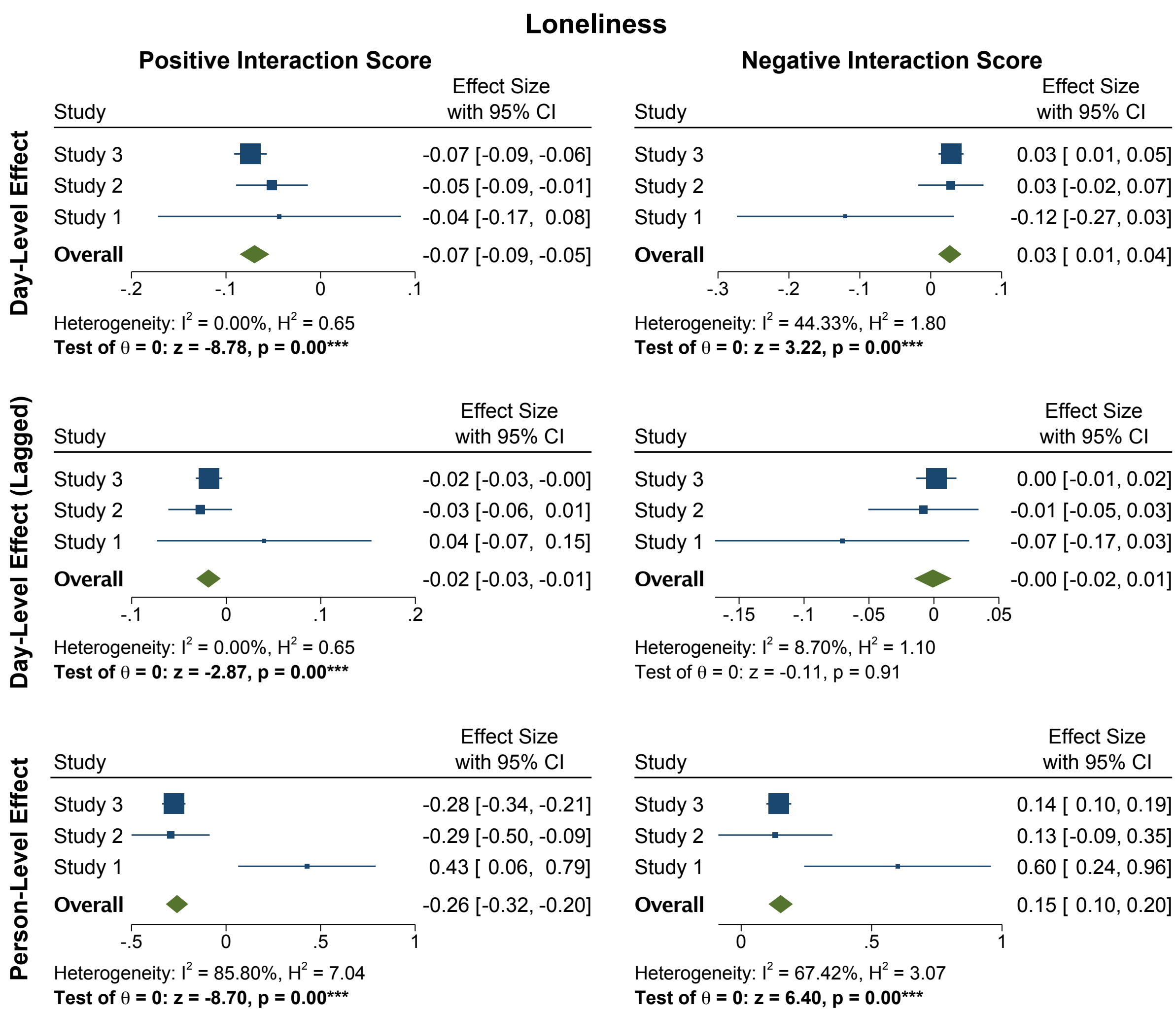

FIGURE 5.9: Loneliness: This figure visually shows the meta analysis results for the effect of subjective experience on **loneliness**. The 2 columns are the positive and negative interaction scores. The 3 rows are for the 3 types of effect, i.e., day-level (within) effects, day-level (within) effects of the lagged variables, person-level (between) effects. The size of the square symbols represent the weight of the study. It is the largest for Study 3 due to large sample size and smallest for Study 1 due to its small sample size. A significant test of θ indicates that the effect of a variable is significant based on the meta analysis.

For interaction experiences from the day before, there are no significant associations between either of the subjective experience variables and depression. This lack of results are consistent across the three studies.

On a person-level, the only significant effect is between negative interaction scores and depression – people who experience higher levels of negative interactions, on average, are associated with higher levels of depression (z=11.15, p<0.001). This result is consistent across the three studies (I^2 = 33.52%, H^2=1.50). There was no significant effect of average positive interaction score on depression.

Thriving

For thriving, only Study 2 and Study 3 measured thriving at the end of the day. Therefore, the meta analysis only includes the 2 studies. At day-level, the meta analyses showed that days with more positive interactions during the day are positively associated with thriving at the end of the day (z=7.18, p<0.001). Heterogeneity test showed that this result is consistent for the 2 studies (I^2 = 0%, H^2=0.14). Days with more negative interactions are negatively associated with thriving at the end of the day (z=-2.30, p=0.02). This result is consistent between the 2 studies (I^2 = 0%, H^2=0.97).

For interactions that happen from the day before, a positive interaction score from the previous score is positively associated with current day thriving (z=2.02, p=0.04). This result is consistent between Study 2 and Study 3, although it is not significant for Study 2 (I^2 = 0%, H^2=0.29). Negative interaction score from the day before was not significantly associated with thriving at the end of the current day.

On a person-level, only positive interaction score has a significant effect on thriving – people who experience higher levels of positive interactions, on average, are associated with a higher level of thriving (z=7.01, p<0.001). This result is consistent across both studies (I^2 = 0%, H^2=0.10). There was no significant effect of average negative interaction score on thriving.

5.6 Discussion

The meta analyses combined the results across the three studies to examine how subjective experience of interactions affect well-being, i.e., stress, loneliness, depression, and thriving. Below are the key takeaways from the analyses.

Interaction experiences explain more variances in positive well-being than negative well-being.

In both Study 2 and 3, more variances in thriving are explained by positive and negative interactions, as well as personal characteristics, compared to negative well-being outcomes, i.e., stress, loneliness, and depressive symptoms. This remains true when the personal characteristics variables are removed from the models, suggesting that one's thriving is more affected by the interactions they have. The negative well-being, on the other hand, are less explained by the interactions. Part of this difference in variance explained may be because the thriving items contain multiple dimensions of positive well-being (e.g., support, life satisfaction, etc) while the items for each negative well-being survey only measure behaviors related to the single dimension of negative well-being, e.g., stress.

However, this may also be suggesting that positive and negative aspects of well-being are, similar to positive and negative interactions, not uni-dimensional, i.e., the absence of negative well-being does not mean the presence of positive well-being. This is supported by many research studies and conceptual

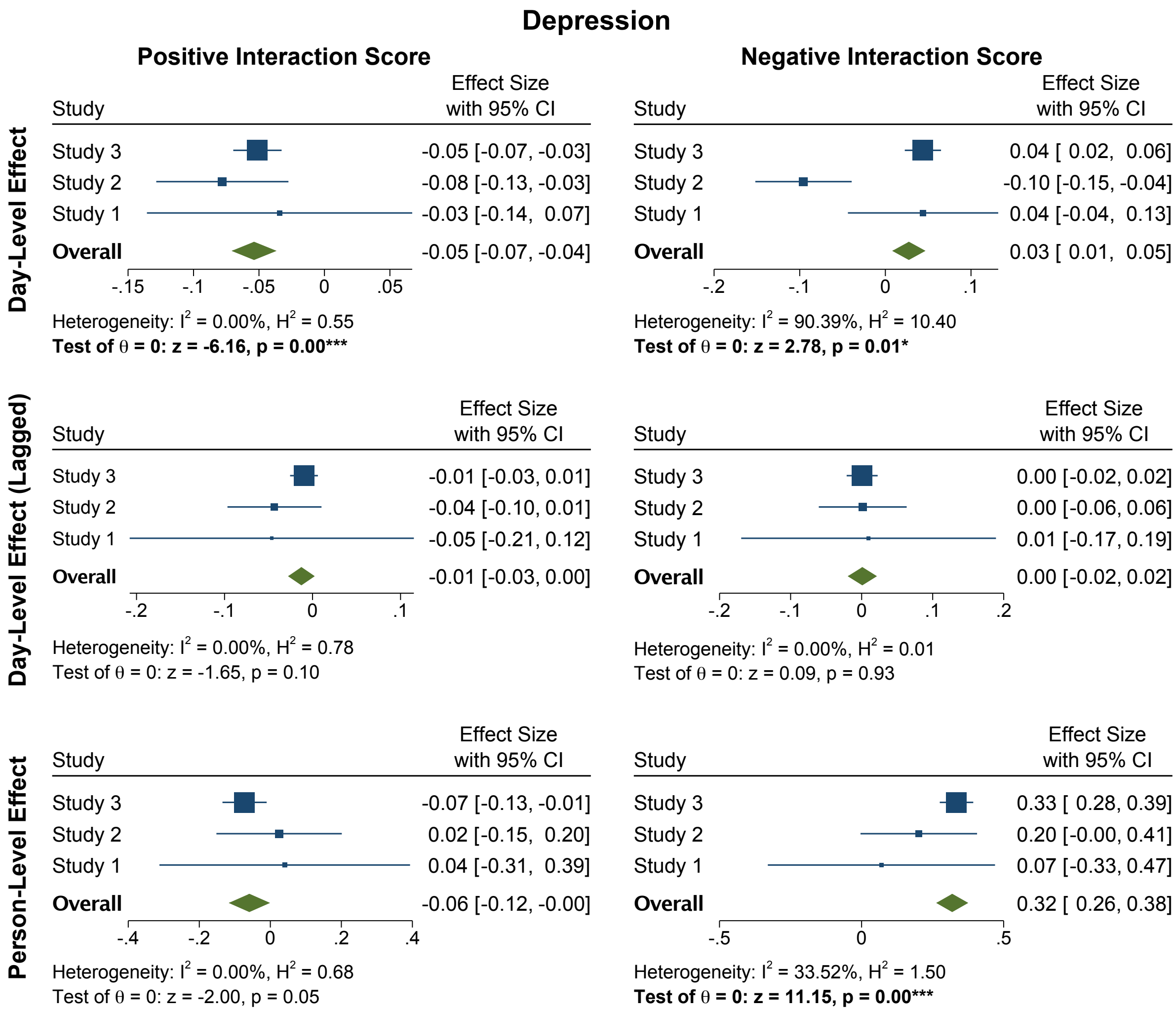

FIGURE 5.10: Depression: This figure visually shows the meta analysis results for the effect of subjective experience on **depression**. The columns are the positive and negative interaction scores. The 3 rows are for the 3 types of effect, i.e., day-level (within) effects, day-level (within) effects of the lagged variables, person-level (between) effects. The size of the square symbols represent the weight of the study. It is the largest for Study 3 due to large sample size and smallest for Study 1 due to its small sample size. A significant test of θ indicates that the effect of a variable is significant based on the meta analysis.

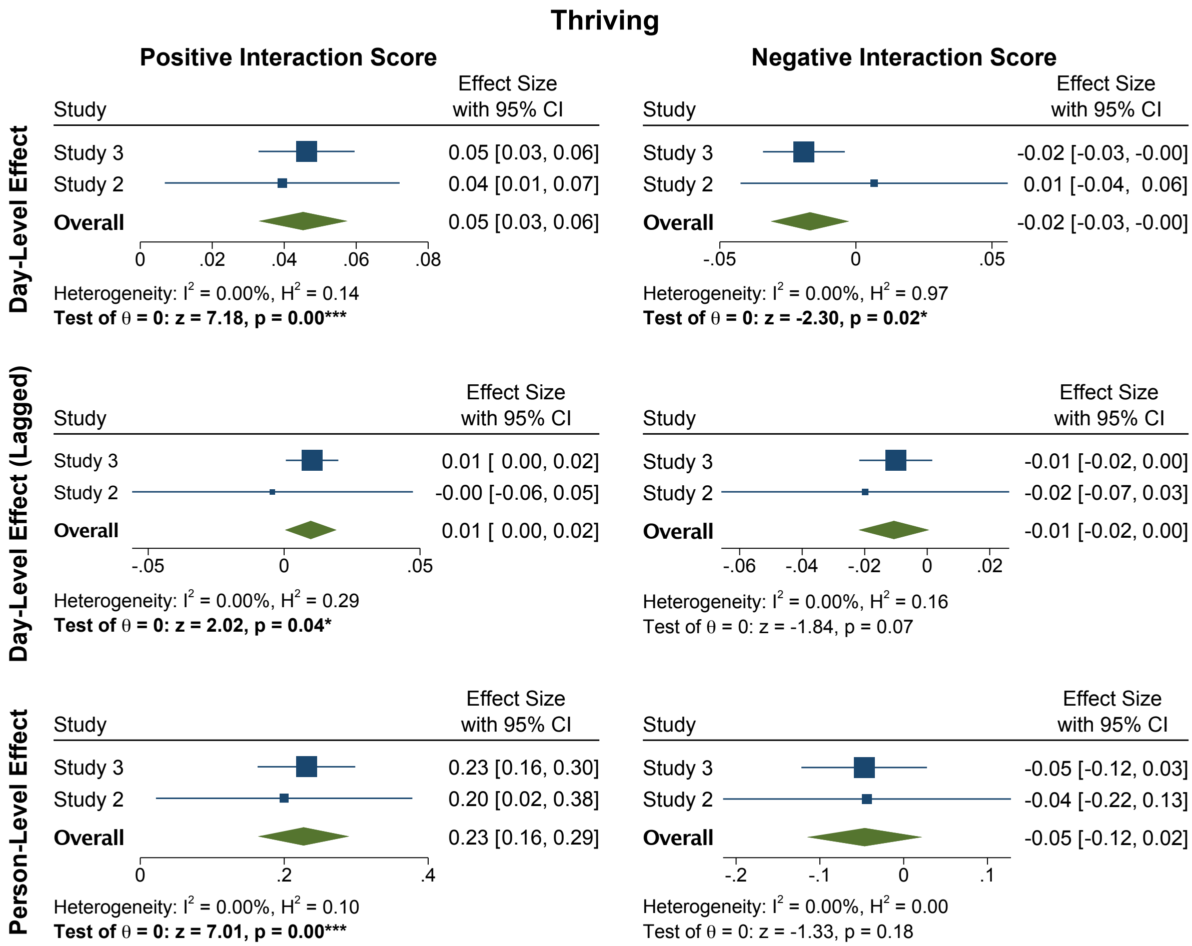

FIGURE 5.11: Thriving: This figure visually shows the meta analysis results for the effect of subjective experience on **thriving**. The columns are the positive and negative interaction scores. The 3 rows are for the 3 types of effect, i.e., day-level (within) effects, day-level (within) effects of the lagged variables, person-level (between) effects. The size of the square symbols represent the weight of the study. Only Study 2 and Study 3 measured thriving at the end of the day. A significant test of θ indicates that the effect of a variable is significant based on the meta analysis.

frameworks on well-being [67, 43]. In addition, the World Health Organization defines mental well-being as not merely the absence of mental disorders but also the presence of a positive state, suggesting that an independence of the positive and negative state for well-being [167]. Therefore, in the current work, the data suggests that social interactions promote more positive well-being than it does on the lack of negative well-being.

Days with more positive interactions are negatively associated with stress, loneliness, depression and are positively associated with thriving; days with more negative interactions are positively associated with stress, loneliness, depression and are negatively associated with thriving.

Both positive and negative social interactions one has during the day have a significant impact on the positive and negative aspects of well-being. While this may not be a surprising finding, theoretically, this is very intriguing. There has been much debate about how social interactions influence one's well-being and 3 may threads of conceptual models have been proposed [88, 68]. First is a domain-specific model, where positive interactions only impact positive aspects of well-being and negative interactions influence negative well-being. Second is a direct effect model that suggests that positive and negative social interactions have additive effects on psychological well-being. Third is a buffering model that proposes positive social interactions buffer the deleterious impact of negative social interactions on psychological well-being. While our study did not test the direct vs mediated effect that interaction experience has on well-being, the results from the studies reject domain-specific models. Positive interactions have a significant influence on both positive and negative aspects of well-being. So do negative interactions.

In addition, a closer look at the magnitude of the coefficients generated by the meta analyses seem to suggest that positive interactions are associated with more change in well-being score than negative interactions, e.g., the 95% confidence interval for the coefficient of positive interaction score on loneliness is -0.05 to -0.09 while it is 0.01 to 0.04 for negative interactions. While no formal tests are conducted to confirm if the difference is statistically significant, this may hint that positive interactions are more strongly associated with well-being than negative interactions and can counteract damages of negative interactions. This does not align with findings from Rook in [127]. This difference in finding could be due to the participant sample. In Rook's work, her participants consist of the elderly while the studies in the current work are younger in age. This is further supported by Okun and Keith's work where they found, in a younger sample (between age 28 to 59 years old), that positive social interactions are more important for positive mental health outcomes [105].

Positive interactions from the previous day have a significant association with loneliness and thriving; Negative interactions from the previous day are not associated with current-day well-being.

To further demonstrate the importance of positive interactions, we also found that positive interactions from the previous day can have a lasting impact on today's well-being, specifically loneliness and thriving. No such effect is found for negative interactions. The magnitude of the effect is smaller compared to the social interaction score of the current day. However, it is significant nonetheless. This indicates that interactions that one has in a day, not only influences how they feel on that day, but also how they feel the day after. The current work did not test the reason why positive interactions have a more lasting effect than negative interactions. However, the difference may point to a difference in mechanism between how positive and negative interactions influence well-being.

People who generally experience more positive interactions report lower stress, lower loneliness, and higher thriving; people who generally experience more negative interactions report higher stress, loneliness, and depression.

In addition to the day-level effect of interactions, the analyses also showed that there are more general individual traits that also come into play. These traits are likely to influence both people's experience of social interactions, as well as their well-being. A few of them that were examined in the current work are gender, relationship status, and personality. However, these are by no means a full list of possible factors. Some other personal traits that may be important but was not captured in the studies are attachment style [114, 115, 56], one's appraisal processing (i.e., the ability to cognitively evaluate the significance of an event) [102], social skills [33, 166], perception of others [144], and so on. All of these have been shown to have a significant impact on multiple aspects of one's social lives.

Some takeaways for the statistical models

There are additional considerations that went into constructing the statistical models, which may be of help for other researchers. The models used in this chapter is a with-between random effect model (as outlined in section 5.1. The dependent variable is the end-of-day well-being measure of day *t* and the independent variables are interaction-related variables from day *t* and *t-1*.

I considered adding a lagged dependent variable, i.e., a well-being measure from day *t-1*, as an independent variable in a random-effect model. This would account for the effect of how one feels from the day before on how they feel today, which conceptually makes sense – e.g., how depressed one feels in a day is probably fairly stable and would predict how depressed one feels on the next day. However, introducing a lagged dependent variable would create an issue of error term being non-independent from the dependent variable [5, 4]. In addition, this method is commonly used in Econometric to account for sudden fluctuations that are not common, e.g., a sudden increase in a country's GDP in a single year that is not commonly observed across other years. As we do not expect one's well-being to make sudden changes across days, under normal circumstances, introducing a lagged dependent variable is not an appropriate modeling of the data and produces more difficulties in the analyses.

Another alternative model considered was using the differenced well-being score, between two consecutive days, as the dependent variable. The motivation is to model change in well-being without using previous-day well-being score as an independent variable. However, modeling change as the outcome is a rare practice and is typically avoided unless there is a strong theoretical support for why one believes the independent variable would influence change in the dependent variable. In addition, a baseline is normally introduced into the model as the independent variable. Intuitively, this is because the same change may mean very different things based on the baseline level. For example, for a low-stressed individual, a sudden increase in stress is more indicative than the same amount of increase in stress for a typically highly stressed individual as the latter being stressed is a norm while for the former, it is an atypical behavior. By including a baseline account for this difference. However, adding a baseline value introduces the same non-independent error issue as mentioned previously. Therefore, I did not adopt this model.

Another consideration that I chose not to address is simultaneity bias, i.e., independent variables can influence the dependent variable, which can in turn affect the independent variables. Typically, this is addressed using instrumental variables for the independent variables. However, this was not viable for the current study. To instrument the social interaction variables, specifically the experience outcomes, the instrumental variables have to be strongly correlated with the independent variables, while not correlated with the dependent variables. In the current study, there are no such variables that can serve as good instrumental variables for the interaction experience variables. While simultaneity bias is still a concern, there is no appropriate way to address this issue.

Chapter 6

Mediating Effect of Interaction Experience Between Interaction Details and Well-Being

Knowing that the details of the interactions influence people's subjective experience, which has significant associations with people's end-of-day well-being, it is natural to hypothesize that interaction details may have a direct or indirect effect on well-being, mediated by one's experience of the interaction. I examine this possibility in this section of the thesis. Specifically, I will use mediation analysis, under the framework proposed by Shrout and Bolger [143], to study the possible mediation effect of subjective experience between interaction details and well-being (highlighted section in Figure 6.1).

Our analyses show that interaction details can have both direct and indirect effect on well-being. Emotional support, tangible support, and some joint activities (e.g., physical activity) have direct associations with well-being. Interactions with close ties and interactions involving most joint activities are indirectly associated with well-being, mediated by positive interactions, i.e., interactions with close ties and with joint activities are associated with more positive interactions, which is associated with better well-being. A summary of these findings can be found at the end of the document in Table 8.1.

6.1 Methods

The mediation analyses were done in Stata using command -gsem-, which accounts for the multi-level nature of our data. The independent variables of the models, i.e., the interaction details, are aggregated daily sum of reported surveys, divided by the total number of surveys people reported on that day. This converts the independent variables so they are ratios in proportion to the number of surveys reported. This division also converts the independent variables to be on the same level (day-level) as the mediating variable, (day-level subjective experience), and the outcome variables (day-level stress, loneliness, depressive symptoms, and thriving). I reduced the independent variables to only include the critical ones in order

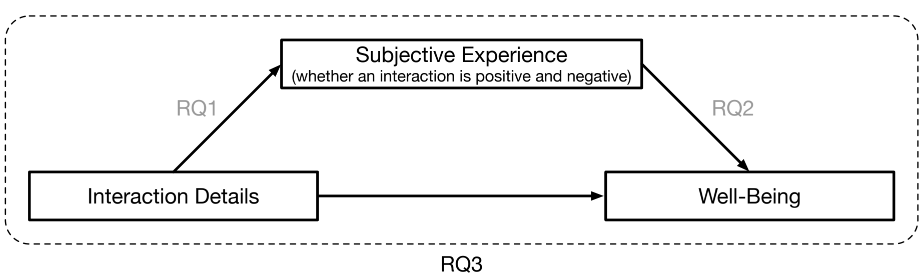

FIGURE 6.1: This chapter examines the third research question: Does subjective experience of social interactions mediate any effect between social interaction details and well-being?

to limit the complexity of the models. The independent variables that are entered are total number of reported interactions, number of interactions with close and non-close ties, number of interactions longer than 20 minutes, number of interactions that occur in-person, activities (except for celebration and other activities. These were removed due to their low occurrences in the dataset), and both support gestures. All variables are standardized for the models.

For the mediating variables, both positive and negative interaction scores are included as potential mediators for stress, loneliness, depression, and thriving. Covariance between positive and negative interactions is specified. Because of concerns about multivariate non-normality, we used maximum likelihood with Satorra–Bentler corrections for chi-square and standard error [134].

To obtain standard errors of coefficient estimates for the indirect and direct effects, I will use bootstrapping (100 sets; command -bootstrap-) with -gsem-. In addition to the standard error value, this produces a p-value which shows whether an indirect or direct effect is significant.

6.2 Results

I did not run this analysis on Study 1 data due to its small sample size and short duration, which only contains a total of 107 data points from 35 people. As there are a total of 12 variables included in the model, more than 120 data points are required to generate a trustworthy estimate, based on [103]. In addition, Maas and Hox recommend a minimum of 50 second-level cases, i.e., participant-level in this case, for a reliable multilevel analysis result [93].

Therefore, in the thesis, I will only show the result from Study 2 and 3.

6.2.1 Study 2 (6-Week Local Sample)

The direct and indirect effects of the interaction details on stress, loneliness, depressive symptoms, and thriving are shown in Figure 6.2, Figure 6.3, Figure 6.4, and Figure 6.5.

Direct Effect

Only a few of the interactions details do not have a direct effect on well-being measures and they differ by the measure. For stress, the number of interactions longer than 20 minutes (as a ratio of total number of reported surveys) is positively and directly associated with stress (b=0.08, p=0.002). The number of in-person interactions are negatively associated with stress (b=-0.08, p=0.03). For loneliness, number of interactions longer than 20 minutes, number of sedentary entertainment, and number of tangible support behaviors are all directly associated with loneliness. For depression, only the number of in-person interactions is directly associated (b=-0.09, p=0.02). For thriving, interactions with close ties, number of study/work sessions, and physical activities are all directly influencing thriving.

Indirect Effect

Across all well-being variables, negative interactions did not mediate any effect between interaction details and well-being. Positive interactions had a mediating role for a few variables, depending on the well-being outcome. Number of study and work session and number of emotional support behaviors have an indirect effect on stress, mediated by positive interactions ($b_{indirect,\#studywork}$=0.01, p=0.04;

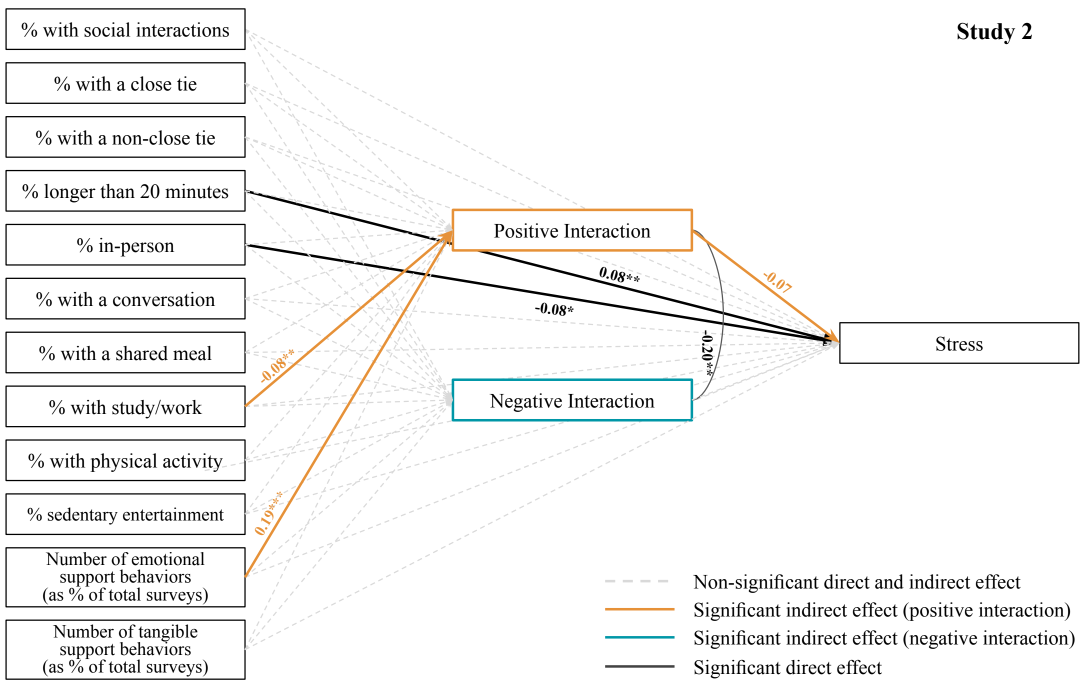

FIGURE 6.2: Stress: This figure visually shows the indirect and direct effect between interaction details (as a ratio of total number of surveys reported in a day) and stress, mediated by positive and negative interaction scores. The numbers on the lines are the standardized coefficients between the two boxes the lines connect. All independent variables were normalized by the total number of reported surveys. Solid lines indicate a significant effect while dashed lines insignificant effect. * p<0.05, ** p<0.01, *** p<0.001.

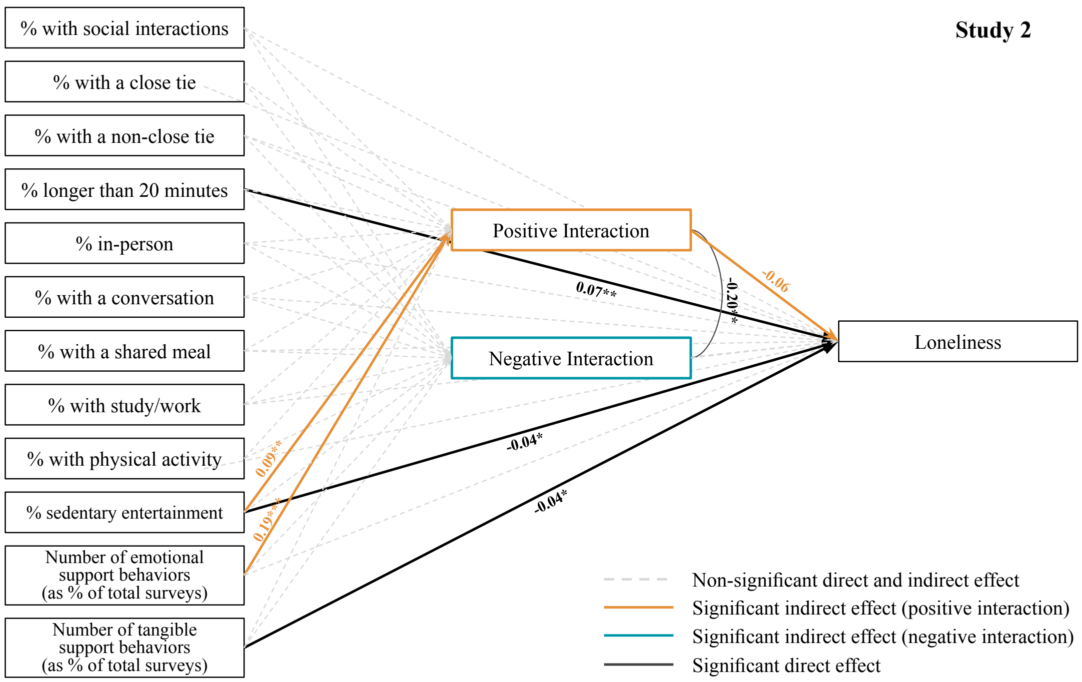

FIGURE 6.3: Loneliness: This figure visually shows the indirect and direct effect between interaction details (as a ratio of total number of surveys reported in a day) and loneliness, mediated by positive and negative interaction scores. The numbers on the lines are the standardized coefficients between the two boxes the lines connect. All independent variables were normalized by the total number of reported surveys. Solid lines indicate a significant effect while dashed lines insignificant effect. * p<0.05, ** p<0.01, *** p<0.001.

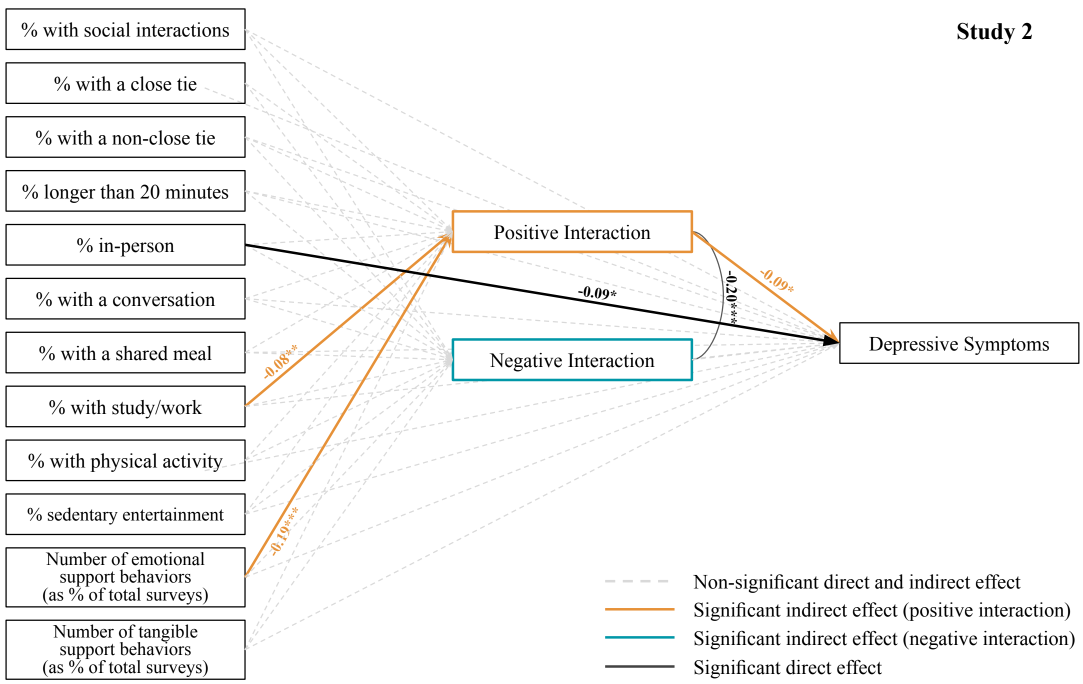

FIGURE 6.4: Depressive symptoms: This figure visually shows the indirect and direct effect between interaction details (as a ratio of total number of surveys reported in a day) and depressive symptoms, mediated by positive and negative interaction scores. The numbers on the lines are the standardized coefficients between the two boxes the lines connect. All independent variables were normalized by the total number of reported surveys. Solid lines indicate a significant effect while dashed lines insignificant effect. * p<0.05, ** p<0.01, *** p<0.001.

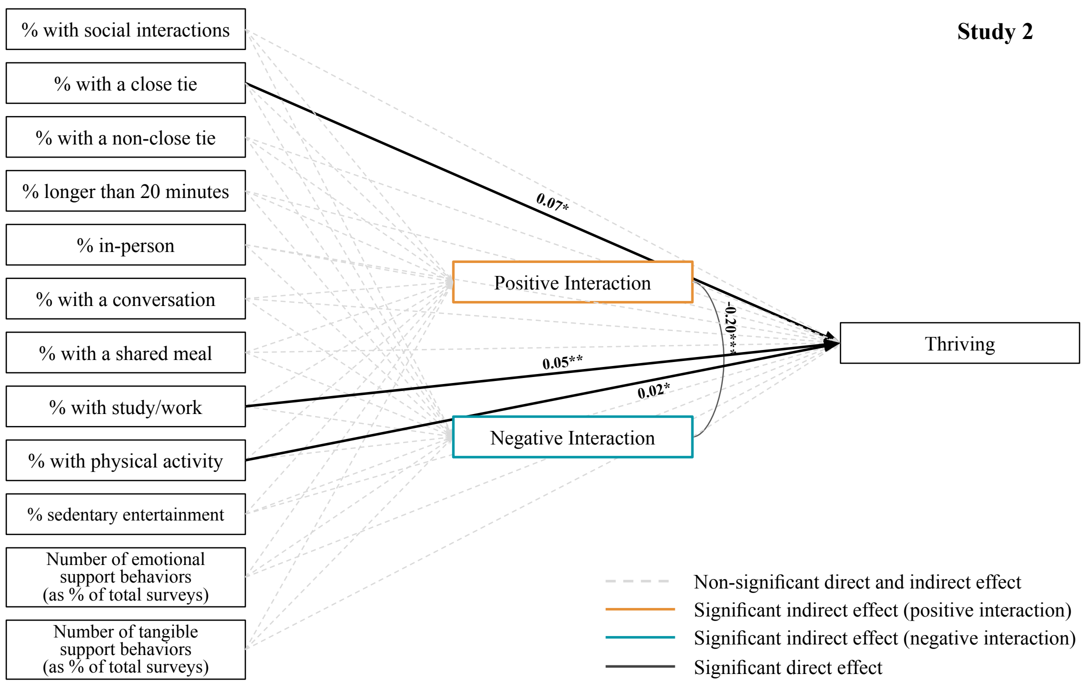

FIGURE 6.5: Thriving: This figure visually shows the indirect and direct effect between interaction details and thriving, mediated by positive and negative interaction scores. The numbers on the lines are the standardized coefficients between the two boxes the lines connect. All independent variables were normalized by the total number of reported surveys. Solid lines indicate a significant effect while dashed lines insignificant effect. * p<0.05, ** p<0.01, *** p<0.001.

Study 2: Stress

	Total Effect		Direct Effect		Indirect Effect via Positive Interaction		Indirect Effect via Negative Interaction	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Total number of interactions (normalize by reported surveys)	0.022	0.086	0.040	0.074	0.008	0.008	0.003	0.005
% with close tie	−0.084	0.054	−0.078	0.045	−0.005	0.005	−0.004	0.003
% with non-close tie	−0.007	0.043	−0.009	0.036	0.001	0.003	−0.003	0.003
% longer than 20 minutes	0.089*	0.039	0.087**	0.028	−0.004	0.003	0.000	0.003
% in-person	−0.076	0.042	−0.082*	0.037	0.007	0.005	−0.005	0.005
% with conversation	−0.003	0.037	−0.012	0.036	−0.003	0.003	0.004	0.004
% with shared meal	−0.017	0.020	−0.016	0.019	0.000	0.002	0.000	0.002
% with study/work	−0.007	0.027	−0.010	0.022	0.006*	0.003	−0.002	0.002
% with physical activity	−0.024	0.013	−0.025	0.013	−0.002	0.002	0.003	0.002
% with sedentary entertainment	−0.018	0.030	−0.006	0.023	−0.007	0.004	0.002	0.002
Number of emotional support (normalize by reported surveys)	−0.018	0.030	−0.003	0.026	−0.014*	0.007	0.003	0.002
Number of tangible support (normalize by reported surveys)	−0.040	0.028	−0.042	0.025	−0.003	0.002	0.000	0.002

TABLE 6.1: Stress: Total, direct, and indirect effect of interaction details on end-of-day stress. The coefficients and SE of direct and indirect effect is generated using bootstrapping. * p<0.05, ** p<0.01, *** p<0.001.

$b_{indirect,\#emotionalsupport}$=-0.01, p=0.04). For loneliness, positive interactions mediate the effect for number of sedentary entertainment and number of emotional support behaviors ($b_{indirect,\#sedent}$=-0.01, p=0.04; $b_{indirect,\#emotionalsupport}$=-0.01, p=0.03). For depression, similar to stress, the number of study and work session and number of emotional support behaviors have an indirect effect on depression, mediated by positive interactions ($b_{indirect,\#studywork}$=0.01, p=0.03; $b_{indirect,\#emotionalsupport}$=-0.02, p=0.02). No mediating effect of positive interaction for thriving was reported.

6.2.2 Study 3 (3-Week National Sample)

The direct and indirect effects of the interaction details on stress, loneliness, depressive symptoms, and thriving are shown in Table 6.6, Table 6.7, Table 6.8, and Table 6.9. To reduce the visual complexity of the figures, only significant paths are shown with their estimated coefficients and p-value.

Direct Effect

The interaction details had varying effects on the well-being measures. But, in general, the majority of the details did not have a direct effect on well-being. For stress, the number of tangible support behaviors that one has in a day is directly positively associated with the end-of-day stress level (b=0.03, p=0.04). For loneliness, the number of in-person interactions was directly correlated with loneliness (b=-0.03, p=0.02), so was the number of emotional support behaviors (b=-0.06, p<0.001). None of the interaction details that happened during the day had a direct effect on depressive symptoms. For thriving, the number of physical activities done together was positively associated with end-of-day thriving (b=-0.01, p=0.02). In addition, the number of emotional support behaviors was also directly associated with thriving (b=0.03, p=0.01).

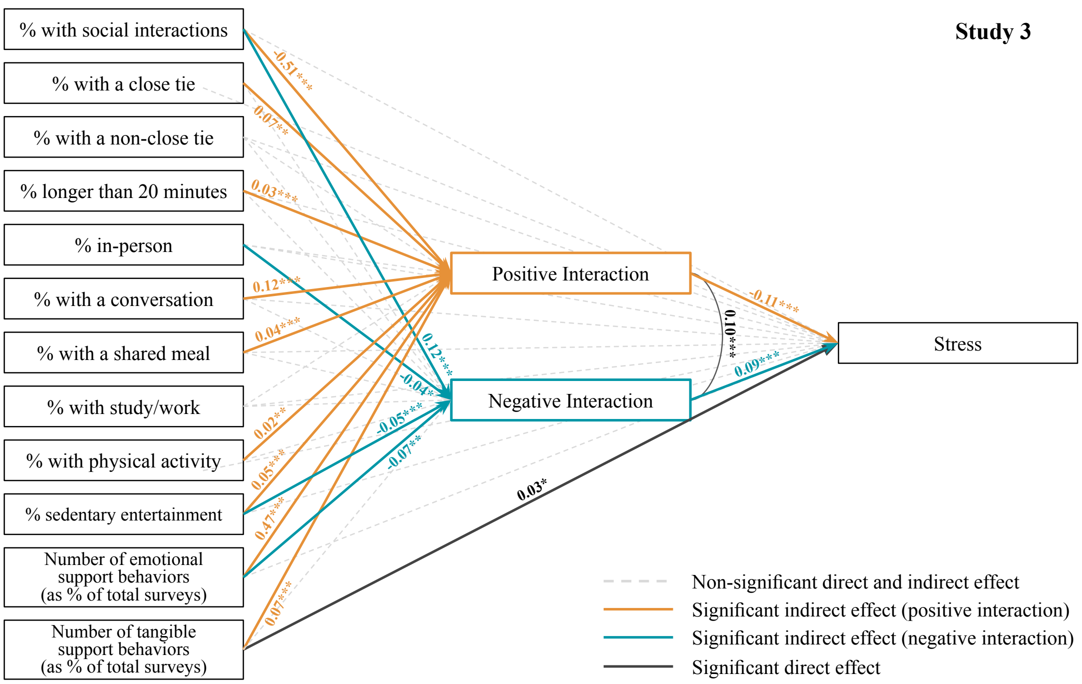

FIGURE 6.6: Stress: This figure visually shows the indirect and direct effect between interaction details (as a ratio of total number of surveys reported in a day) and stress, mediated by positive and negative interaction scores. The numbers on the lines are the standardized coefficients between the two boxes the lines connect. All independent variables were normalized by the total number of reported surveys. Solid lines indicate a significant effect while dashed lines insignificant effect. * p<0.05, ** p<0.01, *** p<0.001.

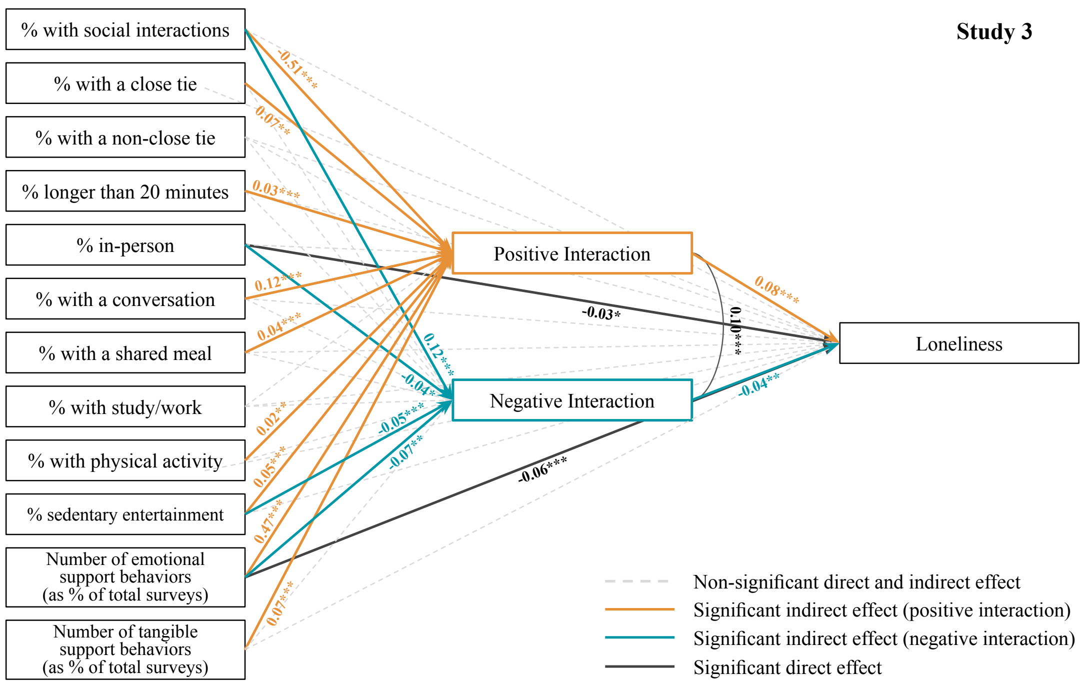

FIGURE 6.7: Loneliness: This figure visually shows the indirect and direct effect between interaction details (as a ratio of total number of surveys reported in a day) and loneliness, mediated by positive and negative interaction scores. The numbers on the lines are the standardized coefficients between the two boxes the lines connect. All independent variables were normalized by the total number of reported surveys. Solid lines indicate a significant effect while dashed lines insignificant effect. * p<0.05, ** p<0.01, *** p<0.001.

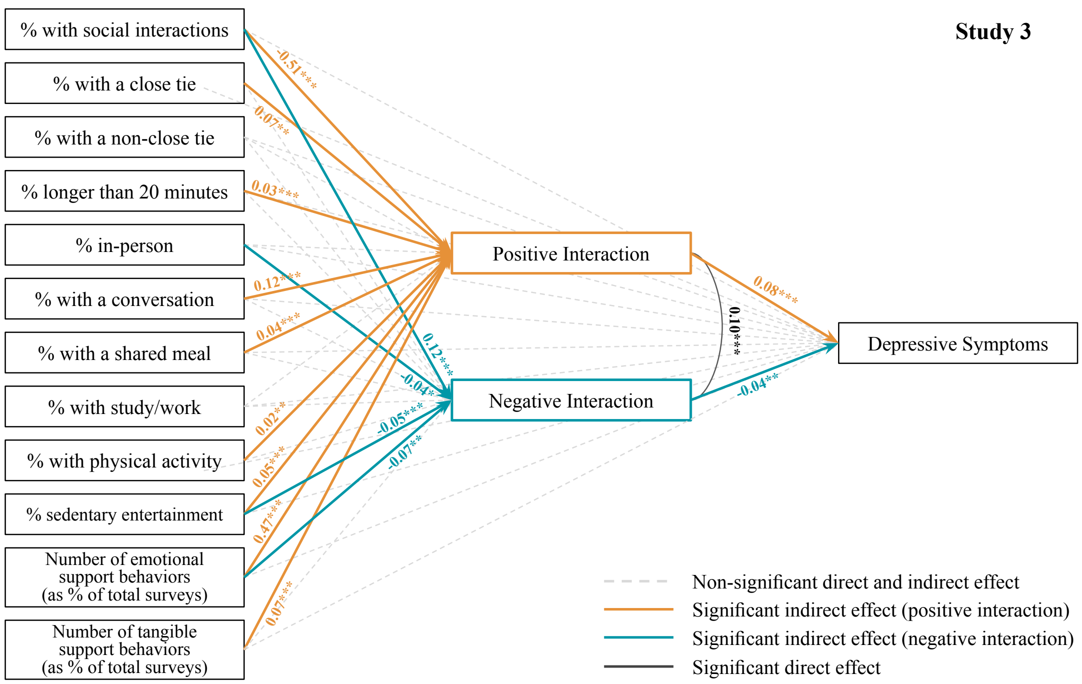

FIGURE 6.8: Depressive symptoms: This figure visually shows the indirect and direct effect between interaction details (as a ratio of total number of surveys reported in a day) and depressive symptoms, mediated by positive and negative interaction scores. The numbers on the lines are the standardized coefficients between the two boxes the lines connect. All independent variables were normalized by the total number of reported surveys. Solid lines indicate a significant effect while dashed lines insignificant effect. * p<0.05, ** p<0.01, *** p<0.001.

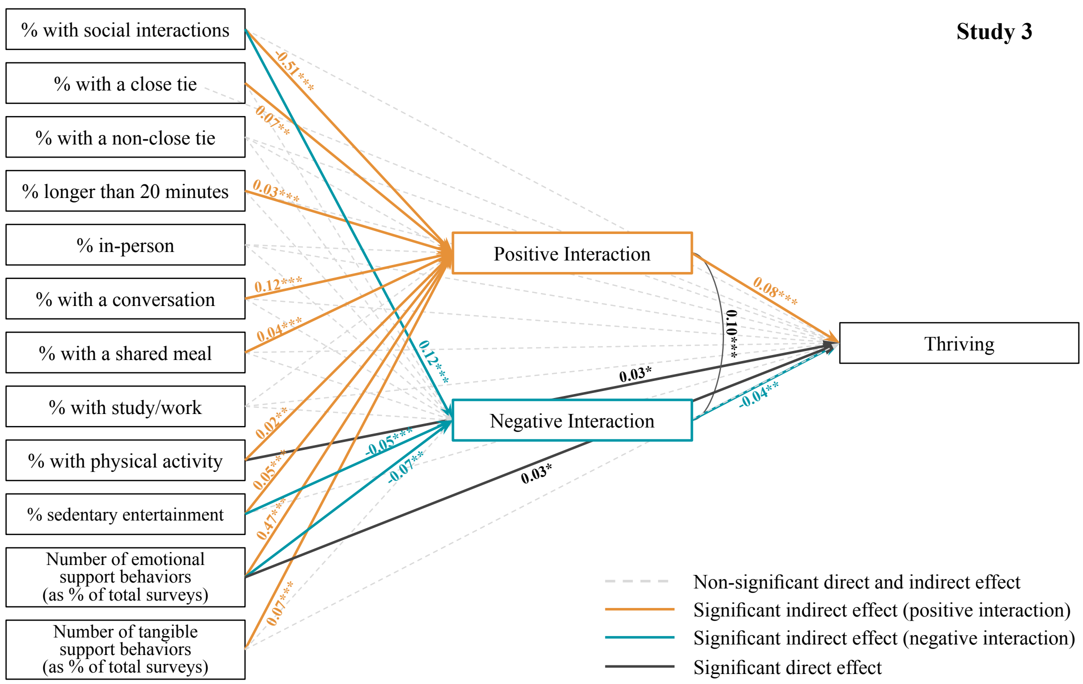

FIGURE 6.9: Thriving: This figure visually shows the indirect and direct effect between interaction details and thriving, mediated by positive and negative interaction scores. The numbers on the lines are the standardized coefficients between the two boxes the lines connect. All independent variables were normalized by the total number of reported surveys. Solid lines indicate a significant effect while dashed lines insignificant effect. * p<0.05, ** p<0.01, *** p<0.001.

Study 2: Loneliness

	Total Effect		Direct Effect		Indirect Effect via Positive Interaction		Indirect Effect via Negative Interaction	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Total number of interactions (normalize by reported surveys)	−0.014	0.072	−0.034	0.050	0.006	0.005	−0.002	0.003
% with close tie	−0.019	0.034	−0.010	0.030	−0.004	0.003	0.002	0.002
% with non-close tie	0.016	0.028	0.020	0.026	0.001	0.002	0.001	0.002
% longer than 20 minutes	0.067	0.039	0.066**	0.024	−0.003	0.003	0.000	0.002
% in-person	0.015	0.024	−0.001	0.025	0.006	0.003	0.002	0.003
% with conversation	−0.004	0.033	0.004	0.032	−0.002	0.002	−0.002	0.002
% with shared meal	0.013	0.017	0.014	0.016	0.000	0.001	0.000	0.001
% with study/work	0.010	0.020	0.004	0.019	0.004	0.002	0.001	0.001
% with physical activity	−0.018	0.016	−0.015	0.011	−0.002	0.001	−0.001	0.002
% with sedentary entertainment	−0.050*	0.022	−0.036*	0.016	−0.005*	0.002	−0.001	0.001
Number of emotional support (normalize by reported surveys)	−0.042	0.023	−0.024	0.023	−0.011*	0.005	−0.002	0.002
Number of tangible support (normalize by reported surveys)	−0.038	0.020	−0.037*	0.018	−0.002	0.002	0.000	0.001

TABLE 6.2: Loneliness: Total, direct, and indirect effect of interaction details on end-of-day loneliness. The coefficients and SE of direct and indirect effect is generated using bootstrapping. * p<0.05, ** p<0.01, *** p<0.001.

Indirect Effect

Most interaction details have an indirect effect on well-being with the results being consistent across the four well-being variables. This is especially true when the positive interaction score is the mediator of the effect. Across all four well-being measures, almost all of the interaction details measured had a significant indirect effect on well-being, with the exception of number of interactions involving non-close ties, number of in-person interactions, and number of study/work sessions. Except for the quantity of interactions, i.e., number of interactions reported in a day adjusted for total number of reported surveys, all other interaction details have a positively indirect associations with well-being, by positively influencing how pleasant the interactions are, which is positively associated with positive well-being (or negatively associated with negative well-being). Quantity of the interaction, on the other hand, has a negative association with positive interactions, meaning more interactions one has in a day is negatively associated with how positive the interactions are. As a result, more interactions are negatively associated with well-being (stress:$b_{indirect,total\#}$=0.05, p<0.001; loneliness: $b_{indirect,total\#}$=0.06, p<0.001; depressive symptoms: $b_{indirect,total\#}$=0.04, p<0.001; thriving: $b_{indirect,total\#}$=-0.04, p<0.001).

For effects mediated by negative interactions, only 4 interaction details had a significant indirect effect on well-being through negative interactions. These are total number of interactions, number of in-person interactions, number of sedentary entertainment interactions, and number of emotional support behaviors. Similar to positive interactions, quantity of interactions have an opposite association with well-being measures from the remaining interaction details. For all well-being measures, more interactions are associated with more negative interactions, which is positively associated with negative well-being or negatively associated with positive well-being (stress:$b_{indirect,total\#}$=0.01, p<0.001; loneliness: $b_{indirect,total\#}$=0.01, p=0.001; depressive symptoms: $b_{indirect,total\#}$=0.01, p=0.001; thriving: $b_{indirect,total\#}$=-0.004, p=0.02). In contrast, the interaction details have a negative association with how negative interactions are likely to

Study 2: Depressive Symptoms

	Total Effect		Direct Effect		Indirect Effect via Positive Interaction		Indirect Effect via Negative Interaction	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Total number of interactions (normalize by reported surveys)	0.078	0.074	0.087	0.063	0.010	0.009	0.003	0.005
% with close tie	−0.013	0.035	−0.011	0.042	−0.006	0.005	−0.005	0.004
% with non-close tie	−0.017	0.035	−0.019	0.032	0.001	0.003	−0.003	0.003
% longer than 20 minutes	0.029	0.045	0.032	0.031	−0.005	0.004	0.000	0.003
% in-person	−0.082*	0.040	−0.091*	0.039	0.009	0.005	−0.005	0.005
% with conversation	−0.007	0.024	−0.009	0.029	−0.003	0.004	0.005	0.004
% with shared meal	−0.012	0.021	−0.013	0.020	0.000	0.002	0.001	0.002
% with study/work	−0.026	0.024	−0.032	0.021	0.007*	0.003	−0.002	0.003
% with physical activity	−0.028	0.019	−0.027	0.015	−0.003	0.002	0.003	0.002
% with sedentary entertainment	−0.037	0.029	−0.023	0.023	−0.008	0.004	0.002	0.002
Number of emotional support (normalize by reported surveys)	−0.059	0.047	−0.037	0.033	−0.017*	0.007	0.004	0.003
Number of tangible support (normalize by reported surveys)	−0.040	0.033	−0.039	0.027	−0.003	0.003	0.000	0.002

TABLE 6.3: Depressive symptoms: Total, direct, and indirect effect of interaction details on end-of-day depressive symptoms. The coefficients and SE of direct and indirect effect is generated using bootstrapping. * p<0.05, ** p<0.01, *** p<0.001.

turn out. For example, number of sedentary entertainment activities, e.g., watching TV with someone, one does in a day is positively associated to thriving, by being negatively associated with the average negative interaction score ($b_{indirect,\#ofsedentaryentertainment}$=0.002, p=0.01).

6.3 Discussion

Between Study 2 and Study 3, there are some key high-level take-aways.

6.3.1 The importance of interaction details for well-being.

The analyses across the two studies show evidence that what happens in an interaction can have both a direct and indirect impact on well-being. Specifically, the indirect impact is mediated by how positive and negative people perceive the interaction to be. That is, what happens in an interaction influences well-being outcome by affecting the positive and negative experience of the interaction. For direct effects, emotional and tangible support behaviors are positively associated with well-being, i.e., stress, loneliness, and thriving. Doing joint physical activity is also directly and positively associated with thriving. For indirect effect of interaction details that is mediated by positive interactions, most of the interaction details, except for interactions with non-close ties and in-person interactions are associated with change in well-being. Among these variables, number of interactions and emotional support behaviors are associated with the largest amount of indirect change on all well-being measures (mediated by positive interactions). This is also observed for indirect effect mediated by negative interactions — number of interactions and emotional support behaviors are associated with the largest indirect effect on well-being. In addition, doing sedentary entertainment activities and having in-person interactions also had a significant indirect effect on well-being, mediated by negative interactions.

Study 2: Thriving

	Total Effect		Direct Effect		Indirect Effect via Positive Interaction		Indirect Effect via Negative Interaction	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Total number of interactions (normalize by reported surveys)	−0.049	0.070	−0.065	0.052	−0.005	0.006	0.000	0.002
% with close tie	0.062	0.034	0.066*	0.029	0.003	0.003	0.000	0.002
% with non-close tie	−0.004	0.032	0.003	0.024	−0.001	0.002	0.000	0.002
% longer than 20 minutes	−0.020	0.025	−0.022	0.022	0.003	0.003	0.000	0.001
% in-person	0.008	0.036	0.023	0.029	−0.005	0.003	0.000	0.003
% with conversation	0.003	0.025	0.007	0.025	0.002	0.002	0.000	0.002
% with shared meal	0.008	0.016	0.008	0.012	0.000	0.001	0.000	0.001
% with study/work	0.045*	0.022	0.054**	0.016	−0.004	0.002	0.000	0.001
% with physical activity	0.019	0.010	0.017*	0.008	0.001	0.001	0.000	0.001
% with sedentary entertainment	0.012	0.015	0.003	0.014	0.004	0.003	0.000	0.001
Number of emotional support (normalize by reported surveys)	0.026	0.025	0.013	0.023	0.009	0.005	0.000	0.001
Number of tangible support (normalize by reported surveys)	0.036	0.024	0.025	0.018	0.002	0.002	0.000	0.001

TABLE 6.4: Thriving: Total, direct, and indirect effect of interaction details on end-of-day thriving. The coefficients and SE of direct and indirect effect is generated using bootstrapping. * p<0.05, ** p<0.01, *** p<0.001.

In addition to establishing the mediating pathway of interaction experience, our analyses also suggest that interaction details other than interaction partner, which is what existing literature has mostly focused on [125, 26], contribute to well-being as well. The models suggest that support gestures and almost all of the joint activities, including conversation, shared meals, physical activity, sedentary entertainment, have a significant indirect impact on well-being, by making interactions more positive and less negative. This suggests that there is much value to broadening the focus of current research on social interactions beyond who are involved in the interaction.

It is worth-noting that in-person interactions did not show a direct effect on well-being measures. This may be because in-person interactions only support occurrences of other pro-well-being interactions. For example, many of the joint activities are more likely to occur when people are in-person, e.g., people are more likely to work-out together when they meet up in-person. Similarly, interactions with close-ties are also more likely to occur in-person. Therefore, being in-person itself does not contribute to well-being. It serves as a "prerequisite" for other more beneficial interactions.

6.3.2 Emotional support influences well-being by both boosting positive experience and reducing negative experience while tangible support gestures only affects well-being by boosting positive experience.

The current analyses showed that individual emotional and tangible support behaviors exchanged during interactions can indirectly and directly impact well-being. This finding is novel in 2 aspects. First, most existing literature has focused on the impact of social support through stress-buffering in stressful times [33, 40, 154]. The current work proposes an additional alternative, i.e., social support impacts well-being by influencing the subjective experience of social interactions. This does not contradict the stress-buffering theory. Instead, it proposes an additional mechanism through which stress-buffering is enacted.

Study 3: Stress

	Total Effect		Direct Effect		Indirect Effect via Positive Interaction		Indirect Effect via Negative Interaction	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Total number of interactions (normalize by reported surveys)	0.045	0.025	−0.008	0.026	0.055***	0.007	0.011***	0.003
% with close tie	−0.010	0.020	−0.004	0.018	−0.007**	0.002	0.002	0.002
% with non-close tie	−0.015	0.016	−0.013	0.015	0.001	0.002	−0.003	0.001
% longer than 20 minutes	−0.013	0.007	−0.009	0.007	−0.003***	0.001	0.000	0.001
% in-person	−0.024	0.013	−0.024	0.012	0.003	0.002	−0.004*	0.002
% with conversation	−0.013	0.014	0.004	0.012	−0.013***	0.002	−0.003	0.001
% with shared meal	−0.004	0.008	0.001	0.008	−0.004***	0.001	0.000	0.001
% with study/work	0.000	0.007	0.001	0.006	−0.001	0.001	0.001	0.001
% with physical activity	0.002	0.006	0.006	0.007	−0.002**	0.001	−0.001	0.001
% with sedentary entertainment	−0.009	0.009	−0.001	0.007	−0.005***	0.001	−0.004***	0.001
Number of emotional support (normalize by reported surveys)	−0.079***	0.018	−0.027	0.016	−0.050***	0.006	−0.006**	0.002
Number of tangible support (normalize by reported surveys)	0.024	0.016	0.028***	0.014	−0.008***	0.002	0.003	0.001

TABLE 6.5: Stress: Total, direct, and indirect effect of interaction details on end-of-day stress. The coefficients and SE of direct and indirect effect is generated using bootstrapping. * p<0.05, ** p<0.01, *** p<0.001.

It is possible that social interactions, more specifically what happens in social interactions, buffer negative effects of stress on well-being, by enhancing the pleasant experience of social interactions and decreasing conflicts in social interactions. The improved experience may contribute to the buffering of stress on well-being. In addition to the stress-buffering theory, the current mechanism of subjective experience can also be applied in non-stressful times. For example, Feeney and Collins proposed a second possible pathway that social support influences well-being, which is when in absence of stressors, social support serves as a Relational Catalyst that encourages people to actively pursue life opportunities for growth and development. One way this is achieved may be by positively influencing the subjective experience of interactions – by having more positive interactions and less negative ones, people with more social support are more willing and likely to pursue their own personal goals, which can positively affect well-being. These are all hypotheses and more work is needed to confirm whether support gestures provide these benefits via influencing subjective experience of social interactions.

The second novel aspect of the finding is that current work quantifies support behaviors as individual gestures that occur during a social interaction. This is in contrast to more high-level assessments of perceived social support, which commonly ask about support gestures that happen in a longer time frame, under hypothetical scenarios. While these more high-level measurements provide a lot of value to our understanding of social support, the more detailed measurements used in the current studies provide a different level of understanding – the specific exchanges of social support, rather than one's level of perceived support, can have an impact on well-being.

On the topic of received and perceived support, the results in this chapter do not align with Bolger and colleagues' finding that received support is associated with negative outcomes and in particular with increased negative mood [18]. While the support gestures measured in the study heavily consisted of received support, our results showed that despite the receivers being aware of these support behaviors, the behaviors were still associated with both direct and indirect positive changes in well-being. This is

Study 3: Loneliness

	Total Effect		Direct Effect		Indirect Effect via Positive Interaction		Indirect Effect via Negative Interaction	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Total number of interactions (normalize by reported surveys)	0.059*	0.022	0.023	0.020	0.060***	0.006	0.008**	0.002
% with close tie	−0.018	0.017	−0.011	0.016	−0.008**	0.002	0.001	0.001
% with non-close tie	−0.025	0.013	−0.022	0.012	0.002	0.002	−0.002	0.001
% longer than 20 minutes	−0.012	0.007	−0.007	0.008	−0.003***	0.001	0.000	0.001
% in-person	−0.031*	0.014	−0.034*	0.014	0.003	0.002	−0.003*	0.001
% with conversation	0.006	0.014	0.022	0.012	−0.014***	0.002	−0.002	0.001
% with shared meal	−0.015	0.008	−0.010	0.008	−0.005***	0.001	0.000	0.001
% with study/work	0.001	0.007	0.001	0.007	−0.001	0.001	0.000	0.001
% with physical activity	−0.002	0.006	0.002	0.006	−0.002***	0.001	−0.001	0.001
% with sedentary entertainment	−0.019*	0.009	−0.012	0.007	−0.005***	0.001	−0.003***	0.001
Number of emotional support (normalize by reported surveys)	−0.118***	0.019	−0.061***	0.016	−0.055***	0.005	−0.004*	0.002
Number of tangible support (normalize by reported surveys)	0.014	0.015	0.021	0.014	−0.009***	0.002	0.002	0.001

TABLE 6.6: Loneliness: Total, direct, and indirect effect of interaction details on end-of-day loneliness. The coefficients and SEs of direct and indirect effect is generated using bootstrapping. * p<0.05, ** p<0.01, *** p<0.001.

more consistent with a recent work by Jakubiak, Feeney, and Ferrer and colleagues where they found that context-general support can benefit well-being, even if the support is visible [70]. Therefore, we believe that more nuances are needed in support behaviors to fully understand why received and perceived social support have varying effects on well-being (see [70] for more detail).

On a broader scale, the current work demonstrates the importance of individual support behaviors and the social interactions that contain these behaviors. Thoit in her well-cited review paper called for researchers' attention to the "emotional, informational, and instrumental assistance swapped in everyday interactions" (p. 150) [154]. The paper wrote that these "routine or everyday emotional, informational, and instrumental acts are helpful in themselves [...] and thus indirectly maintain psychological well-being [...]" (p.150). The current chapter provides evidence that these minor support exchanges that occur in daily social interactions can have an indirect, as well as direct, impact on one's well-being. Hopefully, this will encourage future researchers to focus more on the specific gestures of social support to better understand how these low-level behaviors can have a bigger impact.

6.3.3 Difference in effect between how many interactions one has and what happens during the interaction.

Another interesting dichotomy in the results is the difference in well-being between the number of interactions and what happens during the interaction. There has been great interest in separating the effects of quantity and quality of interactions. For example, studies have found while the quantity of social interactions and social ties alone may be associated with social connectedness [41], mortality [142], and self-reported health [54], the effect on health is lowered once the quality of the interactions was introduced [54]. In line with these studies, the current work also showed a contrast between the effect of quantity of reported interactions on well-being and what happens during the interactions on well-being –

Study 3: Depressive Symptoms

	Total Effect		Direct Effect		Indirect Effect via Positive Interaction		Indirect Effect via Negative Interaction	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Total number of interactions (normalize by reported surveys)	0.035	0.025	0.014	0.025	0.036***	0.006	0.014**	0.004
% with close tie	−0.024	0.018	−0.023	0.019	−0.005**	0.001	0.003	0.002
% with non-close tie	−0.028	0.015	−0.028	0.014	0.001	0.001	−0.003	0.002
% longer than 20 minutes	−0.010	0.008	−0.007	0.008	−0.002***	0.001	0.000	0.001
% in-person	−0.019	0.014	−0.017	0.014	0.002	0.001	−0.005*	0.002
% with conversation	0.007	0.015	0.017	0.015	−0.009***	0.002	−0.004	0.002
% with shared meal	−0.011	0.008	−0.009	0.008	−0.003***	0.001	0.000	0.001
% with study/work	0.009	0.008	0.008	0.007	−0.001	0.001	0.001	0.001
% with physical activity	−0.006	0.006	−0.004	0.007	−0.001**	0.000	−0.001***	0.001
% with sedentary entertainment	−0.016	0.010	−0.009	0.008	−0.003***	0.001	−0.006**	0.001
Number of emotional support (normalize by reported surveys)	−0.040*	0.019	0.000	0.016	−0.033***	0.006	−0.008	0.003
Number of tangible support (normalize by reported surveys)	−0.022	0.017	−0.020	0.012		0.001	0.004	0.002

TABLE 6.7: Depressive symptoms: Total, direct, and indirect effect of interaction details on end-of-day depressive symptoms. The coefficients and SEs of direct and indirect effect is generated using bootstrapping. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

while more reported interactions is positively (indirectly) associated with negative well-being, i.e., stress, loneliness, and depression, more interactions of a particular kind, e.g., with a close tie, is negatively (indirectly) associated with negative well-being. This highlights that more interactions are not as necessarily positive to well-being as people would think.

Study 3: Thriving

	Total Effect		Direct Effect		Indirect Effect via Positive Interaction		Indirect Effect via Negative Interaction	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Total number of interactions (normalize by reported surveys)	−0.032	0.020	0.001	0.016	−0.040***	0.006	−0.005*	0.002
% with close tie	−0.007	0.013	−0.011	0.011	0.005**	0.002	−0.001	0.001
% with non-close tie	−0.002	0.010	−0.004	0.009	−0.001	0.001	0.001	0.001
% longer than 20 minutes	−0.003	0.005	−0.006	0.005	0.002**	0.001	0.000	0.000
% in-person	0.008	0.011	0.012	0.009	−0.002	0.001	0.001	0.001
% with conversation	0.008	0.012	−0.002	0.010	0.010***	0.002	0.001	0.001
% with shared meal	0.006	0.005	0.004	0.006	0.003***	0.001	0.000	0.000
% with study/work	−0.005	0.006	−0.006	0.005	0.001	0.001	0.000	0.000
% with physical activity	−0.009*	0.004	−0.011*	0.004	0.002**	0.001	0.000	0.000
% with sedentary entertainment	0.006	0.008	0.002	0.006	0.004***	0.001	0.002*	0.001
Number of emotional support (normalize by reported surveys)	0.067***	0.014	0.028*	0.011	0.037***	0.005	0.002*	0.001
Number of tangible support (normalize by reported surveys)	0.010	0.012	0.004	0.011	0.006***	0.001	−0.001	0.001

TABLE 6.8: Thriving: Total, direct, and indirect effect of interaction details on end-of-day thriving. The coefficients and SEs of direct and indirect effect is generated using bootstrapping. * p<0.05, ** p<0.01, *** p<0.001.

Chapter 7

Mining Interactions with Mobile Sensing

As mentioned in previous chapters, one difficulty of studying one's social interactions is data collection. While EMAs provide more accurate measures than traditional proxies, self-reports, especially EMAs, are time- and energy-consuming, requiring constant attention from participants. In addition, daily recollection surveys have been shown to be prone to recall and memory biases [121, 150], e.g., people can only report what they remember. Ideally, data collection of social interactions is unobtrusive and is able to log as many social interactions as one has throughout the day. In addition, an optimal method of data collection can also provide information about details of the interaction, e.g., how it occurred, who it is with, in addition to how many interactions occurred. These low-level details can provide insights on how social interactions affect our well-being.

In this chapter, I show exploratory work towards reaching this goal, present current prediction results, and discuss limitations and difficulties of this approach.

7.1 Data Processing and Feature Extraction

Data processing was required to convert collected raw data to features needed to predict interaction survey labels. As the survey data was roughly once every 30 minutes, we calculated features for mobile data collected up to 20 minutes prior to a survey response. All features were aggregated at 5-minutes windows. Therefore, for each survey label, we calculated features for 4 time windows, i.e., 0 to 5 minutes prior to the survey, 5 to 10 minutes prior, 10 to 15 minutes prior and 15 to 20 minutes prior. The extracted features are summarized in Table 7.1.

I grouped the features into 3 categories – time, context, communication. **Time** features include time of day and day of week. Because this information is readily available at low computation and battery cost while highly informative [52], they are separated from context features that require readings from sensors. **Context** features contain data from the sensors that do not directly reflect one's social interactions, i.e., location, physical activity, and screen usage. However, these features may indirectly indicate the medium of a social interaction, i.e., being in a public location is positively associated with having more in-person interactions 7.1. **Communication** features are data that directly show if a person is having a social interaction, i.e., app usage, call log, message log, and audio.

7.1.1 Imputation

As any mobile sensing studies, missing data are inevitable. There are 2 types of missing sensor data in the current study. One is random, due to the app being closed by Android or crashing at unpredictable time. Since this type of missing data is random, we account for it using multivariate imputation on the features before training models. Multivariate imputation uses the entire set of available features to estimate the

Data Type	Feature Name	Feature Description
Time	Time of day	4 binary variables representing if a survey is taken between 9-12pm, 12-6pm, 6-9pm and 9pm-midnight.
	Day of the week	7 binary variables representing 7 days of the week.
Location	Number of unique clusters	Count of how many location clusters, based on DBSCAN,were visited during a time window.
	Total distance travelled	Total amount of geographic displacement, calculated from latitude and longitude: $\sum_i \sqrt{(lat_i - lat_{i-1})^2 + (long_i - long_{i-1})^2}$ where lat_i and $long_i$ are latitude and longitude of i.
	Location variance	Combined variance of latitude and longitude: $log(\sigma^2_{lat} + \sigma^2_{long})$, where σ_{lat} and σ_{long} are the variance of latitude and longitude, respectively.
	{Average, Std} of travel speed	The speed is calculated using changes in latitude and longitude between two entries: $\sqrt{\left(\frac{lat_i - lat_{i-1}}{t_i - t_{i-1}}\right)^2 + \left(\frac{long_i - long_{i-1}}{t_i - t_{i-1}}\right)^2}$, where lat_i, $long_i$, and t_i are the latitude, longitude and time of i.
	Entropy	Measures how a participant's time was distributed over different location clusters, based on DBSCAN. Entropy of a location i is defined to be $-\sum_{i=1}^{N} p_i log(p_i)$, where p_i is the percentage of time spent at location i. N is the total number of location clusters.
	Home stay	Percentage of time spent at the home cluster.
	Work stay	Percentage of time spent at the work cluster.
	Public location stay	Percentage of time spent at public location clusters.
	Phone sessions	Number of times the phone screen is turned on.
Physical Activity	Percent of time {walking, running, biking, in a vehicle and still}.	
Screen Usage	{Total, Avg, Std} screen on	{Total, Average, Std} of percentage time screen on.
App Usage	Typing	Percentage of time the user types in a time window.
	Communication app usage	Percentage of time on messaging applications, e.g., Messenger, WhatsApp.
	Typing in communication app	Percentage of time people typing while using a communication application.
	Social app usage	Percentage of time on social media applications, e.g., Facebook, Instagram.
	Typing in social app usage	Percentage of time people typing while using a social media application.
	Call app usage	Percentage of time on call applications.
Call Log	Total call count	The sum of incoming and outgoing calls.
	{Average, Std} of call length	The {mean, std} of call lengths in a time window.
Message Log	Sent count	Number of messages sent out.
	Receive count	Number of messages received.
	LIWC scores	Scores calculated using LIWC [112] for all categories.
Audio	Voice percentage	Percentage of time microphone picks up voice.
	Noise percentage	Percentage of time the microphone picks up noise.
	{Average, Std} of audio energy	Average and standard deviation of the amplitude of audio sample (L2-norm of the audio frame).

TABLE 7.1: Features used to predict aspects of social interactions and their descriptions.

missing values. This allows us to keep the training samples with missing features while minimizing biases that other methods would yield, e.g., deleting missing values.

The second type of missing data is missing of all data for at least one data type, i.e., UI action. This was mostly due to older phones not having the memory or processing capability to keep the background data collection threads running. When this happened, the Android system killed the data collection threads so that the user could use their phone for other tasks. In Study 1 data, this happened to 6 participants. Since an entire data type is consistently missing, this violates the missing-at-random assumption for multivariate imputation. Therefore, we excluded these 6 participants' data in the prediction task for Study 1.

7.2 Results

7.2.1 Study 1 (Pilot)

With the remaining 29 participants from Study 1, there are a total of 2854 survey labels.

Performance Evaluation

To evaluate the prediction performance, we calculated precision, recall, F score, and kappa values. While accuracy is a common and standard measurement of performance, it is not a meaningful measurement for our data due to imbalanced classes in the data – always predicting the majority class will lead to a high accuracy. Since the classification task needs to identify the minority cases, e.g., phone-mediated interactions, I will report precision, recall, F1 scores, and Kappa instead of accuracy [81].

Precision measures the percent of positive classifications that are truly positive while recall reflects how much of the positive instances are correctly classified as positive. There is a trade-off between precision and recall. If an algorithm is very generous in its positive predictions (considering most cases to be positive), while the algorithm is more likely to correctly predict a lot of truly positive instances (high recall), the precision will be low because many truly negative cases will be falsely classified as positive. On the other hand, if an algorithm is very strict in its decision on whether a case is positive, e.g., unless the algorithm is absolutely certain of a positive case, it classifies the case as negative, the recall will be poor because few positive instances will be classified. However, the precision will be high. An ideal algorithm will try to maximize both precision and recall.

F-score combines both precision and recall scores and is a popular metric for imbalanced classes. In principle, a F-score is the harmonic mean of precision and recall scores, which tends to be closer to the smaller of the two [151]. Therefore, a high F-score indicates that both precision and recall are "reasonably high" [151].

Kappa (also Cohen's Kappa) was originally designed to assess the agreement between two raters. Different from the other measures, Kappa accounts for the accuracy that would be generated simply by chance [81]. A positive Kappa indicates performance higher than chance. Therefore, it serves as an additional check for our results.

Commonly, the class with very few training samples but high identification importance is referred to as the positive class. For our purposes, in-person interactions (vs. not in-person ones), phone-mediated interactions (vs. non-phone-mediated ones), and computer-mediated interactions (vs. non-computer mediated ones) contain fewer training samples than their counter-class and are more of my interest, therefore,

Interaction Medium	# Labels	% of Total Labels
In-Person	1298	45.48%
Phone-Mediated	415	14.54%
Computer-Mediated	87	3.05%
No Interaction	1054	36.93%

TABLE 7.2: Distribution of interactions over different media. Note that all of the labels have unbalanced number of cases per class.

they will be considered as the positive class. For the presence of interactions, as the goal of building a prediction model is to detect when a social interaction occurs, predicting the presence of one is of more importance. Therefore, I will treat having an interaction as a positive case even though it has more training samples than the negative classes.

Two different classification algorithms were used to evaluate the classification performance, selected based on [151]. The algorithms are Support Vector Machine (SVM) with polynomial kernel, and XG-boost.

To address the unbalanced class issue, SMOTE (Synthetic Minority Oversampling Technique) is used. SMOTE over-samples the class with fewer cases [23] by first randomly selecting a case A from the minority class and locating k of its nearest neighbors. Then, one of the neighbors B is randomly selected and a synthetic example is created at a randomly selected point between A and B in feature space. Running SMOTE on the training data will produce an unbiased classification algorithm.

Classification tests are reported on 10-fold cross-validation. Following results from paper [133], SMOTE is applied during each fold on the training set. This method, compared to re-sampling before cross-validation, produces more accuracy performance measures and less over-optimized results.

Interaction Medium Classification

The distributions of the responses for interaction medium are shown in Table 7.2.

A correlation analysis between the features and the interaction medium classes is plotted in Figure 7.1. Most of the features that are highly correlated with the phone-mediated class are Communication features from UI action data. For in-person interactions, both Context and Communication features are highly correlated with the class. Interestingly, the amount of time in public locations is positively associated with in-person interactions while time at home is negatively associated with it. This suggests that people are more likely to meet up with others in public than at home. Computer-mediated interactions are the least correlated with the features. This raises a slight concern as the features may not be very predictive of interactions happening over computers. Correlations for the no-interaction class shows a positive association with time spent at home. This indicates that people are more likely to spend time alone without socializing when at home. These correlations are confirmed when examining the distribution of the features for different mediums (Figure 7.2).

To benchmark the performance of different algorithms, we introduce a simple rule-based algorithm for medium. It is a good baseline to test if a complex model can yield a higher performance.

The rules we used for each prediction outcome is below. For this rule-based approach, we reduced the time window to 11 minutes. As the survey asked participants to report interactions up to 10 minutes

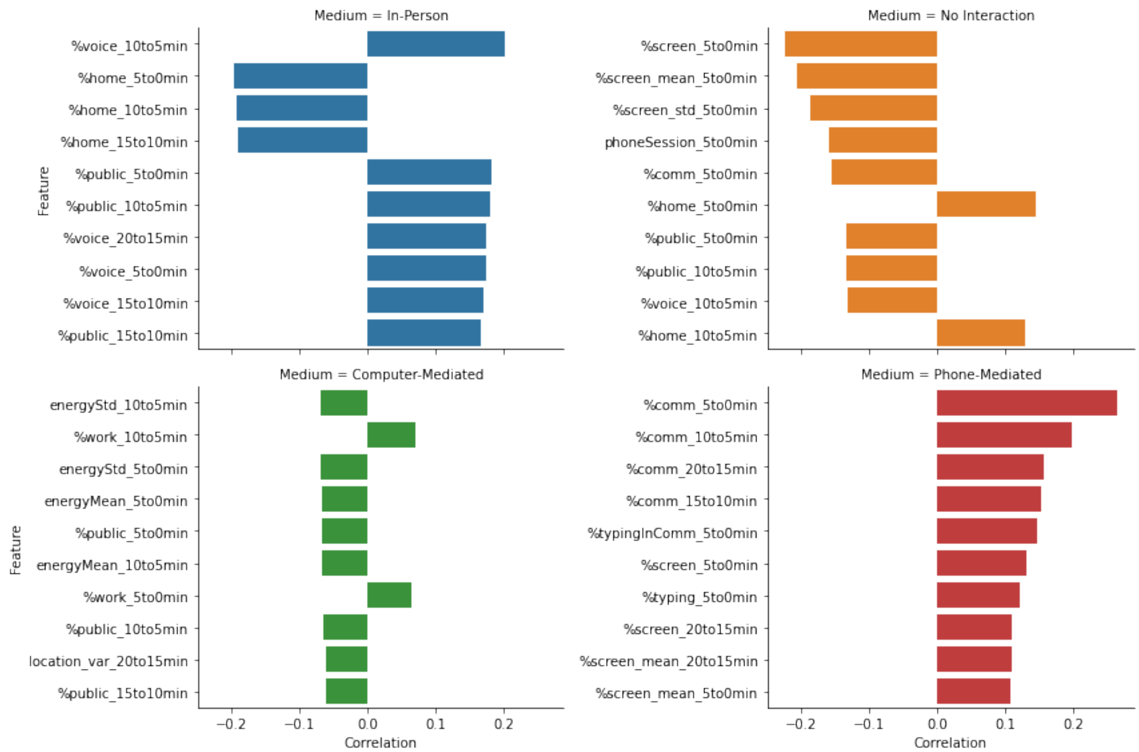

FIGURE 7.1: Top 10 most correlated features for each interaction medium. The name of the feature in the plots contains both the feature name and the time window where the feature was calculated from.

before the survey, setting the time window to 11 minutes allows detection of interactions that happen up to 10 minutes prior to the survey. In exploratory analyses, we found that having time windows larger than 11 minutes introduces noise and decreases classification performance.

In-person interactions. If there is an in-person interaction, there should be voice detected through the microphone during the time window. To eliminate voice detection due to noise or false positives of the conversation algorithm, there should be at least 5 seconds of voice present during the entire 11 minutes time window.

Phone-mediated interactions. If there is a phone-mediated interaction, at least one of the following things should be observed in the sensor data: 1) a call in the call log that is longer than 10 seconds. 10 seconds is determined to filter out answered spam calls or outgoing calls that were not picked up; 2) more than 1 sent messages; 3) typing in either a communication app or social app; 4) presence of call app usage longer than 10 seconds.

No interaction. The rules for classifying no interaction is the reverse of all rules above, i.e., 1) no voice detected through microphone during the time window that is longer than 5 seconds to eliminate voice detection due to noise; 2) there is a call in the call log that is longer than 10 seconds. 10 seconds is determined to remove answered spam calls or outgoing calls that were not picked up; 3) more than 1 sent messages; 4) typing in either a communication app or social app; 5) presence of call app usage longer than 10 seconds.

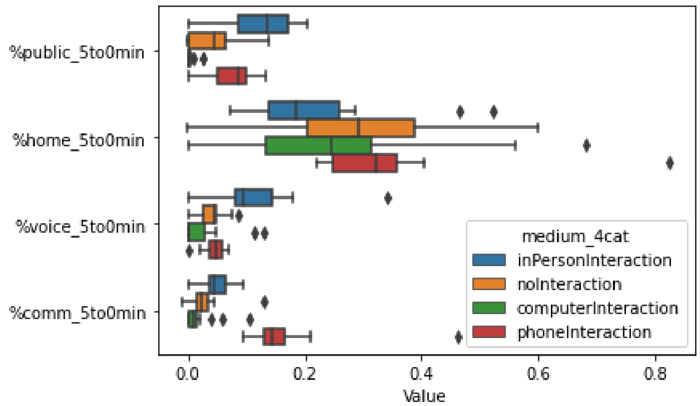

FIGURE 7.2: Distribution of the features by interaction medium.

Computer-mediated interactions. If the rule-based algorithm returns false for all of the 3 classes above, the label is categorized as a computer-mediated interaction.

Table 7.3 shows the results of the baseline and the 2 chosen algorithms, i.e., SVM and XGBoost.

XGBoost had the best performances for all classes compared to the baselines and other algorithms. For both SVM and XGBoost algorithms, adding the context features provides an increase in the predicting in-person interactions and no-interaction labels. This is consistent with the feature-label analysis earlier. For phone-mediated classes, on the other hand, context-features are not as crucial to performance.

Table 7.4 shows the confusion matrix of XGBoost, using all features. Low prediction performance of computer-mediated interactions is not surprising given that there are no clear data features that are uniquely predictive of these interactions. However, to my surprise, none of the models performed well in classifying phone-mediated interactions. Given our data collection is on people's primary cell-phones, the carriers of phone-mediated interactions, it should be expected to have good prediction results. I have 3 possible explanations.

First, participants tend to have more than 1 social interaction simultaneously. For example, among the 139 cases that were falsely classified as phone-mediated interactions but in reality are interactions over other media, 46 of them contain messages in message log, a call in the call log, or typing while in a communication app. This means that in addition to the reported interaction, the participants were having parallel phone-mediated interactions. Similarly, out of the 152 phone-mediated interactions that were falsely categorized as in-person interactions, there are 23 cases that contain voice in the audio recordings. Future surveys should account for these simultaneous interactions. However, researchers should be aware that asking participants to report all of their interactions in a time window will bring more burden to the participants.

Second, the conversation algorithm that we use cannot finely differentiate between voices from other people (e.g., when in public), sound from the phone while playing a video or music and a conversation from the participants. In the results, 53 instances of the 152 error cases where phone-interactions are mis-predicted as in-person interactions occurred either while in public or while the participant was using a video player, e.g., YouTube, or a music player. This also accounts for 108 of the 322 no interactions being mis-classified as in-person interactions. Improving the accuracy of the conversation algorithm,

Algorithm	Class	Time	Context	Comm	Time+Comm	All
Baseline (Rule)	In-Person	- / -	- / -	0.46 / 0.44	- / -	- / -
		-	-	0.45	-	-
	Phone-Mediated	- / -	- / -	0.25 / 0.48	- / -	- / -
		-	-	0.33	-	-
	Computer-Med	- / -	- / -	0.52 / 0.38	- / -	- / -
		-	-	0.44	-	-
	No Interaction	- / -	- / -	0.32 / 0.29	- / -	- / -
		-	-	0.31	-	-
	Kappa	-	-	0.18	-	-
SVM	In-Person	0.41 / 0.24	0.58 / 0.26	0.65 / 0.16	0.63 / 0.17	0.62 / 0.27
		0.30	0.36	0.26	0.27	0.37
	Phone-Mediated	0.13 / 0.21	0.22 / 0.27	0.34 / 0.19	0.32 / 0.19	0.28 / 0.22
		0.16	0.24	0.24	0.24	0.25
	Computer-Med	0.03 / 0.25	0.04 / 0.32	0.05 / 0.56	0.06 / 0.54	0.05 / 0.47
		0.06	0.07	0.09	0.10	0.09
	No Interaction	0.39 / 0.29	0.47 / 0.47	0.41 / 0.51	0.43 / 0.57	0.47 / 0.52
		0.33	0.47	0.46	0.49	0.49
	Kappa	-0.00	0.11	0.06	0.08	0.13
XGBoost	In-Person	0.38 / 0.18	0.57 / 0.37	0.59 / 0.31	0.57 / 0.34	0.62 / 0.36
		0.24	0.45	0.41	0.43	0.46
	Phone-Mediated	0.14 / 0.25	0.20 / 0.32	0.24 / 0.52	0.25 / 0.54	0.28 / 0.53
		0.18	0.25	0.33	0.35	0.37
	Computer-Med	0.03 / 0.25	0.04 / 0.28	0.04 / 0.30	0.04 / 0.28	0.06 / 0.36
		0.05	0.07	0.08	0.08	0.10
	No Interaction	0.37 / 0.25	0.48 / 0.36	0.48 / 0.31	0.52 / 0.32	0.51 / 0.38
		0.30	0.41	0.37	0.40	0.43
	Kappa	-0.02	0.11	0.12	0.13	0.17

TABLE 7.3: Precision, recall, F-Score, and Kappa of predicting interaction medium of the baseline and 3 selected algorithms, i.e., SVM and XGBoost, using different combination of features. Each cell shows the precision (top left), recall (top right), F1 scores (bottom 1), and Kappa. Note that since this is a multi-class classification, there is one Kappa value per model.

	In-Person	Phone-Mediated	Computer-Mediated	No Interaction
In-Person	821	132	4	341
Phone-Mediated	152	140	2	121
Computer-Mediated	31	7	2	47
No Interaction	322	125	9	598

TABLE 7.4: The confusion matrix (row: actual, column: predicted) for predicting different interaction medium.

for example, integrating speaker-identification, can improve the accuracy for the predictions of phone-mediated interactions.

Third, there were 41 instances where participants sent a small handful of messages (according to the message log), made short phone calls, or typed in a messaging app, but these interactions were not reported. This accounts for approximately one-third of the 125 error cases where the model predicts a phone-mediated interaction but no interaction was reported. Two reasons may be behind this. One is that participants made a mistake while reporting their social interactions, either because they did not recall the interaction or did not catch their mistake before submitting the response. Another possibility is that participants did not consider short digital exchanges as a social interaction, e.g., sending messages without a response. Refining a clearer definition of a social interaction, e.g., a back-and-forth exchange (both synchronous and asynchronous), may improve the quality of labels and the performance of prediction models.

Related to this point, people have different patterns of using messaging and social-media apps, which makes it difficult to operationalize phone-mediated interactions. For instance, while examining the 121 instances where a phone-mediated interactions were falsely predicted as no interaction, the majority of these cases contain UI action data that suggests people using messaging and social media apps without typing any content (e.g., scrolling through old messages).

Beyond phone-based interactions, another major type of mis-classification is in-person interactions being predicted as no interaction. A main cause is that the phone was not with the participants. Out of the 341 errors, 96 of them contained no voice in the recorded audio during the 20 minute window before the survey. As co-location of the phone and the user is critical to the success of the prediction of social interactions, this poses a constraint on the prediction task. To address this, smart watches may be a good wearable device to use to capture the data.

Interaction Partner Classification

As previous analysis showed the importance of interactions with close ties (see Chapter 4 and Chapter 9), classification of interaction partners focused on classifying people as either a close tie or a non-close tie. As many interactions involved both close and non-close ties, we trained 2 separate binary models for each label. Table 7.5 shows the distribution of the 2 types of interaction partners we tried to predict. As the prediction for interaction medium, both XGBoost and SVM were tested. There was no baseline no clear rule existed for categorizing close and non-close ties. Test performance for various features combinations and the 2 algorithms is shown in Table 7.6.

Interaction Partner	# Labels	% of Total Labels
Close tie	757	42.01%
Non-close tie	1344	74.58%

TABLE 7.5: Distribution of interactions partners. Similar to interaction medium, all classes have unbalanced number of cases per class. The sum exceeds 100% as both close and non-close ties could be present in the same interaction.

Algorithm	Class	Time	Context	Comm	Time+Comm	All
XGBoost	Close Tie	0.52 | 0.64	0.44 | 0.40	0.42 | 0.39	0.49 | 0.47	0.49 | 0.46
		F: 0.57	F: 0.42	F: 0.40	F: 0.48	F: 0.47
		K: 0.20	K: 0.06	K: -0.04	K: 0.09	K: 0.10
	Non-Close Tie	0.78 | 0.50	0.75 | 0.82	0.74 | 0.73	0.77 | 0.81	0.76 | 0.86
		F: 0.61	F: 0.78	F: 0.74	F: 0.79	F: 0.81
		K: 0.07	K: 0.05	K: 0.02	K: 0.09	K: 0.09
SVM	Close Tie	0.52 | 0.65	0.47 | 0.51	0.46 | 0.34	0.51 | 0.63	0.51 | 0.55
		F: 0.58	F: 0.49	F: 0.39	F: 0.56	F: 0.53
		K: 0.21	K: 0.11	K: 0.01	K: 0.17	K: 0.19
	Non-Close Tie	0.79 | 0.51	0.77 | 0.63	0.78 | 0.43	0.79 | 0.61	0.77 | 0.64
		F: 0.62	F: 0.69	F: 0.55	F: 0.69	F: 0.70
		K: 0.08	K: 0.10	K: 0.05	K: 0.09	K: 0.07

TABLE 7.6: Precision, recall, F-Score, and Kappa of predicting interaction partners using SVM and XGBoost, using different combination of features. Each cell shows the precision (top left), recall (top right), F1 score (bottom) and Kappa (bottom).

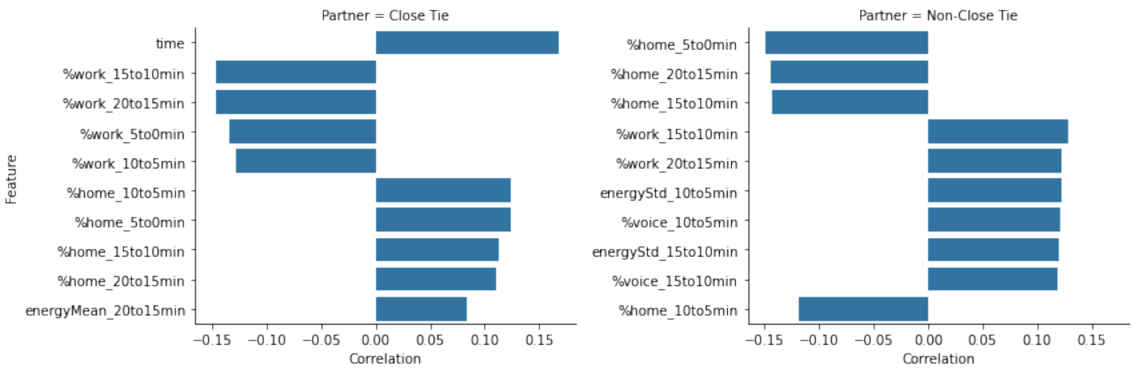

FIGURE 7.3: Top 10 correlations between of all features and interaction partner. Time feature is the most correlated with interactions with a close tie while interactions with non-close ties are mostly correlated with location-based features (Context features).

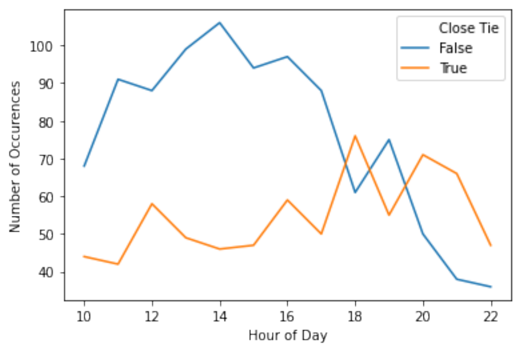

FIGURE 7.4: Number of interactions happening with a close tie or not with a close tie throughout the course of a day. Interactions that happen during the day are much more likely to not involve a close tie.

For both categories, SVM and XGBoost performed similarly, with SVM having slightly better performance (measured by higher Kappa). For close tie, time features alone, i.e., time of the day and day of the week, had the highest performance. Correlation between the features and the class showed that for close tie, time feature is the most correlated among all features, followed by mostly location-based features (Figure 7.3). A breakdown of how many interactions occur throughout a day by whether the interaction is with a close tie (Figure 7.4) indicate that interactions during the day are much less likely to involve a close tie while interactions after 8 pm show the opposite trend. This explains the high importance of Time features.

For non-close ties, context variables alone showed highest Kappa score. Correlation between the features and the class (Figure 7.3) indicated that time spent at work and home are the highest correlated features with interactions with non-close partners. In addition, audio features, e.g., standard deviation of audio energy, were also highly correlated with non-close partners.

The prediction performance of partner type is far from ideal and useful in a real-world setting. However, it is worth noting that both prediction models performed much better than chance, suggesting that there are valuable features in the phone sensor data.

Interaction Activity	# Labels	% of Total Labels
Having a conversation	1254	80.44%
Sharing a meal	147	9.43%

TABLE 7.7: Numbers of talk and sharing a meal. Both classes have unbalanced number of cases per class.

Algorithm	Class	Time		Context		Comm		Time+Comm		All	
XGBoost	Having a conversation	0.82	0.55	0.81	0.90	0.80	0.83	0.81	0.86	0.81	0.93
		F: 0.66		F: 0.85		F: 0.82		F: 0.83		F: 0.86	
		K: 0.05		K: 0.08		K: 0.09		K: 0.10		K: 0.03	
	Sharing a meal	0.11	0.49	0.23	0.14	0.19	0.16	0.20	0.14	0.24	0.09
		F: 0.18		F: 0.17		F: 0.18		F: 0.16		F: 0.13	
		K: 0.04		K: 0.07		K: 0.11		K: 0.09		K: 0.08	
SVM	Having a conversation	0.82	0.54	0.13	0.37	0.85	0.44	0.13	0.37	0.14	0.34
		F: 0.66		F: 0.19		F: 0.58		F: 0.19		F: 0.20	
		K: 0.05		K: 0.05		K: 0.06		K: 0.07		K: 0.09	
	Sharing a meal	0.11	0.53	0.16	0.36	0.17	0.36	0.23	0.31	0.24	0.23
		F: 0.18		F: 0.22		F: 0.23		F: 0.69		F: 0.74	
		K: 0.05		K: 0.07		K: 0.11		K: 0.08		K: 0.10	

TABLE 7.8: Precision, recall, F-Score, and Kappa of predicting interaction activity, specifically having a conversation and meal sharing using 3 selected algorithms, i.e., SVM and XGBoost, using different combination of features. Each cell shows the precision (top left), recall (top right), F1 score (bottom), and Kappa (bottom.

Interaction Activity Classification

As prediction performance for medium and partner type was not ideal, for interaction activity, I only focused on 2 activities, conversation and meal-sharing. Conversation was the most frequently reported activity. Meal-sharing, which happens less frequently than study/work session, has shown to have a significant impact on well-being in Chapter 9. Therefore, I decided to try predicting joint meals. The number of positive cases for these two activities are shown in Table 7.7. XGBoost and SVM were tested on the same combinations of features as the previous two prediction tasks. Prediction results are shown in Table 7.8.

Prediction performance is generally similar for both classes, using either algorithm. The Kappa value ranged between 0.03 to 0.11, showing that the prediction is far from ideal. Unsurprisingly, Communication features produced the top performances. However, it is surprising that the prediction performance for having a conversation is so poor, considering that audio features from the microphone data collected, which should directly reflect whether a person is engaged in a conversation.

Three reasons may have contributed to this. First, the "conversation" category contains both in-person talking (842 instances) and communication on the phone, e.g., messages (340 instances). Features that are predictive of these two separate types of conversations are very different. Audio recordings are probably

Study 3		
Interaction Medium	# Labels	% of Total Labels
In-Person	1795	23.71%
Phone-Mediated	801	10.58%
Computer-Mediated	664	8.77%
No Interaction	4311	56.94%

TABLE 7.9: Distribution of interactions over different media. Note that all of the labels have unbalanced number of cases per class.

more useful for in-person conversations while UI action, message, and call features are more critical for messaging or phone call. The models may have a difficult time combining these two types of features into a consistent prediction result.

The phone being not co-located with the user was another main reason for prediction error. Of the prediction errors for the conversation, using SVM and Time and Communication features, there were 359 error cases where a reported in-person interaction with a conversation was not correctly being predicted as such. Out of these cases, 150 of them contained no conversation (but still had audio data). This indicates that the data collection app was working, however, the phone was not around the user.

Moreover, there were 127 cases where there is no conversation reported by the participant but the algorithm falsely thought that there was. Among these cases, two main causes may be 1) environment noise captured by the microphone being mis-characterized as human conversations or conversations from other people in the shared public space (38 instances) or 2) the user was playing a video or audio that was captured by the microphone (14 instances).

7.2.2 Study 2 (6-Week National Sample)

Machine-learning tasks were replicated for Study 2 as they were done for Study 1. A total of 38 participants were included in the training and testing data. These participants contributed a total of 7578 survey labels. The same sets of machine learning features were calculated as in the previous study. For study 3, we only replicated the models for predicting interaction medium, i.e., in-person, phone, computer, or no interaction. The prediction result, as shown below, was suffering from the same issues as pointed out in Study 1. But due to the pandemic, the issues that were brought up in Study 1 were further exaggerated and confirmed in Study 2.

As the details of the machine learning pipeline is identical to that of the previous section, I will not reiterate.

Interaction Medium

Table 7.9 shows the distribution of the interaction medium in the machine-learning data set.

While XGBoost with all features used still performs the best, as shown in Study 1, the overall performance has decreased (Kappa was 0.17 for Study 1 and was 0.13 for Study 2). In particular, the precision of in-person interactions and recall of phone-mediated have dropped by a lot (precision of in-person interaction was 0.62 for Study 1 and was 0.39 for Study 2; recall for phone-mediated interaction was 0.53 for Study 1 and was 0.21 in Study 2). This means that among the cases that Study 2 model labelled as

Algorithm	Class	Time		Context		Comm		Time+Comm		All	
Baseline (Rule)	In-Person	-	-	-	-	0.11	0.32	-	-	-	-
		-		-		0.16		-		-	
	Phone-Mediated	-	-	-	-	0.43	0.28	-	-	-	-
		-		-		0.34		-		-	
	Computer-Med	-	-	-	-	0.21	0.08	-	-	-	-
		-		-		0.11		-		-	
	No Interaction	-	-	-	-	0.54	0.59	-	-	-	-
		-		-		0.57		-		-	
	Kappa	-		-		0.07		-		-	
SVM	In-Person	0.27	0.47	0.35	0.29	0.27	0.51	0.31	0.44	0.36	0.38
		0.34		0.32		0.35		0.37		0.37	
	Phone-Mediated	0.09	0.06	0.12	0.16	0.28	0.37	0.26	0.34	0.25	0.33
		0.08		0.13		0.32		0.30		0.28	
	Computer-Med	0.13	0.64	0.12	0.23	0.06	0.15	0.11	0.44	0.12	0.35
		0.21		0.15		0.09		0.18		0.18	
	No Interaction	0.58	0.08	0.67	0.58	0.67	0.23	0.67	0.21	0.68	0.41
		0.14		0.62		0.34		0.32		0.51	
	Kappa	0.04		0.08		0.04		0.08		0.09	
XGBoost	In-Person	0.27	0.45	0.39	0.35	0.30	0.28	0.34	0.32	0.39	0.33
		0.34		0.37		0.29		0.33		0.36	
	Phone-Mediated	0.09	0.13	0.13	0.32	0.21	0.37	0.20	0.32	0.21	0.21
		0.11		0.13		0.26		0.25		0.21	
	Computer-Med	0.13	0.52	0.11	0.11	0.08	0.11	0.11	0.13	0.11	0.08
		0.21		0.11		0.09		0.12		0.09	
	No Interaction	0.62	0.11	0.64	0.67	0.64	0.53	0.62	0.56	0.65	0.72
		0.19		0.66		0.58		0.59		0.68	
	Kappa	0.04		0.08		0.07		0.06		0.12	

TABLE 7.10: Precision, recall, F-Score, and Kappa of predicting interaction medium of the baseline and 3 selected algorithms, i.e., SVM and XGBoost, using different combination of features. Each cell shows the precision (top left), recall (top right), F1 scores (bottom 1), and Kappa. Note that since this is a multi-class classification, there is one Kappa value per model.

	In-Person	Phone-Mediated	Computer-Mediated	No Interaction
In-Person	588	165	199	843
Phone-Mediated	133	174	37	457
Computer-Mediated	187	85	49	343
No Interaction	598	429	174	3110

TABLE 7.11: Study 3: The confusion matrix (row: actual, column: predicted) for predicting different interaction medium.

in-person interaction, a significantly small portion of these were actual in-person interactions, compared to the Study 1 result. The model for Study 2 was much less precise at identifying in-person interactions than the model for Study 1. For phone-mediated interactions, among all reported phone-mediated interactions, the model for Study 2 only correctly labeled half as many of these interactions as the model for Study 1. We hypothesize that the decrease in performance may be a result of participants not carrying their phone with them as they were staying in-doors during the pandemic.

This is confirmed when examining closely the confusion matrix (Table 7.11). Out of the 843 in-person interactions that were faultily labelled as no interaction, 589 of these cases (70%) was due to lack of voice in the audio recording data, suggesting that the phone was not around the user when they had the in-person interaction. This is a significant increase from Study 1, where 96 out of 341 (28%) was due to this reason.

Another evidence that supports this hypothesis is that %voice feature, which was highly correlated with in-person interactions in Study 1, was no longer so in Study 2 (Figure 7.5). Instead, percent of time the screen was on became one of the top correlated features as when the screen was on, the phone was much more likely to be with the user and hence could pick up useful data on surroundings. Therefore, in Study 2, due to people staying at home, they did not bring their phones with them when they moved around and interacted with others. This meant that the phones no longer had access to the useful data that provided information on their social interactions.

7.3 Discussion

This chapter showed unsatisfactory prediction results for predicting medium of interaction, whether an interaction partner is a close or non-close tie, and what type of activity is involved in the interaction. Three main reasons have contributed to the prediction performance. First, participants did not physically have their phone with them all the time. This means there are gaps in the sensed data where the data are not indicative of the users' behavior. This was observed to a greater extent in Study 3, where many participants were mostly staying at home. Furthermore, there were inaccuracies in the survey reports where when participants had simultaneous interactions, they only reported one of them. This could either be due to forgetting to report the concurrent interactions or not considering brief exchanges as an interaction. The third reason for less-than-ideal prediction performance was due to limitations in the conversation algorithm. In cases where the phone was in the pocket or in a bag, the conversation detection accuracy dropped. In addition, the conversation algorithm could not well distinguish between audio

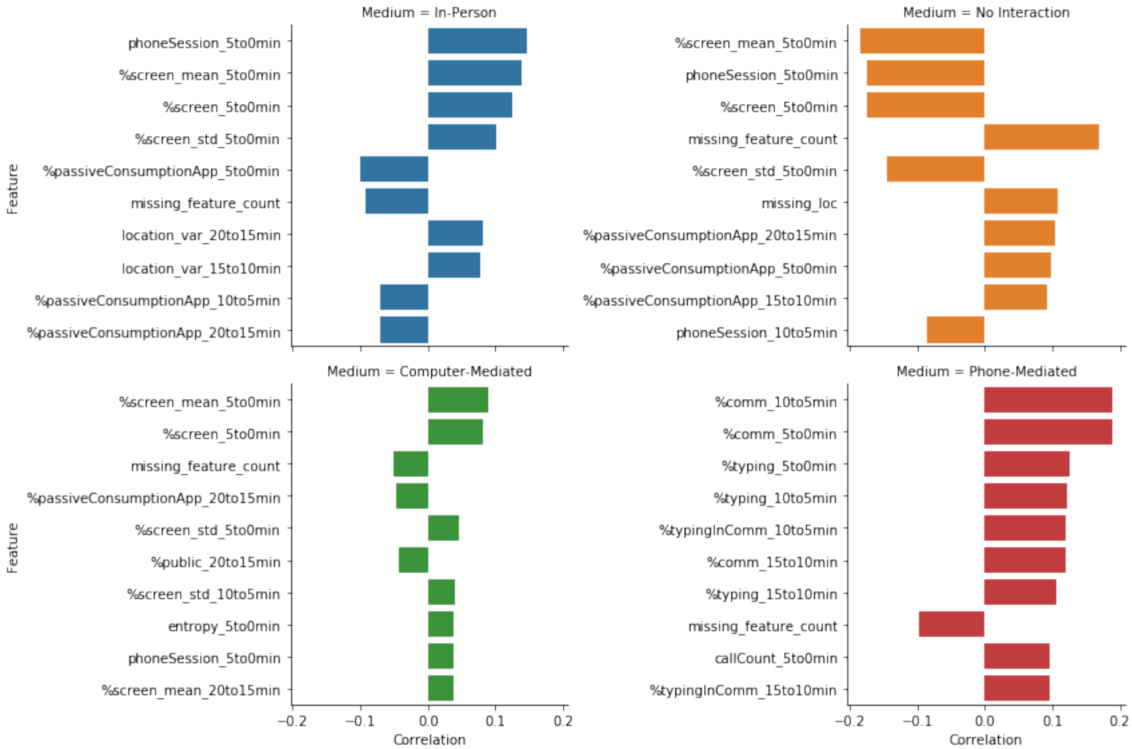

FIGURE 7.5: Study 3: Top 10 most correlated features for each interaction medium. The name of the feature in the plots contains both the feature name and the time window where the feature was calculated from.

generated by people vs by devices, e.g., video playing on the phone. These limit the overall accuracy of the interaction prediction as conversation data were critical to the overall performance.

While the machine learning models performed far from ideal, there are some lessons that may be useful for future researchers.

A need for more forms of sensors.

For the purpose of improving prediction performance, both results for Study 1 and, in particular, Study 2 suggest the need for a sensor (in addition to or to replace mobile phones) that either stays with the user throughout the day, e.g., smartwatches, or can be present to capture behavioral data when the user does not have their personal devices , e.g., a room-scale sensor. By combining sensors of more forms, it will guarantee continuous data collection of one's close surroundings without relying on the user carrying their phones with them. However, this can pose a challenge to using sensor data to predict social interactions — as much of the data can contain sensitive information, such as microphone data, having a sensor that is with the user all the time and that is on throughout the day can raise significant privacy concerns. Development of anonymous conversation detectors, e.g., [169, 168], can help alleviate this concern.

Another helpful feature to implement in the future data collection tool is a "heartbeat" data signal the status of the app. It was observed in both studies that from time to time data collection would stop working. Since the data collection thread was not associated with the interface part of the app, participants may not be aware of the crash. Therefore, data was not collected for a period of time until it was caught and the app was restarted. One way to address this is to have a separate processing thread to check that if the data collection is running periodically and logs the status every five or ten minutes. If it detects that the app has stopped, it can prompt the users to restart the data collection. In addition, the heartbeat log can help researchers to determine if missing gaps in data are a result of app crash or an inactive user.

Determining operational definitions of social interaction for mobile sensing.

One challenge encountered in the current work is determining what a phone-based social interaction would look like from the digital traces they left behind. For instance, if a user messaged someone on their phone, from the data perspective, one would expect to see that the screen was on and a messaging app was used, followed by some tapping actions (for typing). However, in reality, it is more complicated. For one, as UI Action data only registers tapping action and not the content of tapping (for security reasons), the same sequence of actions above could also be someone looking through their message log to find old information, e.g., an address or a photo. To a researcher and a machine learning algorithm, the actions may look identical but one signalled a social interaction and one did not. Another challenge to operationalizing social interactions using mobile sensed data is that there are many forms of interactions that can take place on the phone and their data traces may look very different, e.g., messaging, taking a voice call, playing a collaborative game on the phone, etc. Therefore, determining a set of definitions to operationalize social interactions, specifically phone-mediated ones, is a challenge that needs to be resolved.

What would be an ideal performance for deployment?

One point worth-discussing is what an ideal performance is for a social-interaction detection system to be deployed in-the-wild. While a 100% accuracy is not possible and is not necessary, the system should have a high recall rate so that it can capture the interactions. In Study 2, we down-sample the surveys from 21 from Study 1 to 8 a day (40% of that for Study 1), which provided useful data to learn about one's social interactions. If a system can sample at least the same amount of social interactions (40% of the social interactions) without the users frequent self-report, the system can help researchers collect usable and rich data to learn about impact of social interactions. However, this should not be done at the expense of precision. With a decent precision, it is possible to ask the users to manually confirm a portion of the predictions. But a low precision would create distrust and cause frustration.

Considerations for survey design to collect more accurate labels.

Another observation from the study was that participants had the tendency to report interactions that they remember or to overlook short interactions that occur on the phone. While this is difficult to avoid, having the survey designed differently can make it easier for participants to report their social interactions. In fact, having a deployed social interaction detection system running in the background, predicting social interactions in real-time, and prompting users to confirm its predicted results can greatly help alleviate the burden of the participants who currently need to remember to fill out the survey and have to fill out all items manually. These prediction confirmations may also capture and prompt users with social interactions that the users may otherwise have missed to report, e.g., a quick message reply. Another idea is to design the surveys so that participants can actively submit responses after having a social interaction rather than waiting for them to be prompted. Having the option to proactively submit responses immediately after the end of the interaction can help increase reports of shorter interactions.

As co-occurrences of social interactions was also commonly observed in the current studies, having a confirmation screen asking participants to confirm their responses and that there are no other social interactions happening at the same time can prevent this. In addition, the setup of the surveys in the current studies did not support reporting co-occurring interactions. Having separate survey question screens for each individual interaction can help prompt participants to report all interactions that they have had in the requested time period.

Other possibilities for mobile sensing of social interactions

While the current work only attempted to predict interaction medium, partners, and 2 types of the activities, there are many other interaction details that can be predicted using mobile sensed data. One is support gestures. As previous chapters highlight the importance of support gestures, being able to sense these gestures will be particularly of value. This may be done using affect detection of tones in audio signals [66, 16, 44]. For example, highly positive affect in tones may be associated with supportive gestures. Sequence of screen actions may also suggest certain support behaviors. For instance, jumping back and forth between a messaging app and a browser app may indicate a person looking up information, which may be a gesture of helping offer useful information for other people through messaging.

There are other future research directions that can greatly help sense interaction details. First is more advanced conversation detectors that can function when the audio sensor, e.g., mobile phones, is in users' pockets or not in the open. Such a detector will allow more accurate conversation detection and even speaker detection when the sensor is at suboptimal places, which is typical in everyday use of mobile phones. Another key direction is speaker detection in a privacy-conserving fashion. Such a speaker detection does not need to distinguish between every individual. It is sufficient to distinguish between close ties and non-close ties as earlier chapters showed the importance of interactions with close ties. In addition, it is possible to use meta data, such as type of location based on Google Maps information, to help infer people's social interaction details. For example, Google or Yelp typically have customer reviews of restaurants, coffee shops, and other public places. By using the verbal reviews, it may be possible to uncover keywords, e.g., eating here with a good friend, which suggests a place is likely to be a social location. In addition, these keywords can be used to infer what the popular activities are done, e.g., rock climbing, dining, karaoke, etc, which can be integrated into models that predict interaction activity. Leveraging these available data can help with model performance without additional inputs from participants. Another potential direction to explore is action-based partner interaction, predicting interaction partners based on the app usage pattern of the mobile phone, e.g., certain partners are more likely to communicate using Facebook Messenger while others are more likely to occur over phone calls.

Chapter 8

Discussion

In summary, this dissertation examines, at an interaction-level, how one's daily social interactions affect their well-being at the end of a day. Specifically, the dissertation focused on the effect of what happens during the interaction (interaction details) and how people feel about the interaction (subjective experience). Through three longitudinal studies, the thesis illustrates the importance of one's social interactions at a micro-level, as well as their subjective experience of the interactions. A summary of all findings is listed in Table 8.1. Below, I discuss general lessons learned from the current dissertation for future researchers.

8.1 Interaction details and well-being

The fundamental question that the current thesis addressed is whether interaction details can affect the experience outcome of the interaction and to demonstrate a pathway that these details can affect well-being, through the subjective experience outcome. In another word, one's daily social interactions impact their well-being by influencing how positive and negative their interactions were. Even though the work is not experimental in nature, the analyses implicitly controlled for the temporal order of the events, i.e., examining how interactions that occurred before well-being reports are associated with the reports. The fact that the social interactions happened prior to the well-being reports allows us to speculate the pathway from social interactions to well-being, i.e., certain social interactions (e.g., with exchanges of support and joint activities) **promote** better well-being at the end of the day by influencing the subjective experience.

So how does the pathway proposed by the current thesis fit in what existing work have theorized about how social interactions affect health? First, the current work did not differentiate between stressful vs. non-stressful situations, which is what a majority part of literature has focused on, e.g., stress-buffering theory [34]. This means that the pathway of "interaction details - subjective experience outcome - well-being" (or "interaction details - well-being" directly) function in general-context settings, regardless of one's stress level. This is more in-line with Thoit's argument that " 'everyday' support intervenes in the social ties to health relationship" ([154], p.151). The pathway in the current thesis supports this argument in that everyday social interactions can have an impact on one's well-being, both directly or indirectly. As social interactions are small instantiations of a social tie, this pathway can possibly explain why social ties affect health.

Furthermore, operating under general-context settings, the pathway between interaction details and well-being can be explained by other mechanisms proposed by Thoit [154]. For example, one hypothesized mechanism that social ties influence health is through a sense of belonging and companionship. Social ties signal a sense of "being a part of a group", which enhances physical and psychological well-being. While the current thesis did not examine these two concepts, it is possible that people cultivate a sense of acceptance and belonging through positive interactions, or experience a loss of acceptance after

Research Question	Key Finding
RQ1: Interaction details and subjective experience	- Interaction details better predict positive interactions than negative interactions. - Exchange of emotional and tangible support is a strong predictor of positive interactions. - Interactions with close ties, longer interactions, and joint activities are strong predictors of positive interactions. - Where interactions occur and what medium they occur on are not strong predictors of either positive or negative interactions.
RQ2: Subjective experience and well-being	- Subjective experiences of social interactions affect both positive and negative well-being, with a stronger effect for positive well-being. - Days with more positive interactions are associated with better well-being and days with more negative interactions are associated with poorer well-being. - Positive interactions from the previous day are associated with lower loneliness and higher thriving on the current day. However, this effect is less strong compared to the effect of current-day positive interactions on current-day well-being. - Negative interactions from the previous day are not associated with current-day well-being. - People who generally experience more positive interactions report better well-being and people who generally experience more negative interactions report poorer well-being.
RQ3: Pathways between interaction details, subjective experience, and well-being	- Interaction details, especially support exchange and joint activities, have indirect effects on well-being, mediated by positive interactions. - Social interactions where there are exchanges of social support have a direct effect on well-being. - Quantity of interactions, i.e., having more interactions, is associated with poorer well-being while interaction details are associated with better well-being.
Predicting social interactions with mobile sensing	- While prediction performance for interaction medium, interaction partner, and interaction activity was not ideal, it was above chance, suggesting that there is useful information in mobile sensing data for predicting social interactions. - Three key challenges identified are: - Users do not carry their phones with them all the time; - Concurrent interactions were not all being reported; - Conversation detection algorithm under-performs when the phone is in pocket or bag and when there is voice from a media player.

TABLE 8.1: A high-level summary of all findings from the thesis work.

having a negative interaction. This increase and decrease of belonging, as a result of having positive and negative interactions, may explain the pathway outlined in the current work. Another possible mechanism that the current pathway supports is perceived social support [155]. Positive interactions can signal, and even deliver, social support while negative interactions can suggest that less support is available in case it is needed. Through various positive and negative interactions, one may have an internal sense of how much support is available to them. This perceived level of available support mediates the relationships between social ties and various health measures. Therefore, the current pathway may be explained by the hypothesized mechanism of social support.

In general, the finding in the thesis that interaction details can both directly influence well-being and indirectly influence well-being through affecting people's subjective experiences of the interactions presents a novel alternative explanation for how social ties affect well-being. It contributes confirming evidence for some mechanisms hypothesized by existing literature.

8.2 Each individual interactions can have a downstream impact on well-being: Design implications

One of the key contributions of the current work is the focus on each instance of social interactions. The work highlights the critical role of emotional support behaviors during a specific instance of social interaction on end-of-day well-being. It also showed evidence that shared activities, like dining together, can also impact one's well-being.

These findings carry practical implications on what one can do to increase one's well-being. While the current work is not causational, it sheds light on concrete types of interactions that one can cultivate and are associated with improved well-being. First, for individuals who are interested in their well-being, they can pay more attention to the types of social interactions they have in a day. Providing more emotional support and arranging social interactions that involve more than a simple conversation are simple changes one can make in their daily-lives that can affect their general well-being.

For designers and innovators, there are interesting design implications of the work. While most existing technologies are created with the concept of relationships (e.g., messages are grouped by contacts, social media pages are displayed by user), it could be interesting to design around interactions. For example, chat interfaces could be visually grouped by a "session", a sequence of continuous back-and-forth exchanges. During a "session", interfaces can support specific behaviors that are beneficial, such as recommending fun activities for interaction partners to do or suggest supportive gestures and phrases when support is needed. When a session ends, the session can be shown as a single item so that people can revisit a positive interaction (or session) or a negative but memorable one. These design considerations around a single interaction can help people be more aware of their social interactions and have the potential positive influence on people's well-being.

In addition, for researchers, the current dissertation showed the value of studying the impact of social relationships at the level of a single interaction. While the current work has addressed some fundamental questions, e.g., what makes an interaction positive and negative, there are more questions unanswered. For instance, the current dissertation did not touch upon the effect of interactions on mood, which can also influence one's perception of the interaction outcome [162, 163]. In one of our exploratory analyses not included in the document, we found some evidence that one's perceived closeness of a partner may vary as a result of the interaction, e.g., a good and positive interaction is associated with higher closeness between two people, despite of how close they are before the interaction. This is an intriguing finding that the current thesis did not dive deeper in. But hopefully more future studies can confirm this observation.

8.3 Effect of Pandemic on the Study Results

It is important to address the elephant in the room. The thesis overlapped with the onset and continuation of the Coronavirus pandemic that dramatically changed people's lives across the world. Not surprisingly, our study collection was also affected by the pandemic. wThere are some key differences in our data that are likely to be a result of the pandemic. For example, Chapter 3 mentioned the high amount of in-person interactions in Study 2 and 3, compared to Study 1, as well as a dramatic increase in the proportion of interactions being at home in Study 2 and 3 (compared to Study 1). Similarly, more interactions reported in Study 2 and Study 3 were with close ties than Study 1. This may be a result of people staying at home because of the pandemic, limiting the interaction partners to those participants were close with.

However, despite changes in the kinds of interactions that people were having, i.e., interactions with different interaction details, the effect that interaction details have on subjective experience and the effect of subjective experience on well-being are consistent across the three studies. This strongly suggests that, despite the pandemic and its effect on people's lives, the majority of the findings of this thesis on the relationships between social interactions, subjective experience, and well-being remain the same.

There is an exception, which is the findings in Chapter 5 on the mediation effect of social interaction details on well-being. Between Study 2 and 3, there are discrepancies in the findings. For example, Study 2 showed a significant and direct effect of tangible support on loneliness, which is not present in Study 3. Similarly, Study 3 had a significant direct effect of emotional support on loneliness, which is not significant in Study 2. In addition, Study 3 analysis showed significant indirect effects of many interaction details that were mediated by positive interactions. However, the same analysis on Study 2 data showed no significant indirect effect mediated by positive interactions. It is not clear whether the pandemic is the cause of the difference between these finding differences as the two studies also differed in sample size and population — it is possible that the lack of indirect effects seen in Study 2 is a result of lack of power or the presence of effect in Study 3 is due to the more nationally represented population. Unfortunately, the current thesis cannot draw a conclusion on the role of pandemic for these findings.

8.4 Positive, Negative, And Meaningful Interactions

While the main focus of the thesis is on the positive and negative interactions, some of the findings mirror a recent paper published by Litt and colleagues on meaningful interactions [90], e.g., the importance of interaction partner and activity and the lack of effect of medium. This prompts a few interesting future research questions. First, what is the relationship between positive, negative, and meaningful interactions? How do meaningful interactions affect well-being? Are there other variables beyond these three that may have a mediating role between interaction detail and well-being?

First, a meaningful interaction are those that are of higher quality [62] and may contain both positive and negative interactions [90]. Given these findings, it is likely that meaningful interactions overlap with positive and negative interactions. Meaningful interactions not only encompass positive and pleasant interactions, they also contain constructive and negative interactions, e.g., a constructive argument with a partner to identify differences in individual needs and how to work through them. This finer distinction between negative interactions that are constructive and the other negative interactions is a limitation of the current thesis.

Considering the definition of meaningful interactions and its relationship with positive and negative interactions, I hypothesize that meaningful interactions can affect well-being both directly and indirectly. In fact, meaningful interactions may affect well-being more than positive interactions do as it also contains any benefit that constructive yet negative interactions may have on well-being. This is of interest for future research to examine.

Beyond these three constructs, other concepts may also mediate the effect of social interactions and well-being. For example, Reis and colleagues have looked at perceived autonomy, competence, and relatedness of social interactions on well-being [122]. Interactions that promote autonomy and sense of competence, which happens more likely with close ties, are associated with increase in well-being. Another possible factor is intimacy and responsiveness of partner [84]. In the current thesis, the statistical models included partner types as a pre-determined role, i.e., a person is a close tie or not and this categorization does not change as a result of the interaction. However, it is likely that interactions can promote changes in perceived closeness and intimacy of a relationship, which can benefit well-being. Relatedly, a sense of belongingness may also mediate the effect between interactions and well-being – interactions that promote belongingness may promote well-being [155, 158]. More work is needed to examine and test the mediating effect of these variables.

8.5 Social Fitbits as a concept to enhance our understanding of social interactions

The bigger end-goal of the current thesis is to promote the idea of a "social Fitbit", a device that can measure one's social life, in increments of social interactions, continuously throughout the day. Parallel to how current Fitbit devices can quantify and detect one's physical activity continuously, a social Fitbit can use embedded sensors in wearable devices to passively collect data that contain information about the users' interaction details. By using machine learning algorithms, the social Fitbit can recover information about one's social interactions from the sensed data. In particular, given the current dissertation presents evidence that certain interaction details (such as partner type and support gestures) are critical to the experience and well-being outcomes, the social Fitbit can focus on using the passively sensed data to recognize the presence of these interaction details.

While the attempts to detect the interaction details in the current thesis are not ideal, we have proposed future directions to improve the performance (see Section 7.3 in Chapter 7). I hope that the theoretical work in this thesis provides a strong argument for why detecting one's social interactions can be of value.

Being able to automatically quantify one's social interactions can change the landscape of how social interactions are studied by researchers. Similar to how physical activity devices have completely renovated how researchers study the impact of physical activity on physical and psychological well-being, we hope that the introduction of a social Fitbit can be a valuable tool for future researchers to capture and study social interactions at a more granular and fine-detailed level. Even if the accuracy of the social Fitbit is not perfect, such a device can still provide value by being combined with self-reports to reduce the burden of the participants. For example, the social Fitbit can prompt the users with its sensed results of what type of interactions participants are having and ask them to quickly review whether the predicted details are correct. This hybrid use of the social Fitbit and self-reports can help future researchers to collect data for longer periods of time, shedding light on longitudinal impact of social interactions on health.

A key consideration to designing a social Fitbit is privacy of the users. As the social Fitbit will be logging a large amount of users' data, it is important to consider how the data collection can be done while giving the users the control of their own data. First, the collection of each data type, e.g., location or microphone data, can be done in a privacy-conserving manner. For instance, in our own data collection, all microphone recordings were processed on the device, not relying on any third-party cloud-based services for analysis. In addition, all recordings were immediately deleted after the useful features were extracted. This can maximize the protection of the users' data while still being able to obtain the features that are useful for the prediction. Similar programming packages for location-feature extraction exist as well. In addition to collecting data in a privacy-sensitive manner, it is also important to give the users the control to only contribute the types of the data that they are comfortable providing. This can be done by building independent toggle switches for each type of data in the data collection device such that the users can choose to turn off the data collection of any data at any time. Along with explicit controls of data types, it is also important to provide transparent and clear explanations of how each data type is processed and used for the prediction.

8.6 Going from social interactions to social relationships

While the current thesis has deepened our understanding of how details of interactions can have an effect on one's subjective experience of the interaction and on one's well-being, it raises interesting questions for future work.

One assumption that much of the literature has been working under is that social relationships are influenced (though probably not exclusively) through social interactions (or phrased differently, social interactions and social relationships are similar in their nature and effects on well-being). While the current thesis adopts this assumption, experimental efforts are needed to confirm this assumption as there may be nuances worth examining. For example, are the effect of social interactions on social relationships relationship-specific — interactions with a certain partner only contribute to the relationship with that partner — or is it non-relationship specific — social interactions with others can impact one's general relationships? Do social interactions affect all aspects of a relationship, e.g., relationship quality, satisfaction, or connectedness? If so are the magnitude of the effects similar? Does a relationship also influence the quality of the social interactions? These questions can conceptually separate social interactions from social relationships. In addition, these works can provide more practical advice for how people can improve their well-being through adapting their social lives. While building more relationships can be daunting to achieve, reaching out to someone and having more social interactions can be more tangible suggestions for some people. Therefore, future works should look into these research directions.

Chapter 9

Conclusion

The current thesis examines 3 research questions: 1) how details of social interactions influence how positively and negatively people experience the interactions; 2) how one's experience of the interactions affect well-being at the end of the day; and 3) whether the details of social interactions have any direct or indirect effect on well-being, mediated by one's experience of the interactions. Through 3 separate studies, we found that the details of an interaction significantly impact how positively the interaction is perceived. In addition, days with more positive interactions and less negative interactions are associated with better well-being. Combined, analyses showed that interaction details, specifically longer interactions, interactions with close ties, interaction activity, and support behaviors, are associated with better well-being, by creating more positive interaction experiences. The work shows experimental evidence that an individual instance of social interactions can have downstream effects on well-being.

Beyond the theoretical understanding of how social interactions affect well-being, the current work also demonstrates that details of social interactions, i.e., medium of interaction, partner, and activity, can be automatically predicted using mobile-sensing data. I hope that current work will call for more effort in improving the prediction algorithm as a social interaction sensing system can greatly help our current understanding of the importance of social interactions.

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