The Social Journal: Investigating Technology to Support and Reflect on Meaningful Social Interactions

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ABSTRACT

Social interaction is a crucial part of what it means to be human. Maintaining a healthy social life is strongly tied to positive outcomes for both physical and mental health. While we use personal informatics data to reflect on many aspects of our lives, technology-supported reflection for social interactions is currently under-explored. To address this, we first conducted an online survey (N=124) to understand how users want to be supported in their social interactions. Based on this, we designed and developed an app for users to track and reflect on their social interactions and deployed it in the wild for two weeks (N=25). Our results show that users are interested in tracking meaningful in-person interactions that are currently untraced and that an app can effectively support self-reflection on social interaction frequency and social load. We contribute insights and concrete design recommendations for technology-supported reflection for social interaction.

CCS CONCEPTS

• **Human-centered computing → Collaborative and social computing**; *Human computer interaction (HCI).*

KEYWORDS

Social Interaction, Reflection, Well-being

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1 INTRODUCTION

Humans are social creatures. There is a plethora of research demonstrating that social interactions significantly influence both our physical [14, 29, 110] and mental health [3, 45, 80]. The German Foundation for Patient Protection has, in fact, identified loneliness as the most critical public health problem [105], with the number of people who feel lonely increasing significantly in recent years [106]. Research in Human-Computer Interaction (HCI) has shown that technology-supported reflection can benefit mental well-being in other domains [6, 35], and recent work has recognized the need for self-tracking tools to support reflection on social interactions [20]. Outside of text-based interactions, we currently do not have traces that provide an easy method to reflect on social interactions, such as synchronous in-person conversations. Consequently, there is a clear need to develop design concepts for technology systems to support users in reflecting on the entirety of their social interactions in everyday life.

Previous work in Psychology has shown that self-reflection increases self-awareness and self-knowledge [6], motivates behavioral change [81], and improves overall well-being [23]. Self-reflection is also essential to cognitive and behavioral therapy [51], where self-reflection on social interactions has been shown to positively impact the social lives of individuals [76]. Self-tracking and self-reflection using technology is a growing field in HCI [6, 11], particularly in the areas of quantified self [64] and personal informatics [57]. Prior work has investigated mood tracking applications [22], lifelogging [8], and reflection on everyday life [71]. While digital interactions leave digital footprints to social interactions automatically, the capturing of in-person social interactions is currently lacking technological support although they oftentimes have an even more profound emotional impact. Research on social sensing has explored methods to automatically track such in-person social interactions through smartphone sensors [97]. Social sensing has been used to detect loneliness [58], social context [26], and quality of social interactions [52]. However, social sensing is primarily concerned with providing objective measurement techniques for social interactions [13] or providing tools for behavioral science research [15]. There has been limited research in this field that presents the collected data to the user as feedback [97].

In this paper, we present an investigation of technology-supported reflection on social interactions. In particular, we focus on meaningful, synchronous social interactions that do not have existing traces (e.g., in-person conversations). We first conducted an online survey with 124 participants to gain insights into current reflection practices and how people prefer to reflect on their social interactions using technology. Based on the responses, we developed *Social Journal*, a smartphone application that supports users in tracking and reflecting on their social interactions, daily mood, and social load. Finally, we deployed the prototype in a two-week in-the-wild study with 25 participants and collected usage data, questionnaire responses, and exit interviews. Specifically, this paper investigates the following three research questions:

RQ1 *How do people prefer to reflect on their social interactions using technology?*
RQ2 *How can a mobile application support reflection on social interactions?*
RQ3 *How do users track and reflect on social interactions in everyday contexts?*

Our results show that most people are interested in reflecting on their social interactions, particularly regarding the frequency and associated emotions. We found that the *Social Journal* application can effectively support users in reflecting on their social interactions, and it can provide greater self-awareness of social contacts for some users. However, technology-supported reflection on social interactions may not benefit all users, as some are uncomfortable with tracking private interactions. We discuss design recommendations for future systems, including concrete improvements to our system. Overall, this paper contributes (1) results from an online survey revealing how users prefer to reflect on their social interactions, (2) the design and in-the-wild evaluation of an app that supports users in tracking and reflecting on their social interactions, and (3) design considerations for future systems that support reflection on social interactions.

2 RELATED WORK

In this section, we review the role of social interactions and their impact on health. We then discuss personal informatics for social interactions and finally give an overview of relevant research on social sensing.

2.1 Social Interactions & Health

A significant amount of human life occurs in a social context, with adults spending 32%-75% of their waking hours interacting with others [68]. Reis and Wheeler [86] define social interactions as "*...situations involving two or more people in which the behavior of each person is in response to the behavior of the other.*" Social interactions occur in various settings, including in-person, in-group discussions, online, or through social media [88]. As humans are social beings [5], social interaction can be considered a fundamental aspect of human nature, and it plays a formative role in shaping an individual's social skills, personality, and identity [40, 103].

Sztompka [104] describes social interactions as the core of social relationships. When two individuals have recurring social interactions that they perceive as meaningful, their connection is defined as a social relationship [41]. Social relationships include family members, friends, neighbors, coworkers, and other associates but typically exclude contacts and interactions that are fleeting, casual, or judged to be of low importance (e.g., temporary interactions with service providers or shop cashiers) [3]. In the context of this work, we focus on social interactions that aim to form social relationships including social interactions that have personal meaning for the individual [3].

Social well-being is a reflection of how an individual evaluates their social interactions in relation to themselves and society [49]. Social well-being encompasses more than just social interaction and includes a qualitative dimension related to life satisfaction and interpersonal relationships [92]. Research exploring the relationship between health and social life consistently shows the positive influence of social support on physical and mental health [3], and conversely, studies show that individuals with fewer social ties are more likely to experience mental health problems, such as anxiety [45], depression [17, 95], and sleep deficits [37]. Furthermore, individuals with mental health problems tend to have better outcomes when they have access to social support [80].

Social relationships also significantly impact physical health. Individuals with fewer social interactions are more likely to experience heart attacks [110], colds [29], and increased inflammation [27] than those with more social interactions. Long-term studies indicate that individuals with weak social networks have significantly higher mortality risks independent of age, gender, race, smoking, alcohol consumption, physical activity, and chronic health conditions [14]. Although many studies focus on strong social ties, such as family or close friends, there is also evidence that weak social connections, such as distant friends or a delivery person, also improve well-being [94].

The quality of social interactions also significantly impacts health. Some studies suggest that negative interactions, such as conflict, criticism, and neglect, affect mental well-being more than social support [60, 89]. Individuals with more negative interactions experience a lower quality of life [111] and have higher rates of relapse after therapy in patients with drug abuse [79], schizophrenia [42], and post-traumatic stress disorder (PTSD) [25]. Negative interactions can also increase symptoms in patients with rheumatoid arthritis [87] and inflammation [50].

Too many social interactions, called social overload [66] or social fatigue [36], can also have negative consequences. Social overload was first proposed to describe a consequence of living in densely populated areas, where residents experience stress due to an overwhelming number of social interactions [66]. In the context of social media, social overload is the experience of more social support than an individual can cognitively handle, leading to stress and exhaustion [63]. However, there is surprisingly little research on the negative effects of too many social interactions.

Acknowledging the vital impact of social engagement on well-being and health, our goal is to explore the potential for technology to support users' social lives. We first aim to understand users' needs and expectations to support them with their social interactions and subsequently identify features and functionalities of technology to support social interactions.

2.2 Personal Informatics for Social Interactions

Self-tracking and self-reflection have gained popularity in HCI in recent years in the field of personal informatics [5, 9, 73]. The increase in personal informatics and quantified self systems stems from the increasing availability of commercial self-tracking applications and low-cost wearables. Although much of the research in the field focuses on physical activity and fitness [10, 35, 57, 90], personal informatics also deals with a wide variety of domains, including psychological body state (e.g., tracking mood or dreams), physiological health (e.g., tracking blood glucose, menstruation, or symptoms of chronic disease), finance, sustainability, productivity [46, 85], and personal habits [39].

Behavioral and cognitive psychologists have significantly shaped the role of self-reflection in personal informatics [23]. Self-reflection, which involves contemplation of thoughts, feelings, and behaviors, aids in gaining insight into mental states and motivations. This process aligns behavior with goals and values and enhances understanding of emotions, motivations, and overall well-being Carver and Scheier [23]. In HCI, Schön [98] introduces *reflection-in-action* and *reflection-on-action*, describing thinking about actions during performance and analyzing experiences in hindsight. In the developing reflection support systems, Bentvelzen et al. [12] emphasizes temporal perspective, conversation, comparison, and discovery as key design elements that can be leveraged to create technologies that positively impact users' well-being.

With increasing interest in technology support for mental health, past work has also investigated how self-tracking and self-reflection using technology can improve well-being [48]. Self-tracking can actively engage individuals in managing their health and data, leading to better clinical decision-making, research, and improved overall health and self-awareness [100]. For example, prior work has tracked mental health symptoms [65], stress [48], and mood [54]. Mood tracking applications can help individuals manage and reflect on their mood patterns, helping them to learn what may be beneficial or detrimental to their overall well-being and mental health [18, 22]. *MoodScope* [59] proposed the integration of a social support component to daily mood tracking, where users can select buddies who receive a notification about their reported mood and can respond with support.

Researchers have increasingly recognized social context as an important aspect of personal informatics systems. Viewing reflection and tracking as a social activity, past work has explored how sharing, comparing, and discussing tracked data with others can enhance engagement and reflection with personal computer systems, in general [5, 11, 83] and in the context of mental health management [74].

Personal informatics systems have a demonstrated capability to empower users in self-management and reflection. Drawing from success in handling other mental health-related data, our work explores technology as a tool to help users track social interactions to foster self-awareness and reflection.

2.3 Social Sensing

Schmid Mast et al. [97] divides social sensing into two main areas: ubiquitous computing and extracting verbal and nonverbal cues using machine learning. Social sensing through ubiquitous computing involves using sensing devices integrated into the everyday environment to unobtrusively collect data about social interactions [97]. Machine learning, on the other hand, has been used to predict the perceived quality of social interactions based on nonverbal cues, interpersonal orientation, and distance measured by wearable sensors [52]. While ubiquitous computing studies are often implemented and investigated in the wild, machine learning approaches based on verbal and nonverbal cues currently are often in laboratory settings.

Past work has used a variety of sensors to track social interactions. For example, *SociTrack* [15] uses wearable sensors equipped with Bluetooth and ultra-wideband radios to detect the relative position and motion and *SociPhone* uses smartphone-based sensors to detect physical proximity, speech, and body language to identify in-person social interactions [55]. Prior research has investigated predicting loneliness using social sensing [84], for example, using smartwatch sensors [96], smartphone call logs, GPS data, Bluetooth proximity [58], and app usage [2]. Other work has used machine learning to predict companionship type (e.g., alone, close relationship, or non-close relationship) [109], and social interaction type (e.g., significant other, friend, colleague, etc.) [61]. Additionally, prior work has predicted social-behavioral contexts using Bluetooth data [26] and additional smartphone-based sensors [67].

Most of the work in social sensing either aims to provide new, objective measurement tools [13], new methods for behavioral science research [15, 55], or in-situ intervention [109]. Conversely, there is very little research on presenting the measured social data back to the user. Cuttone et al. [31] visualized social interactions as bubbles with sizes proportional to the interaction time, but the interactions were only tracked if both individuals were users of their application. Li et al. [56] developed an app concept that uses both active and passive methods to track social interactions. However, this work lacks any evaluation to understand the impact on users.

While prior research confirms the technical feasibility and interest in tracking social data, there is a lack of work investigating how to communicate this information back to the user. Moreover, optimal methods for technology to facilitate reflection on social interactions are yet to be defined. Consequently, our investigation focuses on determining how technology can best support users in tracking, monitoring, and reflecting on their social interactions.

2.4 Summary

The frequency and quality of social interactions have a significant impact on both mental and physical health [60], emphasizing need for more reflection on social interactions [20]. There is a growing trend in personal informatics, the intersection of technology and self-tracking, to support users in self-managing various aspects of their personal lives. While previous research has demonstrated the benefits of technology-supported self-reflection for mental health [6, 35], and social sensing has explored the feasibility of tracking social interactions with technology [26, 84, 109], there exists a notable research gap in self-tracking of online and in-person social interactions. This oversight is particularly significant considering the substantial impact of social interactions on users' well-being. Our paper aims to address this gap by investigating the

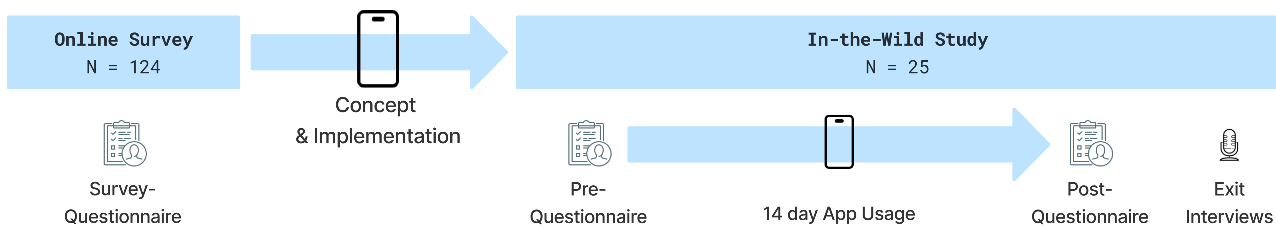


Figure 1: Overall Study Procedure containing the online survey to inform the concept and implementation of the *Social Journal* which was studied in the wild for 14 days.

untapped potential of self-tracking social interactions and its implications for enhancing users' self-reflection and overall well-being. In this study, we explore how technology can actively support tracking social encounters, their impact on mood, and reflection on everyday social interactions.

3 METHODOLOGY

To answer our research questions, we first conducted an online survey ($N = 124$) to identify relevant aspects of social interactions along with current practices and perceptions of people's social life to understand how people want to self-reflect on social interactions using technology. Building on these findings, we conceptualized and implemented the *Social Journal* app. In an in-the-wild study ($N = 25$) participants used the app for 2 weeks and then completed pre- and post-study questionnaires and exit interviews. This study was designed to gain real-life insights into how people use and perceive a mobile application that supports reflection on social interactions and understand the impact on users' reflection process and social behavior. The overall procedure is depicted in Figure 1.

3.1 Measurements

All surveys consisted of both closed- and open-ended questions. Closed-ended questions were either a list of pre-defined answers or Likert scales for greater objectivity [75]. We used open-ended questions to obtain qualitative feedback. All questionnaires and study materials are included in the supplementary material.

We measured the perception of participants' social life (e.g. frequency of social interactions) using an adapted too-little-too-much (TLTM) scale [107] ranging from -3 (*far too seldom*), 0 (*right amount*), to +3 (*far too often*).

We aimed to investigate how the *Social Journal* supports users in tracking and reflecting on social interactions in real-life settings. As such, we collected data on app usage including the time spent on different screens in the app, the number of social interactions and daily recaps entered, the number of passive calls tracked, and notifications.

Finally, to gain a deeper insight into the user's experiences, we also collected qualitative responses through exit interviews. We asked participants about their experience, what they liked and disliked about the app, how the app influenced the way they reflect on social interactions, and whether this reflection impacted their social interactions. While all other study material was in English, we conducted 20% ($N = 5$) of the interviews in English and the remaining 80% ($N = 20$) in German (the native language of the participants).

3.2 Analysis

For the quantitative data collected by the Likert and TLTM scales, we assumed an interval-scaled level due to the equidistance of the intervals [33]. We used Spearman's rank correlations for ordinal data and Pearson correlations for interval data. We applied Holm-corrections to the correlation p-values and interpret all correlation effect sizes using the convention by Cohen [28].

To analyze the qualitative data, we imported text files containing all open-ended responses to a single question into the Atlas.ti analysis software[1]. For the open-ended answers to the online survey, three researchers labeled the responses verbatim using the interpretive coding method [93]. We used an inductive approach to coding, meaning we generated and constantly revised codes in a bottom-up manner by reading and re-reading the responses to the open-ended questions. Thus, we ensured that categories that we might not have thought about before were captured [75]. Subsequently, we structured the coded data and visualized it to provide a better understanding and overview of the results.

For the exit interviews following the in-the-wild study, three researchers first used open coding to code a representative sample of 15% of the material. Following this, the researchers discussed and agreed on a coding tree. Finally, one researcher coded the remaining material. This process is in line with Blandford et al. [16]. Finally, all three researchers engaged in discussions how to organize and group the interview codes and establish overarching themes. In total, we created 116 open codes that we initially assigned to a total of 12 code groups. We iteratively refined them and created three themes.

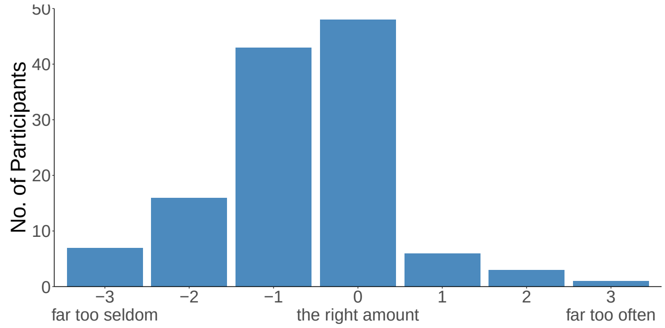
4 STUDY I: UNDERSTANDING REFLECTION ON SOCIAL INTERACTIONS

We conducted an online survey asking people about their current social practices, reflection habits, and preferences for technology-supported reflection on social interactions. Our aim was to understand how and on which aspects of social interaction people reflect, and to inform the design of our prototype.

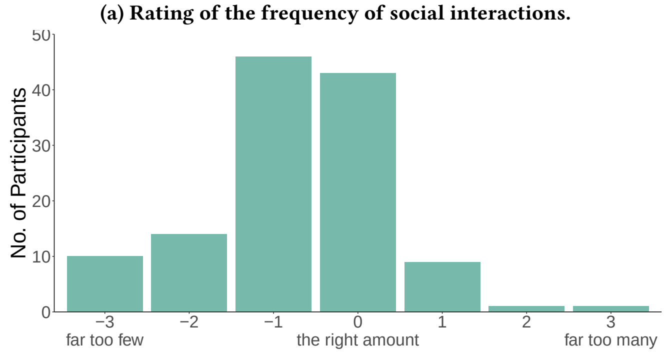
[1]https://atlasti.com/

4.1 Participants

We conducted an online survey with N=124 participants, aged 18-71, M = 28.5, SD = 11.5. 88 participants identified as female, 32 as male, 3 as non-binary/third gender, and 1 preferred not to provide gender information. We recruited participants using a university mailing list. Besides the ability to read and complete the survey in English, we did not instate any other eligibility criteria. The recruitment text stated that the survey would be about "self-reflection on social interactions." We estimated the survey to take approximately 10 minutes based on pilot testing, in practice the participants required 17 minutes on average. All participants who completed the survey were entered into a raffle to win one of five 10€ Amazon gift cards. The study was approved by the ethics committee within the University Faculty. 62 (50.0%) participants are full-time students, 22 (17.7%) are students and work part-time, 34 (27.4%) work full-time, 3 (2.42%) work part-time, and 3 (2.42%) are retired. Regarding the working environment, 29 participants (23.4%) primarily work or study at home, 65 (52.42%) at other places such as offices or universities, and 29 (23.4%) report an equal distribution between the two options. One participant does not work or study. For the frequency of social interactions, 30 participants (24.2%) reported meeting friends/family every day, 55 (44.4%) more than once per week, 15 (12.1%) once per week, 13 (10.5%) several times per month, 10 (8.06%) several times per year, and one person never.



(a) Rating of the frequency of social interactions.



(b) Rating of the number of social contacts.

Figure 2: The distributions of the Participants subjective ratings for their own frequency of social interactions and number of social contacts.

4.2 Survey Content

First, participants answered demographic questions. We then asked participants about their current practices and self-tracking in general. Next, we asked participants how often they reflect on various aspects of social interaction, how much these aspects influence their well-being, and how (if at all) they reflect on social interactions using technology. The measurements and analysis for the survey are described in Section 3.

4.3 Online Survey Results

Participants' perception of their social interaction frequency (see Figure 2a) was most commonly 0 (*right amount*). At least 50% of the participants report a rating of -1 or lower and 90% a rating of 0 (right amount) or lower. Similarly, we measured participants' perceptions of the number of social contacts they have (see Figure 2b). Most participants responded with -1 or 0, approximately the *right amount*. At least 50% of the participants showed a rating of -1 or lower, and 90% a rating of 0 (right amount) or lower. A Shapiro-Wilk test for normality revealed in both cases that the distribution departed significantly from normality ($W = 0.90$ / $W = 0.91$, $p < .001$).

For perceived satisfaction with the quality of social interactions, we used a bipolar seven-point Likert scale ranging from 1 (*extremely dissatisfied*) to 7 (*extremely satisfied*). The results showed a median of 5.00 and a mean of 4.60 ($SD = 1.61$).

4.3.1 Understanding users' social context. We used Pearson correlations to identify which variables influence perceptions of social interaction technology. A summary of the correlations is displayed in Figure 3.

The rating of the frequency of social interactions was significantly positively correlated with the rating of the number of contacts ($r_p(122) = .40$, $p< .001$), the rating of the quality of interactions ($r_p(122) = .31$, $p< .001$), and comfort with data tracking ($r_p(122) = .20$, $p= .027$). The rating of the number of contacts was also significantly positively correlated with the rating of the quality of interactions ($r_p(122) = .48$, $p< .001$) The rating of the quality of interactions showed a significant negative correlation with the perceived influence of social interactions on well-being ($r_p(122) = -.19$, $p= .039$) and the current reflection practice ($r_p(122) = -.19$, $p= .037$).

The perceived influence of social interactions on well-being showed a significant positive correlation with the perceived usefulness of reflection technology ($r_p(122) = .31$, $p< .001$) and the current reflection practice ($r_s(122) = .50$, $p< .001$). The perceived usefulness of reflection technology showed a significant positive correlation with the current reflection practice ($r_s(122) = .36$, $p< .001$), comfort with data tracking ($r_s(122) = .47$, $p< .001$), and all proposed app features (all $p< .001$). The current reflection practice showed a significant positive correlation with comfort with data tracking ($r_s(122) = .21$, $p= .017$), interest in receiving overviews ($r_s(122) = .21$, $p= .018$), and judgments ($r_s(122) = .19$, $p= .034$). Comfort with data tracking was significantly positively correlated with all proposed app features (all $p< .001$).

Finally, the perceived usefulness of all proposed app features were positively correlated with one another (all $p< .001$).

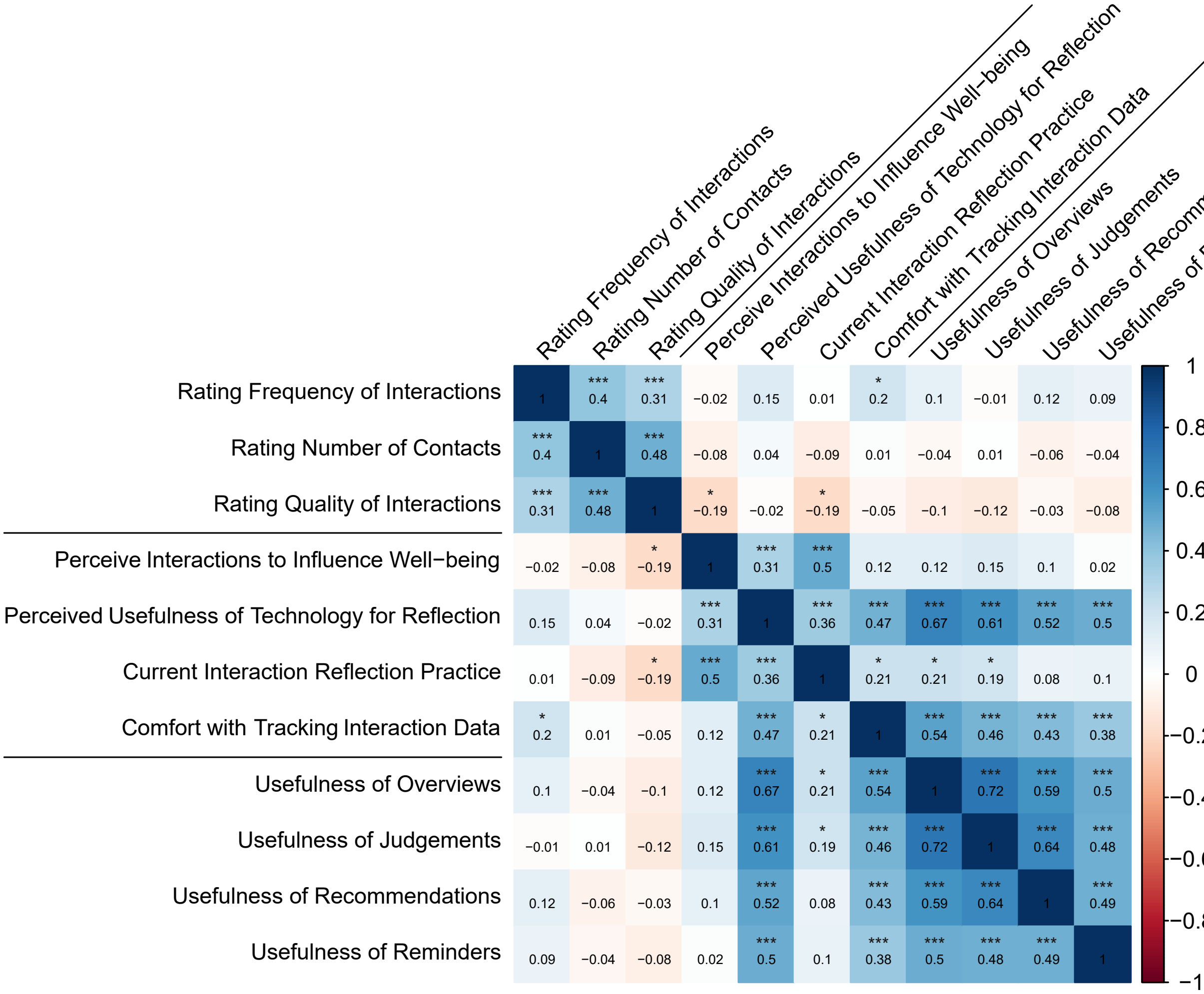


Figure 3: Pearson correlation table showing the correlation coefficient. The color of the squares indicates the height and direction of the correlations. Significance levels are represented as follows: *=$p<.05$, **=$p<.01$, ***=$p<.001$.

We introduced eight different aspects of social interactions: activity, circumstances, frequency, location, number of social contacts, person, reason, and type of interaction. We asked participants how often they reflect on these aspects, how the aspects impact their well-being, how useful it would be to reflect on these aspects using technology, and how comfortable they would be with an application tracking these aspects. All of the questions used 7-point Likert scales, and the results are summarized in Figure 4.

4.3.2 Desirable app features. We asked participants to rate the usefulness of the following four types of information they could receive via a smartphone app to support their social interactions: overviews (e.g., statistics), judgments (e.g., these three people are most helpful to you), recommendations (e.g., you had a lot of social contacts last week, maybe you have a night in), and reminders (e.g., ask Sara how her exam went). All categories had means above 4 out of 7, indicating that all were perceived as useful. Reminders received the highest average rating ($M = 5.17$, $SD = 1.86$).

Participants listed both objective and subjective data when asked what information they would want from a digital application about their social interaction. For objective data, the most frequent responses were the frequency of their social interactions ($N = 32$, 25.81%), the person ($N = 11$, 8.87%), and the duration ($N = 10$, 8.06%). For subjective data, the most common responses were the emotion associated with an interaction ($N = 23$, 18.55%) and the impact on well-being ($N = 11$, 8.87%). When asked what they would expect from a digital application that supports their social interactions, participants reported that they would want it to help them track and reflect on their social interactions in a diary style:

> *I would expect an app where I can every day write whether I feel fulfilled with my relationships, and through this, I can get to know myself better and tell exactly what type of people/situations help me.* (P58)

More than half the participants (58.06%, $N = 72$) would consider using a smartphone application to support their social interactions.

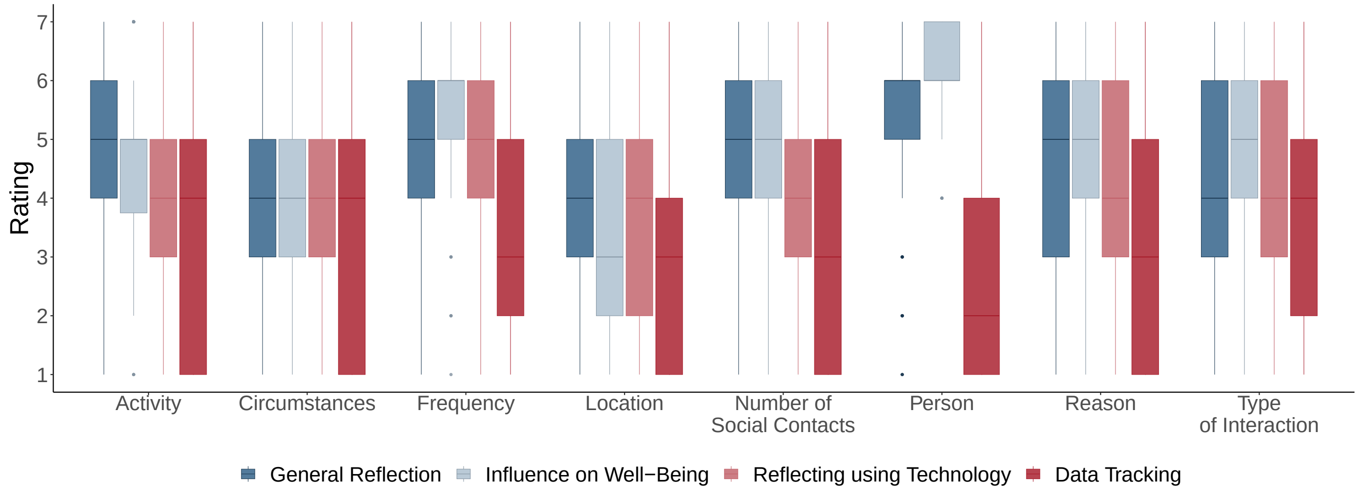


Figure 4: Boxplots representing the ratings for the frequency of reflection, influence on well-being, the usefulness of reflecting using technology, and comfort of being tracked over eight different aspects of social interactions.

Emotions	Valence	Arousal	Color Hex Code	Color	Pictogram
Excited, Delighted, Happy	Positive	High	#FFC300		
Calm, Relaxed, Content	Positive	Low	#1F72E1		
Depressed, Bored,Tired	Negative	Low	#9B51E0		
Tense, Frustrated, Angry	Negative	High	#EB5757		

Table 1: Classification of emotions by valence and arousal [91] and the corresponding colors and pictograms are shown in the prototype.

The most frequent motivations for using such an application were curiosity (N = 13, 10.48%), to help with reflection (N = 13, 10.48%), and to improve well-being (N = 10, 8.06%):

> *It would be an interesting approach to reflect on myself and my well-being as I think that social interactions and how we evaluate them reveal more about ourselves than the social contacts.* (P85)

For those who would not want to use such an app, the main reasons were data security (N = 29, 23.39%) and that they see no need (N = 14, 11.29%).

4.4 Summary

The results suggest that people think they have relatively too few social interactions and contacts rather than too many. Participants are most interested in reflecting on the frequency of their social interactions and the associated emotions. Participants would like to be supported in keeping track of their social interactions, with some participants mentioning that a diary-style format would be useful for tracking and reflecting. Another important finding of the survey is a general concern regarding data privacy.

5 DESIGN & IMPLEMENTATION OF THE *SOCIAL JOURNAL*

Based on the findings from the Online Survey, we developed a concrete concept for a mobile application to support users in tracking and reflecting on their social interactions. We then implemented a smartphone application to be deployed in the wild. The *Social Journal* is intended as a research probe, enabling us to gain insights into how users interact with a social interaction reflection technology in practice.

5.1 Tracking Meaningful Social Interactions

We designed an application that tracks all aspects of social interactions that users perceived as relevant in our online survey. The five aspects of social interactions that users felt were important and felt comfortable tracking are: (1) time and duration, (2) type of interaction, (3) associated emotions, (4) number of people, and (5) type of relationship. In addition, we included an open text field where the user could record additional information, such as the specific person, location, or discussion content if wanted. While these additional aspects could greatly impact interactions, users expressed privacy concerns about them in the initial survey. Thus, we did not implement them as mandatory inputs.

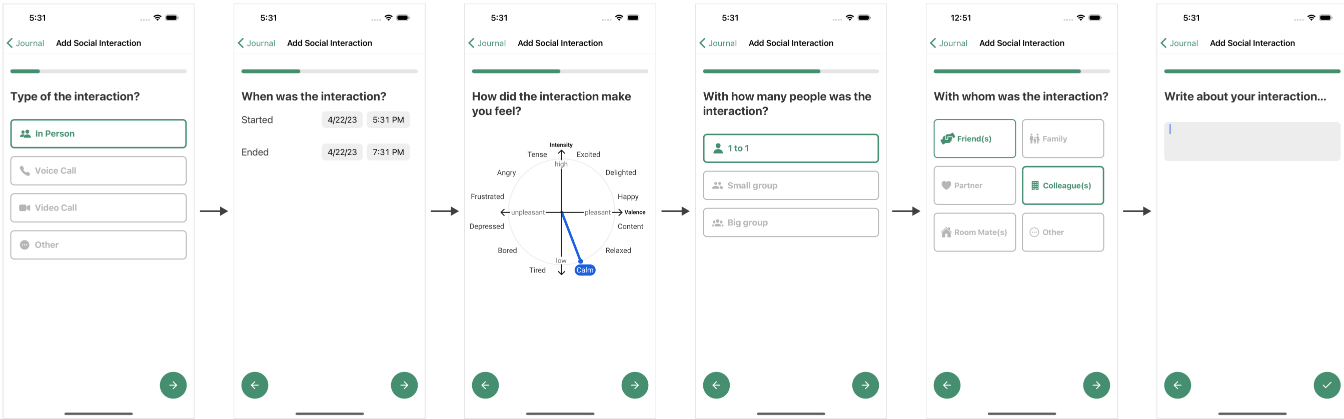


Figure 5: User flow to track social interactions entering the type of interaction, date and time, emotion, number of people, type of relationship, and notes step-by-step.

To prompt users to reflect on their emotional experiences during social interactions, we use the valence-arousal model, also known as the Circumplex model of emotions [91]. This model is used by psychologists to help people identify and report their emotions [112]. The model categorizes emotions in a two-dimensional circular space (arousal vs. valence), dividing the space into four quadrants representing four base emotions.

We assigned different colors to specific emotions as shown in Table 1 to support fast recognition of emotional states in the app. Researchers map different colors to emotions [78] and color-emotion mappings vary across cultures [1, 32, 70], so we chose a mapping supported by many researchers with participants in western countries (e.g. students in the U.S.A [47] and Europe [44]). For accessibility reasons, we use colorblind-friendly colors. We also use emoji-like pictograms to represent the four quadrants, as facial expressions can also effectively represent emotions [34](see Table 1). To allow the user to select one of the twelve emotions, we implemented a circular slider so the user can drag the indicator to the appropriate position pointing to the desired emotion (see Figure 5).

Further, we distinguish between three types of interactions: *in-person*, *voice call*, *video call*, and *other*. We added options to track voice and video calls because they do not typically provide traces of the content of the conversation. We included the *other* category so that users have the ability to add meaningful text-based interactions, but as text messages inherently provide a detailed trace, they are not the primary focus of our investigation. Text-based interactions are also typically asynchronous and do not have well-defined beginning and endpoints, so we leave the decision to the users to actively log text interactions when they decide they are meaningful rather than passively tracking each message. The application also allows users to track the number of people involved, distinguishing between *1 to 1*, *small group*, and *big group*. We follow the classification of companionship types by Wu et al. [109] for the type of relationship: *friend*, *family*, *partner*, *colleague*, *roommate*, and *other*. Users can add new social interactions as shown in Figure 5.

5.2 Tracking Daily Social Load

We use daily recaps for the user to enter their daily mood and social load to help them reflect on how their individual social interactions throughout the day may have contributed to their overall experience (see Figure 6b). We again utilize the Circumplex model for users to input an emotion to represent their day. We implemented the social load scale as a circular tachometer from *lonely* to *socially exhausted* with *right amount* in the middle.

5.3 Social Interaction Diary

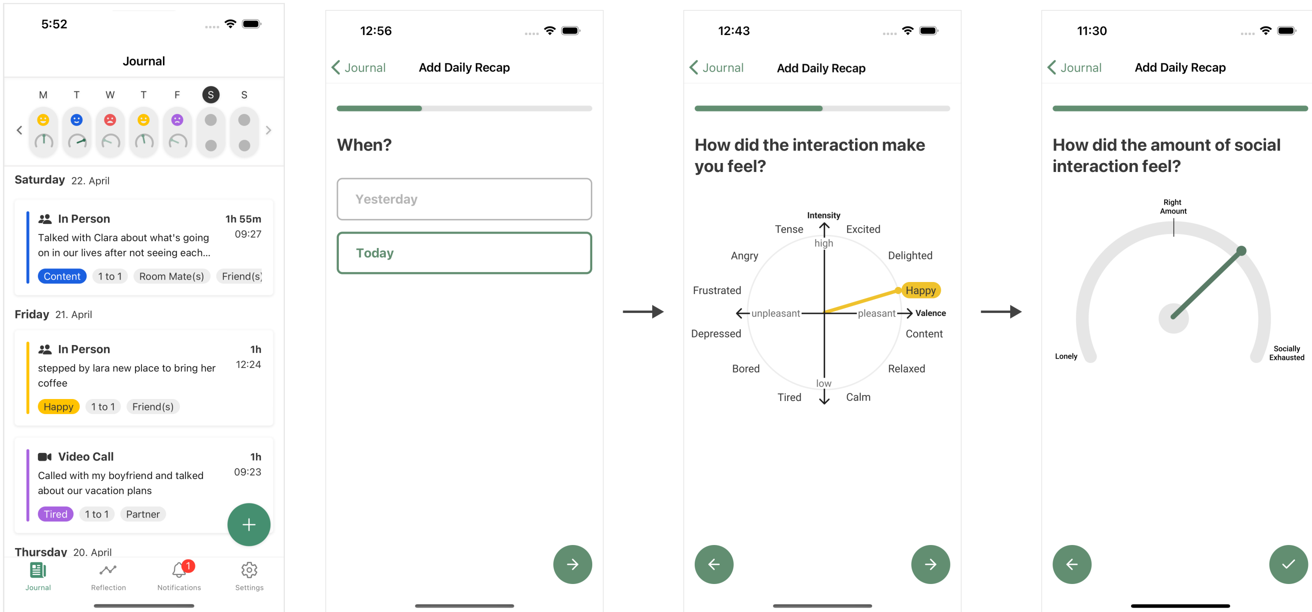
The main screen of the application is the Journal (see Figure 6a). On this screen, users can add social interactions and daily recaps and review previous entries. The Journal screen shows the dates and corresponding entries chronologically. We added a week banner on the top of the screen to give an overview of the daily recaps.

We integrated several visualizations into the Reflection screen to support the user in exploring their data and gaining more self-awareness and self-knowledge of their social interactions. We use an area chart to visualize the data, allowing users to reflect on the duration of their social interactions in relation to the recorded social load and daily mood. Users can view and explore weekly (Figure 7a) or monthly data (Figure 7b). The x-axis of the chart represents the days with a pictogram indicating the entered emotion for each day. The left y-axis shows the social load, while the right y-axis displays the total duration of social interactions. We also implemented an interactive overview table where users can reflect on various aspects of social interactions based on the emotions they entered, shown in Figure 7c. The user is first presented with an overview of the different basic emotions and the frequency of the various influences on social interactions (person, amount, and type).

5.4 Implementation

We used React Native[2] to implement the app on both iOS and Android. We use Firebase[3] as a backend to store the collected data. We implemented passive call tracking for users with Android phones

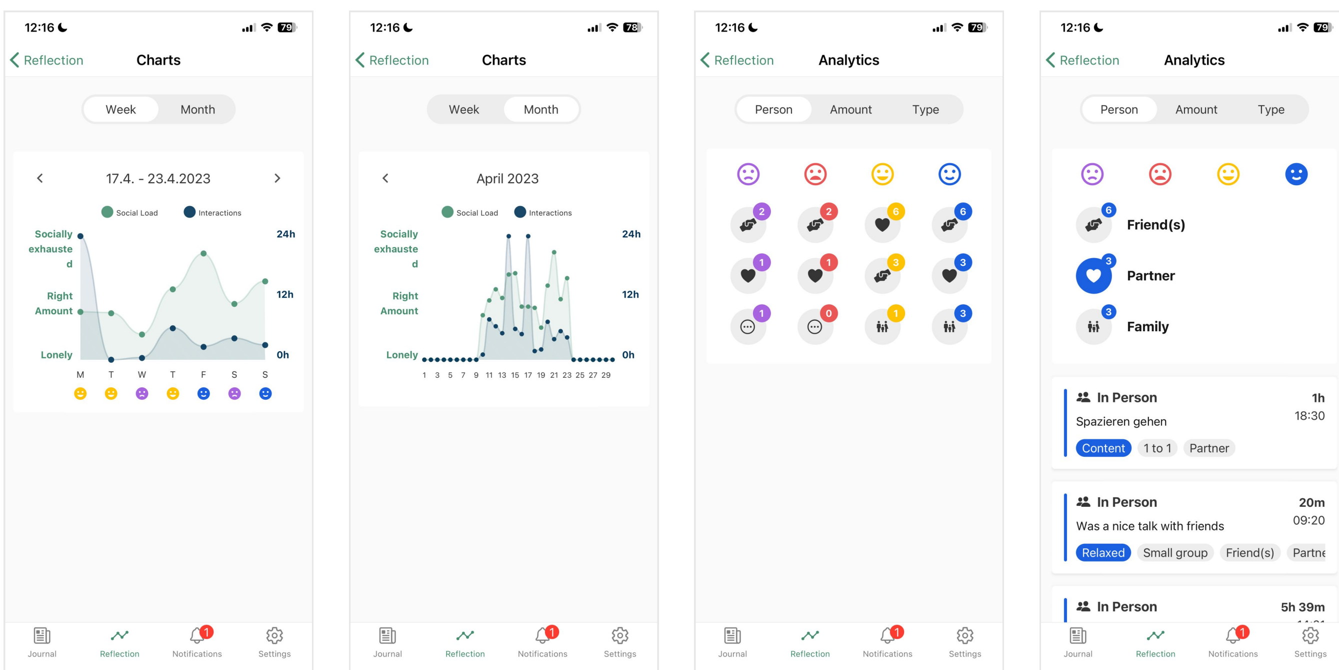
[2]https://reactnative.dev/
[3]https://firebase.google.com/



(a) Journal screen

(b) User flow to add a daily recap entering the daily mood and social load for the day.

Figure 6: The Journal screen gives a weekly overview of all tracked encounters. Adding daily recaps capture users perceived social load in the evening retrospectively for the whole day.



(a) Week chart

(b) Month chart

(c) Analytics table

(d) Analytics table filtered

Figure 7: The reflection screen displays charts on tracked mood, social interactions, and perceived social load for the week or month. The analytics tables show the moods associated with the entered relationship type, amount, and type of social interactions.

(not possible on iOS due to system limitations). *Social Journal* automatically adds a new social interaction after the user completes a call. The app sends two push-notifications per day to remind the user to input their social interactions and complete their daily recaps. The default notification times are 1 p.m. and 8 p.m., and can be adjusted by the user in the settings screen. In addition to the design considerations discussed in the previous section, we followed HCI design principles (e.g., [77, 101]) and followed Web Content Accessibility Guidelines [4].

Given the needs of users summarized in Section 4.4, the app should track social interactions in a diary-style format. Specifically, participants wanted to reflect on the frequency, partner, duration, and associated emotions. Our implementation enables each of these features. *Social Journal* features a diary-style screen and provides additional screens that enable the users to view and reflect on important variables. We excluded an explicit option to track conversation partners for the sake of privacy, since many participants mentioned in the survey that privacy is an important factor.

6 STUDY II: IN-THE-WILD EVALUATION

We conducted an in-the-wild study to collect data in a real-world setting and gain deeper knowledge about how people self-reflect on their social interactions using technology in everyday life.

6.1 Participants

We recruited *N*=25 participants, aged 20-63, M = 27.9, SD = 10.5. 16 participants identified as female and 9 as male. Participants were recruited using a university mailing list and snowball sampling. Participants were required to have an iOS or Android smartphone and understand sufficient English to participate in the study. Although we did not target a specific user group with our recruitment or eligibility criteria, the recruitment text called for people who were "interested in gaining a better understanding of [their] social interactions." We compensated participants with 30€ for their time. The study was approved by the ethics committee within the University Faculty. 5 (20%) participants are full-time students, 11 (44%) are students and work part-time, 5 (20%) work full-time, 3 (12%) part-time, and 1 (4%) is a stay-at-home parent. Regarding the working environment, 5 participants (20%) primarily work or study at home, 13 (52%) at other places like offices or universities, and 7 (28%) reported an equal distribution between the two. 13 participants (52%) used *Social Journal* on an iOS phone, and 12 (48%) on an Android phone. Regarding the frequency of their current interactions, 7 participants (28%) reported meeting friends/family every day, 13 (52%) more than once per week, 2 (8%) once per week, and 3 (12%) several times per month.

6.2 Procedure

After a verbal introduction to the study via a video call, participants completed the pre-study questionnaire, downloaded the app, and received a short tutorial. To ensure comparability, we instructed participants to use the app until they had completed 14 daily recaps, resulting in additional study days for each missed recap. After 14 recaps, participants filled out the post-study questionnaire followed by a semi-structured exit interview via a video call. The pre- and post-study questionnaires took an average of 35.0 min and 24.9 min respectively, and the exit interviews lasted an average of 6.79 min. Figure 1 shows the entire study procedure. The measurements and analysis for the study are described in Section 3.

6.3 App Usage

We logged usage data measured between the date they first opened the app and the date they entered the 14th daily recap to ensure comparability across participants.

6.3.1 Screen Time. Over the course of the study, participants used the app between 14 and 19 days (M = 14.80, SD = 1.22). They spent an average of 8.40 min per day using the app (SD = 5.13 min, MIN = 2.67 min MAX = 21.32 min). Participants spent the most time using the app on the first day (M = 24.60 min, SD = 44.69 min). Figure 8 shows the average usage of the different screens for all days.

The Journal screen was the screen participants spent the most time on each day (M = 5.12 *min*, SD = 4.57 *min*), followed by the screen to add social interactions (M = 1.72 *min*, SD = 0.88 *min*), and the Reflection screen (M = 0.57 *min* (34.20 *s*), SD = 0.60 *min* (36.00 *s*)).

On the Reflection screen, participants spent on average most time on the overview (M = 0.29 *min* (17.40 *s*), SD = 0.42 *min* (25.20 *s*)), followed by the chart visualization (M = 0.18 *min* (10.80 *s*), SD = 0.33 *min* (19.80 *s*)) and the overview table (M = 0.10 *min* (6.00 *s*), SD = 0.60 *min* (36.00 *s*)).

6.3.2 Social Interactions. Participants added an average of 1.82 (SD = 0.65, MIN = 0.80, MAX = 3.60) interactions per day, resulting in a total of 685 interactions entered throughout the study. Of those interactions, participants deleted 2.04% (14 interactions). Participants added 554 (80.88 %) of all interactions after the interaction had ended. When added afterward, participants recorded interactions an average of 667.45 *min* (11.12 *h*) after the interaction ended (SD = 1646.76 *min* (27.45 *h*), Mdn = 254.40 *min* (4.24 *h*), MIN = 0.00 *min*, MAX = 20521.10 *min* (∼ 14 days)). When reported before ending, interactions were entered on average 453.50 *min* (7.56 *h*) before the interaction ended (SD = 532.01 *min* (8.87 *h*), Mdn = 144.75 *min* (2.41 *h*), MIN = 0.87 *min*, MAX = 1537.35 *min* (25.62 *h*)). Figure 9a shows that participants added most interactions (13.87%) between 8 p.m. and 9 p.m., after they had received the second reminder of the day.

Most of the interactions were *in person* interactions (73.69%), followed by *voice calls* (14.80%), *video calls* (8.22%), and the category *other* (3.29%).

Regarding the number of people involved in the social interaction, 359 (53.66%) of the interactions were categorized as *1 to 1* interactions, 237 (35.43%) as happening in a *small group*, and 73 (10.91%) as happening in a *large group*.

Participants chose a single relationship type for 605 (90.43%) interactions. The most frequently selected relationship type was *friend* (40.96%), succeeded by *family* (23.17%), *partner* (17.04%), and *colleague* (15.70%). The categories *other* (8.82%) and *roommate* (4.48%) were the least recorded relationship types.

As emotion resulting from the tracked social interactions, most participants chose *happy* (26.01%), followed by *content* (16.59%), and *delighted* (15.70%). The least chosen emotions were *angry* (0.75%) and *depressed* (0.75%). Participants entered additional notes for

[4] https://www.w3.org/WAI/standards-guidelines/wcag/

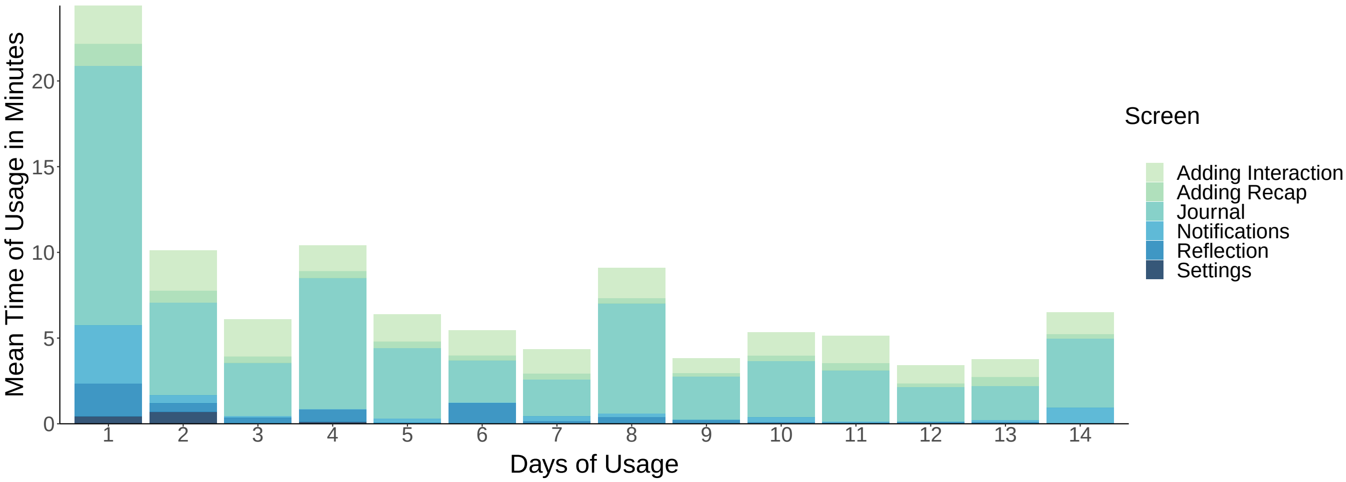
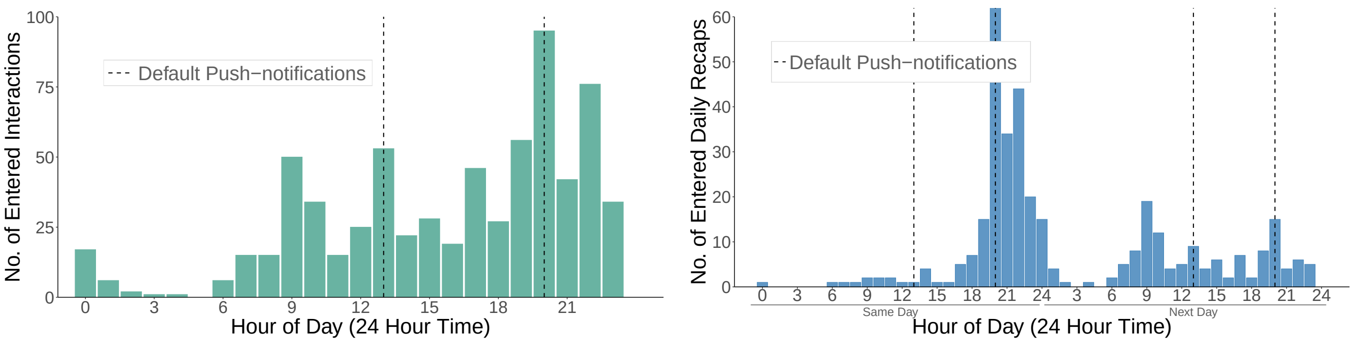


Figure 8: Average time of usage over the days for the different screens.



(a) Distribution of the time interactions were added.

(b) Distribution of the time daily recaps were entered.

Figure 9: User input of social interactions and daily recaps to the *Social Journal* app throughout the day.

nearly half of the interactions (48.73%). When notes were entered, they were, on average, 5.56 words long ($SD = 5.95$, $MIN = 1$, $MAX = 47$).

6.3.3 Daily Recaps. Participants entered 206 (58.86%) of all collected daily recaps on the same day and 144 (41.14%) the next day. They added most daily recaps (18%) between 8 p.m. and 9 p.m. (see Figure 9b). Participants deleted none of the entered daily recaps. On average, participants missed 0.80 recaps ($SD = 1.22$, MIN = 0, MAX = 5) throughout the study.

For the daily recaps, the most commonly chosen emotion was *happy* (29.71%), followed by *content* (14.86%) and *tired* (14%). Participants selected *angry* (0.57%) and *depressed* (1.43%) the least often.

In the app, we represented social load by a scale ranging from 0 (*lonely*) to 100 (*socially exhausted*), with 50 in the middle (*the right amount*). Participants reported social loads between 11.00 and 99.00 ($M = 51.07$, $SD = 12.45$, $Mdn = 50$).

6.3.4 Passive Tracking. Seven participants (28%) had at least one call passively detected. For these seven participants, an average of 3.14 calls were detected during the study ($SD = 2.19$, $MIN = 1$, $MAX = 6$). Participants deleted 31.82% of all detected phone calls. Of the remaining 15 detected phone calls, 13 (86.67%) had additional information added.

6.3.5 Notifications. Most participants ($N = 19$, 76%) did not change the time of the push notifications, leaving them at 1 p.m. and 8 p.m. Four participants changed the first reminder to 12 a.m., and three participants changed the second reminder to 9 p.m. and one participant to 7 p.m. One participant set both reminders to the same time, 9 p.m.

6.4 Interaction Experience

In the following, we present the results regarding user experience, usability, and technology-supported self-reflection.

The User Experience Questionnaire *UEQ* [99] measures user experience across five dimensions: Attractiveness ($M = 1.99$, $SD = 0.78$), Perspicuity ($M = 2.38$, $SD = 0.65$), Efficiency ($M = 1.81$, $SD = 0.91$), Dependability ($M = 1.83$, $SD = 0.84$), Stimulation ($M = 1.63$, $SD = 0.69$), and Novelty ($M = 1.17$, $SD = 0.95$). All dimensions show an overall positive evaluation for *Social Journal*.

We used the System Usability Score *SUS* [19] to assess usability. The app scored an average of 87.80 ($SD = 8.52$, MIN = 65.00, MAX = 100), implying *excellent* usability according to the adjective rating scale by Bangor et al. [4].

Further, the Technology-Supported Reflection Inventory *TSRI* [9] measures how well an interactive system supports reflection using three dimensions: *insight*, *exploration*, and *comparison*. *Social Journal* scored an average rating of 37.5 (SD = 8.05). The highest rating a sub-scale can reach is 21. In our study, the sub-scale *exploration* scored the highest average score (M = 16.4, SD = 3.27), followed by *insight* (M = 10.8, SD = 3.18) and *comparison* (M = 10.2, SD = 4.28).

6.5 Exit Interviews

In the following, we present the findings from the interviews based on our three themes. The theme INPUT relates to the frequency, routine, and general tracking capabilities of users' social interactions. The theme IMPACT refers to the impact of *Social Journal* on users' social interactions and reflection on those interactions. The third theme SYSTEM DESIGN is concerned with system adaptations and feature requests.

6.5.1 Input. Participants found it was quick and easy to enter interactions and recaps into the app. P19 stressed: *"...it's not a big time commitment overall. That's why I think it's such an easy app to implement in everyday life."*

Some participants reported that they sometimes found it difficult to identify which social interactions to record in long-lasting, frequent, or professional contexts. Such interactions might include flatmates, romantic partners living together, or workplace interactions. For example, P1 stated *"...sometimes I was still unsure, should I enter the social interaction with my partner, with whom I live, every day? "*. Several participants expanded on this, explaining that they did not record all social interactions but focused on those that were meaningful or challenging:

> *I just entered the ones where I had a noticeable burden or where it was difficult. I didn't write down every patient because that would be too much. It didn't bother me that much, or I didn't have to reflect on it at all. Only the ones that were really important.* (P11)

Others concluded from this that they might only want to track *"mood extremes"* (P5, P8) or reduce the *"tracking to only once a day"* (P23), in the form of a daily recap.

For daily recaps, mood capture was retrospective for the whole day, however, participants noted that *"there are more influencing factors on mood than only social interactions"* (P24). This also raised the idea to expand the tracking and include more context information, such as *"activities during the day"* into the application (P24).

Contrasting to the findings in the online survey in Section 4, participants suggested adding more *"automated and passive tracking"* of social interactions (P9, P11, P17). Participants also reported that they expect that over the long term, self-tracking through the app will become a routine, where users regularly track their social interactions once they are used to the process (P3, P7, P12).

6.5.2 Impact. Eight participants (32%) reported that using the app affected their social interactions, while 17 (68%) said it had not. However, most participants mentioned that they were more mindful and thoughtful about their social interactions: *"Definitely, after each meeting, it made me think more about how I felt there now, which I probably wouldn't have done"* (P8).

Some participants mentioned that the simple act of entering social interactions already made them more reflective on their interactions: *"...while entering, it prompted me to think..."* (P9).

Participants also enjoyed the visualizations, overviews, and notifications. The visual feedback fostered awareness and realizations about the impact of social interactions: *"I was able to see very clearly who is not really making me feel as great... it was very visible"* (P21).

The visualizations and data analysis supported users in understanding their data in a way that a physical journal could not: *"These graphics really got me hooked. [...] That would be a key reason for me [to keep using the app] because no book can do that."* (P21).

For several participants, using the app also gave them new insights into their social interactions and helped them detect patterns and influences on their own well-being. Participants mentioned, for example, identifying healthy and unhealthy contacts and realizing that certain social interactions that they initially thought had no effect on their mental health actually did: *"I noticed that I had a call with my mum...even a phone call like that has an effect, and I wasn't even aware of it before."* (P22).

Additionally, several participants mentioned that the app helped them reflect on factors that impacted their social exhaustion:

> *I found it interesting, for example, that even though you had more or less social interactions on one day, you still didn't feel overloaded or lonely, but it was a finding for me that it has to be spread out over the days.* (P20)

The app also encouraged them to reflect on which types of contacts they were spending time with and which could use more attention: *"...for example, I have now spent the whole day talking only to colleagues and not to friends. And then I realized that maybe I should call someone."* (P1)

Going a step further, some participants not only became more aware of their social life but actually changed their behavior based on these insights:

> *It helped me a lot to understand that sometimes... well, I'm actually an extrovert, but sometimes it doesn't do me any good to do things with so many people. And it helped me to listen to that.* (P4)

Conversely, some participants did not find that the prototype impacted their social interactions, often because their social plans are pre-scheduled and not easily changed: *"...a lot of fixed appointments have already been made, which I couldn't have canceled again or something."* (P11).

6.5.3 System Design. Most participants mentioned the usability and the design as positive aspects of the application:

> *...very intuitive, because it didn't take a long time to learn how it worked, but you could click on it and start right away.* (P24)

Although some participants mentioned the emotion wheel positively, *"...this barometer, the one where you can enter how you feel and so on, super clear and interactive. I liked that very much."* (P22), some found it challenging to decide on one of the given emotion options and other participants would have liked to choose more than one emotion at a time:

> *When you do the daily recap or even when you add the social interaction, you can only point to one emotion that you felt like you only felt happy or tired or frustrated, but usually, you feel more than one emotion, especially within the day.* (P23)

Participants were split on this issue; some participants wished for *"more options"* (P16) for emotions, while others *"wouldn't add any more feelings"* (P12). Some participants would have preferred to be able to indicate how strongly they felt an emotion rather than having more options: *"...the intensity could be specified; for example, the line could be made longer or shorter."* (P20).

Moreover, participants would find it useful if the application had more automatic tracking to reduce the burden of manual tracking while still capturing all relevant interactions.

6.6 Summary

Our findings revealed how participants used the app to track and reflect on social interactions in their everyday lives. The app could support users to track their social interactions and associated emotions. The app was mainly used in a diary manner, capturing and reflecting on the interactions after they happened. Daily recaps and high app usage in the evening highlighted a tendency to reflect on social interactions within the bigger picture, considering experiences throughout the whole day. Participants mostly tracked in-person interactions, in 1 to 1 or small group settings, implying that participants considered those interactions to be the most meaningful and impactful ones. The app triggered participants to reflect on their social lives in different ways: (1) by the act of entering social interactions along with additional information prompted by the app, (2) by visualizing the diary entries, and (3) by providing charts, tables, and overviews to help interpret the data.

7 DISCUSSION

In this paper, we set out to answer three research questions: (**RQ1**) *How do people want to self-reflect on social interactions using technology?*, (**RQ2**) *How can a mobile application support reflection on social interactions?*, and (**RQ3**) *How can a mobile application support reflection on social interactions in everyday contexts?* We designed the online survey primarily to answer RQ1 and RQ2. We then built a prototype to further investigate all three research questions, and conducted a field study to add additional insights. In the following, we will discuss insights gained from the online survey and the design, implementation, and evaluation of the *Social Journal* for technology-supported reflection on social interactions and discuss how the results address our research questions.

7.1 Self-Reflection on Social Interactions (RQ1)

The results from the online survey provide insights into how people currently self-reflect on their social interactions and what they expect from a digital application to help them do this. Our results suggest that people think they have relatively too few social interactions and contacts rather than too many. The more social interactions people have, the more satisfied they tend to be with this frequency of interactions and number of social contacts. The results also indicate that the more frequently people have social interactions, the more satisfied they are with the overall quality of their social life. Our findings underscore recent research showing that loneliness, the state in which individuals feel that the quality or quantity of their social relationships is inadequate, is a global and growing social problem [21].

Interestingly, participants who are generally more reflective about their social interactions and who believe that the various aspects of social interactions have a greater impact on their mental well-being also find it more useful to reflect on these aspects with a digital application and have fewer privacy concerns about tracking these aspects with a digital application. This suggests that people who rated the usefulness and comfort of tracking social interactions low may also have been influenced by the fact that they generally do not see a need to reflect on their social life, and suggests that such an application should be targeted at people who are interested in reflecting on their social interactions.

7.2 Design Considerations for Technology-Supported Reflection on Social Interaction (RQ2)

The results from the survey and field study provide insights into what people expect from an application that supports them in their social life. These results can be used to guide future design efforts in this area.

7.2.1 *Relevant Social Interaction Variables.*

The two main aspects highlighted by participants are the frequency of social interactions and the emotions connected to them. We identified five important aspects of social interactions that participants claim are relevant while also acceptable to track through technology, namely *time and duration*, *type of interaction*, *associated emotions*, *number of people*, and *type of relationship*. Further information, such as the specific person, location, or discussion content are additional aspects that could greatly impact social interactions, but users commonly expressed privacy concerns about tracking them.

7.2.2 *Desired User Interactions.*

From an interaction perspective, users highlighted that they are interested in technology providing them with overviews (statistics about their social interactions), judgments (pattern recognition), actionable recommendations, and specific, actionable reminders. Participants also frequently mentioned that they wanted a diary-style interaction, enabling them to log their social interactions and revisit past events, building up the information over time. Users were divided between appreciating the simplicity of entering their emotions with the emotion wheel and wishing for a more complex representation of emotions. Consequently, adjusting the logging input to different user preferences is important to ensure consistent logging over time.

7.2.3 *Track Meaningful Social Interactions.*

Our field study highlights that participants primarily track in-person social interactions. Other than phone calls, no digital interactions were logged in the app. We speculate that two factors may have influenced this result. First, in line with our motivation for this work, participants may find it more useful to track interactions that do not currently provide a trace. Text-based interactions inherently provide a full transcript and may therefore not be an interesting modality to track separately. Second, we did not include a dedicated option for logging text-based interactions. This may have influenced users to refrain from logging text messages even when they were meaningful. In either case, our results suggest that users might favor logging in-person interactions not only because they have an impact but also because such interactions do not leave traces, adding to the value of an app in supporting social life. Additionally, participants deleted nearly one-third of the passively tracked phone calls, indicating that not *every* interaction should be tracked, but rather only *meaningful* ones. As such, designers of future systems for tracking social interactions should support the detailed tracking of in-person encounters. Presently, this is typically accomplished through manual logging. However, participants in the field study were interested in additional automated data collection, suggesting opportunities to incorporate social sensing technologies. However, designers should clearly consider privacy issues in developing social interaction technologies that feature automated data collection and consider the additional reflection opportunities that arise from manual entry [43].

7.2.4 Tracking Social Interactions is not for Everyone. Over 40% of the online survey participants were not interested in tracking their social interactions, motivated by data privacy concerns and a lack of interest. As such, future work should investigate the characteristics of users who are interested in tracking their social interactions. Understanding this user group is crucial to designing a useful tool. Our participants, in general, felt that they had too few social contacts rather than too many and were interested in reflection and improving their well-being.

7.3 Technology-Supported Reflection on Social Interactions in Practice (RQ3)

The in-the-wild study provides insights into how people actually track and reflect on their social interactions using technology in everyday life. The findings of this study shed light on the usage patterns and potential impacts of a reflective app designed to capture and analyze social interactions. The participants used the app primarily as a reflective diary, reporting social interactions after they occurred. This behavior aligns with the idea of using reflective practices to enhance self-awareness and emotional understanding.

The app usage logs and insights gathered from interviews highlight that interactions and daily recaps are typically entered in the evening. This temporal pattern suggests that participants found value in reviewing their day's interactions. This observation coincides with the psychological concept of reflection-in-action and reflection-on-action, where real-time introspection and subsequent analysis contribute to deeper understanding and insight [53, 72]. However, especially when reflecting on the whole day retrospectively, participants wished to add additional factors beyond social interactions that may have contributed to their mood.

Users mainly tracked in-person contacts, particularly 1 to 1 or small group interactions. This preference for close-knit interactions could be attributed to the intrinsic nature of these encounters, which often involve higher levels of emotional engagement. We speculate that the emphasis placed on in-person interactions could indicate that in-person interactions are generally more meaningful to users, however, this could also be motivated by the fact that many digital interactions inherently leave traces. Users, therefore, are already exposed to some evidence of their digital interactions, while in-person interactions typically leave no tangible trace. Given that a lot of participants aimed to record only meaningful interactions, it is reasonable to hypothesize that these types of social contacts have a more pronounced influence on users' emotional well-being. This aligns with research on the quality of relationships and their impact on psychological health [60, 89]. An interesting observation is the prevalence of reported interactions resulting in positive affect.

Furthermore, the qualitative results revealed emotion selection as an issue for some participants, as they expressed difficulty in reporting their emotional state by selecting one or just one of the given emotion options. How we simplified the Circumplex model to make emotion selection easier for the user could explain this. The Circumplex model normally includes a neutral emotion in the middle of the emotional spectrum [91], which we did not represent in the app's emotion circle for simplicity. Hence, one possible approach to allow for a more comprehensive representation of emotions would be to allow users to indicate the intensity of the selected emotion by positioning it relative to the neutral mood state in the middle of the circle. Recent research has discussed if the two-dimensional representation of emotions, such as the Circumplex model, may not adequately capture the full range of human emotions [38]. This suggests the consideration of alternative, more complex models for emotion selection, such as the Plutchik Model [82] or the PAD Model [69], or to rely on more recent research about human emotion that suggests that humans can feel up to 27 different emotions [30]. However, as some participants already found our simplified version to be time-consuming, adapting a more complex model would require additional user testing.

In general, users perceived the passive tracking of phone calls positively. During the interviews, none of the users gave negative feedback but instead expressed a desire for more passive data collection to minimize time and effort. This suggests an opportunity to incorporate additional passive tracking features into the application. However, it is essential to consider that, as highlighted by Jacob and Zheng [43], journaling itself is intended to foster self-awareness, particularly in the context of mental health applications. This finding also applies to the *Social Journal* app, as the act of manually entering social interactions already contributed to increased self-awareness. Thus, too much automated data collection could potentially undermine the core purpose of promoting self-reflection and self-awareness [102]. Too much automation can also lead to user frustration and loss of control [57] and privacy concerns [85]. Therefore, it is important to investigate the integration of additional social sensing in a social reflection application through research to identify the right balance between reflection benefits, effort, and privacy.

Connecting social interactions to emotions provided users with a new perspective on the relationship between the two and raised their awareness. Overall, the users appreciated having a visual overview to reflect on their social interactions. The interviews and the TSRI scores showed that *Social Journal* supported users in reflecting on their social interactions. Insights gathered through the app indicate that *Social Journal* also led to active changes in behavior in some cases. In all, the results of the in-the-wild study highlight the potential for technology-supported reflection on social interactions to foster introspection and self-awareness.

7.4 Privacy Concerns

Interestingly, although privacy concerns were an important result in the online survey and are often discussed in personal informatics literature [85], none of the participants of the user study mentioned this aspect. We ensured that the *Social Journal* app gave users the freedom to decide what data to track and share with the application. This may have reduced some of the participants' privacy concerns as control is a significant factor in overcoming privacy concerns in tracking applications [7, 85]. Some participants even proactively suggested including more automatic tracking into the application to reduce effort.

As the main task of the study was to track social interactions using a smartphone application, which we communicated at the time of recruitment, people who were particularly concerned about privacy may not have even considered participating in the study. This could have led to a selection bias and a less representative sample [108]. This selection bias may also have been present in the survey, which may have impacted the results concerning the willingness to track social interactions with a smartphone.

7.5 Limitations & Future Work

There are several limitations that should be considered in interpreting our results. Due to the exploratory nature of this work, this investigation offers valuable initial insights into technology-supported reflection on social interactions and suggests numerous research directions for further investigation. We expect future research to further investigate and validate the findings and directions identified in our work.

Conducting an in-the-wild user study allowed us to explore the prototype in real-life scenarios and provided ecologically situated findings [24]. However, this is also a limitation of our work as field studies have inherently weaker internal validity [33] since many variables cannot be controlled. Our study did not feature a control group because it would not be possible to make meaningful comparisons without tracking any social interactions at all. Therefore, we recommend that future work evaluates the influence on user behavior in a more advanced study design, such as including a control group, although it remains to be determined how to track the social interactions for a control group which would, by definition, not be tracking their social interactions.

There are also limitations to our work due to the study sample. We recruited participants using a university mailing list, which draws from a large range of potential participants both within and outside of the university. However, our study sample is relatively young, majority female, and includes many students, which may reduce the generalisability of the results. Additionally, given that about half of the study participants couldn't experience call recognition due to its absence on iOS, we do not have any insights as to whether there are differences between different OS users regarding the meaningfulness of their phone calls.

Another limitation is the duration of the study. Although two weeks is long enough to gain initial insights into how users interact with a social interaction reflection system and uncover valuable information that would not be available in a lab study, this is not long enough to observe long-term effects. Self-reflection, in particular, is a process that needs a longer period to show its full potential [62]. As our results already indicate that using the *Social Journal* app can lead to increased self-awareness and behavior change, this work serves as motivation for future work to investigate the long-term impacts of the *Social Journal* app on social interactions and self-reflection in general. Prior work recommends several weeks or even months to reveal sustainable and long-term effects in an in-the-wild study setting [24]. The usage time (see Figure 8) shows a slight downward trend other than the first day. Likely, heavy usage on the first day is due to the users setting up and familiarizing themselves with the app. A longer-term future study would be useful to investigate whether users are able to maintain a journaling habit with the *Social Journal* over a long period of time.

8 CONCLUSION

In this paper, we investigated technology-supported reflection on social interactions using a survey, a mobile app, and an in-the-wild study. We first conducted an online survey with 124 participants to understand how people currently reflect on their social interactions and how they would prefer technology to support this task. We found that users are interested in reflecting on the frequency of their social interactions and the associated emotions. Based on these findings, we designed and developed *Social Journal*, an app that enables users to track and reflect on their social interactions. We deployed the prototype in a two-week in-the-wild study with 25 participants and collected quantitative and qualitative feedback. The results of the field study demonstrated that the *Social Journal* app can effectively support self-reflection on social interaction frequency and social load. The results also provided insights into how individuals use such an app in everyday life, which can be used to improve the prototype or develop new concepts to help people reflect on their social interactions. We also identified key challenges associated with tracking and reflecting on social interactions, including privacy concerns and long-term motivation. Overall, this research contributes important insights into how users prefer to reflect on their social interactions using technology and lays a strong foundation for future work.

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