Doctoral thesis submitted to
the Faculty of Behavioural and Cultural Studies
Heidelberg University
in partial fulfillment of the requirements of the degree of
Doctor of Philosophy (Dr. phil.)
in Psychology

Title of the publication-based thesis

Social Interactions in Daily Life: Personality Processes in Contexts

presented by
Yannick Roos

year of submission
2024

Dean: Prof. Dr. Guido Sprenger
Supervisor: Prof. Dr. Cornelia Wrzus

Table of Contents

Acknowledgements

First and foremost, I would like to express my heartfelt gratitude to my supervisor, Prof. Dr. Cornelia Wrzus. Your constant support, insightful feedback, and dedication to our research have been pivotal in my development. Your guidance has challenged me to give my best, and I am deeply thankful for all the time and effort you have invested in me.

Overall, I am honored to have collaborated with such a group of inspiring and brilliant minds as coauthors and project collaborators. I would like to especially thank Prof. Dr. David Richter, Prof. Dr. Ramona Schödel, and Dr. Michael D. Krämer. Special thanks also go to Florian Bemmann for the exceptional technical support during two of the studies. I would also like to thank Prof. Dr. Peter Kuppens for his willingness to review this dissertation.

My journey would not have been the same without the companionship and friendship of my amazing colleagues. Anna, you were the greatest officemate one could hope for. Kira and Gabriela, you made the office a joyful place. Yang and Kira, our lunchtime conversations were always a highlight of my day, and I am grateful for those moments. Michael, I did not see you only as a project collaborator, but also as a friend. I have learned so much from all of you.

To my friends who supported me along the way, thank you so much. I further want to extend my appreciation to my dancing community. Special thanks go to Anastasija, Estelle, Dominik, and Natali. Without you, the dancing community in Heidelberg wouldn't be the wonderful place it is, a place to celebrate life.

My deepest gratitude goes to my family for their unwavering support. Mum and Dad, you have paved the way for me in countless ways, and I consider myself incredibly fortunate to be your son. To my grandparents, as well as to Marianne and Adam, your support has been invaluable, and I cherish the many wonderful moments we shared. I would also like to thank my siblings, who I know I can always count on. I am equally thankful to the family of my wife, who have embraced me as one of their own. Dieter, Petra, Patrick, and Vanessa, your warmth and acceptance have made me feel truly at home. Thank you for welcoming me into your family with open arms.

Lastly, I want to express my deepest thanks to my wife, Kim. You are an amazing person, and I am incredibly happy to have you in my life.

Abstract

People spend much of their day interacting with other people, and such social interactions are pivotal for health and well-being. While previous research thoroughly elaborated on stable interindividual differences in social relationships, such as associations between personality and the composition of people's social networks, much less research has focused on the processes governing daily social interactions and interindividual differences therein. In this dissertation, three empirical studies, involving more than 1,000 adults from a broad age range and diverse backgrounds, examined the interplay between personality, daily social interactions, as well as micro-, meso-, and macro-context factors. The dissertation extends previous research in two ways: First, various methodological approaches to measuring daily social interactions and social traits are compared and their unique strengths and weaknesses are elaborated. Second, context effects on daily social interactions are empirically demonstrated on various timescales and analysis levels (i.e., micro, meso, and macro). Following the general introduction, the three studies are presented in five chapters:

In Chapter 2, three different methods for the assessment of social interactions in daily life are compared: day reconstruction, experience sampling, and mobile sensing. Measurements of face-to-face interactions showed substantial agreement and agreement between measurements of smartphone-mediated interactions was high. Yet, none of the methods comprehensively measured social interactions, that is, many social interactions were captured by only one of the methods, and qualitative aspects of social interactions remained difficult to capture with smartphone sensors.

Chapter 3 focuses on a comparison of social traits related to dynamic social processes in daily life. The chapter describes the development of a brief self-report questionnaire of social dynamics, the Social Dynamics Scale, and examines its predictive validity regarding changes in social contact across time and different social relationships. The results showed considerable overlap between social traits. Additionally, the new scale measured individual differences in social dynamics reliably, validly, and with predictive value for changes in daily contact. Still, next to the assessment of social traits, the measurement of processes at a higher time resolution is needed for understanding processes governing social interactions as they occur in daily life.

Chapter 4 examines the temporal dynamics of momentary social desires and social interactions within and across days, accounting for social traits as well as contributions of the micro-context, i.e., situational affordances. The affiliation motive predicted momentary social desires but no changes in future social interactions, except when social interactions were

assessed with mobile sensing. Situational affordances, such as the valence and voluntariness of social interactions, predicted social desires and future contact.

Chapter 5 explores how aspects of the meso-context, that is, the number of relationships people maintain and the density of people's living arrangements, contribute to social interactions in daily life. While transitions from solitude to social interactions were faster for people living in densely populated households, contrary to expectations, they were slower for people living in dwellings with more homes. Additionally, people living in densely populated households transitioned slower from social interactions to solitude. Current social desires predicted subsequent social interactions within days, but not across days—independent of individuals' social network size or social density.

Chapter 6 examines changes in social contact, life satisfaction, and depressivity/anxiety during a time that was characterized by the macro-context of the COVID-19 pandemic and associated pervasive social contact restrictions. The affiliation motive, need to be alone, and social anxiety moderated the resumption of personal contact under loosened restrictions, as well as associated changes in life satisfaction and depressivity/anxiety.

Overall, the chapters demonstrate how innovative multi-method intensive longitudinal studies can provide unprecedented opportunities for researchers to study social behaviors in the contexts they are embedded in. The results call for a greater integration of specific context factors in theories on the dynamic regulation of social interaction in daily life and for a continued development of measurement and analysis methods.

Chapter 1: General Introduction

A large group sits gathered around a table in a dimly lit restaurant. The atmosphere is vibrant with lively conversations, resulting in a noticeable level of noise. A spotlight shines on a person in a red pullover trying to decipher the menu with a furrowed brow. Suddenly, with a contemplative sigh, the person turns to her neighbor and whispers: “I hate it when people always want to talk. That makes it impossible to properly study the menu. Please pardon me, I am heading to the bathroom”. Ignoring the perplexed expressions of her fellow diners, she takes the menu and leaves the stage.

In improvisational theatre, the art lies in navigating interactions with other actors by reacting authentically to the given circumstances but also staying true to the own character. The stage of life is bigger than the stage of theatre, but people’s behavior may follow this same principle: Just as actors adapt their behavior to fit their character and the scene, in their everyday lives, people adapt their social interactions based on who they are and the contexts they are in (Barker, 1975; Carver & Scheier, 1982; Huxhold et al., 2022; Lewin, 1936). Still, it remains an open question what precisely guides people in discerning when to act on their social desires or when to adapt to external demands of their current situation.

Many psychologists agree that behaviors are jointly shaped by characteristics of the person as well as characteristics of the environment (Back et al., 2023; Barker, 1975; Carver & Scheier, 1982; Huxhold et al., 2022; Lewin, 1936). This is often expressed with the formula $B = f(P,E)$, which—broadly interpreted—posits that behavior is a function of the person and environment characteristics (Asendorpf & Rauthmann, 2020; Buss, 1987; Lewin, 1936). Accordingly, the combined influences of person and environment characteristics are at the core of many theoretical approaches to social behavior (Carver & Scheier, 1982; Hall & Davis, 2017; Huxhold et al., 2022; Kuper et al., 2023). Yet, rigorously testing influences of both person and environment characteristics in people’s daily lives has proven difficult and more research on the processes by which person characteristics and environments jointly shape social behavior is needed (Back et al., 2023; Meagher, 2020). The complexity of testing dynamic theories of social interaction regulation is compounded by the many challenges of accurately measuring social interactions and environment characteristics in everyday contexts. Accordingly, researchers call for a continued development of measurement and analysis methods to allow testing (new) theories on social behavior (Back et al., 2023; Montgomery & Duck, 1991).

The aims of this dissertation are twofold: to improve measurements in the context of daily life social interaction research and to extend models on the regulation of social interactions in daily life. To this end, I compare different approaches to the measurement of social interactions, social traits and social desires, and context factors in daily life. Furthermore, using data gathered from three sizeable age- and gender-heterogenous samples totaling more than 1,000 adults, I examine how characteristics of the person and environmental aspects jointly contribute to the dynamic regulation of social interactions in daily life.

1.1 Definition and Measurement of Social Relationships and Social Interactions

Social relationships are defined as connections between people who influence each other and maintain regular contact through repeated social interactions (American Psychological Association, n.d.-a; Back et al., 2011). Whereas plenty of research focused on rather static aspects of social relationships, such as the structure (e.g., social networks characteristics) or the function (e.g., social support) of social relationships, less research has examined social relationships from a dynamic process perspective (Back et al., 2023; for an overview of static approaches to relationships, see Valtorta et al., 2016). Yet, social relationships are inherently dynamic and change over the lifespan (e.g., Carstensen, 1992; Wrzus et al., 2013), within weeks or months (e.g., separation of couples or friendship formation; Easterbrook & Vignoles, 2015), or sometimes even within days or a single interaction (Back et al., 2011; Hall & Davis, 2017). Accordingly, social interactions—processes that involve reciprocal stimulation between two or more individuals—are the building blocks of social relationships (American Psychological Association, n.d.-b; Back et al., 2011).

Different methods have been used in prior research to examine social interactions in daily life. For example, environmental psychologists used behavioral observation to study social interactions (Barker, 1975; Festinger et al., 1950). Because behavioral observation is effortful, these studies were often restricted to small and specific samples. Other researchers asked participants to fill out daily diary data of different kinds. For example, the Rochester Interaction Record (Nezlek, 2001; Wheeler & Nezlek, 1977) asks participants to record their daily social interactions. Time use surveys let participants estimate how long they engage in different activities (Ortiz-Ospina et al., 2024), and the day reconstruction method (Kahneman et al., 2004) assists participants in reconstructing their daily activities as accurately as possible, using a list of activities as a memory aid. In the 1980s, experience sampling methods became more common (Csikszentmihalyi & Larson, 1987). Compared to daily diary methods, these methods were able to assess behavior, thoughts, and emotions much closer in time to when they occurred (i.e., within seconds after participants interrupt their current activity). Experience sampling is still frequently used, yet disadvantages, such as the disruptions caused by repeatedly questioning participants, led researchers to explore alternative approaches, for example mobile sensing (Harari et al., 2016; Roos et al., 2023; Wrzus & Mehl, 2015). Mobile sensing promises increased objectivity and reduced participant burden by using (smartphone) sensors to passively collect information on behaviors and surroundings in everyday life (Harari et al., 2016; Niemeijer et al., 2023; Roos et al., 2023).

Given the broad availability of all these methods, researchers interested in social interactions have to make many choices prior to conducting any study. Moreover, new methods such as smartphone sensing need to be further developed, tested, and finally reconciled with earlier work using other methods. Accordingly, in Chapter 2, I compare mobile sensing assessments of social interaction with assessments obtained using day reconstruction and experience sampling methods. I discuss advantages and disadvantages of different methods, and explore the question of how measuring social interactions with a combination of methods can help us understanding daily social interactions better. Still, to understand social interactions, it is essential to not only measure them accurately but also to consider the underlying processes that govern how individuals manage their social interactions in their daily lives.

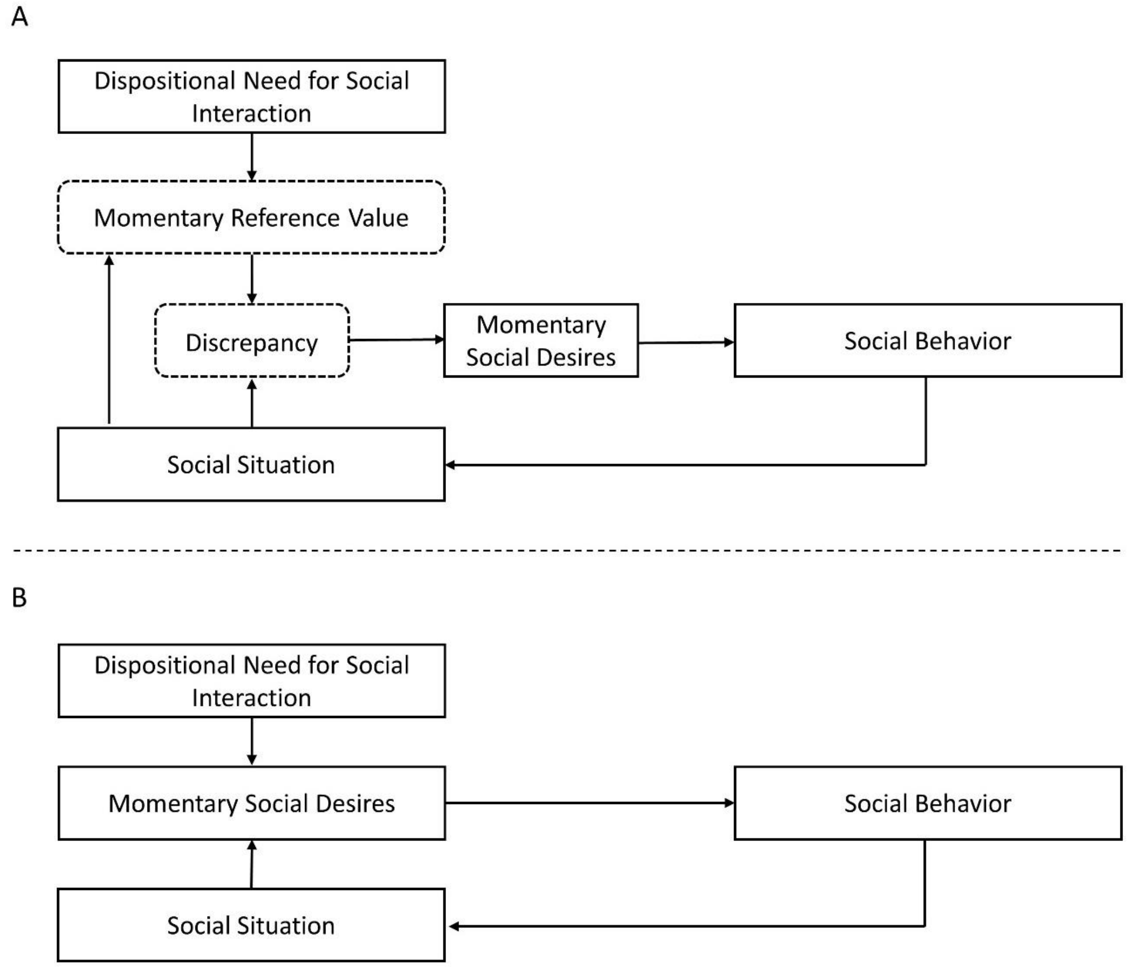
1.2 The Dynamic Regulation of Social Interactions in Daily Life

Current psychological theories posit that people actively manage social interactions in their daily lives by reducing the gap between the amount of social interaction they currently desire (i.e., momentary reference value; see Figure 1.1, Panel A), and the amount they actually experience (Hall & Davis, 2017; Huxhold et al., 2022; Sheldon, 2011; Wrzus, Roos, Krämer, Schoedel et al., 2024). That is, if a person is alone for an extended period, and opportunities to fulfil the person’s need for social interaction are missing, the person should become motivated to change the situation and try to seek social interactions (Hall & Davis, 2017; Huxhold et al., 2022; Krämer et al., 2022, 2024; Sheldon, 2011). Eventually, a transition from solitude to (positive) social interaction should become possible and satiate the person’s need for social interaction. Conversely, if a person socially interacts for an extended period, and opportunities to be alone are missing, the person should be motivated to change the situation and try to seek solitude (Figure 1.1; Hall & Davis, 2017; Huxhold et al., 2022; Krämer et al., 2022, 2024; Sheldon, 2011).

Yet, translating this model into empirically testable predictions is challenging. First, it is unclear how a momentary reference value and discrepancy between such a value and the situation should be assessed independently from the supposed outcome—the social desires. For now, the momentary reference value remains an auxiliary theoretical construct that is not exactly defined in theories on social interactions. Accordingly, empirical studies usually test simplified versions or only certain parts of this model (e.g., Hall, 2017; Neubauer et al., 2018; O'Connor & Rosenblood, 1996). Second, the model predicts different associations between its components depending on the current state of the system and the timescale of the underlying processes. For example, if deviations from the desired reference value are large, a single short social interaction might not be sufficient to fulfill current social desires. In this system state, the model would predict positive associations of current social interaction, current desire to interact, and future social interaction. Consequently, only at an appropriate system state, that is, when the need for social contact (or solitude) approaches satiation, does the model predict negative associations between current social interactions, desires to interact, and further social interaction. Moreover, the sampling rate with which observations are obtained critically influences whether the underlying processes can be adequately captured. Next, I elaborate on how empirical evidence aligns with the model shown in Figure 1.1, Panel B, starting at the top of the model.

Figure 1.1

Dynamic Regulation of Social Interactions as a Negative Feedback Loop



Note. Boxes with dotted borders indicate constructs that are usually not directly measured in empirical studies. Panel A: The core dynamic regulation mechanism of current theories on social interactions in daily life (e.g., Hall, 2017; Hall & Davis, 2017; Huxhold et al., 2022; Sheldon, 2011). Panel B: Empirical studies usually test a simplified version of these theories, because it is unclear how momentary reference value and discrepancy should be measured independently from social desires. That is, researchers usually measure aspects of the social situation and momentary desires and then infer that there must have been a discrepancy.

1.3 Interindividual Differences in Social Behavior: Social Traits

Whereas all people need some amount of positive social interactions (Baumeister & Leary, 1995; Deci & Ryan, 2000; Dweck, 2017), people differ in how much social interaction they need, as well as in their strategies to get their need for social interaction met (Hall & Davis, 2017; Schönbrodt & Gerstenberg, 2012). Indeed, differences in social behaviors are some of the most important markers of differences between people, so much that how social a person is lies at the core of several of the most important descriptions researchers use to differentiate between people (Harris & Vazire, 2016; Soto & John, 2017). Still, researchers have proposed diverse—to a certain degree overlapping—constructs to describe different facets of how people behave socially. For example, affiliation motive, extraversion, communal orientation, agreeableness, as well as social anxiety are considered important for how people manage their social relationships (Back et al., 2023; Wrzus, Roos, Krämer, & Richter, 2024).

Several studies have shown that social traits such as extraversion go along with larger offline and online friendship networks, as well as a higher quality of friendships (e.g., Cheng et al., 2019; Harris & Vazire, 2016; Selfhout et al., 2010; Wagner et al., 2014). Additionally, highly extraverted people spend more time with face-to-face and technology mediated social interactions (Kroencke, Harari, et al., 2023; Wrzus et al., 2016). Furthermore, highly agreeable people tend to get along better with others, are more popular, and thus also have larger social networks (Harris & Vazire, 2016; Selfhout et al., 2010; Wagner et al., 2014).

To summarize, many traits have been suggested as central to the social behavior of a person: affiliation motive, extraversion, communal orientation/agreeableness, and also social anxiety (for a review, see Back et al., 2023). All of these measures are operationalized differently, yet overlap conceptually to a certain degree. Therefore, researchers interested in social interactions are challenged on which (combination of) measures to use.

In Chapter 3, I describe the development of the Social Dynamics Scale. This scale was developed to measure relatively stable tendencies in how people experience the lack or abundance of social interactions. The same chapter also presents a nomological network that shows associations between several social traits. Still, besides relatively stable traits, momentary social desires play a major role in processes governing social interactions in daily life.

1.4 Social Desires, Social Behaviors, and Social Situations in Daily Life Studies

Empirical research strongly supports a positive association between momentary desires and social behavior, as well as subsequent changes in the social situation. For example, people's desire to interact predicted more social interaction, and their desire to be alone predicted less social interaction later the same day (Hall, 2017; O'Connor & Rosenblood, 1996). Likewise, students who desired to be in contact with their close others more than usual for them reported that they felt a stronger sense of intimacy on the same and also the following day (Neubauer et al., 2018). In another study, when romantic partners reported a higher communal motivation (i.e., the desire to share experiences, thoughts, or feelings with their partner, and the wish to receive emotional affection), this was indeed related to experiencing more of such moments with their partner on the same day (Zygar et al., 2018). These findings also fit well to literature showing positive associations between intentions—people's self-instructions to achieve desired outcomes—and behavior (Sheeran & Webb, 2016).

Contrarily, empirical findings on the associations between social interaction and subsequent social desires have sometimes been interpreted as being in conflict with the assumed homeostatic regulation principle. Oversimplified, the homeostatic regulation principle could be (mis)understood as indicating that less social interactions than usual should always go along with subsequently increased desire to interact, and that more social interaction than usual should always go along with subsequently decreased desire to interact. However, such an oversimplified account of the homeostatic regulation principle finds little support in the literature. For example, with regards to associations between previous social situations and momentary social desires, students who reported to feel less intimate than usual with people they spend time with did not report an increased momentary desire to be in contact with their close ties (Neubauer et al., 2018). Additionally, in couples, communal behavior earlier on the same day was positively associated with later communal motivation (Zygar et al., 2018). Yet, because the timescales of the underlying processes of social interaction regulation are unknown, it is unclear whether these findings actually contradict the theory. As explained earlier, for example by assuming a rather slow process of discrepancy reduction, it is well possible to derive the prediction of positive associations between previous social interactions and an increased motivation for even more social interaction a few hours later.

Further, some researchers assumed that prior interaction should be negatively associated with future social interaction, because at some point the desire to interact should be satiated. In line with this, older adults spend longer than usual time alone after longer than usual social interactions and vice versa (Luo, Pauly et al., 2022). However, contrarily, prior interactions were not a good indicator of future interactions in Hall (2017).

To summarize this far, there are astonishing differences between people in the way they interact socially. Depending on people's social desires, they engage in different situation management behaviors (e.g., maintaining vs. terminating; Asendorpf & Rauthmann, 2020; Rauthmann & Sherman, 2016) and more often than chance, such behaviors influence the actual social situation (e.g., presence of other people is more likely when interaction was desired). However, the homeostatic regulation principle alone fails to explain why people would find themselves in prolonged states of mismatch between their desires and the actual social situation (Carver & Scheier, 1982; Huxhold et al., 2022). Accordingly, while a lot of attention has been given to the negative feedback loop of self-regulation, the expectancy-process described by Carver and Scheier (1982) has received considerably less attention, especially in empirical studies. These authors argue that behavior depends not only on people's desires, but also on their assessment of whether they can successfully change a mismatch between the situation and their desires (Carver & Scheier, 1982). That is, to better understand social interactions, researchers need to understand the opportunity structures of the contexts in which social interactions are embedded (Huxhold et al., 2022; Meagher, 2020).

1.5 The Role of Context and Environment

Environments are defined as an aggregate of situations, that is a relatively stable exposure of a person to external conditions that are causally connected to them (Asendorpf & Rauthmann, 2020). As an umbrella term, *context* is used to describe a nested system of factors contributing to how a given situation is experienced. These factors, which may be characteristics of previous situations, the current situation, or more stable situational contexts, can further be broken down to the micro-, meso-, and macro-context—depending how tangible they are in space and time to the individual. I use the term micro-context to refer to the situational embedding of social interactions in daily life, in line with Bronfenbrenner's (1994) suggestion of the microsystem as "a pattern of activities, social roles, and interpersonal relations experienced by the developing person in a given face-to-face setting" (p. 39). Next, the meso-context is understood as the concrete living situation of an individual (e.g., socioeconomic conditions or neighborhood; Bronfenbrenner, 1994; Huxhold et al., 2022). Lastly, the macro-context refers to aspects of the social structure of the society that influence the individual in some way (e.g., laws or institutions; Bronfenbrenner, 1994; Huxhold et al., 2022).

While the context is relevant for all kinds of behaviors, it is especially relevant for face-to-face interactions, because such interactions can only occur if another person is physically present. Besides the physical presence of other people (a rather objectively quantifiable information), people's perceptions of situations, that is, their psychological representations, also matter (Carver & Scheier, 1982). Theorists have thus argued that nested context factors work together in creating a social opportunity structure (Fiori et al., 2020; Huxhold et al., 2022). That is, the context influences the availability of social interaction partners as well as the perceived costs of engaging with them (Fiori et al., 2020). Yet, theoretical reasoning on context effects has remained rather unspecific and empirical studies focused on rather specific samples (e.g., Devlin et al., 2008; Festinger et al., 1950; Ullán et al., 2012).

Chapter 4, Chapter 5 and Chapter 6 of this dissertation explore how certain aspects of the micro-, meso-, and macro-context contribute to social interactions in daily life. Chapter 4 focuses on situational affordances, for example examining if it makes a difference whether the interaction was self-initiated or initiated by others or due to circumstances. Chapter 5 examines how the current living situation contributes to social interactions, for example examining associations between how dense people live together in their household or dwellings and social interactions. Finally, Chapter 6 explores how contact restrictions during a pandemic (i.e., laws that heavily restricted face-to-face social interactions) influence social behavior.

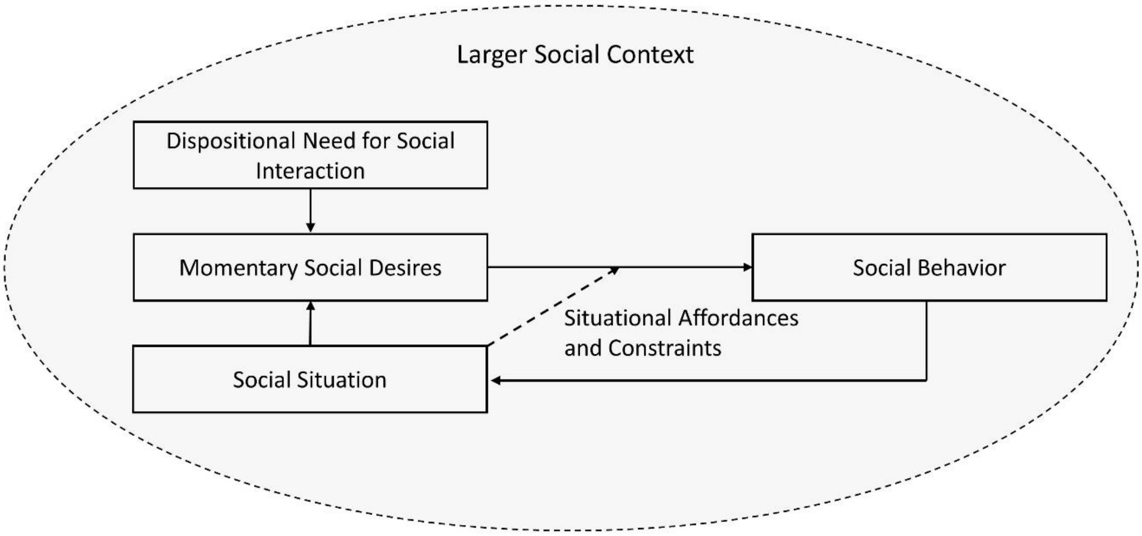
1.6 Dissertation Overview and Objectives of Empirical Studies

Prior research in personality psychology focused on the measurement of traits and how these traits are connected with rather stable relationship indicators (e.g., social networks). Still, the scarce research on processes governing daily social interactions has primarily been guided by theoretical arguments of a negative feedback loop steering social interactions in daily life. In this dissertation, I aim to advance prior research in two broad ways.

First, this dissertation is concerned with the measurement of social interactions, personality traits concerning social behavior, and aspects of the context that may play a role in shaping social behaviors in daily life. Second, this dissertation is concerned with the dynamics of personality processes relating to social interactions. That is, this dissertation explores whether personality differences—in addition to being detected on aggregate, stable outcomes—can also be detected in daily life, i.e., whether interindividual differences in the processes that are thought to lead to stable outcomes can be detected (Back et al., 2023; Baumert et al., 2017; Kuper et al., 2021). Throughout, I emphasize the important role of the contexts in which behavior is embedded. These contexts may either facilitate or constrain people’s ability to behave according to their needs and to their personality and is fundamentally important to understand behavior in people’s daily lives. Thus, besides the further development of measurement methods, the aim of this dissertation is to complement the models presented in Figure 1.1 to include two more factors: The larger social context and situational affordances and constraints (i.e., the social opportunity structure; see Figure 1.2).

Figure 1.2

Extended Model of the Dynamic Regulation of Social Interactions



Note. Social interactions take place in a larger social context. People perceive situational affordances or constraints of situations which influence whether, when, and how people react on their social desires.

To this end, three studies including more than 1,000 adults with a broad age range and from diverse backgrounds are described in five Chapters. Chapter 2 and 3 focus on measurement topics, with Chapter 2 focusing on the comparison of three methods to measure social interactions in daily life, and Chapter 3 focusing on the assessment of social traits relating to social dynamics. Chapters 4 to 6 incorporate different context aspects to complement understanding the interplay of personality and social interactions, which is embedded in concrete contexts in daily life. These chapters are structured from the more proximal micro-context (Chapter 4), to meso-context (Chapter 5), and macro-context (Chapter 6). More specifically, Chapter 4 deals with the question how situational affordances and personality states (i.e., social desires) are connected to transitions from solitude to social contact and to transitions out of social contact. Chapter 5 examines how social network size and social densities influence social interactions in daily life. Finally, Chapter 6 investigates how a strong situation, that is governmental restrictions on social contact during a pandemic, influenced face-to-face as well as technology-mediated social interactions, and how personality related to differential readjustment of social interactions once restrictions were loosened.

Chapter 2: Does Your Smartphone "Know" Your Social Life? A Methodological Comparison of Day Reconstruction, Experience Sampling, and Mobile Sensing

Yannick Roos[1], Michael D. Krämer[2,3,4], & David Richter[4,5], Ramona Schoedel[6] & Cornelia Wrzus[1]

[1] Ruprecht Karls University Heidelberg, Germany, [2] German Institute for Economic Research, Germany,

[3] International Max Planck Research School on the Life Course (LIFE), Germany,

[4] Freie Universität Berlin, Germany, [5] SHARE BERLIN Institute GmbH, Germany,

[6] Ludwig Maximilians University Munich, Germany

Abstract

Mobile sensing is a promising method that allows researchers to directly observe human social behavior in daily life using people's mobile phones. To date, limited knowledge exists on how well mobile sensing can assess the quantity and quality of social interactions. We therefore examined the agreement among experience sampling, day reconstruction, and mobile sensing in the assessment of multiple aspects of daily social interactions (i.e., face-to-face interactions, calls, and text messages) and the possible unique access to social interactions that each method has. Over 2 days, 320 smartphone users (51% female, age range = 18–80, *M* = 39.53 years) answered up to 20 experience-sampling questionnaires about their social behavior and reconstructed their days in a daily diary. Meanwhile, face-to-face and smartphone-mediated social interactions were assessed with mobile sensing. The results showed some agreement between measurements of face-to-face interactions and high agreement between measurements of smartphone-mediated interactions. Still, a large number of social interactions were captured by only one of the methods, and the quality of social interactions is still difficult to capture with mobile sensing. We discuss limitations and the unique benefits of day reconstruction, experience sampling, and mobile sensing for assessing social behavior in daily life.

Roos, Y., Krämer, M. D., Richter, D., Schoedel, R., & Wrzus, C. (2023). Does your smartphone "know" your social life? A methodological comparison of day reconstruction, experience sampling, and mobile sensing. *Advances in Methods and Practices in Psychological Science*, *6*(3), 1–12. https://doi.org/10.1177/25152459231178738.

2.1 Introduction

Social interactions are the building blocks of social relationships and are fundamental to well-being (Back et al., 2011; Baumeister & Leary, 1995). Accordingly, many researchers are interested in when and for how long people interact with others and how social interactions affect well-being in everyday life (Krämer et al., 2022; Kroencke, Harari et al., 2023; J. Sun et al., 2020). Research on social interactions in daily life has traditionally relied on daily diaries (Nezlek, 2001), such as the day-reconstruction method (DRM; Srivastava et al., 2008), or experience sampling assessments (ESM; i.e., repeated short questionnaires administered in daily life; e.g., Hall, 2017). Both daily diaries and experience sampling require effort from the participants in answering questions repeatedly, and thus these methods constrain the study duration and the time resolution of the measurement (Wrzus & Neubauer, 2022). Furthermore, both methods are prone to memory biases, a problem that is aggravated for daily diaries because of the greater temporal distance between assessment and occurrence of the reported behavior (Lucas et al., 2021).

Because of the obtrusiveness and biases of both methods, researchers seek for alternatives, and mobile sensing (MS) promises some solutions (Harari et al., 2016; G. Miller, 2012). "Mobile sensing" refers to measurement methods in daily life that use the sensors of a mobile device (e.g., smartphones, smartwatches) to acquire data from the person handling the device or from the environment (for a detailed discussion of challenges and advantages of MS, see Harari et al., 2016). Smartphones, which have spread rapidly among large parts of the world's population (Newzoo, 2021), are currently used most often for MS.

MS with smartphones offers important advantages compared with self-reports. First, sensor measurements decouple the number of assessments from participant burden (Wrzus & Neubauer, 2022), enabling longer assessments with higher time resolution. Second, MS offers access to more objective data than self-reports and thus promises to reduce memory biases (e.g., forgotten interactions) and report biases (e.g., socially desirable responses, demand effects). Third, MS allows automatic event-triggered sampling, that is, presenting questions in response to sensed information (e.g., self-report questions after a call was detected).[1] Last, smartphone usage, for example, of communication apps, may also be assessed and is of great interest for

[1] Event-triggered sampling is a hybrid method that combines elements of both ESM and MS: Participants answer questions actively, yet the question is triggered through passive sensing of mobile phone use, in our case, through the sensing of calls. To simplify communication, we treat event-triggered sampling as part of MS in this article.

psychological research and beyond (Aharony et al., 2011; Kroencke, Harari et al., 2023; Stachl et al., 2020).

Accordingly, MS promises to overcome many drawbacks of self-report methods. Still, interpreting the results of MS studies remains challenging because the quality of the sensed data is largely unknown and researchers mainly assume that MS works accurately. Earlier research compared emotional experiences measured with ESM and DRM (Lucas et al., 2021), yet MS of social interactions has not yet been compared with either ESM or DRM using a comprehensive database. Furthermore, standard practices for gathering, analyzing, and reporting MS data are largely missing (Bähr et al., 2022), and the reliability and validity of sensor data are mostly unknown (Struminskaya et al., 2020).

2.1.1 The Present Study

In a multilaboratory collaboration, we assessed social interactions in daily life with three methods, that is, day reconstruction, experience sampling, and MS, to compare similarities and differences of the methods. Specifically, we examined the temporal overlap between methods, the agreement of the methods, and unique aspects of social interactions that each method captures. Accordingly, we did not regard any of the methods as a "gold standard" and assumed that each method captures unique aspects in addition to shared information on social interactions. For social interactions, we focused on face-to-face interactions, calls, and text messages and posed two research questions:

> *Research Question 1:* How similar are assessments of social interaction quantity and quality using ESM, DRM, and MS?

For a just comparison of the methods, Research Question 1 examines the conditional agreement between methods, that is, how methods compare if they collected data at the same time (i.e., when matched measurements were available for the compared methods). As a prerequisite, we first needed to assess the temporal overlap in measurement coverage between the methods, which also provides information for our second research question:

> *Research Question 2:* What differences exist between the methods, and which social interactions do certain methods overlook?

In general, we expected the agreement between DRM and MS to be lower than the agreement between ESM and MS because of the greater time delay and increased memory biases of DRM compared with ESM and MS. We further expected DRM and ESM to agree more on face-to-face interactions than DRM and MS or ESM and MS because of a closer alignment of operationalizations (e.g., social interactions assessed in DRM and MS may include periods without conversation) and because of technical challenges of MS, such as accurately identifying speakers (e.g., the participant or a surrounding group of people) and filtering out background noise (Hebbar et al., 2021). Accordingly, we derived the following hypotheses:

Hypothesis 1: Regarding the occurrence of face-to-face interactions, we expected higher agreement between the measurements of DRM and ESM than between both methods and MS.

Hypothesis 2: Regarding the occurrence and duration of calls, we expected ESM and MS to show higher agreement than DRM and MS.

Hypothesis 3: We expected ESM and MS to agree more than DRM and MS regarding the interaction partner and valence of calls.[2]

Hypothesis 4: Compared with MS (i.e., smartphone logs of messages), people underestimate the number of sent messages in subjective reports (i.e., in ESM).[3]

2.2 Methods

Data collection took part in Germany from September 2021 to mid-December 2021 and from March 2022 to April 2022. We paused study enrollment between January and March 2022 because of increased COVID-19 infections and associated governmental regulations on social events (Appendix A). Overall, no broad restrictions on everyday social interactions were present during the study period. The preregistration, deviations from the preregistration, documentation of assessed variables, anonymised data sets, preprocessing and data analysis scripts, and a list of all used software packages are available at https://osf.io/t4c6n.

[2] The interaction partner and valence of calls were assessed with event-triggered sampling (i.e., presentation of short questionnaires directly after calls were sensed).

[3] Deviating from the preregistration, we did not examine differences in the number of people text messages were sent to because MS did not provide this information. We did not examine Hypothesis 5 from our preregistration because the metric of the effect sizes for occurrence and type of interaction partner were not comparable with the metric for duration and valence.

2.2.1 Participants

Because the majority of previous MS studies contained highly selective samples of well-educated young adults, we deliberately aimed at an age- and gender-heterogeneous sample of 207 to 374 participants (see preregistration for sample size rationale and power analyses). Thus, we chose appropriate country-wide recruitment strategies such as online advertisements, email lists, flyers, news articles, and word of mouth. The diverse country-wide sample allows a broader generalisation of the results, especially given that social interactions differ with age and gender (Sander et al., 2017; Wrzus et al., 2013).

Overall, 320 participants took part in the study, of which 51% identified as female, 48% identified as male, and 1% identified as neither male or female in terms of their gender identity (e.g., non-binary). On average, participants were M = 39.53 years old; 28% were 18–30, 24% were 30–39, 23% were 40–49, and 25% were 50–80 years old. Most participants were in a stable romantic relationship (60%); 33% were single, 8% were divorced; also 34% of participants had children. Regarding education, 47% of participants had completed college or university, 34% of participants had completed high school, 17% had completed other schools, and 1% had not yet completed their school education. Regarding occupation, 36% of the participants were working full time, 32% were students, 15% were working part time, 9% were retired, and the remaining participants were unemployed or did not indicate their occupational status.

2.2.2 Procedure and Measures

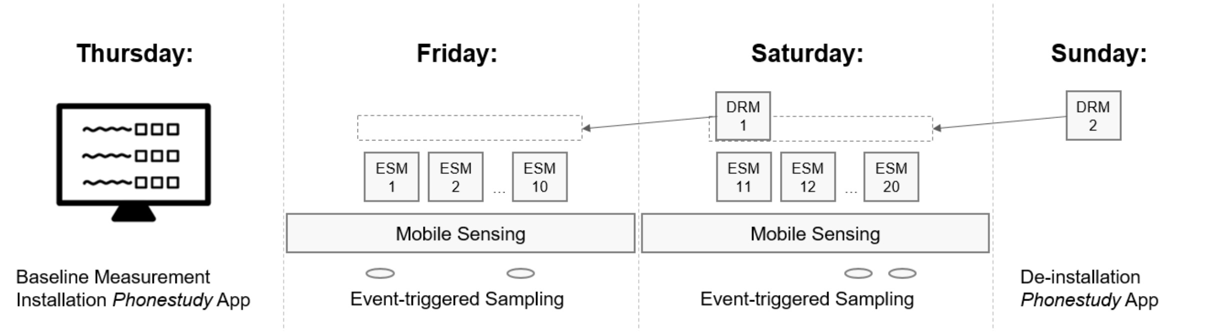
The study started for all participants on a Thursday with a video call. Participants received information about the study, gave informed consent, and installed the PhoneStudy research app (Schoedel et al., preprint).[4] Participants answered a baseline questionnaire on their demographics, personality traits, and social network. Over the next 2 days (Friday and Saturday, to capture both workdays and weekends), participants were prompted by the app to answer 10 ESM questionnaires per day between 9:00 a.m. and 9:00 p.m. The prompts were delivered roughly every 80 min to avoid participants knowing exactly when the next assessment would occur (for details see Appendix B). In addition, on Saturday and Sunday morning, participants

[4] The PhoneStudy app (Schoedel et al., preprint) allows the assessment of different features of mobile phone usage and sensors and runs on the Android OS, which 65% of German mobile phone owners use (Keusch et al., 2020). We provide additional information about the different data logging modes of the PhoneStudy app in Appendix C.

received an email reminder to fill out day reconstruction questionnaires on their computer regarding the Friday and Saturday, respectively (Kahneman et al., 2004). MS ran continuously in the background on participants' phones until Sunday (Figure 2.1). We chose this assessment schedule to assess as many social interactions in daily life as possible, while keeping participant burden acceptable, especially regarding the number of ESM and DRM reports. Participants received €40 (~USD40) for study participation with the option to receive another €10 if they filled out 17 or more ESM questionnaires out of 20.

Figure 2.1

Study Procedure



Note. DRM = day reconstruction method; ESM = experience sampling method.

Experience Sampling Method

Participants reported whether they were in a social interaction at the time of measurement or had had other social interactions (i.e., face to face, calls/video calls) since the last assessment. Participants were instructed that being around other people without any direct interaction (e.g., in a waiting room) does not count as face-to-face interaction. For each reported interaction, participants indicated the duration on a scroll wheel (answer options: 5 min, 10 min, 15 min, and 30 min, followed by steps of 30 min until 24 hr), the kind of relationship (e.g., partner, friend), and how they experienced the interaction (using a 7-point rating scale that ranged from 1 = *unpleasant* to 7 = *pleasant*). In addition, participants indicated with a slider how many text messages they had sent since the last measurement (range: 1–100 messages, increased sensitivity in the lower range).

Day Reconstruction Method

Participants divided their previous day into episodes consisting of activities with a start and an end time (Kahneman et al., 2004). For each activity, participants indicated the location, whom they spent the activity with, and how pleasant they perceived the activity on a scale that ranged from 1 = *unpleasant* to 7 = *pleasant* (adapted from Anusic et al., 2017). The online questionnaire initially displayed one episode and allowed participants to add up to 25 episodes to their diary, which proved sufficient in previous studies (Anusic et al., 2017). Episodes with activities that were conducted together with other people (except ‘calling’, ‘occupation with computer or internet’, and ‘end of day’) were used as indicators of face-to-face interactions, and episodes with ‘calling’ as indicators for calls. Short calls (e.g., <15min) might be less likely to be listed in day reconstruction diaries because participants were instructed that most people report episodes with durations between 15 min and 2 hr (for a distribution of DRM episode duration, see Appendix D).

Mobile Sensing and Event-Triggered Sampling

In MS, a privacy-protective algorithm inferred whether conversation or noise predominated in ambient sound (AWARE-Conversations plug-in; Ferreira & Mulukutla, 2020). The algorithm was programmed to follow a cycle of 1-min sampling and 3-min pause. In practice, differences in the number of samplings per episode occurred on different smartphone models (for the distribution of AWARE-Conversations samplings, see Appendix E). For each episode (in ESM or in DRM) with five or more samplings, we calculated the proportion of detected conversation as an indicator of face-to-face interactions. The proportion of conversation was calculated as the number of samplings indicating conversation divided by the total number of MS samplings in the respective episode.

Furthermore, information on incoming and outgoing calls was extracted from usage logs of the smartphones’ native call function. Whenever MS detected a call that lasted 10 s or longer, a short questionnaire (available for 15 min) was triggered, asking for the type of interaction partner and the perceived valence of the call using the same answering options as for ESM and DRM. Last, metadata on smartphone keyboard use (e.g., number of outgoing text messages) were collected in the form of time-stamped texting events (Bemmann & Buschek, 2020). We only included messages that were typed in communication apps (which includes SMS and emails send from the phone; for the used app categorization see Schoedel et al., 2022) and excluded messages that were typed into search or navigation text fields.

2.2.3 Analytical Approach

We differentiate between (a) *aggregated agreement*, that is, agreement between the methods when indicators were aggregated across all periods where each individual method collected data; and (b) *conditional agreement*, that is, agreement between methods if the methods collected data at the same time. For aggregated agreement, Pearson correlations between the aggregated measures were calculated. To examine conditional agreement, the different sampling rates of the raw data from the three methods had to be aligned first. For example, for each ESM questionnaire all MS data since the previous ESM questionnaire were matched.[5] The details of the matching procedures for face-to-face interactions, calls, and text messages are described in Appendix F. Temporal overlap between measurements of face-to-face interactions and text messages was calculated by the sum of the duration of matched episodes (see Figure 2.2, B; Figure 2.3, B and D). Contrary to face-to-face interactions and text messages, calls could be matched one-by-one, accordingly, we present overlap between the methods for calls as the number of calls that were assessed by multiple methods (Figure 2.3, C).

After preprocessing, the data consisted of matched ESM episodes, matched DRM episodes, or matched calls clustered at the person level. For conditional agreement of continuous variables (i.e., duration and valence), multilevel-correlations (r_{ml}) were calculated using the R-package correlation (Version 0.8.2, Makowski et al., 2022). Multilevel correlations are a special case of partial correlations in which the grouping variable is included as a random effect in a mixed model and are appropriate because they consider the nested data structure. We further included Bland-Altman plots in the supplement to provide additional information on whether the methods showed systematic over- or underestimation when compared to each other (Appendix G). For categorical variables (i.e., relationship type for interaction partner) percentage agreement was calculated, that is, the number of matched observations indicating the same relationship type divided by the total number of matched observations.

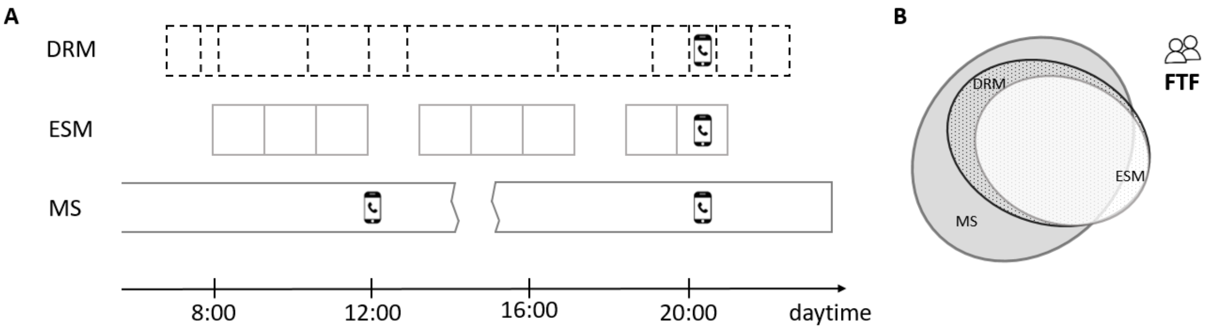
2.3 Results

Previous MS studies often did not report the percentage of the intended sampling period during which data were unavailable. Yet, such reports provide information central to the generalisability of the results and—in the context of the current study—on differences between measurement methods. For each type of social interaction—that is, face-to-face interactions, calls, and text messages—we first report the data availability and temporal overlap between the methods and then present results on the conditional agreement of the methods, which are based on the overlapping data segments. An illustration of the data structure is presented in Figure 2.2.

[5] If the previous questionnaire was skipped (or for the day's first questionnaire), data points from the last 80 min were matched.

Figure 2.2

Schematic Data Structure for One Day of One Example Participant



Note. DRM = day reconstruction method; ESM = experience sampling method; MS = mobile sensing; FTF = face-to-face interactions. Panel A: Social interactions of the example participant were measured with three methods and there were some gaps in the covered time span of each method. Whereas some social interactions were picked up by all three methods (see the three phone icons across the lines), other interactions were only documented in one or two methods (see the single phone icon). Panel B: Euler diagram of the temporal overlap in coverage of face-to-face interactions for the example participant. The size of the ellipses is proportional to the time covered with each method and the size of the intersections is proportional to the temporal overlap between methods. In this example, DRM covered 13.33 hr, ESM covered 10.67 hr (i.e., 8 times 80 minutes) and MS covered 21.33 hr. The temporal overlap of all three methods (intersection of all three ellipses) in this example was 9.67 hr.

Data collection lasted for 2 days (i.e., 48 hr). We aimed at measuring as many social interactions as possible with each method, but some design choices restricted the covered time: To reduce participant burden, ESM questionnaires were distributed only between 9:00 a.m. and 9:00 p.m., amounting to a maximum covered time of about 26 hr per participant.[6] DRM was limited to the time from when participants got up until they went to bed, with the maximum total time actually covered being about 30 hr on average (48 hr minus sleep, M = 8.9 of self-reported hours sleep per day). MS was set to sample continuously for 48 hr, but technical issues as well as participant behaviours led to reduced coverage, especially for face-to-face interactions (Figure 2.3, A).

[6] Questionnaires referred back to behaviour starting about 80 min ago; therefore, behaviours between 7:40 a.m. and 9:00 p.m. were assessed in ESM.

2.3.1 Face-to-face Interactions

The average time covered with each method was calculated on the basis of participants who had at least one valid data point on face-to-face interactions in each method (*n* = 256, Figure 2.3, B).[7]

Across both assessment days, participants reported on average 9.74 DRM episodes they spent with other people, which lasted on average 86.30 min per DRM episode. In ESM, participants reported on average 9.38 episodes with at least one face-to-face interaction, with an average of 40.52 min of face-to-face interactions. In MS, an average of 8.85 ESM episodes containing conversations were recorded, with the average proportion of conversation being 0.24 (which could be interpreted, very cautiously, as an average of 19.20 min per ESM episode).

Differences in interaction duration between methods may, to a considerable degree, result from different operationalisations: Whereas participants chose the duration of DRM episodes themselves, ESM episodes were about 80 min long by design. Therefore, it is possible that interactions reported in DRM as one episode were divided across multiple ESM episodes. Furthermore, DRM likely indicated more time spent in interaction because, contrary to ESM, participants did not specify how long they interacted with others during an episode but reported only whether the episode as a whole was spent with or without someone. In contrast, MS likely underestimated interaction duration because only conversation was measured, yet social interactions may also include periods without constant conversation, such as watching a movie or having dinner together.

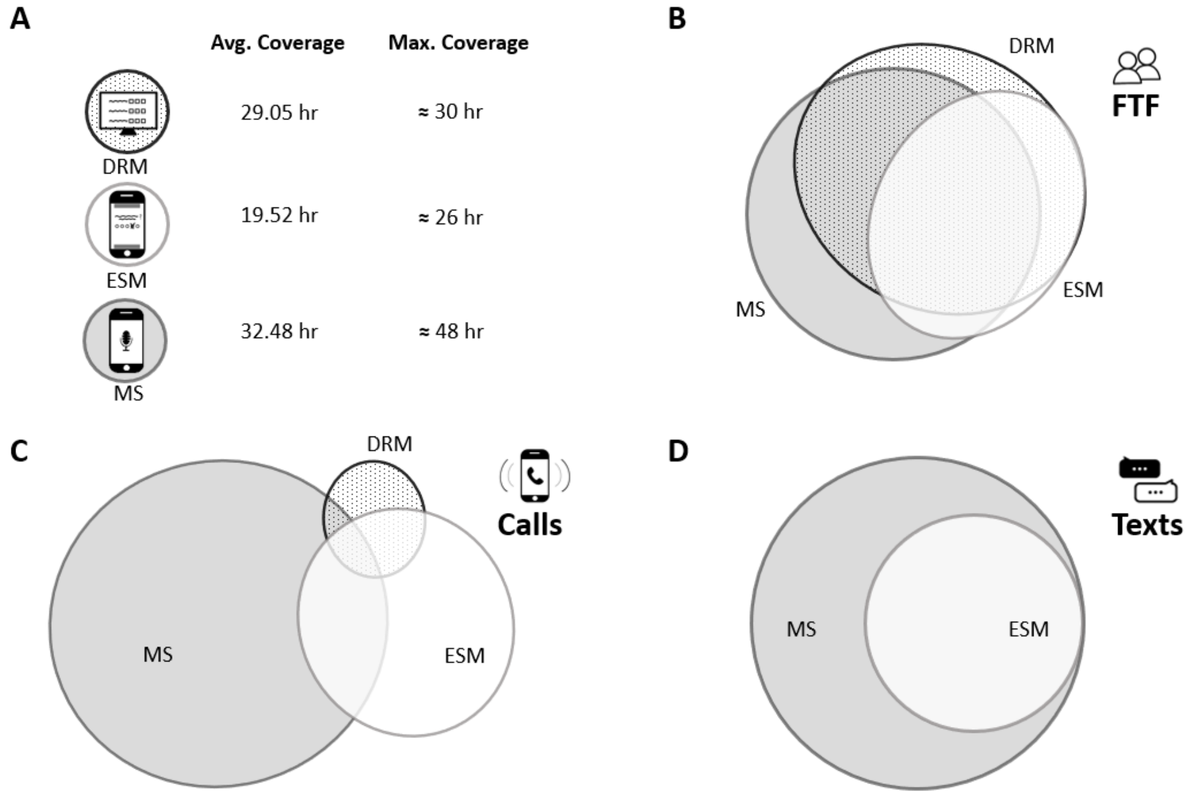
For examining conditional agreement between DRM and MS (Hypothesis 1), we aggregated MS on the level of DRM episodes. The duration of interactions reported in DRM showed a small but substantial association with the proportion of conversation measured with MS (r_{ml} = .20; 95% confidence interval [CI] [.17, .23]). Next, DRM and MS were transformed to match the level of ESM episodes (see Appendix F). As predicted, the association between self-reported duration of interactions in ESM and DRM was stronger (r_{ml} = .51; 95% CI [.48, .53]) than the association between self-reported duration in ESM and proportion of conversation

[7] Out of 320 participants who installed the app, 28 did not answer any DRM (2 of those also without MS), 12 did not answer any ESM and had no valid MS of face-to-face interactions, 23 had no valid MS of face-to-face interactions, and 1 had no data on face-to-face interactions at all.

detected through MS which was again small, but still substantial (r_{ml} = .24; 95% CI [.20, .27]).[8] For a comparison of the methods using Bland-Altman plots (Bland & Altman, 1999), please see Appendix G (Panels A, D, and G).

Figure 2.3

Data Availability and Temporal Overlap for Day Reconstruction, Experience Sampling, and Mobile Sensing



Note. DRM = day reconstruction method; ESM = experience sampling method; MS = mobile sensing; FTF = face-to-face interactions. Panel A: Face-to-face data availability averaged across participants who had at least some data on all three methods. Panel B: Temporal overlap in coverage of face-to-face measurements. The areas of the elipses are proportional to the average coverage of the methods depicted in Panel A. On average, there were 13.96 hr of temporal overlap between DRM, ESM and MS. Panel C: Overlap in call occurence between the methods. On average, 0.08 calls per person were matched between all three methods, and 0.6 calls per person could be matched between ESM and MS. Panel D: Temporal overlap in the

[8] The multilevel correlations between DRM or ESM measurements of face-to-face interaction duration and the proportion of conversation assessed with MS were mostly unaffected by the choice of minimum number of AWARE samplings required to qualify an episode as a valid measurement (Appendix H).

covered timespan of text message measurements. On average, measurements of ESM and MS overlapped 19.52 hr. Please note that participants differed considerably in their data availability.

2.3.2 Calls

Overall, *n* = 279 participants had at least one valid data point in DRM, ESM, and MS of app activities including calls.[9] Across the 2 days, these participants reported, on average, 0.42 calls in DRM and 1.57 (video) calls in ESM. In MS, an average of 3.61 calls were recorded, but only 24% of these calls were 5 min or longer (0.86 calls). The aggregated number of calls for each participant correlated: *r* = .27, 95% CI [.16, .38] between DRM and ESM; *r* = .19, 95% CI [.08, .30] between DRM and MS; and *r* = .37, 95% CI [.26, .46] between ESM and MS.[10]

Because the exact time of calls were reported in neither DRM nor ESM, calls were matched using either liberal (i.e., call occurred in the same period; Figure 2.3, C) or strict criteria (i.e., excluding calls with substantial deviations in duration, interaction partner, and valence; see Appendix F). The conditional agreement of methods regarding call duration, valence, and relationship type is shown in Table 2.1. The correlational patterns partly supported Hypothesis 2 (i.e., fewer calls could be matched between DRM and MS than between ESM and MS). Interestingly, participants reported a considerable number of calls in ESM that were not recorded in MS. This might be because people used other devices (e.g., their landline phone or computer) or used third-party apps to conduct video calls. Only a few calls were reported in DRM—yet, contrary to Hypothesis 3, regarding these matched calls, conditional agreement was high. Bland-Altman plots for a comparison of the methods are provided in Appendix G (Panels B, C, E, F, H, and I; Bland & Altman, 1999).

[9] Of the 320 participants, 28 had no DRM, 12 had no ESM (*n* = 9 of those without MS of app activities), and 1 had no DRM and ESM.

[10] If only calls longer than 5 min were considered for MS, then the aggregated number of calls correlated *r* = .37, 95% CI [.26, 46] between DRM and MS; and *r* = .32, 95% CI [.22, .43] between ESM and MS.

Table 2.1

Conditional Agreement of DRM, ESM and MS regarding Duration, Valence, and Type of Relationship of Calls

	r_{ml} Duration				r_{ml} Valence[a]				Relationship type percentage agreement[a]			
	Liberal		Strict		Liberal		Strict		Liberal		Strict	
	r_{ml}	95% CI	r_{ml}	95% CI	r_{ml}	95% CI	r_{ml}	95% CI	*agr*	95% CI	*agr*	95% CI
DRM & ESM	0.64	[.37,.81]	0.54	[.16,.78]	0.68	[.43,.83]	0.67	[.36,.85]	0.71	[.54,.89]	0.96	[.87,1]
DRM & MS	0.77	[.64,.85]	0.89	[.80,.94]	0.71	[.54,.82]	0.78	[.63,.88]	0.65	[.50,.80]	0.93	[.79,1]
ESM & MS	0.57	[.45,.66]	0.85	[.78,.89]	0.56	[.44,.66]	0.78	[.69,.84]	0.72	[.63,.80]	0.99	[.97,1]

Note. Sample sizes of compared calls were as follows: n = 31 (strict: n = 23) for DRM and ESM, n = 62 (strict: n = 43) for DRM and MS, and n = 162 (strict: n = 112) for ESM and MS. r_{ml} = multilevel correlation (Makowski et al., 2022); *agr* = percentage agreement; DRM = day reconstruction method; ESM = experience sampling method; MS = mobile sensing.

[a]Valence and relationship type were assessed with event-triggered sampling.

2.3.3 Text Messages

The following results refer to 250 participants for whom at least one message was recorded in MS and in ESM (Figure 2.3, D).[11] For these participants, MS recorded more outgoing messages (on average, 33.63 messages across 2 days) than participants reported in ESM (23.81 messages), $t(457) = 3.18$, $p = .002$, supporting Hypothesis 4. This is likely because ESM covered a shorter time span than MS. Accordingly, the number of recorded messages did not differ if MS was restricted to episodes for which ESM data were available (22.93 messages), $t(495) = 0.32$, $p > .05$, indicating that participants neither generally over- nor underreported sent messages in ESM. In 25% of ESM episodes, participants reported sending out more text messages in ESM than recorded by MS (on average, 3.03 messages more), and in 23% of ESM episodes participants reported fewer messages than measured with MS (average underestimation in ESM was 3.02 messages). A comparison of ESM and MS regarding the number of sent messages in each episode yielded a correlation of $r_{ml} = .43$, 95% CI [.40, .46].

[11] In ESM, 29 participants reported not sending out any text messages. In MS, out of 311 participants with at least some sensing data, MS did not record any text messages typed in communication apps for 66 participants.

2.4 General Discussion

Researchers have increasingly called for examining social processes in daily life, such as the dynamic regulation of social behaviour (Back et al., 2011; Hall, 2017). Yet, measurements of daily social interactions using traditional self-report methods (i.e., diaries or experience sampling) are affected by self-report biases and limited in their comprehensiveness and time-resolution because of participant burden (Lucas et al., 2021; Wrzus & Neubauer, 2022). Smartphone sensing was promised to overcome these drawbacks of self-report measures, and to become the gold standard for many areas of psychological research—up to the point of substituting most questionnaire research (e.g., G. Miller, 2012). However, ten years after G. Miller's influential smartphone psychology manifesto, knowledge on the quality of sensor data is still largely missing (Struminskaya et al., 2020) and standard practices for gathering, analysing, and reporting mobile sensing data are just emerging (Bähr et al., 2022; Harari et al., 2023; Wrzus & Schoedel, 2023).

In a multi-laboratory collaboration, we compared the temporal overlap of DRM, ESM, and MS measurements, as well as their conditional agreement on different aspects of social behaviour in people's daily life. In contrast to many previous studies using MS, we recruited a large age- and gender-heterogeneous sample, which increases the generalisability of our findings. The following discussion examines comparisons between the methods from the perspective of MS, as it currently is the least established method for measuring social interactions in daily life. Yet, these comparisons equally contribute to a better understanding of ESM and DRM. We argue that, at present, neither method is necessarily superior, and each can provide unique advantages and insights into different aspects of daily social interactions.

Regarding face-to-face interactions, MS showed some agreement with questionnaire reports of social interactions in daily life, but the methods were far from being interchangeable. This might in part be due to technical limitations of the used MS algorithm: Although the algorithm achieved high accuracies of more than 85% in prior studies (Lane et al., 2012; Rabbi et al., 2011), the algorithm's accuracy in less controlled environments is probably lower as indicated by the size of agreement with DRM and ESM in the current study. In the future, researchers will likely have access to more sophisticated algorithms—for example, first evidence suggests that algorithms based on a distinction of foreground versus background sound might outperform more traditional voice detection algorithms (Hebbar et al., 2021).

Regarding calls, data from the three methods were matched on a call-to-call basis, which provided valuable new insights: Only a subset of calls could be matched between the methods (with DRM performing worst, likely because only longer calls were reported). This suggests that each method captured only a fraction of daily calling behaviours depending on the duration of calls as well as which device or app was used (e.g., video calls through computers or messaging apps vs. mobile phones' native call function). However, for calls that could be matched (i.e., occurred in the same period), conditional agreement between methods was high. This finding indicates that different aspects of calling behaviour such as duration, valence, and the relationship type of the interaction partner can be measured well (although not comprehensively) with ESM and with MS.

Regarding text messages, in ESM, participants neither generally over- nor underestimated the number of messages they had sent in the last 80 min compared with the MS measurement. This is contrary to estimates of daily messaging, which seem to be more biased (Boase & Ling, 2013). Yet, MS allowed a more comprehensive measurement, regarding both the covered time span and the ability to measure multiple aspects of texting (e.g., length of message or use of emotion words).

2.4.1 Limitations

Despite the unique contribution of the study, which compared the assessment of both quantity and quality of daily social interactions with MS, ESM, and DRM in a large age- and gender-heterogeneous sample, several limitations became apparent. Some limitations of the methods reported in our study may not be inherent to the methods itself, but may be a consequence of the specific software and design choices applied in this study. Using DRM, ESM, and MS concurrently in participants' daily lives necessitates restrictions on the study design. For example, whereas passive MS could be conducted 24 hours a day for several weeks or even months (Aharony et al., 2011), ESM and DRM cannot assess participant reports continuously or intensively for long periods because the repeated questionnaires would soon overburden participants (Wrzus & Neubauer, 2022). Despite this design limitation, our study provides first benchmarks on how measurements of social interactions from DRM, ESM, and MS compare with each other. These benchmarks can be built upon in future studies with timeframes longer than two days and different design choices (e.g., different ESM schedules or other conversation detection algorithms). Finally, future meta-analyses may try to distinguish between specific limitations of the methods due to certain design choices and limitations that are largely independent of design choices.

One important limitation independent of the study design is that the quality of the social interaction and the type of interaction partner (e.g., romantic partner, colleague) cannot yet be inferred from passive MS alone. In general, MS rather assesses the physical reality of a certain situation or behaviour (e.g., volume or pitch of a human voice), and self-reports often aim at the psychological reality, such as the occurrence or quality of social interactions (Mehl, 2017; Rauthmann et al., 2015). Although developments in automatic speaker detection and on-board processing of voice and spoken content might provide MS indicators (e.g., voice tone) for the psychological reality (e.g., social interaction quality), more theoretical and empirical work is needed on how to interpret rather technical MS indicators.

Although we aimed at including a country-wide sample, which was diverse in age, gender, and educational background, the current sample of android users is prone to coverage and self-selection biases that are present in many MS studies (Keusch et al., 2019). For example, ownership of a smartphone and the kind of smartphone (e.g., iOS) differs somewhat with sociodemographic variables such as age, educational background, and community size. However, only minor differences in personality traits have been found between users of different operating systems (Götz et al., 2017; Keusch et al., 2020).

Issues of the participant sampling process have been thoroughly discussed during the past few years (Keusch et al., 2020; Struminskaya et al., 2020), yet fewer discussions have focused on how representative the sampled contexts and behaviours are (Fiedler & Juslin, 2005; Yarkoni, 2022). MS showed only moderate agreement with self-report assessments of face-to-face interactions. Additionally, in line with the argument that smartphone measurements are restricted to capturing what is happening on and in close proximity to the device (Harari et al., 2016; Keusch et al., 2022), MS probably missed some face-to-face interactions and also calls conducted through other platforms or devices. Likewise, DRM and ESM were also limited in their sampling of behaviours, for example, in underreporting of short interactions and calls, and because of the limited time span covered.

2.4.2 Recommendations

In addition to establishing standard procedures for mobile sensing studies (see Harari et al., 2016, 2023 for suggestions), we believe that more transparent reporting is key to advance research using MS. For example, most previous MS studies did not report for which percentage of the intended sampling period data was unavailable, for example, because phones were turned off or other apps interfered with MS sampling. Errors in MS studies can have multiple reasons: Total error frameworks (e.g., Bosch & Revilla, 2022; Groves & Lyberg, 2010) differentiate between specification errors (i.e., MS indicators do not correspond to a sufficient degree with the target construct), measurement errors (e.g., technical errors), and processing errors (e.g., inappropriate coding or aggregation procedures during data preprocessing). We recommend transparent reporting of all available information that helps in assessing the magnitude of these errors, which will contribute to more replicable findings (Wrzus & Schoedel, 2023).

Specifically, regarding specification errors, we suggest the following minimal reporting requirements: (1) Define the target construct as clearly as possible. For example, in the case of social interactions, we recommend to specify whether the target behaviour is face-to-face interactions, calling-, or texting behaviour; and we additionally recommend to specify the timeframe to which results can be generalized (e.g., only daytime behaviours, only weekday behaviours, all social behaviours at any time). (2) Define the periods in which sensors are supposed to measure indicators for the target construct. (3) Define the minimum number of data points required to consider a period a valid indicator for the target construct.[12] (4) Report how the validly measured periods compare to the targeted periods. (5) Discuss how the sampled indicators relate to the target construct, e.g., by including a Constraints on Generality statement (Simons et al., 2017). These reporting requirements rely on minimal assumptions regarding different causes of errors and can be applied even in studies where the technology or study design hinder a more fine-grained differentiation of error sources.

Measurement errors may arise because of technical difficulties (e.g., MS apps being incompatible with the OS, interference through other apps, or energy optimization stopping MS apps) as well as participant behaviour (e.g., not carrying the phone, revoking permissions; see Keusch et al., 2022). Whenever feasible, we recommend a differentiated approach for reporting different kinds of measurement errors, for example as suggested by Bähr et al. (2022). Yet, MS researchers face serious challenges: First, research software running on participants' smartphones cannot be tested under all field conditions, such as the multitude of devices and conflicting apps. Second, privacy concerns may require researchers to process some kinds of data—such as audio in our study—directly on participants' smartphones without any storage of the raw data (for more discussion on the topic of privacy in MS studies, see Kargl et al., 2019; Wrzus & Schoedel, 2023). Correspondingly, researchers often have to assume causes for errors without direct insight from the raw data into the causes of these errors. As the field of MS research is still trying to find a balance between rigor and practicability, we believe conducting research with imperfect apps and iteratively improving methods during the process may be more feasible than having too high expectations of MS apps to be able to perfectly differentiate between different sources of measurement errors.

[12] We encourage preregistering the information asked for in steps 1 to 3.

Regarding processing errors, we encourage researchers to report the used procedures in detail (e.g., in supplements), to upload annotated preprocessing code, and to participate in initiatives that try to standardize preprocessing of sensor measurements (e.g., Vega et al., 2021; Wrzus & Schoedel, 2023).

2.4.3 Conclusion

MS indeed offers some solutions to the shortcomings of self-report methods, for example, allowing for a more comprehensive time span of measurement and reducing memory biases. However, MS comes with some biases itself, such as sample selectivity and limited access to behaviours that happen at a distance from the smartphone as measurement device.

We believe that gathering more knowledge and practical experiences with MS will greatly benefit psychology and the behavioural sciences in general (Harari et al., 2016; Struminskaya et al., 2020). At present, the suitability of MS to answer substantial questions largely depends on the kind of question and the sensors used. In our use case—social interactions—using MS to capture different aspects of smartphone-mediated interactions already seems very promising, whereas methods to measure face-to-face interactions, especially their quality, need more refinement. Further research on the validity of sensor measurements is needed to assist researchers in their decisions about the suitability of the chosen methods for their research question.

Chapter 3: Individual Differences in Short-term Social Dynamics: Theoretical Perspective and Empirical Development of the Social Dynamics Scale

Cornelia Wrzus[1], Yannick Roos[1], Michael D. Krämer[2,3,4], & David Richter[2,3,4]

[1] Ruprecht Karls University Heidelberg, Germany, [2] German Institute for Economic Research, Germany, [3] International Max Planck Research School on the Life Course (LIFE),[4] Max Planck Institute for Human Development, Germany

Abstract

People have a need to form and maintain fulfilling social contact, yet they differ with respect to with whom they satisfy the need and how quickly this need is deprived or overly satiated. These social dynamics across relationships and across time are theoretically delineated in the current article. Furthermore, we developed a questionnaire to measure individual differences in three aspects of such social dynamics: (a) family-friends interdependence, (b) social deprivation, and (c) social oversatiation. In a longitudinal study spanning 9 weeks in spring 2020, in total 471 participants (18-75 years, 47% women) answered the newly developed items on social dynamics, questionnaires on social dispositions (e.g., affiliation motive, need to be alone, social anxiety), and questions on personal and indirect contact with family and friends during nationwide contact restrictions related to COVID-19. The results showed that individual differences in family-friends interdependence, social deprivation, and social oversatiation can be measured reliably, validly, and with predictive value for changes in daily contact as contact restrictions were loosened. We discuss potential applications of the *Social Dynamics Scale* (SDS) for studying social relationships in healthy and clinical populations, and conclude that the brief self-report questionnaire of social dynamics can be useful for situations and samples where direct behavioral observations are not feasible.

Wrzus, C., Roos, Y., Krämer, M., & Richter, D. (2024). Individual differences in short-term social dynamics: Theoretical perspective and empirical development of the Social Dynamics Scale. *Current Psychology*. Advance online publication. https://doi.org/10.1007/s12144-024-05868-y

3.1 Introduction

Indisputably, humans are social beings, who need to form and maintain fulfilling relationships with others (e.g., Baumeister & Leary, 1995). At the same time, people vary tremendously in how they maintain social relationships: Some people have very large social networks and frequent contact with many different people, others focus on a few close friends (e.g., Harris & Vazire, 2016; Wrzus et al., 2013). Some people like being with others permanently, while others seek solitude more often (e.g., Coplan et al., 2019; Nestler et al., 2011). Thus, with whom and how quickly social needs are satisfied or deprived varies strongly between people and also within people over time. Still, these variations or dynamics across relationships and time are hardly understood because the majority of relationship research in adulthood focuses on single relationship categories (e.g., friends, romantic partners, or parent-child dyads) and rather static relationship aspects (e.g., the number or quality of friends; for reviews, see Harris & Vazire, 2016; Vangelisti & Perlman, 2018).

The current study thus addresses two aims: As part 1, we conceptualize three different aspects of social dynamics, link these aspects to related, established interpersonal dispositions as well as develop and validate a questionnaire to measure social dynamics across relationships and time. We distinguish three aspects of such social dynamics: (a) Family-friends interdependence, (b) Social deprivation, and (c) Social oversatiation (Figure 3.1). For the validation, we also examine associations between social dynamics and other personality dispositions. As part 2, we examine whether the novel measure on social dynamics can indeed predict changes in contact across time and in different social relationships.

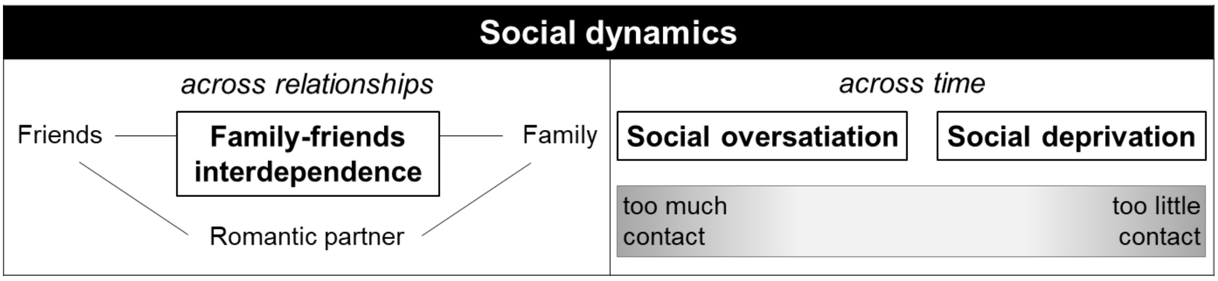
Social dynamics concern the interdependencies across different relationships and across time as people's social interactions are a continuous flow of time alone and time in contact with different people (Luo, Pauly et al., 2022). Consider a theoretical example, where a college student living with a partner has breakfast with the partner before driving to class alone and then meeting fellow students. After class, the student spends some time alone before visiting the grandparents for dinner. After dinner, the student goes to work in a restaurant and meets colleagues as well as guests before returning home to the romantic partner. Although these social interactions seemingly constitute singular encounters, they are often linked—both across relationship types and across time. Whether the student visits family or spends more time with friends in the afternoon depends on whether friends or family are more important (Wrzus et al., 2012)—in addition to other factors, such as who has time or needs support (Nezlek, 2001). In addition, if time is spent with one group (e.g., family) this time is generally not spent with others (except in rare cases of contacts with multiple relationship types, Wrzus et al., 2016).

Furthermore, the amount and quality of earlier social contact, e.g., with friends during and in-between classes, can affect whether a person seeks further contact or some time alone (e.g., Luo, Pauly et al., 2022).

The described interdependencies across different relationships and across time partly result from people's affiliation motive (for an overview see Hofer & Hagemeyer, 2018). A brief definition of the affiliation motive is that people possess an innate need to form and maintain social relationships (Deci & Ryan, 2000; Hofer & Hagemeyer, 2018). Satisfaction or deprivation of affiliative needs in social interactions can occur in different relationships (e.g., friends, family, romantic partner) and elicits affective experiences, which in turn stimulate future behavior towards need satisfaction (Baumeister & Leary, 1995; Neubauer et al., 2018; Sheldon, 2011). Thus, when interactions in social relationships are not considered as singular instances but rather as continuous dynamic of time alone and interactions with different people, these social dynamic can be described regarding linkages across relationships and across time (Figure 3.1). Next, we explain both aspects in more detail.

Figure 3.1

Conceptual Visualization of Central Terms of Social Dynamics



Note. The concepts can be seen as both dynamically changing within-person processes and individual differences between persons in such social processes. As explained in the text, dynamics across relationships always occur also across time and dynamics across time often occur also across relationships. Furthermore, the current study focused on Family-friends interdependence, Social oversatiation, and Social deprivation. During the review process it became apparent that other interdependencies across relationships likely exist as well, e.g., between romantic partners and friends (e.g., Fiori et al., 2017), between (in-law) family and romantic partners (e.g., Bryant et al., 2004).

3.1.1 Social Dynamics Across Relationships

Theories on the affiliation motive agree that the need for forming and maintaining social relationships can be satisfied, albeit to various extents, in different forms of relationships during adulthood such as family relationships, friendships, or romantic relationships (for a review, see Hofer & Hagemeyer, 2018). Accordingly, research on social networks, that is, the entirety of social relationships people maintain, demonstrates that diverse relationships “coexist” within individuals, and most people maintain relationships from different relationship types, such as family members, romantic partners, as well as non-relatives (Mund & Neyer, 2014; Neyer et al., 2011; Wrzus et al., 2013). Family refers to biologically or legally-related relatives (i.e., in-laws), and thus could be (grand)parents, siblings, (grand-)children, and other more distant relatives (Neyer et al., 2011). Romantic partners and non-relatives such as friends are non-kin, that is, biologically unrelated and not legally regulated, except for spousal relationships (Neyer et al., 2011).

The majority of research on individual differences in adult social relationships focuses on specific relationship types separately, such as friends, romantic partners, **or** parent-child dyads (for reviews, see Harris & Vazire, 2016; Rözer et al., 2016; Wrzus & Neyer, 2016; for noticeable exceptions in adolescence see Gadassi Polack et al., 2021; Miller-Slough & Dunsmore, 2019, 2023). Such research omits that people generally maintain a multitude of relationships simultaneously, which can influence each other. As people are limited in their amount of time and energy, spending time with and taking care of some relationships usually leads to less available time and energy for others (Hall & Davis, 2017). Accordingly, interdependencies across relationships can be expected (Fiori et al., 2017; Gadassi Polack et al., 2021; Klärner et al., 2016; Rözer et al., 2016; Wrzus et al., 2012).

Interdependencies across relationships were reliably observed with respect to the existence and importance of certain social relationships: For example, people who reported fewer family members in their personal network named relatively more friends and vice versa (Rözer et al., 2016; Wrzus et al., 2012). Also, feeling less close to family was associated with relatively higher emotional closeness with friends and vice versa (Wrzus et al., 2012). Similarly, some people maintain friends-focused networks, whereas others’ networks mainly consist of family members or a mix (Fiori et al., 2007). Such differences in importance or closeness of friends vs. family might partly result from a stronger personal preference and thus a tendency to invest more into one or the other.

Results on the interdependence of maintaining contact with friends or family are mixed though: In one experience-sampling study with older adults, the relative frequency of contact with family was lower with higher relative contact frequency with friends in daily life (Mueller et al., 2019), whereas no significant association was observed in a larger experience-sampling study (Buijs et al., 2023) as well as in average retrospective reports of contact with family and friends (Wrzus et al., 2012). The inconsistencies in results on contact might partly arise from external constraints and demands (e.g., available time, others' expectations on contact), which were not measured in any of the studies. Such external demands could necessitate contact with some people despite having a preference for other people or for no contact.

Consistent with previous work (Fiori et al., 2007; Mueller et al., 2019; Wrzus et al., 2012), we assume that people have a relatively stable preference for family, friends, or both similarly. To the extent that relationships with family and friends are interdependent, investing heavily into the one will leave less resources for the other (except perhaps in adolescence, Gadassi Polack et al., 2021). We assume Family-friends interdependence (FFI) to be a dimensional construct with exclusive focus on family or friends on either ends and varying degrees of preference for one or the other in between (see Fiori et al., 2007 for a categorial approach).

3.1.2 Social Dynamics Across Time

In addition to social relationships being dynamically linked across different relationships, each specific relationship is inherently dynamic across time. That is, relationships vary and change over days, weeks, and months—both in quantity and quality (e.g., Hall, 2017; J. Sun et al., 2020). For example, contact with family and friends varies approximately as much within and across days as between individuals (Weber et al., 2020; Wrzus et al., 2016). Thus, assessing only average contact frequency or quality can overlook important aspects of social relationships: For example, of two individuals with similar average contact, one might have relatively regular contact, whereas the other bounces between times of too much and too little contact with potentially detrimental effects on well-being (Luo, Pauly et al., 2022).

Theories that view affiliation motives as a central factor in the dynamic regulation of social interactions strongly emphasize the temporal aspects of social interactions and social relationships (e.g., Bischof, 1993; Hall & Davis, 2017; O'Connor & Rosenblood, 1996; Sheldon, 2011). Such theories postulate that people possess an individually varying ideal level of social contact and closeness (i.e., the strength of the affiliation motive). Furthermore, people appraise daily situations regarding how well the actual social experiences fulfill their ideal level. In cases of Social deprivation, that is, when actual experiences do not fulfill the ideal level, or Social oversatiation, that is, when actual experiences exceed the ideal level, the individual is motivated to change the social experience through seeking or avoiding social contact (Bischof, 1993; Hofer & Hagemeyer, 2018; Sheldon, 2011). Empirical work hardly examined regulatory processes in social relationships, and instead focused on static snapshots of relationships (e.g., momentary number, contact, or quality of friendships and family relationships; Harris & Vazire, 2016; Neyer et al., 2011; Wrzus et al., 2013, 2016).

In addition to long-term changes (for reviews Blieszner, 2018; Harris & Vazire, 2016), relationships also vary from hour to hour, from day to day, and week to week. For example, people with higher extraversion and lower neuroticism are less likely to remain alone over the next two hours in daily life; instead, they reported more often being with friends, colleagues, or other people two hours later (Wrzus et al., 2016). These findings match experimental research, which demonstrates immediate effects of unsatisfied affiliation motives on seeking social contact (e.g., Maner et al., 2007). Similarly in romantic partnerships, stronger momentary motivation to be close to one's partner predicted more positive interactions with the partner over the next hours (Zygar et al., 2018). In line with affiliation motive theories, more intense positive contact with partners when people wanted to be with partners was associated with better mood and higher relationship satisfaction, which indicates need fulfillment (Zygar et al., 2018). Surprisingly, people reported being still motivated for further contact with their partner after intense contact with their partner (Zygar et al., 2018)—perhaps needs were satiated, but not oversatiated to the extent that people wanted to be alone.

Other experience sampling studies, which did not focus on couples or distinguish relationship persons, also failed to demonstrate links between previous contact and momentary (motivation for) contact (Hall, 2017; Neubauer et al., 2018). Still, a greater desire to be alone predicted less future social contact (Hall, 2017). Inconsistencies in results regarding the coupling of previous and momentary contact might be due to examining temporal links only over a few hours within days. Perhaps more time has to pass before need oversatiation occurs and people (can) decrease contact.

In summary, social contact varies within individuals across time in quantity and quality. This variation might partly be due to existing opportunities (i.e., other people being available to engage in contact with or accessible places to be alone) and also individuals' efforts to satisfy their affiliative needs, which differ as well between individuals: Satisfaction of affiliative needs can occur through increases in contact in cases of Social deprivation and decreases in contact in cases of Social oversatiation. Such dynamics across time could be assessed in daily life, for example, using ecological momentary assessments or mobile sensing (Krämer et al., 2024) or in generalized questionnaires describing such dynamics, an approach chosen for the current study. The assumption behind this approach is that relevant differences between people in average patterns of dynamic daily-life social behaviors manifest over time in the self-concept similar to other generalized self-reports of behaviors or thoughts (i.e., personality questionnaires). Measuring these individual differences in social dynamics could offer an economical approach to study social dynamics when ecological momentary assessments or mobile sensing are too demanding.

3.1.3 Relation to Other Interpersonal Dispositions

This section highlights similarities and differences of individual differences in social dynamics from other interpersonal dispositions, such as the affiliation motive and related need dispositions, social anxiety, and broad Big Five traits to demonstrate the necessity of separately measuring social dynamics.

Affiliation Motive and Related Dispositions

Several interpersonal characteristics describe people's stable tendencies to engage in and maintain social relationships and this section provides a brief overview: Affiliation Motive, that is, the need to form and maintain close, satisfying social relationships, contains several aspects (Hofer & Hagemeyer, 2018; Schönbrodt & Gerstenberg, 2012). Some researchers further distinguish an Intimacy Motive, which focuses on positive, approach-oriented aspects of close social relationships, from avoidance-oriented aspects of the affiliation motive that focus on the Fear of Rejection, that is, losing social connection in general (for reviews see Hofer & Hagemeyer, 2018; Schönbrodt & Gerstenberg, 2012). The Need to Belong (Baumeister & Leary, 1995) also refers to individual differences in the need to form and maintain social relationships and integrates aspects of social contact as well as feelings of belonging into one concept. Empirically, with higher affiliation motive, people also report a higher need to belong, and higher Sociability (i.e., a facet of Extraversion; Leary et al., 2013; Schönbrodt & Gerstenberg, 2012). Theoretically, with a higher Need to Belong, people should dislike being alone often, while empirically, the Need to Belong was only weakly related to the Need to be Alone and to do things alone (Leary et al., 2013; Nestler et al., 2011), perhaps because both needs can co-occur in individuals and are satisfied at distinct times.

In summary, most contemporary conceptualizations and measurements view the affiliation motive as a superordinate construct with aspects oriented towards initiating and maintaining social interactions (e.g., affiliation, need to belong) as well as aspects oriented towards reducing social interactions (e.g., need to be alone). As the affiliation motive can be satisfied in diverse close relationships such as family, romantic partners, or friends (for review

Hofer & Hagemeyer, 2018), we do not assume associations with Family-friends interdependence. Instead, we assume that people with a higher general affiliation motive and also higher need to belong will experience more Social deprivation because it is more difficult to meet the stronger need for social contact most of the time. In contrast, we assume that people with a greater need to be alone and lower affiliation motive will experience Social oversatiation more often because unwanted social interactions might occur more often.

Social Anxiety

Social anxiety describes feelings of unease and fear when interacting with strangers and less familiar people (Peters et al., 2012). Extreme levels are considered a specific anxiety disorder (i.e., social anxiety disorder), whereas low to moderate levels are reported for the general population (Peters et al., 2012). Conceptually, the strength of the affiliation motive and the level of social anxiety are distinct. For example, people with strong affiliation motive and simultaneously strong social anxiety (i.e. fear of rejection, Asendorpf, 1990; Poole et al., 2017) are often described as shy. In contrast, sociable people also possess a strong affiliation motive, yet do not or only hardly experience social anxiety. Empirically, social anxiety was also only weakly associated with affiliation motive and need to belong in the general population (Leary et al., 2013; Schönbrodt & Gerstenberg, 2012). As social anxiety mainly manifests in interactions with unknown and less familiar people (Asendorpf, 1990; Poole et al., 2017), one could assume that people with higher values in social anxiety have a stronger preference for being with familiar family. At the same time, close friends can be family-like (Buijs et al., 2023; Wrzus et al., 2012), and we thus expect weak associations between social anxiety and Family-friends interdependence. Given the weak association between social anxiety and affiliation motive, we expect Social oversatiation and Social deprivation (i.e., mismatches between the affiliation motive and social experiences) to also show only weak associations with social anxiety.

Big Five Traits

Big Five personality traits are assumed to broadly summarize patterns of human behavior, with extraversion and agreeableness being central to interpersonal behavior (DeYoung et al., 2013; McCrae & Costa, 2008). Associations between Big Five traits and the preference for family over friends (or vice versa) can be inferred only indirectly from previous work. With higher values of extraversion, people have larger friendship networks, spend more time with friends, and report higher quality of friendships (e.g., Harris & Vazire, 2016; Selfhout et al., 2010; Wagner et al., 2014; Wrzus et al., 2016). Also, with higher values in agreeableness, people get along better with others, which results in high popularity and larger social networks (Harris & Vazire, 2016; Selfhout et al., 2010; Wagner et al., 2014). As people invest slightly more time in friendships with higher agreeableness (Wrzus et al., 2016), this could come at the cost of family relationships. However, empirically, agreeableness was not meaningfully associated with the frequency of being with either family or friends (Mueller et al., 2019; Wrzus et al., 2016; but see Buijs et al., 2023). Yet, measures of being with specific people, that is, friends or family, might only partly reflect a preference for one or the other as external constraints might enforce or restrict contact (Buijs et al., 2023). Given the inconsistent findings, we assume that, if at all, only weak associations between Big Five traits and Family-friends interdependence exist.

From a conceptual point, specifically the extraversion facets Sociability and Energy as well as the facet Compassion of the trait agreeableness should be closely linked to the affiliation motive and the quantity of social interactions (DeYoung et al., 2013; Leary et al., 2013). Extraversion as a broad trait additionally captures Assertiveness, and agreeableness also captures politeness, which refer more strongly to the quality of the interactions instead of the quantity (DeYoung et al., 2013; Soto & John, 2017). Thus in contrast to specific facet effects, we expect relatively low associations of the broad trait levels with Social deprivation and Social oversatiation. We expect no substantial association of Social deprivation and Social oversatiation with the other traits, that is, neuroticism, conscientiousness, and open-mindedness.

3.1.4 Current Study

The current longitudinal study pursues two aims. The first research question in part 1 aims at developing a brief self-report questionnaire of social dynamics, the *Social Dynamics Scale* (SDS), to measure individual differences in (a) Family-friends interdependence, (b) Social oversatiation, and (c) Social deprivation. The second question in part 2 aims at examining the predictive validity of the *Social Dynamics Scale*, that is, whether the new measure can indeed predict changes in social contact across time and in different social relationships. Previous questionnaires assessing affiliation motive, the need to belong, or extraversion are relationship-unspecific and focus on social needs and social behavior. However, theses questionnaires do not address interdependencies across relationship types or consequences of unmet social needs. The *Social Dynamics Scale* is supposed to fill this gap. Next, we summarize the hypotheses outlined throughout the theoretical background.

3.1.5 Research Question 1 and Hypotheses on Scale Development

Research question 1 examines whether it is possible to measure individual differences in social dynamics reliably and validly. This part 1 focuses on the item selection, internal, and retest reliability, as well as factorial, divergent, and convergent validity of measuring social dynamics. To determine which of the newly developed items were best suited to measure social dynamics, we followed standard conventions for scale development (Boateng et al., 2018). We thus examined item difficulty, item variance, and interitem correlation. Proceeding from the theoretical background regarding the dynamic regulation to satisfy people's affiliation motives (e.g., Hall, 2017; Hofer & Hagemeyer, 2018), we derived the following preregistered hypotheses (https://osf.io/n8jrv).

H1a: We assumed that social dynamics can be described in three subscales: Family-friends interdependence (FFI), Social oversatiation (SOS), and Social deprivation (SOD). Social oversatiation and Social deprivation are assumed to be weakly to moderately negatively correlated. FFI (scored towards friends) and Social deprivation are assumed to be weakly positively correlated, whereas FFI (scored towards friends) and Social oversatiation are assumed to be weakly negatively correlated.

H1b: We expected convergent validity, that is, moderate positive correlations between Social deprivation and affiliation motives, as well as between Social oversatiation and need to be alone.

Based on theoretical definitions of Big Five traits and social anxiety (e.g., Asendorpf, 1990; DeYoung et al., 2013; McCrae & Costa, 2008; Poole et al., 2017), we expected:

H1c: We expected divergent validity for all three subscales, that is, little overlap, with Big Five traits and social anxiety.

We did not preregister a separate hypothesis regarding the temporal stability, yet assumed that individual differences in social dynamics are similarly stable over several weeks—as indicated through retest correlations—as other personality constructs for adult populations (for a review, see Soto & John, 2017) because (a) social networks are relatively stable (Mund & Neyer, 2014; Wagner et al., 2014) and (b) individual differences in affiliation motive are rather stable (Fraley & Roberts, 2005), contributing to stable individual differences in deprivation or oversatiation.

3.1.6 Research Question 2 and Hypotheses on Predicting Changes in Social Contact Across Time

The second longitudinal part of the study utilized the social distancing rules during the first wave of the COVID-19 outbreak in Germany in spring 2020. The nationwide restrictions in social contact (Figure 3.2) can be seen as an environmental factor inducing Social deprivation, with the opportunity to study as Research Question 2 how individual differences in Social deprivation predict subsequent changes in social contact when contact restrictions were progressively loosened. The data collection started on April 6th, when schools, restaurants, public facilities (e.g., gyms, theaters), and most shops were closed, and reoccurred every three weeks until June 14th, 2020, when most facilities were open again (see Procedure section and Figure 3.2). Data collection was conducted online due to contact restrictions.

As described in the theoretical background, if (high) affiliation motives are not satisfied in social interactions, Social deprivation occurs, and people are motivated to change the dissatisfying states and seek social contact (Bischof, 1993; Hall, 2017). Accordingly, we assumed that after restrictions of social contact, contact would increase more strongly over time for people generally higher in Social deprivation (H2a). Similarly, when people are rather satisfied with low levels of social contact, they will delay seeking further social contact (Bischof, 1993; Hall, 2017). Thus, we expected that after restrictions social contact would increase less over time for people generally higher in Social oversatiation (H2b).[13]

During national contact restrictions due to the COVID-19 pandemic, missing personal contact might be partly compensated for through indirect contact (e.g., messaging, calling). We did not explicitly preregister hypotheses specifically for indirect contact and explored associations with general Social deprivation and Social oversatiation.

---

[13] Due to a lapse, we preregistered only a moderation through need to be alone for H2b. Since we specified in H1b that need to be alone will be positively associated with social oversatiation, we extended H2b to include social oversatiation. In the preregistration, SD and SS were used as abbreviations for social deprivation and social satiation, which we updated to “social oversatiation”. Also, additional hypotheses were specified, which are addressed in other publications; see https://osf.io/n8jrv.

3.2 Methods

3.2.1 Open Science Information

Following open science guidelines, we transparently report the determination of the sample size, assessed variables, further articles using the same data sets, exclusion of data, as well as adjustment of outliers (none), and its effects on the analyses. Our preregistered a priori power estimation based on a repeated-measures approach with $\alpha = .05$, power = .90, and effect size f =.10 suggested assessing at least 195 people. The preregistration of hypotheses, documentation of assessed variables, as well as data used in the analyses, scripts, and outputs of data analyses are available on https://osf.io/8xubm. Data on social contact have been used to examine a distinct research question regarding associations with well-being (Krämer et al., 2024).

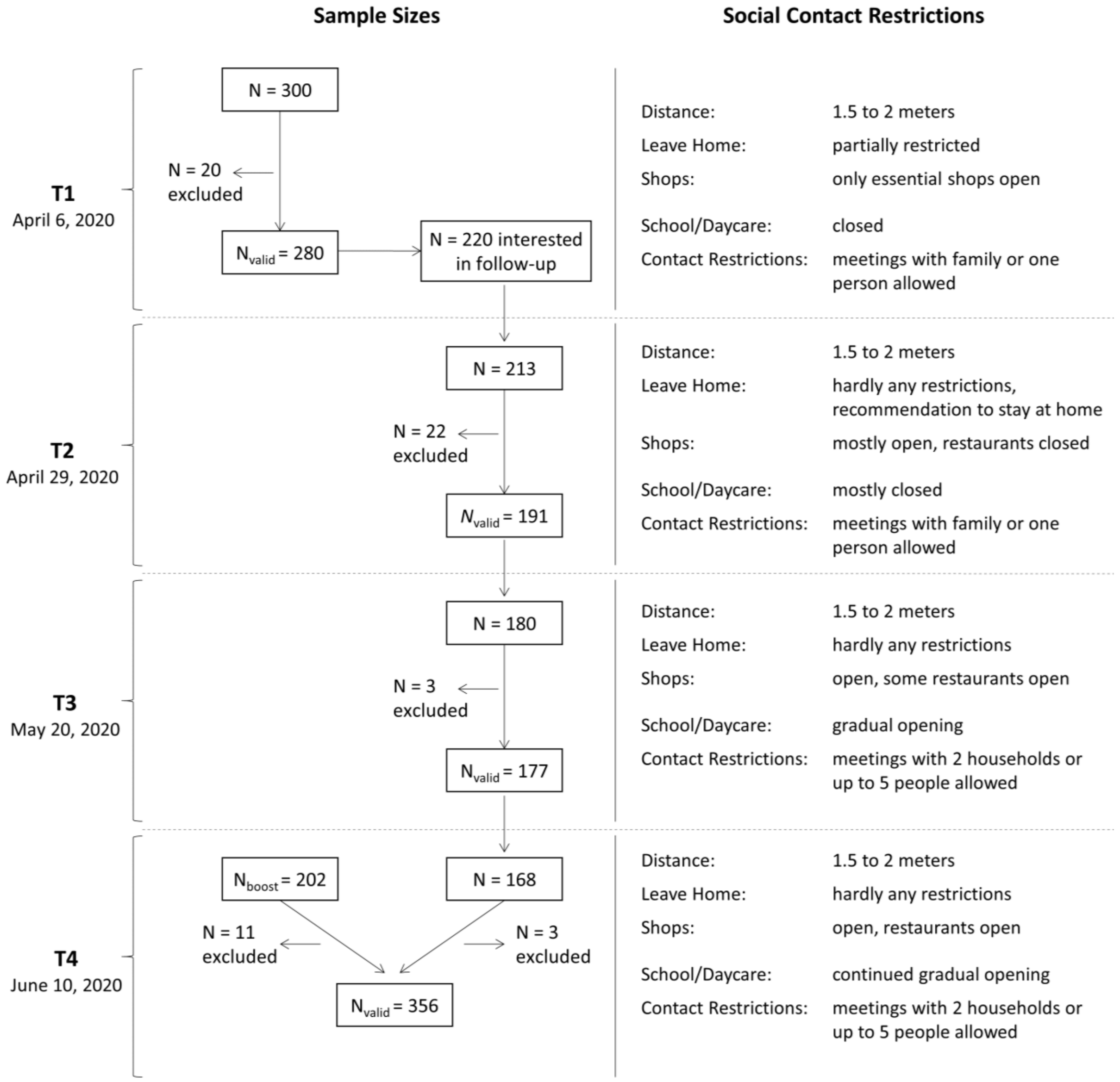
3.2.2 Participants

Through the survey agency www.clickworker.de we recruited 300 participants stratified across gender and five age groups (18–29, 30–39, 40–49, 50–59, and 60–75 years), of which 280 participants provided valid data (see Figure 3.2). These participants ranged in age from 19 to 75 years (M = 45.2, SD = 14.3, 53% men). The majority of participants (66%) were married or in a stable romantic relationship, the remaining participants were single (25%), divorced (7%), or widowed (2%), and 41% of participants had children (number of children M = 1.79, SD = 0.83). Regarding completed education, 42% held a college/university degree, 29% had completed high school, and 28% had completed other schools. The majority of participants (41%) were working full-time, 19% were self-employed, 11% were students, 11% were working part-time, 9% were retired, and the remaining participants were unemployed or did not indicate their occupational status. The participants were diverse with regard to residential region in Germany and size of hometown.

At the end of the first assessment, participants could opt in to the longitudinal part of the study with three additional assessment waves. For the last assessment, we recruited 202 additional participants to boost the sample size. Figure 3.2 depicts participation rates and data exclusion over the four assessment waves.

Figure 3.2

Sample Size Flow and Social Contact Restrictions



Note. The displayed dates refer to the activation of the online surveys. Participants had up to five days to answer after activation of the surveys. Participants were excluded if their response times indicated speeding, they showed unusual response patterns, or if they did not provide a valid identifier for follow-up (see section on Data Exclusion).

3.2.3 Procedure

Participants answered four online surveys with approximately three weeks between surveys. The survey periods were chosen to reflect the gradual easing of social contact restrictions, which existed in 2020 to manage the COVID-19 pandemic. The strictest social-distancing regulations were in place at T1 when schools and most shops were closed, and severe restrictions regarding social contact existed. At T2, the social-distancing regulations were still very strict, but most shops were allowed to reopen. Social-distancing rules continued to be gradually loosened during the following weeks at T3 and T4 (Figure 3.2). During each assessment wave, the surveys were available for five days to achieve similar assessment periods. Most participants (79% average across waves) answered the surveys on the same days that they were activated. All participants gave informed consent before answering the survey questions. The study was exempt from IRB approval because it focused on healthy, mature participants, assessed uncritical content, which was fully explained to participants, and followed the Helsinki declaration for treatments of participants. Participants received €4.50 for each of the first three surveys and €5.00 for answering the last survey.

3.2.4 Measures

We describe the measures used to answer the research questions and examined in subsequent analyses. A complete documentation of all variables assessed in the project is available on https://osf.io/8xubm.

Social Dynamics Scale (SDS)

Based on the theoretical considerations outlined in the introduction, we developed items for the three SDS subscales using a rationale, inductive construction approach (Bühner, 2011). The items described past behavior (e.g., "After spending all day alone…") and self-concept aspects (e.g., "I am…") and followed the current suggestions for item construction (Bühner, 2011). We pretested the items in small focus groups and removed ambiguities in phrasing. The initial item pool consisted of 39 items, which were assessed at the first assessment: 14 items for Family-friends interdependence, 11 items for Social oversatiation, and 14 items for Social deprivation. Table 3.1 reports the final item set after item selection (see *Results* section *Part 1: Item Selection*; see Supplementary Table S1 for complete list of German items and English translation). During the data collection, items were answered on a 7-point Likert scale with 1 = *not at all* and 7 = *completely* as anchors.

Affiliation Motive and Fear of Rejection

Affiliation motive and fear of rejection were assessed using the short affiliation motive subscale and the items from the "fear of rejection" facet of the Unified Motive Scale (Schönbrodt & Gerstenberg, 2012). Sample items include "I try to be in the company of friends as much as possible" for affiliation motive and "When I get to know new people, I often fear being rejected by them" for fear of rejection. The Unified Motive Scale includes items formulated as statements, which require an agreement rating, and items formulated as goals, which require an importance rating. Both were rated on a 6-point Likert scale (Statements: 1 = *strongly disagree* to 6 = *strongly agree*; Goals: 1 = *not important to me* to 6 = *extremely important to me*). The internal consistencies are reported in Table 3.2.

Need to Belong

Need to belong was assessed with the 10-item Need to Belong Scale (Leary et al., 2013[14]). A sample item is "I want other people to accept me". We used the German translation provided by Hartung and Renner (2014), $\omega = .75$. Items were answered on a 5-point scale (1 = *not at all*, 2 = *slightly*, 3 = *moderately*, 4 = *very*, 5 = *extremely*).

Need to be Alone

Need to be alone was assessed using the four-item appetence subscale of the desire for being alone from the ABC Scale of social desires (Hagemeyer et al., 2013), $\omega = .83$. A sample item is "I like to be completely alone". Items were answered on a 7-point frequency scale ranging from 1 = *never* to 7 = *always*.

Social Anxiety

Social anxiety was measured using the SIAS-6 (Peters et al., 2012). Sample items include "I have difficulty talking with other people". We used the corresponding German translations of the SIAS-6 items provided by Stangier et al. (1999), $\omega = .88$. Items were answered on a 5-point Likert scale (1 = *not at all*, 5 = *extremely*).

Big Five traits

The BFI-2 consists of 60 items and measures the Big Five personality traits extraversion, negative emotionality, agreeableness, conscientiousness, and open-mindedness (Soto & John, 2017; German version: Danner et al., 2016). In addition, each trait consists of three facets, such

[14] Due to the limited number of allowed references, we provide the references from the method section (e.g., regarding questionnaires and statistical software) in a separate reference list in the supplementary material.

as Sociability, Energy, and Assertiveness for the trait Extraversion, with four items each (all items are listed in Soto & John, 2017). Items were answered on a 5-point Likert-scale (1 = *disagree strongly* to 5 = *agree strongly*). The internal consistencies are reported in Table 3.2.

Social Contact

Participants were asked "How often did you engage in social interactions during the last week?" for three different relationship categories (family, friends, colleagues) and four contact channels (personal contact, calls, video calls, texts). Answer categories included 1 = *not at all*, 2 = *once*, 3 = *multiple days*, 4 = *daily*, and 5 = *multiple times a day*. We analyzed personal contact with each relationship category separately, while the mean across all digital communication channels served as indicator for *indirect contact* for each relationship type.

3.2.5 Data Exclusion and Outlier Detection

We used multiple criteria to screen the data for noncompliant responding behavior (see Meade & Craig, 2012), and excluded participants (a) who answered dozens of items on one page unrealistically quickly (i.e., less than 70 seconds for 39 items of the *Social Dynamics Scale*, less than 90 seconds for 60 items of the BFI-2), (b) failed the attention check[15], and (c) demonstrated odd answering patterns as detected through the *careless* package in R (i.e., max. longstring, psychometric synonym metrics). Participant exclusion and attrition are shown in Figure 3.2. Outliers ($M \pm 3$ SD) concerned less than 1.5% of the sample. The analyses were conducted twice using the original or the winsorized variables, i.e., outliers recoded to $M \pm 3$ SD. All results were identical after rounding.

3.2.6 Attrition Analyses

To assess sample selectivity due to attrition over time, we compared participants who provided valid data in all four assessments (n =165) with those who were invited to the longitudinal study but dropped out before completing all assessments (n = 55). Participants who

[15] Participants were soft-prompted for missing questions during the online survey for most questions but not for the attention check. Therefore, some participants did not provide any answer to the attention check, entering the result for 2 x 2—a situation we did not anticipate during preregistration. Additionally, some participants who missed or failed the attention check provided rich answers in an open text field and did not show any other signs of noncompliant responding. For the reported analyses, we decided to exclude participants who missed or failed the attention check only if they also showed unusual response patterns. We repeated all analyses after excluding participants who missed or failed the attention check and found comparable results.

remained in the study reported a stronger Social oversatiation (d = 0.39, p = .025), a weaker affiliation motive (d = -0.41, p = .009), weaker social anxiety (d = -0.34, p = .046), and were younger (on average 6 years, p = .007). There were no significant differences between groups with regard to gender, Family-friends interdependence, Social deprivation, Big Five personality characteristics, or fear of rejection (all $|d| < .22$; $p \geq .124$), or need to be alone (d = 0.32, p = .061).

3.3 Results

We first describe results of the item selection procedure, retest reliability, and results from confirmatory factor analyses. The remaining sections of the result section address convergent, discriminant, and predictive validity of the *Social Dynamics Scale*.

3.3.1 Part 1: Item Selection

For reasons of parsimony, our goal was to reduce the initial item pool of 39 items to five or less items per subscale. Using the data from Study part 1 (i.e. first assessment wave), we excluded items that had very low interitem correlations within their respective subscales and either touched on peripheral aspects or mixed the construct in question with other topics (e.g., Social deprivation and Family-friends interdependence “I miss my family, if I am away from them for several days”). Based on discussions of the item content, we also discarded items where answering in a certain way could be considered rude (e.g., “Seeing my family only on holidays and birthdays would be sufficient for me”). We further discarded two highly skewed items and one very long item (see Table S1). The remaining 27 items all showed sufficiently good item characteristics (Table S1). Therefore, our final selection was guided by the following principles: a) avoiding too much overlap in item content and wording, b) choosing items with easy and intuitive wording, and c) including items from a broad range of item difficulties. Based on these considerations, we slightly modified two items measuring Social deprivation.[16] We first selected five items for each subscale; however, this 15-item version later showed insufficient model fit in CFA. Excluding one of two very highly correlated items of the FFI subscale and one item with high cross-loadings on the Social deprivation subscale led to better model fit (see section Factorial Validity). We therefore chose four items per subscale for the

[16] The modified items were assessed together with the original phrasing in the third assessment wave. The modified items differed slightly in items’ difficulty but showed identical correlations with other variables. The scale means calculated with original and modified items were highly correlated (r = .98).

final version and report results on CFA model fits and reliabilities for five-item and three-item versions in the supplementary materials (Tables S2 and S3). Summary statistics and psychometric properties of the final items of the *Social Dynamics Scale* are shown in Table 3.1.

3.3.2 Part 1: Factorial Validity

Using the data from the first assessment wave, the correlation plot of the items (Figure 3.3) showed that items belonging to the same subscale had substantial intercorrelations and, with a few exceptions, no substantial cross-correlations. Since we had strong theoretical reasoning regarding three distinguishable domains of social dynamics, we conducted a confirmatory factor analysis: Specifically, we specified three latent correlated factors and four items for each factor using the three-stage robust diagonally least squares estimator with the *lavaan* package in R. The model showed acceptable fit with X^2 (51) = 147.32, $p < .001$, CFI = 0.915, TLI = 0.890, and RMSEA = 0.088. Table 3.1 displays the factor loadings. As an alternative structure, we specified a two-factor solution with Social oversatiation and Social deprivation combined into one factor and Family-friends interdependence as a second factor, yet this model yielded an unacceptable fit: X^2 (53) = 326.72, $p < .000$, CFI = 0.764, TLI = 0.706, and RMSEA = 0.144.

Figure 3.3

Correlations Between Items of the Social Dynamics Scale (T1, n = 280).

Note. Blue indicates positive correlations, and red indicates negative correlations.

Table 3.1

Wordings and Psychometric Properties of Social Dynamics Scale Items at T1 (n = 280) and T4 (n = 356)

Subscale		Original German item	English version	T1					T4		
				Factor loading	*M*	*SD*	α	r_{iic}	Factor loading	*M*	*SD*
SDS FFI	1	Ich bin ein Familienmensch.#	I am a family person.	.70	3.28	1.74	0.82	0.59	.61	2.94	1.59
	2	Meine Freunde sind mir wichtiger als meine Familie.	My friends are more important to me than my family.	.70	2.77	1.56	0.85	0.50	.54	2.93	1.48
	3	Ich mache lieber mit meiner Familie einen Ausflug als mit Freunden.#	I would rather go on an excursion with my family than with friends.	.71	3.95	1.73	0.85	0.53	.80	3.67	1.54
	4	Ich verlasse mich eher auf meine Familie als auf meine Freunde.#	I rely more on my family than on my friends.	.79	3.24	1.68	0.84	0.55	.82	3.13	1.57
SDS SOS	5	Wenn ich den ganzen Tag unter Menschen war, bin ich abends lieber allein.	When I have been with people all day, I prefer to spend the evening alone.	.85	4.92	1.67	0.80	0.50	.87	5.24	1.54
	6	Ich kann den ganzen Tag unter Menschen sein, ohne dass es mir zu viel wird.#	I can be around other people all day without it getting to be too much for me.	.80	4.51	1.74	0.79	0.51	.78	4.43	1.75
	7	Ich treffe mich mit möglichst oft mit jemandem, ohne dass ich Zeit für mich brauche.#	I get together with other people as often as I can, without needing time for myself.	.70	5.34	1.45	0.81	0.49	.69	5.15	1.49
	8	Ich bin schnell erschöpft, wenn ich mit vielen Menschen zusammen bin.	I become exhausted quickly when I am around a lot of people.	.65	4.01	1.88	0.79	0.51	.66	4.21	1.79
SDS SOD	9	Wenn ich den ganzen Tag allein bin, fehlt mir der Kontakt mit anderen.	When I am alone all day, I miss being around people.	.73	3.46	1.77	0.81	0.58	.67	3.35	1.76
	10	Nach wenigen Stunden allein sein fühle ich mich unwohl.	After spending just a few hours alone, I feel uncomfortable.	.75	2.16	1.48	0.83	0.54	.80	2.08	1.32
	11	Wenn ich den ganzen Tag unterwegs war, muss ich abends jemanden sehen oder anrufen. (initial item 11)	If I have spent all day alone, I have to get together with someone or call someone in the evening.	.60	3.21	1.82	0.82	0.56	/	/	/
		Wenn ich den ganzen Tag allein war, versuche ich abends jemanden zu sehen oder anzurufen. (final item)	If I have spent all day alone, I try to get together with someone or call someone in the evening.	/	/	/	/	/	.73	3.61	1.81
	12	Allein zu sein macht mir auch über einen längeren Zeitraum nichts aus. # (initial item 12)	I have no problem spending time by myself for a long period.	.77	2.99	1.78	0.84	0.52	/	/	/
		Es macht mir nichts aus, ein paar Tage für mich allein zu sein.# (final item)	I have no problem spending a few days by myself.	/	/	/	/	/	.71	2.37	1.51

Note. There were improvements of item language for item 11 and 12, see comments in the table. α = Cronbach's Alpha if item deleted. r_{iic} = average inter-itemcorrelation. Reverse coded items are marked with a #. SDS = *Social Dynamics Scale*. FFI = *Family-friends interdependence*. SOS = *Social oversatiation*. SOD = *Social Deprivation*.

3.3.3 Part 1: Reliability: Internal Consistency and Retest Reliability

We estimated the reliability by calculating total ω and retest correlations of the SDS subscales. The subscales each showed very good internal consistencies at the first assessment wave: Family-friends interdependence ω = .81, Social oversatiation ω = .81, Social deprivation ω = .84. The internal consistencies could be replicated at T4 (n = 356 including the boost sample): Family-friends interdependence ω = .79, Social oversatiation ω = .82, Social deprivation ω = .85. The 3-week retest correlations were r = .87 for Family-friends interdependence, r = .79 for Social oversatiation and r = .83 for Social deprivation. The 6-week retest correlations were comparable with r = .84 for Family-friends interdependence, r = .85 for Social oversatiation and r = .84 for Social deprivation. Overall, all three subscales demonstrated very good reliability.

3.3.4 Part 1: Convergent and Divergent Validity

We used the qgraph package (Epskamp et al., 2012) to visualize how the constructs of the *Social Dynamics Scale* were embedded within the larger nomological network of measures of social behavior and personality (see Figure 3.4). Table 3.2 reports descriptive statistics and point estimates of the intercorrelations among all included variables for the first and last assessment waves. As can be seen in Figure 3.4, Family-friends interdependence, Social oversatiation, and Social deprivation belonged to a part of the nomological network rather independent from the Big Five traits. Since the *Social Dynamics Scale* and most other assessed constructs focused on social phenomena, extraversion emerged as a relatively central node in the network. Most associations between the subscales of the *Social Dynamics Scale* and the other assessed constructs were consistent with our theoretical reasoning.

Table 3.2

Descriptive Information and Intercorrelations at T1 (lower diagonal, n = 280) and T4 (upper diagonal, n=356)

		T1 *M* (*SD*)	ω	T4 *M* (*SD*)	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	SDS FFI	3.31 (1.34)	.81	3.17 (1.20)		**.17**	**-.11**	**.12**	**-.11**	**.11**	**-.23**	**-.24**	-.10	.10	**.14**	**.16**	-.01	-.04
2	SDS SOS	4.69 (1.34)	.81	4.76 (1.32)	.10		**-.53**	**.38**	**-.49**	-.03	**-.30**	-.09	**-.71**	**.34**	**.33**	**.52**	**-.18**	.02
3	SDS SOD	2.96 (1.40)	.84	2.85 (1.32)	**-.21**	**-.44**		-.02	**.32**	-.06	**.11**	-.05	**.63**	.08	-.08	**-.61**	**.42**	**-.17**
4	Neuroticism	2.63 (0.71)	.91	2.63 (0.72)	.02	**.29**	.00		**-.42**	**-.24**	**-.48**	**-.41**	**-.27**	**.59**	**.59**	-.05	**.33**	**-.17**
5	Extraversion	3.10 (0.66)	.88	3.08 (0.65)	.04	**-.43**	**.27**	**-.41**		**.41**	**.26**	**.22**	**.54**	**-.41**	**-.57**	**-.24**	.03	-.04
6	Open-mindedness	3.60 (0.68)	.87	3.70 (0.68)	**.19**	.00	.00	**-.20**	**.42**		**.23**	**.14**	.07	**-.22**	**-.26**	**.14**	-.07	.06
7	Agreeableness	3.69 (0.53)	.83	3.70 (0.53)	-.12	**-.23**	.09	**-.40**	**.23**	**.23**		**.37**	**.36**	**-.27**	**-.38**	**-.15**	.08	.08
8	Conscientiousness	3.67 (0.64)	.89	3.70 (0.63)	**-.15**	-.04	-.01	**-.33**	**.25**	**.15**	**.36**		.10	**-.29**	**-.32**	.08	**-.15**	**.16**
9	Affiliation motive	3.35 (0.93)	.89	3.34 (0.93)	-.01	**-.67**	**.56**	**-.24**	**.60**	**.12**	**.26**	**.16**		**-.19**	**-.29**	**-.56**	**.37**	**-.18**
10	Fear of rejection	3.46 (1.07)	.85	3.58 (1.09)	.01	**.27**	**.15**	**.56**	**-.44**	**-.18**	**-.18**	**-.27**	**-.20**		**.54**	-.03	**.51**	**-.18**
11	Social anxiety	1.79 (0.79)	.88	1.76 (0.75)	.05	**.24**	-.02	**.52**	**-.51**	**-.19**	**-.34**	**-.24**	**-.25**	**.49**		.10	**.21**	**-.29**
12	Need to be alone	5.16 (0.96)	.83	5.12 (0.98)	**.19**	**.54**	**-.65**	-.06	**-.28**	.03	-.07	.07	**-.54**	-.03	.11		**-.37**	.07
13	Need to belong[a]	/	.75	3.22 (0.58)	/	/	/	/	/	/	/	/	/	/	/	/		**-.20**
14	Age	45.2 (14.3)	/	45.7 (14.3)	.01	**.19**	**-.16**	**-.12**	-.05	.08	-.01	.10	**-.31**	**-.14**	**-.18**	**.15**	/	

Note. ω = omega total, internal consistency of items. SDS FFI = Family-friends interdependence, higher scores indicate a stronger preference for friends. SDS SOS = Social oversatiation. SDS SOD = Social Deprivation. Significant correlations ($p < .05$) are printed in bold.

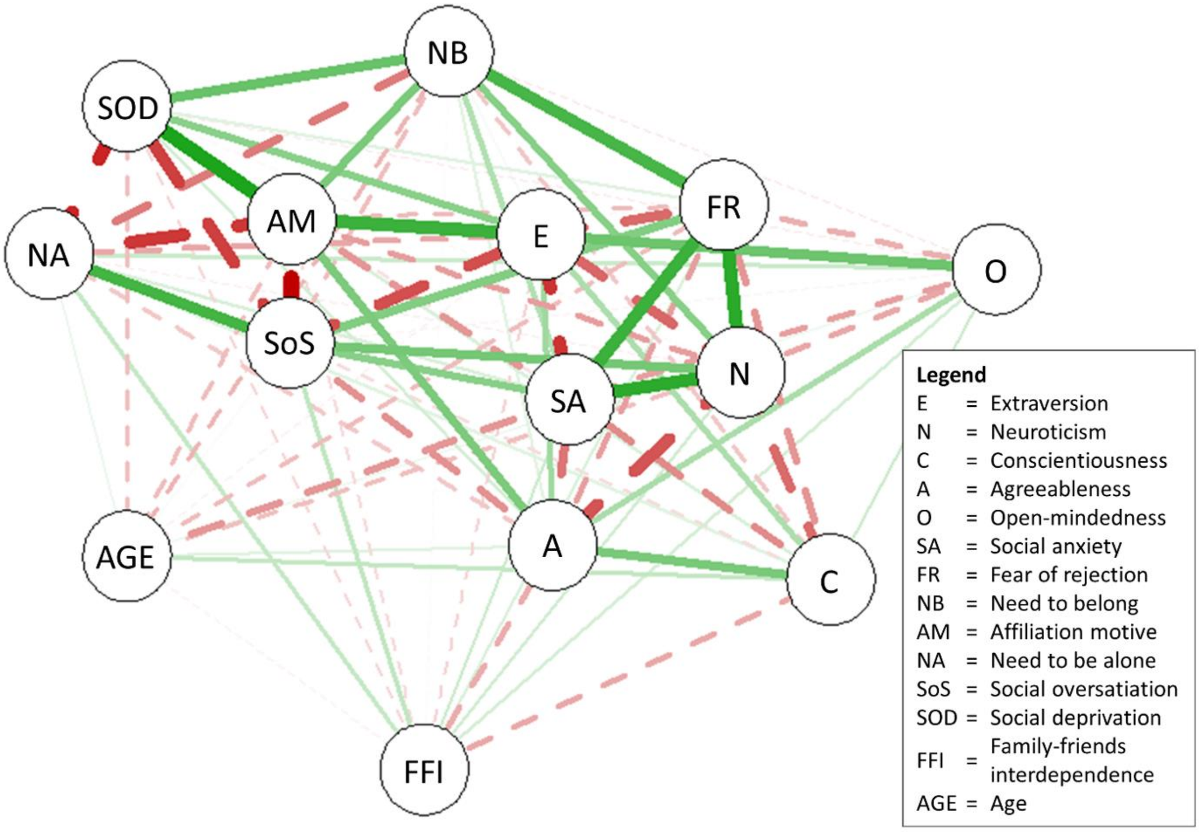
[a]Need to belong was only assessed at T4.

Associations Between the Subscales of the Social Dynamics Scale

As expected, Family-friends interdependence was clearly separable from Social oversatiation (r = .17, p = .001) and Social deprivation y (r = -.11, p = .044). However, the directions of both associations were contrary to our hypotheses: The more people reported preferring friends to their family, the more they felt Social oversatiation and the less they felt Social deprivation generally. Furthermore, as predicted, the more people reported experiencing Social oversatiation, the less they reported experiencing Social deprivation (r = -.53, p < .001); however, this association was stronger than expected.

Figure 3.4

Nomological Network of Social Dynamics Scale (T4, n = 356)



Note. This network graph is a graphical representation of the zero-order correlations between all variables measured at T4 (n = 356). Each node represents a construct, and each edge (line) represents a correlation between two constructs. Green/solid edges indicate positive correlations, red/dashed edges negative correlations, and the width of the edges corresponds to the relative strength of the correlations (i.e., thicker lines denote stronger associations).

Family-Friends Interdependence

Family-friends interdependence could be clearly distinguished from all other assessed constructs (Figure 3.4). The strongest correlations were with conscientiousness (r = -.24, p < .001), agreeableness (r = -.24, p < .001), and need to be alone (r = .16, p = .003). Unexpectedly, with increasing age, people did not report a stronger preference for friends or family (r = -.04).

Social Oversatiation

Social oversatiation emerged as a relatively central node in the network (Figure 3.4). With stronger the Social oversatiation, people's need to be alone was stronger (as hypothesized, r = .52, p < .001), the weaker was their affiliation motive (r = -.71, p < .001), and the less they reported being extraverted (r = -.49, p < .001). Moreover, with stronger Social oversatiation, people had higher values in neuroticism (r = .38, p < .001), fear of rejection (r = .34, p < .001), and social anxiety (r = .33, p < .001), and lower values in agreeableness (r = -.30, p < .001). Social oversatiation was not significantly associated with age (r = .02).

Social Deprivation

With stronger general Social deprivation, people reported stronger affiliation motives (r = .63, p < .001), need to belong (r = .42, p < .001), extraversion (r = .32, p < .001), and a weaker need to be alone (r = -.61, p < .001). In contrast to Social oversatiation and affiliation, Social deprivation was not associated with neuroticism, fear of rejection, or social anxiety (all p > .05). With increasing age, people reported experiencing less Social deprivation (r = -.17, p = .001).

All three subscales were empirically distinguishable from the Big Five measures, fear of rejection, social anxiety, and need to belong (Figure 3.4). Regarding convergent validity, the subscales of the *Social Dynamics Scale* were associated with affiliation motive and need to be alone in the hypothesized directions. The associations of Social oversatiation and Social deprivation with affiliation motive and need to be alone were stronger than expected. Yet, as shown in Table 3.2, Social oversatiation showed correlational patterns distinct from those of Social deprivation and need to be alone, and Social deprivation showed correlational patterns distinct from affiliation motive. Social oversatiation and affiliation motive, as well as Social deprivation and need to be alone showed consistent correlational patterns with measures of social behavior and personality but showed somewhat different associations with age. In sum, the results support the construct validity of Family-friends interdependence and provide partial evidence for convergent and divergent validity of the Social oversatiation and Social deprivation-subscales.

3.3.5 Part 2: Predictive Validity: Predicting Change in Personal and Indirect Social Contact

Analytic Approach

To examine the predictive validity of the *Social Dynamics Scale*, changes in personal and indirect contact with friends or family across time when contact restrictions were loosened were analyzed[17], as well as how the changes varied with general tendencies of Family-friends interdependence, Social oversatiation, and Social deprivation. Because the data formed a multilevel data structure with measurement occasions (i.e., T1 to T4) nested within people, the data were analyzed with multilevel models (MLM) using M*plus* (Version 8.3). Compared to a repeated-measures ANOVA, these models have the advantage of taking missing data into account and retaining participants with missing data. In all models, social contact with friends or family was the outcome, while time, one of the three subscales of the *Social Dynamics Scale* (SDS) measured at T1, and the interaction of time and the respective SDS subscale were predictors. The time variable was zero-centered, with the starting time of the study in the beginning of April 2020 as zero, when contact restrictions were strictest, and scaled in months. All models were set up as conditional growth models, in which the trajectory of contact across time (i.e., slope of time) was allowed to vary between people, and this variation was predicted by the *Social Dynamics Scale*. Values of the *Social Dynamics Scale* were grand mean-centered at Level 2 (i.e., participants) prior to estimating the models. We used separate models to predict personal, as well as indirect contact each separately for family and friends. Thus, 12 models (3 social dynamics subscales by 2 contact modes by 2 relationship types) were estimated using the full information maximum likelihood estimator. The parameter estimates for the fixed effects of all models are reported in Table 3.3, and interaction plots for personal contact are displayed in Figure 3.5.

[17] For reasons of parsimony, we report results for the most important relationships for family and friends in the main text. Results for colleagues are reported in supplementary Table S4.

Individual Differences in Social Dynamics Predict Change in Personal and Indirect Social Contact

Personal contact with both friends and family significantly increased across time, when contact restrictions were gradually loosened (Table 3.3, Figure 3.5). Individual differences in Family-friends interdependence did not moderate changes in personal contact with friends or family (Table 3.3, upper part). People with a stronger tendency to experience Social oversatiation reported a weaker increase in their personal contact with friends, $b = -0.05$, $p = .020$ (Figure 3.5C). As predicted, the stronger people rated their general Social deprivation, the stronger their personal contact with friends increased over the study period during early summer 2020, $b = 0.05$, $p = .005$ (Figure 3.5E). Changes in personal contacts with family were not predicted by Social deprivation nor Social oversatiation (Table 3.3, second column).

Notably, with a stronger general preference for friends, people reported more personal contact with friends, yet less contact with family at T1, despite being advised to only have contact with immediate household members (Table 3.3, main effects of FFI in columns 1 and 2, Figures 3.5A and 3.5B). In contrast, individual differences in experiencing Social deprivation or Social oversatiation were not significantly associated with the amount of personal contact with friends and family at T1, that is, at the time of strictest social distancing regulations (Table 3.3, main effects of Social deprivation and Social oversatiation).

Results for indirect contact partly complemented the results of personal contact such that across time indirect contact with friends and family decreased. People who preferred friends over family also reported less indirect contact with family, $b = -0.17$, $p < .001$ (Table 3.3, last column, upper part). People with a stronger tendency to experience Social oversatiation reported even less indirect contact with friends at T1, $b = -0.19$, $p < .001$. Furthermore, people who experienced Social deprivation more strongly reported more indirect contact with friends and family at T1, that is, at the time of strictest social distancing regulations (friends: $b = 0.14$, $p < .001$; family: $b = 0.13$, $p = .002$).

Table 3.3

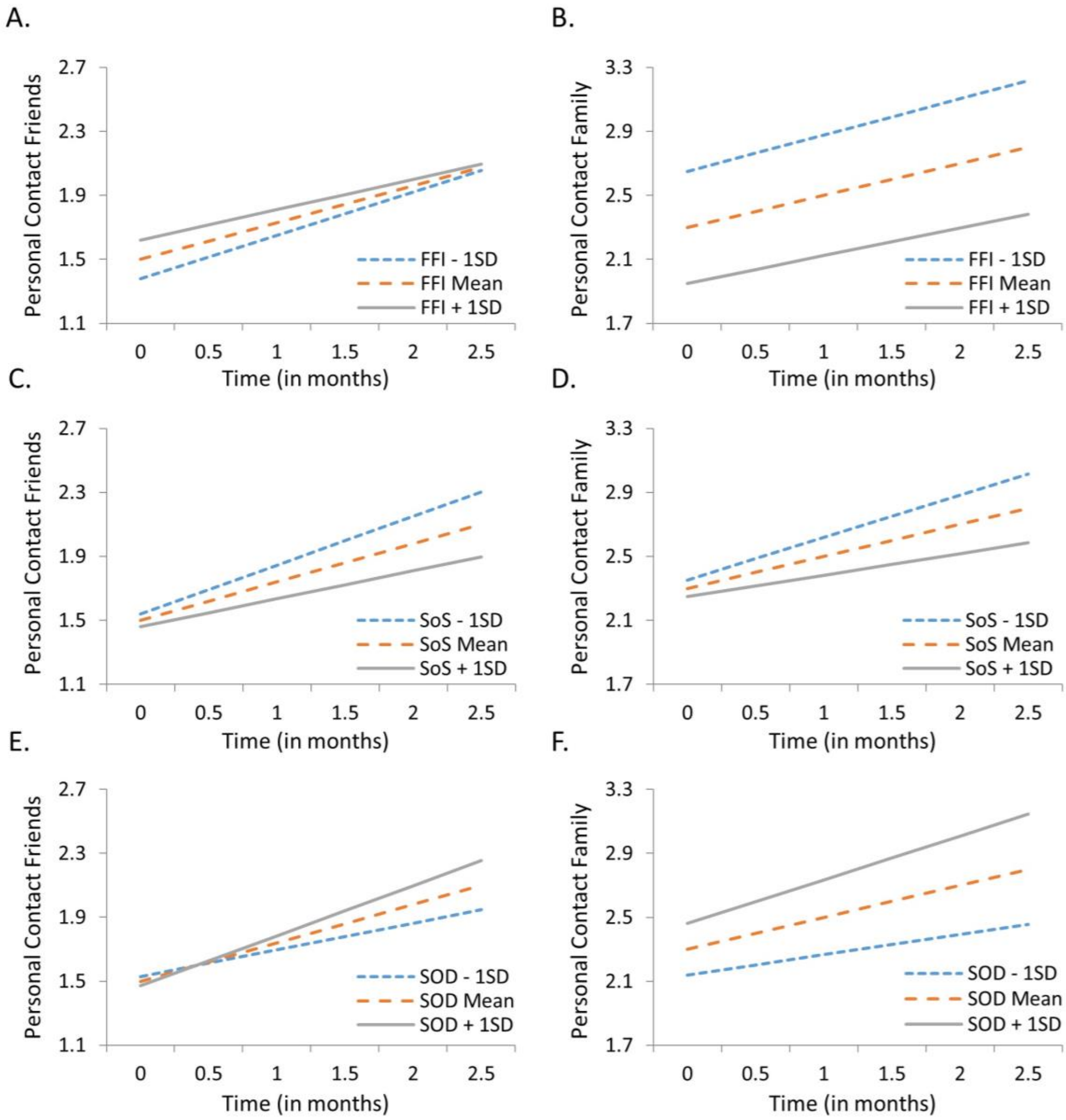
Model Parameters for Changes in Personal and Indirect Contact Frequency by Relationship Type

Effect	Personal				Indirect			
	Friends		Family		Friends		Family	
	b	95% CI	*b*	95% CI	*b*	95% CI	*b*	95% CI
Family-Friends Interdependence Models: Fixed effects								
Intercept	**1.50**	[1.40,1.60]	**2.30**	[2.12,2.49]	**2.64**	[2.53,2.75]	**2.36**	[2.25,2.46]
Time	**0.23**	[0.17,0.30]	**0.20**	[0.11,0.28]	**-0.13**	[-0.17,-0.08]	**-0.08**	[-0.13,-0.04]
FFI	**0.09**	[0.02,0.16]	**-0.26**	[-0.41,-0.12]	0.06	[-0.02,0.14]	**-0.17**	[-0.25,-0.09]
FFI*Time	-0.03	[-0.09,0.02]	-0.02	[-0.08,0.03]	-0.02	[-0.05,0.01]	-0.06	[-0.10,0.02]
Social Oversatiation Models: Fixed effects								
Intercept	**1.50**	[1.39,1.60]	**2.30**	[2.11,2.50]	**2.64**	[2.53,2.75]	**2.36**	[2.25,2.46]
Time	**0.24**	[0.18,0.30]	**0.20**	[0.12,0.29]	**-0.12**	[-0.17,-0.07]	**-0.08**	[-0.12,-0.04]
SOS	-0.03	[-0.11,0.06]	-0.04	[-0.20,0.11]	**-0.19**	[-0.28,-0.10]	-0.08	[-0.17,0.01]
SOS*Time	**-0.05**	[-0.10,-0.002]	-0.05	[-0.11,0.01]	-0.01	[-0.04,0.03]	-0.02	[-0.05,0.01]
Social Deprivation Models: Fixed effects								
Intercept	**1.50**	[1.40,1.60]	**2.30**	[2.11,2.50]	**2.64**	[2.53,2.75]	**2.36**	[2.25,2.46]
Time	**0.24**	[0.17,0.30]	**0.20**	[0.12,0.28]	**-0.13**	[-0.17,-0.08]	**-0.08**	[-0.12,-0.04]
SOD	-0.02	[-0.09,0.05]	0.11	[-0.02,0.24]	**0.14**	[0.06,0.22]	**0.13**	[0.05,0.22]
SOD*Time	**0.05**	[0.01,0.09]	0.05	[-0.01,0.11]	-0.01	[-0.04,0.02]	-0.004	[-0.03,0.02]

Note. FFI = Family-friends interdependence, higher scores indicate a stronger preference for friends; SOS = Social oversatiation, SOD = Social deprivation. The scale of Time is months. In all models, intercept and slope were free to vary. Significant effects are printed in bold ($p < .05$).

Figure 3.5

Fixed Effects of Multilevel Models for Personal Contact with Friends and Family



Note. Personal contact with friends and family is displayed as a function of time, *Social Dynamics Scale* (SDS), and the interaction of time and SDS. For illustrative purposes only, the predicted values for the mean plus and minus one standard deviation on the SDS subscales are displayed, while SDS subscales were always modelled as continuous predictor. The main effect of time was significant in all models (all $p < .05$). Effects of time, all other main effects, and interaction effects are reported in Table 3.3. FFI = Family-friends interdependence, SOS = Social oversatiation, SOD = Social deprivation. Effects for indirect contact, which decreased across time, are not displayed because results mirror effects of personal contact.

3.4 Discussion

The current study addressed individual differences in social dynamics: interdependencies among different social relationships as well as within relationships across time. Specifically, we described a direct approach to measure individual differences in Family-friends interdependence, Social oversatiation, and Social deprivation[18]. To substantiate the theoretical considerations that the three concepts are related, yet distinct aspects of how people maintain social relationships, we reported and now discuss results on internal consistency, factorial structure, temporal stability, as well as convergent, divergent, and predictive validity.

Although social dynamics are inherently short-term social behaviors that manifest in daily life (Back et al., 2011, 2023), we argue that self-concepts of social dynamics can be validly assessed based on self-reports—similar to other self-concept domains, such as Big Five traits (e.g., Soto & John, 2017), attachment (Fraley & Roberts, 2005), the need to be alone (Hagemeyer et al., 2013), or social anxiety (Peters et al., 2012). Similar to how other self-concepts are formed (Quintus et al., 2021; Wrzus, 2021), people likely observe their affective and behavioral reactions after (subjectively) insufficient or excessive social contact with family, friends, and others, and memorize these observations as self-concepts. Also similar to other self-concept domains, these relatively time-stable representations are assumed to be motivated and subjective memories instead of objective, fully accurate accounts (Vazire, 2010; Wrzus, 2021). As we discuss later, such generalized self-concepts still hold value for understanding individual differences in the dynamics of social relationships.

3.4.1 Scale Development: Internal Consistency, Factorial Structure, and Temporal Stability

Based on the theoretical considerations on Family-friends interdependence, Social oversatiation, and Social deprivation, we developed 39 initial items, which were examined in an age- and education-diverse sample. During the item selection process, we selected items with desirable item properties (i.e., skew, kurtosis, item difficulty, interitem correlation; Bühner, 2011). We simultaneously considered semantic aspects (e.g., brief wording, different aspects of covered content) and chose this approach over machine learning algorithms (e.g., ant colonization, genetic algorithms; Olaru et al., 2018) because machine learning usually neglected

[18] During the review process, it became apparent that other interdependencies likely exist as well. For example, friends might dislike a person's romantic partners and vice versa (e.g., Fiori et al., 2017), and conflicts with (in-law) family can impede marital satisfaction and vice versa (e.g., Bryant et al., 2004).

content aspects. Instead, machine learning optimizes item selection based on item or scale properties, such as distribution parameters or item difficulty (Olaru et al., 2018).

To develop an economic scale, we aimed at five or less items per subscale, that is, 15 or less items in total. With at least 4 items per subscale, the subscales demonstrated high internal consistencies of .80 and higher as well as a high 3-week and 6-week retest stability of around .80. The three subscales of social dynamics are thus comparable to other self-report instruments for assessing personality characteristics regarding both internal consistency and temporal stability over several weeks (Hagemeyer et al., 2013; Soto & John, 2017). The 15-item version showed insufficient model fit due to two items on the Family-friends interdependence subscale that were too highly correlated, and one item with high cross-loadings between the Social deprivation and Social oversatiation subscales. Thus, a 12-item version of the *Social Dynamics Scale* is preferred for psychometric reasons. Still, some controversy exists on the strictness when evaluating measurement models of personality scales (i.e., structural validity; Sellbom & Tellegen, 2019). Common criteria for model fit in confirmatory factor analysis seem to be rather strict for personality scales, and several established personality scales (e.g., NEO PI-R, MPQ, HEXACO, 16PF, CPI) often fall short of common model fit criteria (Hopwood & Donnellan, 2010). One viable approach in addition to model fit indices is considering further forms of validity, such as convergent and predictive validity (Hopwood & Donnellan, 2010; Sellbom & Tellegen, 2019).

3.4.2 Divergent, Convergent, and Predictive Validity

As expected, all three social dynamics subscales (i.e., Family-friends interdependence, Social oversatiation, and Social deprivation) emerged as rather independent from Big Five traits in the nomological network—with the exception that the more people rated themselves as extraverted, the less they reported a disposition towards experiencing Social oversatiation. This association between extraversion and (lower) general Social oversatiation might result from the Sociability and Energy facets of extraversion: People who frequently engage in social interactions (i.e., higher Sociability) partly do so because they experience social interactions as pleasant and rewarding and less as straining (Jacques-Hamilton et al., 2019; Soto & John, 2017), and thus they experience less Social oversatiation. Our data support this interpretation because general Social oversatiation was indeed lower with higher Sociability and higher Energy level, while the facet Assertiveness was loosely associated with Social oversatiation (supplementary Table S5).

The newly developed subscales Social oversatiation and Social deprivation showed convincing convergent validity based on strong associations with other interpersonal dispositions (i.e., affiliation motive, need to belong, need to be alone). This was expected based on the theoretical linkage between affiliation motive and consequences of motive dissatisfaction: The more people need and seek social contact, the more it is possible that the need is not (fully) satisfied, which is experienced as Social deprivation. Conversely, the less people need and seek social contact, the more it is possible that (unwanted) social contact exceeds a person's need, which is experienced as Social oversatiation. The complementary nature of Social oversatiation and Social deprivation was also apparent in their bivariate association, that is, with a stronger individual tendency to experience Social oversatiation, the tendency to experience Social deprivation was less pronounced. Still, we kept the two subscales as separate factors because the two subscales describe very distinct processes in daily social interactions, that is, social contact exceeding versus falling below desired social contact. Compared to assessing social contact and whether it exceeds or falls below the social needs with momentary assessments (e.g., experience sampling methods, mobile sensing; Mueller et al., 2019; J. Sun et al., 2020), Social oversatiation and Social deprivation might be difficult to separate in general retrospective reports. This becomes apparent through the negative correlation between the two general tendencies. Nonetheless, the self-ratings of the general tendencies can be valuable for panel studies or samples where behavioral observation is not possible (e.g., some clinical settings).

The complementary nature of individual differences in experiencing Social oversatiation and Social deprivation also became visible when examining predictive validity. After a period of strict, nationwide social contact restrictions in 2020, people who generally experience Social deprivation more strongly increased more strongly in self-reported personal contact with friends, whereas people who experience Social oversatiation more strongly increased contact at a lower rate. Thus, whereas previous research demonstrated short-term effects of Social deprivation or oversatiation (i.e., during laboratory experiments, Maner et al., 2007), the current findings demonstrate that similar effects occur over a period of several months—likely because social contact restrictions were much more severe than in laboratory studies and only gradually loosened.

Family-friends interdependence, the preference to be with family, with friends, or similarly with both, was clearly distinct from Big Five traits and further interpersonal dispositions, such as affiliation motive, need to belong, need to be alone, fear of rejection, or social anxiety. Thus, divergent validity was established. Previous research postulated that the affiliation motive can be satisfied in diverse social relationships (e.g., Hofer & Hagemeyer, 2018). Thus, a stronger preference for family or friends can exist independently from the strength of the affiliation motive (or related constructs)—which is exactly what was observed in the current study. Similarly, social anxiety and fear of rejection mainly manifest in interactions with unknown or scarcely familiar people (Asendorpf, 1990; Russell et al., 2011). Since close friends can be as familiar as family (Mund & Neyer, 2014; Wrzus et al., 2012), a preference for one or the other is also largely independent from social anxiety, which is supported in the current results. Although the number of and contact frequency with friends is often higher for people higher in extraversion and agreeableness (e.g., Wagner et al., 2014; Wrzus et al., 2016), a relative preference for friends of family seems to be rather independent from these two and the other Big Five traits (Buijs et al., 2023). Perhaps, Family-friends interdependence as a preference for one over the other depends more strongly on the specific available friends and family or the quality of the relationships (e.g., Wrzus et al., 2012).

Despite few empirical associations with other (interpersonal) dispositions, Family-friends interdependence seemed to be measured validly, as the associations with the amount of personal and indirect contact demonstrated: With a stronger preference for friends (over family), people reported more contact with friends, yet less contact with family during the contact restrictions.

In summary, the *Social Dynamics Scale* reliably assessed relatively stable individual tendencies towards family or friends, Social oversatiation, and Social deprivation as well as demonstrated convincing divergent, convergent, and predictive validity. The partly very high correlations among Social oversatiation, Social deprivation, affiliation motive, need to belong, and need to be alone might be attributable to common method variance as associations were smaller and still substantial, when assessing social dynamics with momentary assessments in people's daily lives (e.g., Wrzus, Roos, Krämer, Schoedel et al., 2024; Zygar et al., 2018).

3.4.3 Limitations and Future Directions

The current study proposes Family-friends interdependence, Social oversatiation, and Social deprivation as interpersonal dispositions, which capture dynamic interdependencies among social relationships—both across relationship types and time. In addition, the study aimed to develop and validate a brief measure to assess individual differences in these interpersonal dispositions reliably and validly. We embedded the study and the scale development in the strong theoretical background of affiliation motive theory and used a heterogeneous sample as well as strong methodological and statistical approaches to meet the study aims. Still, some limitations and directions for future research need to be addressed.

First, as discussed before, the study measured **self-concepts** of social dynamics. Though this approach is routine for many personality dispositions that intend to capture relatively stable differences in people's thoughts, feelings and behaviors, future studies should aim to directly observe social dynamics in daily life. Mobile sensing might be extended to not only assess whether social contact occurred (e.g., Roos et al., 2023; J. Sun et al., 2020) but also with which person or what kind of relationship (e.g., romantic partner, friend). At the same time, behavioral observation, which is per se blind to internal thoughts and feeling, might detect fewer traces of Family-friends interdependence or Social deprivation, when external constraints override preferences and needs. For example, a person might prefer to spend time with a specific friend, but they might not be able to meet the friend because of family obligations or because the friend is unavailable (e.g., Buijs et al., 2023). Similarly, a person might experience Social oversatiation and the desire for no further personal contact but might not be able to avoid contact because of obligatory appointments or other external demands (e.g., Coplan et al., 2019; Krämer et al., 2024).

Second, data collection ended in June 2020 due to restricted resources, but social-distancing rules were further loosened afterwards and tightened again in the fall. It is possible that (a) under conditions of unrestricted social contact, the subscales of the *Social Dynamics Scale* would show somewhat different intercorrelations, and (b) the effects of *Social Dynamics Scale* to predict change in social contact might have been even stronger if examined over a longer time period. One argument against such temporal effects is that scale intercorrelations were rather similar across the two study periods at the beginning of April and in the middle of June, when different contact restrictions existed. In addition, other studies that examined differences in people's well-being covered a similar time period (e.g., Zacher & Rudolph, 2021), yet focused on loneliness or subjective well-being without taking different forms of social contact into account.

Finally, we developed and tested the *Social Dynamics Scale* in a sample of German adults and future studies could examine the levels of Family-friends interdependence, Social oversatiation, and Social deprivation in other cultures, countries, and age groups (i.e., children, adolescents). We assume that the overall level of Family-friends interdependence or Social oversatiation could differ in these other populations. For example, social network compositions differ between cultures, though not always between ethnicities within a country (Fung et al., 2001, 2008), which could indicate cultural differences in Family-friends interdependence.

Similarly, because social networks and the density of living conditions also contribute to how much oversatiation and deprivation people experience (Roos et al., 2024), cultures with differences in social networks and living conditions could also differ in the average level of Social oversatiation or deprivation people experience. With respect to age, we assume that children will show a higher preference for family over friends on average due to parents and siblings being the central relationships in children's social lives (Berk, 2015; Bowlby, 1991). When adolescents increasingly detach from parents and focus on peer relationships (Hartup & Stevens, 1997; Reitz et al., 2014), individual differences in the Family-friends interdependence will develop depending on how extensively adolescents focus on peer relationships. At the same time, in every culture or age group people likely differ from each other in the three studied aspects of social dynamics. These individual differences in social dynamics result from environmental characteristics as well as the general human need to maintain social relationships, which exists in all people although to a different extent (for review see Hofer & Hagemeyer, 2018).

3.5 Conclusion

People have the need to form and maintain fulfilling social contacts, yet they differ with respect to with whom they satisfy the need and how quickly this need is deprived or overly satiated. Accordingly, the current longitudinal study focused on theoretically delineating such social dynamics as well as on measuring individual differences in (a) Family-friends interdependence and (b) Social oversatiation, and (c) Social deprivation as three aspects of social dynamics. For situations and samples where direct behavioral observation is not feasible or misleading (e.g., strong external constraints, too brief observation periods to detect individual differences reliably), the newly developed brief self-report questionnaire, the *Social Dynamics Scale* (SDS), could provide a useful complementary approach. The current results demonstrate that individual differences in the tendencies to experience Family-friends interdependence, Social deprivation, or Social oversatiation can be measured reliably, validly, and with predictive value for changes in daily contact with family and friends.

Chapter 4: The Dynamics of Personality and Social Relationships in Daily Life: Individual Differences in Social Deprivation and Social Oversatiation

Cornelia Wrzus[1,2], Yannick Roos[1], Michael D. Krämer[3], Ramona Schoedel[4,5], Mitja D. Back[6], & David Richter[7,8]

[1] Psychological Institute, Heidelberg University, Germany [2] Network Aging Research, Heidelberg University, Germany [3] Department of Psychology, University of Zurich, Switzerland [4] Charlotte Fresenius University, Germany [5] Ludwig-Maximilians-Universität München, Germany [6] Department of Psychology, University of Münster, Germany [7] SHARE BERLIN Institute GmbH, Berlin, Germany [8] Freie Universität Berlin, Berlin, Germany

Abstract

Individual differences in the affiliation motive and extraversion are closely linked to social relationships. Most previous research focused on long-term characteristics or momentary assessments of social relationships (e.g., social network size, relationship quality), whereas theoretical accounts have emphasized the temporal processes, that is, how social interactions unfold over time. The present studies focused on how social interactions unfold within days as well as between days, taking personality characteristics and situational affordances into account. In two multi-method studies (Study 1: N = 307, age 18–80 years, 51% female; Study 2: N = 385, age 19–84 years, 48% female), we assessed participants' social interactions in daily life using ecological momentary assessments and mobile sensing over 2 and 14 days, respectively. In addition, participants answered questionnaires measuring the affiliation motive, extraversion, and situational affordances. Multilevel lead-lag analyses showed that the affiliation motive predicted momentary social desires but not changes in future social interactions, except when social interactions were assessed with unobtrusive, continuous mobile sensing. Situational affordances, such as the valence and voluntariness of social interactions, additionally predicted social desires and future contact. Generally, the results were largely specific for affiliation and not observed for extraversion. Future research on social interactions would benefit from (a) examining temporal processes to identify meaningful time scales of social relationships, (b) scrutinizing multiple relationships and multiple personality characteristics simultaneously, and (c) following the renewed interactionist call for integrating person and situation factors.

Wrzus, C., Roos, Y., Krämer, M. D., Schoedel, R., Back, M. D., & Richter, D. (2024) *Affiliation Motive and Social Interactions in People's Daily Life: A Temporal Processes Approach Using Ecological Momentary Assessment and Mobile Sensing*.[Manuscript submitted for publication] Department of Psychological Aging Research, Institute of Psychology, Heidelberg University.

4.1 Introduction

Social interactions are by nature dynamic phenomena as they change over time and previous interactions contribute to future interactions (e.g., Back et al., 2023; Wrzus, Roos, Krämer, & Richter, 2024). At the same time, people differ substantially in how they maintain social interactions: People with a more pronounced affiliation motive or extraversion are more often in social interactions, both in person and digitally, and they maintain larger offline and online social networks (Cheng et al., 2019; Harari et al., 2020; Kroencke, Harari, et al., 2023). The majority of this previous research on social traits focused on such static snapshots of social relationships (i.e., amount of contact, number of social partners at a given time), whereas several theoretical accounts of the affiliation motive, extraversion, and other social traits emphasize the temporal dynamics of social relationships (for integrative overviews, see Back et al., 2023; Denissen & Penke, 2008): For example, people with a higher affiliation motive are assumed to seek out social interactions faster when alone and enjoy social interactions for a longer time compared to people with a lower affiliation motive. Yet, research on such individual differences in the temporal dynamics of interactions, that is, over short periods of time such as hours and days, is still scarce (for similar arguments, see Back et al., 2023; Wrzus, Roos, Krämer, & Richter, 2024).

In two studies using ecological momentary assessment (EMA) and mobile sensing methods in adult lifespan samples, we examined individual differences in the temporal dynamics of social interactions in people's daily life within and across days, and additionally took situational affordances into account (cf. Back et al., 2023). Temporal dynamics refer to changes in social interactions and social desires over time (Back et al., 2023; Kuper et al., 2021). Although people with a higher affiliation motive might want to seek social interactions faster when alone, situational constraints such as working alone on a task might prevent acting upon the need. Similarly, social interactions might not always be avoidable or immediately stoppable. Accordingly, we considered both personality characteristics and situational affordances in examining temporal changes in social interactions. Whereas previous daily life studies focused on personality differences in momentary social interactions (e.g., Breil et al., 2019; Kroencke, Harari, et al., 2023) or momentary well-being in social and non-social situations (e.g., Elmer & Lodder, 2023; Krämer et al., 2024; J. Sun et al., 2020), the present studies addressed an important theoretical point of personality theories, scarcely addressed empirically: How do personality traits and situational affordances predict the temporal dynamic of changes in social interactions over time?

4.1.1 *Social Traits in Daily Life*

Several individual characteristics, such as the affiliation motive, extraversion, communal orientation, agreeableness, but also social anxiety play an important role in how people behave in social interactions and shape their social relationships (see Back et al., 2011; Wrzus, Roos, Krämer, & Richter, 2024). These characteristics have both common and unique theoretical backgrounds. For example, the affiliation motive and extraversion both address how much social interaction people want and how much they enjoy it. Still, the affiliation motive is process- and motivation-oriented, whereas extraversion is often considered descriptive of the personality structure (Hofer & Hagemeyer, 2018; Soto & John, 2017). In addition, extraversion integrates further aspects such as assertiveness in social interactions and unfolds in interactions with strangers (Soto & John, 2017), whereas affiliation emphasizes existing relationships and the feeling of belonging (Hofer & Hagemeyer, 2018). The theoretical and empirical work on these topics fills books (e.g., Rauthmann, 2021b; Vangelisti & Perlman, 2018) and journals and thus cannot be covered comprehensively here. Here, we focus on the affiliation motive because it broadly applies to different established social relationships, and the underlying motivational theory provides a strong theoretical foundation for emphasizing the temporal dynamics of social behavior. In addition, we consider extraversion as a central social trait within the Big Five and HEXACO frameworks, which is conceptually broader and hardly focuses on temporal aspects of social relationships (Harris & Vazire, 2016). We do so to assess the distinct contributions of the affiliation motive and extraversion.

Some previous research has shown that with a higher affiliation motive or higher extraversion, especially higher sociability, people maintain a greater number of social relationships (e.g., Cheng et al., 2019; Kersten et al., 2023), and people respond more positively to social interactions and social stimuli (Dufner et al., 2015; Jacques-Hamilton et al., 2019; Krämer et al., 2022; Kroencke, Humberg, et al., 2023)—which has been interpreted as differential enjoyment of social interactions. Still, other studies have suggested that people with a lower affiliation motive or extraversion enjoy pleasant social interactions equally (Kersten et al., 2023; Ren et al., 2022; Smillie et al., 2015; J. Sun et al., 2020). However, these studies did not assess or control for temporal aspects such as whether enjoyment decreased after some time or how much social interaction people had before the respective interaction. Such temporal aspects are crucial because homeostatic social need theories (Carver & Scheier, 1998; Hall & Davis, 2017; O'Connor & Rosenblood, 1996) postulate that people constantly adjust their social interactions. Such adjustments occur through up- or down-regulating the amount and quality of social interactions depending on the individual social need, previously experienced social interactions, and situational affordances.

4.1.2 Temporal Dynamics of Social Interactions: Effects of Social Traits and Situational Affordances

Several theoretical accounts concur on the dynamic regulation of social interactions over time (Back et al., 2023; Carver & Scheier, 1998; Sheldon, 2011; see overview in Kuper et al., 2021). This work postulates that people continuously regulate their current level of social desires in relation to their subjectively ideal level and then attempt to adjust their social behavior accordingly, in line with situational affordances (Baumeister & Leary, 1995; Carver & Scheier, 1998; Hall & Davis, 2017; O'Connor & Rosenblood, 1996). This means, on the one hand, when people interact with others, the interaction is maintained until it exceeds the desired level, and then solitude is sought. Conversely, when people are alone, they will seek social interactions faster or slower, depending on their typical social need level (i.e., affiliation motive; extraversion) Therefore, social desires and social interactions are in constant co-regulation, with each preceding the other at a future time in a continuous stream involving bidirectional influences (Hall & Davis, 2017; O'Connor & Rosenblood, 1996). Such general social need regulation has received some direct and indirect empirical support (Baumeister & Leary, 1995). The direct empirical support demonstrated that people maintain the current level of their social interactions in daily life (or solitude, respectively) and do not desire to change it when it meets their current need (O'Connor & Rosenblood, 1996). Similarly, people engage in longer-than-usual social interactions after longer episodes of solitude, and vice versa (Luo, Pauly, et al., 2022), which indicates a dynamic up- or down-regulation of social interactions depending on how much the social needs have been met. Regrettably, the previous studies focused solely on self-reported social interactions, and neither examined individual differences in social needs or situational affordances, that is, whether situations facilitate or hinder social interactions or solitude.

4.1.3 Social Traits and Changes in Social Interactions Over Time

The empirical evidence for how affiliation or extraversion might contribute to temporal dynamics of daily social interactions is scarce because the majority of past research focused on (a) static descriptions, even when assessed repeatedly in specific moments (e.g., the momentary quantity or quality of social interactions; Harari et al., 2020; Kroencke, Harari, et al., 2023), or (b) long-term relationship development (e.g., for reviews, see Harris & Vazire, 2016; Winterheld & Simpson, 2018). Similarly, some mobile sensing studies focused on average digital social behavior and showed, for example, that with higher extraversion, people have more contacts stored in their phones, and they also call and text other people more frequently (Harari et al., 2020; Stachl et al., 2017). However, the trait differences in changes in social interactions from moment-to-moment or day-to-day have scarcely been addressed.

Only a few studies have investigated some dynamic aspects of daily social interactions: For example, among young students, a higher similarity in extraversion at the start of college predicted more positive interactions over subsequent weeks (van Zalk et al., 2019), yet this study did not focus on how extraversion predicts day-to-day or interaction-to-interaction changes with novel friends. In another experience sampling study, which assessed contact with different relationship types, people higher in extraversion were less likely to be alone and remain alone over the next few hours, whereas they were more likely to be with friends and also maintain interactions with friends (Wrzus et al., 2016). Furthermore, with a higher affiliation motive momentary social deprivation (i.e., high social desire and too few social interactions) was more likely, yet social oversatiation (i.e., low social desire and too many social interactions) was less likely (Krämer et al., 2024). However, that study focused on affective consequences of social deprivation and oversatiation without examining behavioral changes over time.

These first results suggest that the affiliation motive and extraversion not only predict how many relationships people maintain and how much people interact with others on average, but also how their social interactions change dynamically in daily life. These dynamic changes could represent the assumed adjustment of momentary social interaction to the ideal level, which varies with social traits. Yet, several theoretical accounts emphasize that situational affordances also contribute to how (social) traits can manifest in behavior (Back et al., 2023; Blum et al., 2018; Kuper et al., 2023; Lewin, 1939; Schmitt et al., 2013).

4.1.4 Situational Affordances and Changes in Social Interactions Over Time

Even if people with a high affiliation motive want to engage in social interactions in situations when previous contact fails their desired level, situational constraints can prohibit the realization of social interactions, for example, when no suitable interaction partner is physically or digitally available. The opposite might also occur, if people want to end or reduce interactions with somebody, yet they have to continue interacting, for instance, because a task must be finished or someone impedes the individual from leaving the social situation.

Only a few studies have examined the role choice plays in social situations. In general, people reported most often to be in chosen situations, either alone or with others, and they stated greater well-being, meaning, and feelings of control in chosen compared to involuntary situations (Hall et al., 2021; Tse et al., 2022; Uziel & Schmidt-Barad, 2022). But more important, with higher extraversion, participants were more often in chosen social situations and less often alone by choice, whereas extraversion did not explain differences in being involuntarily alone or with others (Emmons et al., 1986; Tse et al., 2022). This research indicates that personal preferences can be acted out better in situations with some degrees of freedom (e.g., Blum et al., 2018; Schmitt et al., 2013), whereas in situations that are not voluntarily chosen or created, personality traits seem to matter less. Regarding the temporal dynamics of social situations, increasing or decreasing social interactions should be more possible when situations can be chosen or shaped.

4.1.5 The Present Studies

The present studies addressed important gaps in the research on trait differences of social relationships in people's daily lives by examining temporal dynamics, specifically changes in momentary social desires and social interactions within and across days. We accounted for both social traits and situational affordances, which are generally examined separately. To examine how social traits relate to the temporal dynamics of social interactions in people's daily life, we conducted two ambulatory assessment studies (i.e., using ecological momentary assessments [EMAs] and mobile sensing [MS]) with two independent samples spanning the adult lifespan. In Study 1, participants' social interactions were measured densely over 2 days to examine within-day dynamics. Study 2 extended the first study and assessed social interactions across 14 days to examine temporal dynamics across days.

For theoretical reasons, we focused on the affiliation motive and examined whether results would be distinct from effects of extraversion. Previous studies focused on either the affiliation motive or extraversion in predicting specific aspects of daily life social interactions—leaving a scattered pattern of results, which we aimed to clarify through examining both personality characteristics in the same studies. Also, situational affordances were addressed, which likely contribute additionally to changes in social interactions within and across days. We specifically examined whether contact was possible, who or what initiated the contact, and how pleasant the contact was (i.e., interaction quality). The current studies included social interactions within any kind of relationship (e.g., family, friends, colleagues) and did not distinguish between relationship types because the temporal dynamics were assumed to occur across different relationship types (e.g., excessive social interactions with colleagues could also affect later social interactions with family or friends; Hall et al., 2021; Tse et al., 2022; Wrzus, Roos, Krämer, & Richter, 2024).

Transparency and Openness

We report how we determined the sample sizes in the *Participants* section; all data exclusions, as well as all measures in the studies are described in the *Measures* section. Both studies were preregistered on OSF. Study 1: https://osf.io/q9yt5; Study 2: ttps://osf.io/wqj92. Documentation of the assessed variables, analysis code, data for Study 1, as well as data access information for Study 2 are provided on OSF and are available at https://osf.io/7mx38/?view_only=830d317dc6324358855ce2ef89014b22. Furthermore, we followed the APA Journal Article Reporting Standards (Appelbaum et al., 2018).

Ethics Approval Statement

These studies adhered to the principles of the Declaration of Helsinki for research involving human subjects and were IRB-approved by Johannes Gutenberg University Mainz (process number: 2018-JGU-psychEK-002).

4.2 Study 1: Within-Days Dynamics

In Study 1, participants' social interactions were measured densely over 2 days to examine within-day dynamics. We preregistered the following hypotheses (https://osf.io/q9yt5):

4.2.1 Hypotheses Study 1

H1: When being alone, the desire to interact with others increases over time as well as the probability to engage in subsequent social interactions.

H1a: The effect of time is more pronounced with a more pronounced affiliation motive.

H1b: The effect of time is less pronounced with higher situational constraints.

H2: During social interactions, the desire to be alone increases over time, and the likelihood to engage in subsequent social interactions decreases.

H2a: The effect of time is more pronounced with a less pronounced affiliation motive.

H2b: The effect of time is less pronounced with higher situational constraints.

H2c: The effect of time is more pronounced with lower quality social interactions.

4.2.2 Participants

Based on a power estimation for detecting small to moderate between-person effects (effect size r = .20 or r = .15, 1-β = .90; α = .05), we aimed at a sample size of at least 207 and at most 374 participants (see further details on sample size estimation at https://osf.io/q9yt5). Via online advertisement, community outreach, and news articles, we recruited a sample of 320 participants across Germany in Fall 2021 and Spring 2022. Of those, 307 participants took part in the EMA part of the study, and 297 provided mobile sensing data. For the analyses, we generally used all available data. Participants were aged 18 to 80 years (M = 39.44, SD = 14.14) and were about equally distributed per age decade and men and women (50.8% female, 48.5% male, 0.7% non-binary or not reported). The participants had diverse educational (46% college degree, 35% high school degree, 19% other degrees) and occupational backgrounds (33% full-time employed, 14% part-time employed, 32% students, 10% retired, 11% unemployed or no information). Most participants were in romantic relationships (60%), 33% were single, 7% were divorced, and 35% had children.

4.2.3 Procedure

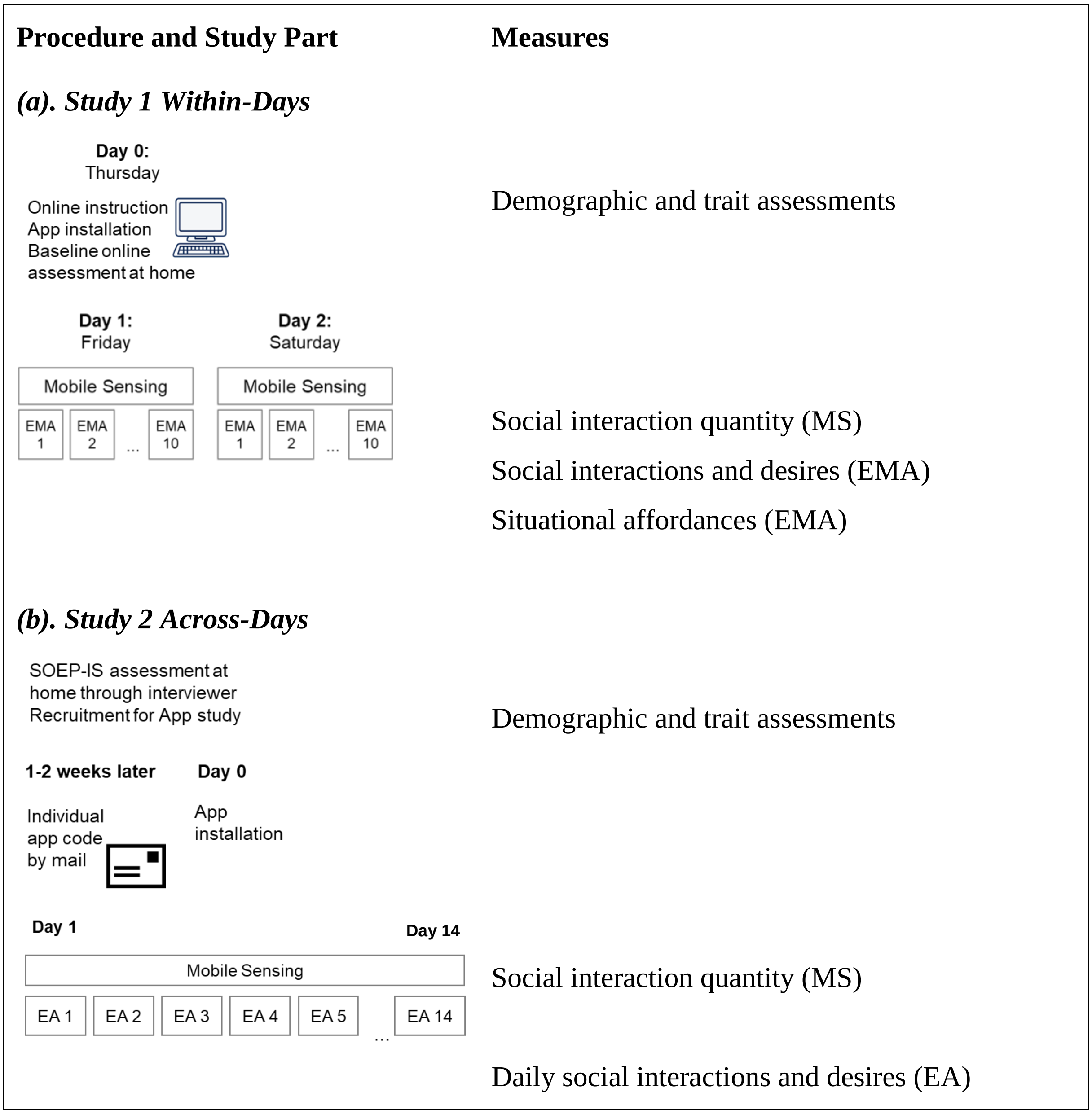
The respondents interested in the study received further information during online video calls, which always occurred on Thursdays in groups of two to eight people, to ensure that participants understood the mobile assessment, data handling, and privacy issues thoroughly. After providing informed consent, participants received instructions on how to install the PhoneStudy research app (https://phonestudy.org/en/) on their Android OS smartphones, and they later answered a baseline questionnaire on demographics and personality traits on their computer (for the complete list of measures see study documentation at https://osf.io/7mx38/?view_only=830d317dc6324358855ce2ef89014b22). During the next 2 days, the app alerted participants 10 times per day to answer brief questionnaires as part of EMA. The signals occurred between 9:00 a.m. and 9:00 p.m., thus roughly every 80 min with some programmed random variation to implement pseudo-random experience sampling. Simultaneously, mobile sensing of sound snippets happened continuously in the background, and the snippets were processed on the phone to assess social interactions unobtrusively. Participants received a reimbursement of €40 (approx. USD$40) and a bonus of €10 if they filled out 17 or more of the 20 EMA questionnaires. On average, the participants answered 74% of the scheduled assessments (SD = 3.81).

4.2.4 *Measures*

A complete overview of all the assessed items is available in the study documentations at https://osf.io/7mx38/?view_only=830d317dc6324358855ce2ef89014b22. Figure 4.1 illustrates the design and social interactions measures for both studies.

Figure 4.1

Study Designs of (a) Study 1 Within-Days and (b) Study 2 Across-Days



Note. EMA = ecological momentary assessment, MS = mobile sensing, EA = evening assessment.

Social Traits. The participants answered the short affiliation motive subscale (six items, ω = .89) of the Unified Motive Scale (Schönbrodt & Gerstenberg, 2012) and the German version of the BFI-2 (Danner et al., 2016; Soto & John, 2017) to measure extraversion with 15 items (ω = .89). Affiliation items were answered on a 6-point scale (1 = *does not apply* to 6 = *applies fully*); extraversion items were answered on a 5-point scale (1 = *strongly disagree* to 5 = *strongly agree*).

Momentary Social Interactions (EMA & MS).

At each EMA questionnaire, we assessed momentary and retrospective social interactions, which were defined for participants as in-person interactions (i.e., engaging with others in communication or joint activities), not merely being in the same place or room. The question “Are you currently in in-person contact with someone or with several people?” assessed momentary social interactions (answering options: *Yes, with one person*; *Yes, with several people*; *No*). To assess social interactions in-between EMA questionnaires, participants reported their social interactions since the last assessment (or the last hour if they missed the last assessment) using identical answer options. After reporting one previous interaction, the questions were repeated if further interactions occurred earlier. Interaction duration was indicated using a scroll-wheel with the options: 5 min, 10 min, 15 min, 30 min, followed by steps of 30 min up to 24 hours. Furthermore, the participants indicated how pleasant each interaction was on a 7-point rating scale (1 = *unpleasant* to 7 = *pleasant*) as contact valence, which served as the measure for social interaction quality.

Based on the information of momentary and recent social interactions and contact duration, a contact ratio was computed to approximate the percentage of time within face-to-face interactions within the last episode (usually about 80 min): First, the self-reported duration of all momentary and recent social interactions was summed within each episode. If the summed duration of social interactions exceeded the episode duration, it was capped at the episode duration. Then, the summed duration of social interactions within each episode was divided by the episode duration to arrive at a proportion of social interaction time. For control analyses, a contact ratio was calculated for the last two episodes (about 160 min).

In addition, social interactions were measured through mobile sensing using the AWARE Conversations plug-in (Ferreira & Mulukutla, 2020). This algorithm samples and processes ambient sound without storing raw audio to protect privacy and infers whether conversation is present in proximity to the phone. The algorithm was configured to follow a 1-min sampling and 3-min pause cycle to balance comprehensive measurement and battery conservation. Based on the samplings indicating the absence or presence of conversations (binary 0 and 1), we computed the proportion of conversation in the previous 80 min to match the approximate episode between EMAs. This proportion was calculated by dividing the number of AWARE Conversation samplings that indicated conversation by the total number of samplings during each 80-min timeframe. If fewer than five samplings were available in a given timeframe because, for example, other apps interfered with the conversation detection, the proportion of conversation was set to “missing”.

In previous studies, the proportion of conversation derived from this algorithm exhibited a small to substantial overlap with social interactions self-reported via EMA (Harari et al., 2017; Roos, Krämer, Schoedel, et al., 2023). Discrepancies can arise due to limitations of both methods, such as the algorithm failing to detect social interactions, detecting conversations not reported in the EMA, or misclassifying conversations (e.g., capturing voices from TV or a group of people the target did not interact with).

Momentary Social Desires (EMA).

Depending on whether participants indicated being in contact or alone at each EMA questionnaire, they additionally answered “Would you like to be alone right now?” or “Would you like to be in the company of others right now?” and “Would you like to be in in-person contact with someone right now?” on a 7-point scale (1 = *not at all* to 7 = *very much*). We formed the mean score of the latter two items to represent individuals’ momentary desire for social interactions.

Momentary Situational Affordances (EMA).

At each EMA questionnaire, the participants indicated whether the social interaction was imposed or self-initiated on a 7-point scale (1 = *self-initiated contact* to 7 = *other people/external circumstances led to contact*). The middle point indicated mixed situations where both participants’ choices and other people or external circumstances played a role, like attending a party that someone deliberately went to yet where they also interacted with others who happened to be around. If participants were alone, they indicated to what extent face-to-face interactions were possible in their situation on a 7-point scale (1 = *not at all*, 7 = *very much*).

4.2.5 Analytic Approach

To test the hypotheses on predicting momentary social interactions or social desires, we used multilevel models including random intercepts and random slopes, with observations (Level 1) nested in participants (Level 2). Logistic multilevel models were used for the binary outcome of social interactions (0 = *no*, 1 = *yes*). In all models, Level 1 predictors were person-mean centered to separate within-person and between-person variance components, and scaled using each person's within-person standard deviation (Hoffman, 2015). Level 2 variables (i.e., the between-person components of Level 1 variables, affiliation motive, extraversion) were grand-mean centered. All models were estimated with the lme4 package (Version 1.1-33; Bates et al., 2015) in R (Version 4.2.3; R Core Team, 2022), using maximum likelihood estimation (Laplace approximation).

The dataset was split depending on participants' current social situation.[19] When *currently alone*, social interaction at the next assessment (Yes/No) or current desire to interact were predicted by affiliation motive, the quantity of previous social interactions (i.e., the proportion of face-to-face interaction in the last episode), and the possibility of social interactions. To test H1a and H1b, we added interaction terms between the quantity of previous social interactions and (a) affiliation motive and (b) the possibility of social interactions. Examples for model equations are provided in the Supplement A1.

When participants were *in a social interaction* right before the assessment, social interaction at the next assessment or current desire to be alone were predicted by affiliation motive, the quantity of previous social interactions (in the approx. prior 80 or 160 min), self-rated contact initiation, and contact valence to examine H2a. To test H2b and H2c, we added interaction terms between the quantity of previous social interactions and (a) self-rated contact initiation and (b) contact valence. Different than specified in the preregistration, we could not model the time of being alone or in social interactions directly because people reported the duration of contact for multiple social interactions, yet not the start and end points (see General Discussion for further explanations). Nonetheless the adjusted analytic approach addresses the underlying temporal dynamics well, because we linked past periods of being alone or in social interactions with future social interactions and social desires, and additionally tested two time periods of distinct length (i.e., 80 and 160 min). In addition, we conducted further analyses using the mobile sensing indicator of social interactions instead of the self-report EMA measure.

[19] The data were split because some items were only asked when participants reported a social interaction, and vice versa (e.g., participants did not provide valence ratings if they were currently alone).

4.2.6 Results: Within-Days Dynamics

Descriptive statistics of the social interaction variables and between-person correlations with the affiliation motive and extraversion are reported for both studies in Table 4.1; complete correlations among study variables are provided in Supplemental Table S1.

Confirmatory Analyses

When Currently Alone. In situations where participants were alone, they were more likely to be in contact at the next assessment about 80 min later, the more contact they had on average (between-person effect) and the more contact was seen as possible, both currently (within-person effect) and generally (between-person effect; Figure 4.2a). Contrary to the hypotheses, individual differences in the affiliation motive did not predict future contact and also did not moderate the association between current and future contact. Desire for social interactions was higher with a higher affiliation motive and when more contact was seen as currently possible, but not significantly associated with the amount of prior contact (Figure 4.2b). The findings remained unchanged when prior contact over a longer timespan (i.e., the last two episodes of approx. 160 min) was considered. Complete model results are reported in Supplemental Table S2.

Table 4.1

Descriptive Information of the Social Interaction Variables in both Studies and Zero-order Correlations with Affiliation Motive and Extraversion

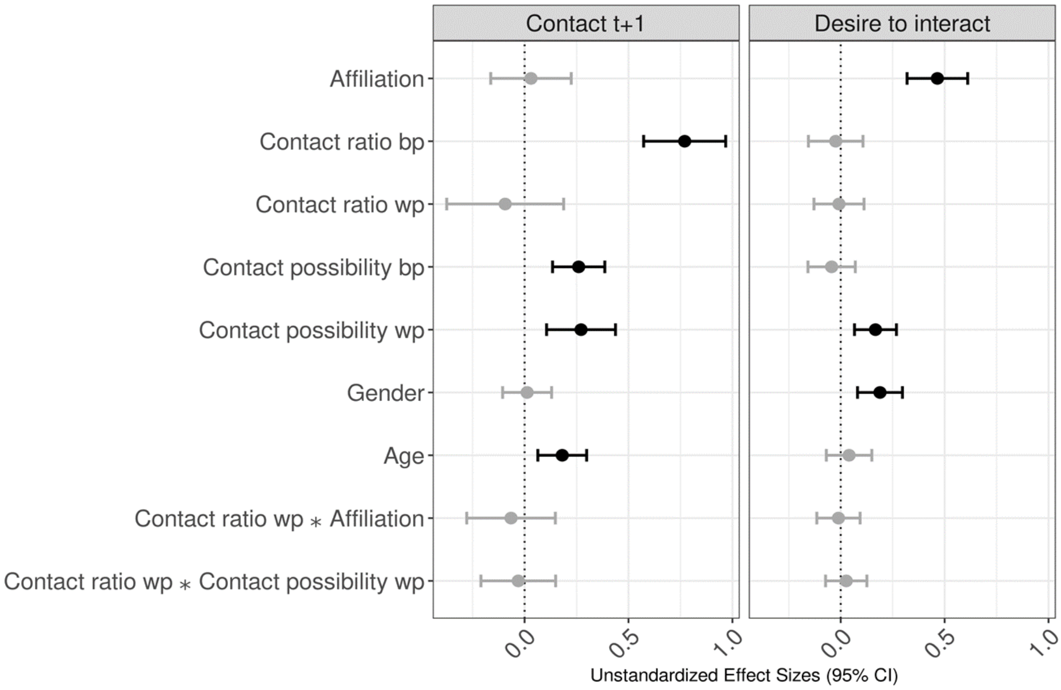
	Study 1 – Within 2 days				Study 2 – Across 14 days			
	i*M*	i*SD*	Affiliation *r* [95% CI]	Extraversion *r* [95% CI]	i*M*	i*SD*	Affiliation *r* [95% CI]	Extraversion *r* [95% CI]
Social interaction quantity (EMA)	0.34	0.31	.00 [-.11, .11]	.07 [-.04, .18]	14.17	6.31	.09 [-.03, .19]	.10 [-.02, .21]
Social interaction quantity (MS)	0.10	0.12	.09 [-.03, .20]	.08 [-.04, .20]	0.13	0.10	**.14** [.02, .25]	.05 [-.07, .17]
Desire to interact	3.28	0.97	**.44** [.34, .52]	.07 [-.05, .18]	3.03	1.30	.04 [-.08, .15]	-.06 [-.18, .05]
Desire to be alone	3.24	1.34	**-.33** [-.43, -.23]	**-.17** [-.28, -.06]	3.00	1.16	**-.13** [-.23, -.02]	-.07 [-.19, .04]
Contact valence	5.71	0.87	**.16** [.05, .27]	**.20** [.09, .31]	5.80	0.62	**.25** [.15, .36]	**.19** [.08, .30]
Contact possibility	4.73	1.13	.04 [-.08, .15]	.01 [-.10, .13]	-	-	-	-
Contact initiated	3.92	1.59	-.05 [-.16, .06]	-.04 [-.15, .07]	-	-	-	-

Note. i*M* = average of the individual within-person means of momentary variables; i*SD* = average of the within-person *SD*s of momentary variables. EMA = ecological momentary assessment; MS = mobile sensing. The correlations were based on individual averages of momentarily assessed contact variables. Estimates in bold indicate $p < .05$; 95% CIs did not cover 0.

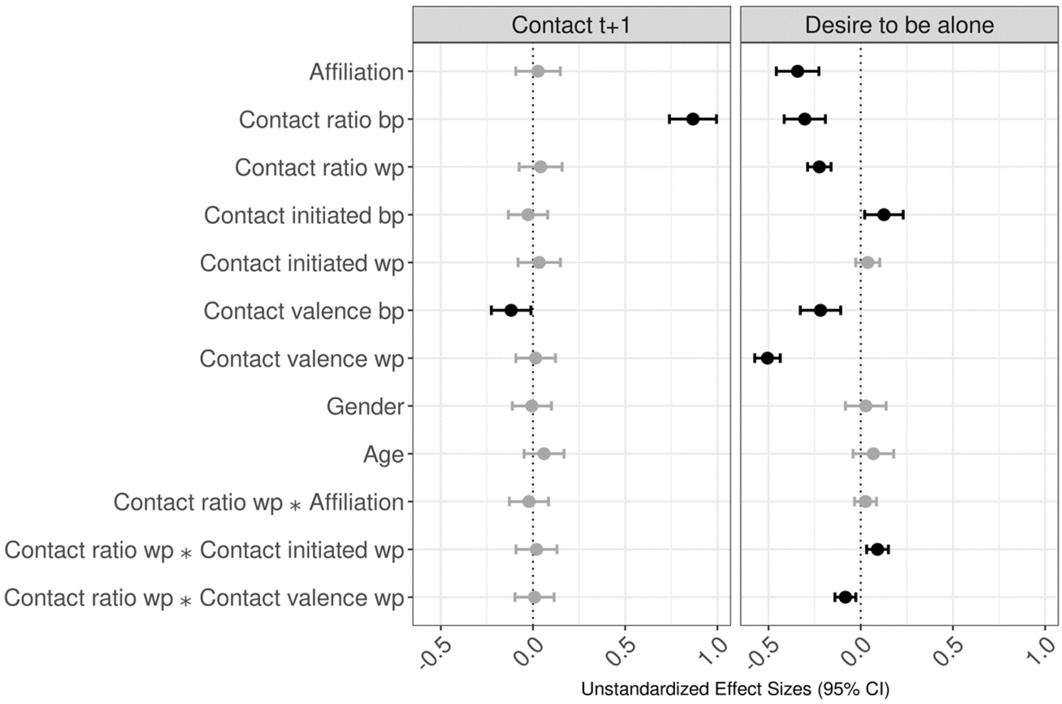
Figure 4.2

Study 1: Overview of Results from Multilevel Regression Models Predicting Future Social Interactions and Current Social Desires in Situations when People were Alone (Panel a & b) or in Social Interactions (Panel c & d)

a & b. When Currently Alone



c & d When Currently in a Social Interaction



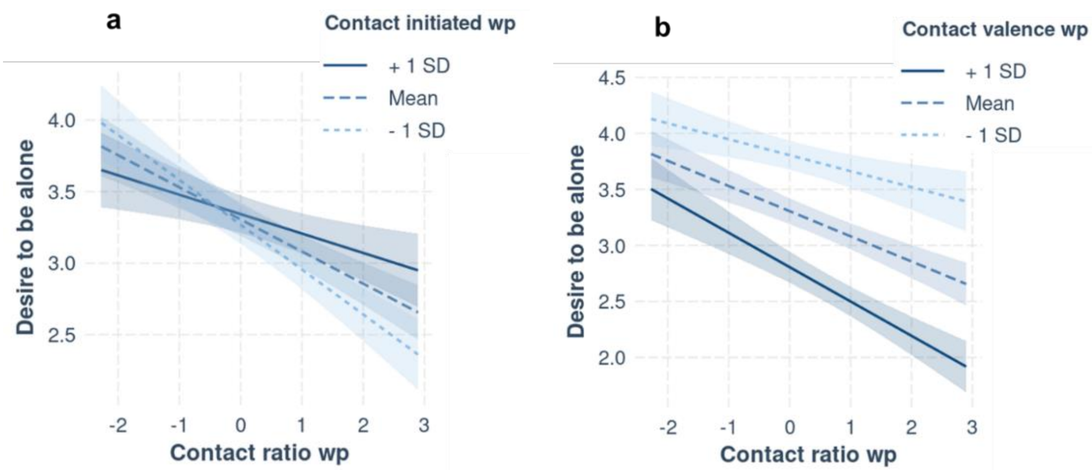
Note. Coefficients in black $p < .05$, coefficients in grey $p > .05$. bp = between-person, wp = within-person.

When in a Social Interaction. In situations where participants were already in social interactions, they were more likely to also be in an interaction at the next assessment about 80 min later, the more social interactions they had generally, and the less pleasant their interactions were generally. No other predictor or hypothesized moderation effects (e.g., of affiliation or voluntariness of prior contact and prior social interactions) were associated with later social interactions (see Figure 4.2c; complete model results are reported in Supplemental Table S2). In addition, when participants were in social interactions, they wished less to be alone with a higher affiliation motive and more prior social interactions, especially if social interactions were more strongly self-initiated and more pleasant (Figure 4.2d).

Simple-slopes analyses of the moderation effects (see bottom part of Figure 4.2d) showed that the association between more prior contact and lower desire to be alone was only significant when prior contact was strongly to moderately self-initiated (i.e., values below 5.27 on the 1 “self” to 7 “other/externally” scale; Figure 4.3a). This indicates that with longer contact people had a lower desire to be alone when the contact was self-initiated. Similarly, the association between more prior contact and less desire to be alone was significant and more pronounced when the contact was more pleasant (i.e., values above 4.27 on the 1–7 scale; Figure 4.3b). Thus, in reverse conclusion, when long contact originated from others/external demands or was rather unpleasant, the desire to be alone became more pronounced over time (compare lines on the right ends of Figures 4.3a and 4.3b).

Figure 4.3

Study 1: Amount of Previous Contact and Desire to be Alone Moderated by (a) Initiator of Contact and (b) Valence of Previous Social Interaction



Note. Mean refers to the respective scale average; + 1SD refers to previous contact being more strongly externally initiated (Figure 4.3a) or contact being more pleasant (Figure 4.3b).

Exploratory Analyses: Social Interactions Based on Mobile Sensing

When using mobile sensing to measure social interactions, participants were more likely to be in future social interactions when they had a higher affiliation motive (b = 0.006, 95% CI [0.001, 0.011]), generally engaged in more social interactions (b = 0.098, 95% CI [0.093, 0.103]), or were in contact during the 80 min before (b = 0.042, 95% CI [0.038, 0.047]); the general (i.e., person average) and recent amount of contact were also classified through mobile sensing (complete model results are reported in Supplemental Table S3). Thus, both situational affordances in the form of previous contact as well as individual differences in the form of affiliation motive were relevant. When the amount of previous contact was statistically held constant, contact occurred more likely with higher levels of the affiliation motive. Unlike in the analyses of the EMA data, the valence or initiator of the social interaction could not be included because this information was unavailable in the mobile sensing data.

In summary, a higher affiliation motive was associated with a stronger momentary desire to interact and a weaker desire to be alone, yet the affiliation motive did not predict future contact or moderated the association between current and future contact, except when social interactions were assessed with unobtrusive, continuous mobile sensing. Situational affordances, such as whether contact was possible and how pleasant the contact was, predicted both social desires and future contact.

Specificity and Sensitivity Analyses

We conducted three sets of specificity and sensitivity analyses. First, analyses were repeated with extraversion replacing the affiliation motive as person-predictor in all models to examine to what extent results were specific for affiliation or generalized to extraversion as a related social trait. In short, extraversion did not predict social desires or changes in social interactions (Supplemental Table S4). Second, to exploratively follow-up on the absent associations between affiliation motive or extraversion and the average amount of social interactions, we analyzed the amount of contact with specific relationship types (Supplemental Table S5): People higher in the affiliation motive or extraversion reported more contact with friends or colleagues but not with family or strangers (Supplemental Table S5). Third, we exploratively repeated the analyses separately for Fridays and Saturdays to examine whether the participants regulated their social interactions differently on weekdays versus weekends, assuming they differ in external constraints (e.g., Harari et al., 2020; van den Berg et al., 2010). Results were largely similar for Fridays and Saturdays (see Supplemental Figure S1), with only one day-specific effect: On Saturdays, the more social interactions people had in the hours before, the less likely they were to remain in an interaction (Supplemental Figure S1g). Furthermore, likely due to reduced statistical power, two effects (i.e., the within-person association between possible contact and actual social interactions; the moderation effect predicting desire to be alone) were not robust when analyzing data from Fridays and Saturdays separately.

4.4 Study 2: Across-Days Dynamics

To complement Study 1, which examined temporal dynamics within two days, Study 2 focused on the temporal dynamics between days over 14 days. We preregistered the following sets of hypotheses https://osf.io/wqj92.

H1a: After days with less social contact than usual, subsequent social contact increases.

H1b: The effect of previously lower social contact on subsequently increased social contact is more pronounced with a more pronounced affiliation motive.

H1c: The effect of previously lower social contact on subsequently increased social contact is more pronounced with lower quality of previous social contact.

H2a: After days with more social contact than usual, subsequent social contact decreases.

H2b: The effect of previous contact on subsequently reduced social contact is more pronounced with a less pronounced affiliation motive.

H2c: The effect of previous contact on subsequently reduced social contact is less pronounced with higher quality of previous social contact.

To test the specificity of the effects of affiliation, analyses will be repeated with extraversion as person predictor.

4.4.1 Participants

Participants were recruited from the existing SOEP innovation sample (SOEP-IS, Richter & Schupp, 2015) which is a yearly German-wide population-based panel study. In 2022, 2,507 respondents participated in the panel assessment and were asked to engage the Social Relationships in Daily Life study. From this sample, N = 385 participants took part in the additional 14-day smartphone study (see Schoedel, Bühner et al., 2023, for selectivity analyses). Participants were between 19 and 84 years old (M = 48.9, SD = 15.7), 48.9% female, and 51.1% male (non-binary gender information was not assessed). Participants had again diverse educational (29% college degree, 17% high school degree, 49% other degrees) and occupational backgrounds (42% full-time employed, 17% part-time employed, 11% students/apprentices, 22% retired, 7% unemployed). Similar to Study 1, most participants (80%) were in romantic relationships, 13% were single, 6% were divorced, 2% widowed, and 63% had children. The data from 72 participants were excluded from analyses focusing on the EMA variables because they received partly different EMA items due to a software error (see further explanations in OSF material app_version_report_2023-08-08.docx at https://osf.io/7mx38/?view_only=830d317dc6324358855ce2ef89014b22).

4.4.2 Procedure

During the SOEP-IS interview, which was conducted as computer-assisted, in-person, or telephone interviews and online questionnaires, participants were asked whether they owned a suitable smartphone (running Android OS 7 or newer) and would like to participate in the smartphone study. Interested participants received a postal invitation that contained further information on data handling and privacy issues, the personalized download link of the PhoneStudy research app, and instructions on how to install the app. During the installation, participants provided informed consent. A personalized participation code ensured that an additional participant ID was stored in the app data to link the SOEP-IS data and the mobile sensing data.

After the app installation, participants received daily notifications on 14 evenings to fill out brief questionnaires before going to sleep. The questionnaires assessed their social interactions as well as their emotional well-being during the day and were accessible each day from 8:00 p.m. until 4:00 a.m. Two reminders occurred between 8:00 p.m. and midnight. As in Study 1, mobile sensing continuously captured sound snippets in the background and stored processed data on in-person contact (i.e., detected conversations) for the 14 days of the study. Participants received €40 (approx. USD$40) as reimbursement. On average, the participants answered 85% of the scheduled 14 daily assessments (M = 11.8 days, SD = 2.8).

4.4.3 Measures

Social Traits. Affiliation and extraversion were assessed as part of the SOEP-IS questionnaire before the additional opt-in smartphone study started. Affiliation was measured with two items (ω = .72[20]) that were also included in Study 1 ("Encounters with other people make me happy" and "I try to be in the company of friends as much as possible"; UMS, (Schönbrodt & Gerstenberg, 2012) on a 6-point scale (0 = *does not apply* to 5 = *applies fully*). Extraversion was assessed with three items (ω = .80) of the BFI-S (Lang et al., 2011) on a 7-point scale (1 = *does not apply* to 7 = *applies fully*). Due to the large number of topics covered in panel studies such as the SOEP-IS, brief measures were used.

Daily Social Interactions (EMA & MS). Each evening, participants reported the amount and quality of personal contact with romantic partners, children, other family, friends, colleagues, and others. For each relationship type, they answered, "How much personal contact did you have today?" and reported the approximate duration using a scroll-wheel (< 0:05h, 0:15h, 0:30h, increasing in steps of 30 min up to 24 hours). The quality of the contact (i.e., "How was the contact?") was rated on a 7-point scale (1 = *unpleasant* to 7 = *pleasant*). The amount of contact per day was winsorized to a maximum M + 3 *SDs* within each relationship type and then summed across the relationship types. Otherwise, distorted self-reporting could have resulted in total contact times exceeding 24 hours per day. The quality of contact per day was averaged across relationship types. As in Study 1, social interactions were measured through mobile sensing using the AWARE Conversations plug-in (Ferreira & Mulukutla, 2020) and aggregated across each day. Figure 4.1 illustrates the design and contact measures for both studies.

Daily Social Desire (EMA). At the end of each evening questionnaire, participants answered two questions regarding their social desires: "Would you have liked to spend more time with other people today?" and "Would you have liked to spend more time alone today?" using a 7-point scale (1 = *not at all* to 7 = *very much*).

[20] In case of two items, Cronbachs α = .72 or Unidimensionality Index =.72 are more appropriate.

4.4.4 Analytic Approach

Similar to Study 1, we used multilevel models to predict the amount of contact at the next day or social desires at the end of the day. The models included random intercepts and random slopes, with observations (Level 1) nested in participants (Level 2). All models were estimated with the lme4 package (Version 1.1-33; Bates et al., 2015) in R (Version 4.2.3; R Core Team, 2022), using maximum likelihood estimation (Laplace approximation).

The desire for more contact or more time alone was asked independently of the current situation of the participants, and consequently, no split of the dataset was necessary. Three models were computed: (a) the amount of social interaction the next day, (b) desire for more contact, or (c) desire for more time alone were predicted by affiliation motive, the amount of social interaction on the current day and mean contact valence that day, and interaction terms between contact duration, affiliation, and contact valence. In all models, the Level 1 variables were person-mean centered to separate the within-person and between-person variance component and scaled using each person's within-person standard deviation (Hoffman, 2015). The Level 2 variables (i.e., affiliation motive, extraversion, person-means of Level 1 variables) were grand-mean centered. Age and gender were included as control variables.

Similar to Study 1, we conducted further exploratory analyses on the mobile sensing-based social interaction quantity. In these models, the proportion of conversation on the next day obtained from the AWARE Conversations Plug-In was predicted by the proportion of conversation on the current day, affiliation motive, and the interaction term between both, with age and gender as control variables.

4.4.5 Results: Across-Days Dynamics

Descriptive statistics of the social interaction variables and between-person correlations with affiliation motive and extraversion are reported for both studies in Table 4.1. The complete correlations among study variables are provided in Supplemental Table S6.

To complement analyses from Study 1 on within-day dynamics in time windows of up to 2.5 hours, we examined changes from one day to the next in Study 2. Furthermore, the sample was also heterogeneous per age, gender, and education and drawn from a population-based panel study.

Confirmatory Analyses

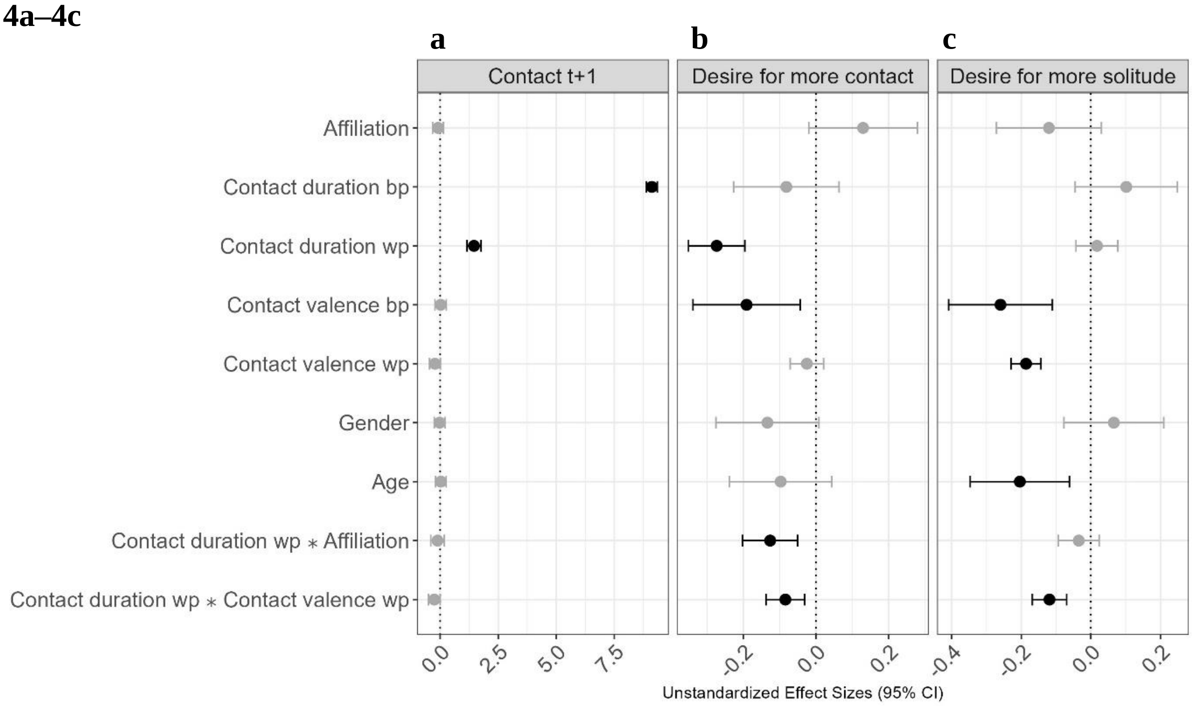
Mirroring results from Study 1, the more contact participants had on one day or in general, the more they were also in contact with others the next day, while affiliation motive and valence of the social interactions (main effects and moderations) did not predict social interactions the next day (Figure 4.4; complete model results are reported in Supplemental Table S7). Thus, people tended to maintain the amount of contact they had on previous days or in general, irrespective of their trait level of affiliation.

Regarding social desires, with less social interactions than usual, people reported in the evening that they wished for more additional time with others, and affiliation motive moderated this association (Figure 4.4b; complete model results are reported in Supplemental Table S7). Simple-slopes analyses showed that for affiliation motive values higher than 2.20, the less contact participants had on a certain day, the more they wished for additional time with others, and this association was stronger with higher values of affiliation (Figure 4.4d). Unexpectedly, people who judged their contacts more pleasant on a certain day reported a lower desire for additional time with others the more time they had spent in social interactions—perhaps because the pleasant contact satisfied their need for contact (Figure 4.4e). Like in Study 1, the desire for more time alone was higher with a lower valence of contact on a given day (and also in general), and especially with longer-than-usual unpleasant social interactions (Figure 4.4f).

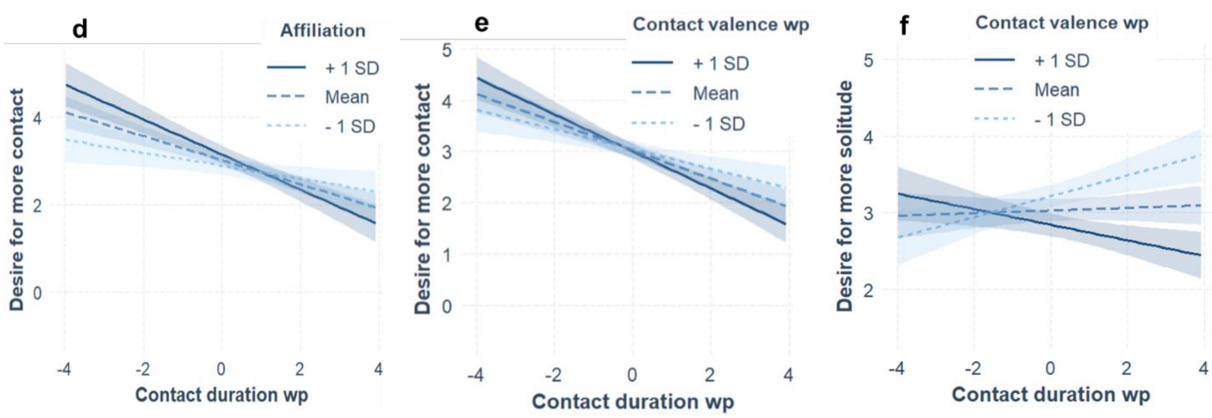
Figure 4.4

Study 2: Overview of Results from Multilevel Regression Models Predicting Future Contact, Current Social Desires (a-c), and Interaction Effects (d-f)

4a–4c



4d–4f



Note: Coefficients in black $p < .05$, grey $p > .05$. bp = between-person, wp = within-person.

Explorative Analyses: Social Interactions Based on Mobile Sensing

As in Study 1, we inferred social interactions through mobile sensing and analyzed the proportion of detected conversations on each day as an indicator of social interactions. Bivariate correlations (Table 4.1) showed that higher proportions of social interactions were sensed with a higher affiliation motive of participants ($r = .14$; 95% CI [0.02, 0.25]). However, this zero-order association of affiliation was reduced when predicting future social interactions from current social interactions and including demographic variables in the model (b = -.001; 95% CI [-0.004, 0.005]; Supplemental Table S3). Instead, participants were more likely to be in social interactions the next day, the more social interactions were sensed during the entire study period (b = 0.089, 95% CI [0.085, 0.094]; complete model results are reported in Supplemental Table S3). The valence of the social interactions could not be included in these models because this information was unavailable in the mobile sensing data.

Specificity and Sensitivity Control Analyses

Again, we repeated the analyses and used extraversion instead of affiliation motive as the personality characteristic of interest in all models to examine to what extent results were specific for affiliation or generalized to extraversion as a related social trait. Like in Study 1, extraversion did not significantly predict changes in social interactions from day to day or the desire for more social interactions. A small moderation effect occurred, such that with more contact on a given day, people low in extraversion reported a greater desire for more solitude (see Supplemental Table S8). This effect mirrors results from laboratory research on exhaustion after social contact in people low in extraversion (Zelenski et al., 2012). Furthermore, we analyzed the associations between affiliation motive or extraversion and the contact with specific relationship types (Supplemental Table S5). Largely replicating the results of Study 1, people higher in affiliation motive or extraversion reported more contact with friends, but not family or strangers, which might point to the voluntary nature of contact with friends. Finally, we repeated the analyses separately for weekdays and weekend days with generally the same results, except for the following: Uniquely on weekends, people with a lower affiliation motivation reported more that they wished they had spent more time in solitude (Supplemental Figure S2). On weekdays, more negatively valent interactions on the previous day were associated with less contact on the next day, and this effect was more pronounced when more than usual social interactions occurred on the previous day (Supplemental Figure S2d). Two effects predicting desires for more contact were not robust when analyzing weekdays and weekends separately, perhaps because of reduced power (Supplemental Figure S2).

4.6 General Discussion

Whereas previous studies often examined trait effects on structural or static aspects of social relationships (e.g., amount, and quality of social interactions at a given time or aggregated over a certain period), the present two studies focused on how the affiliation motive and extraversion might predict dynamic changes in social interactions over time, taking situational affordances into account. In two age-, education-, and gender-heterogeneous samples, we assessed different aspects of social interactions using both experience-sampling and mobile sensing methods over 2 and 14 days, respectively. The general discussion now addresses three points meant to advance theoretical reasoning on personality effects in temporal dynamics of social interactions. First, we evaluate how traits and situational affordances predicted desires for more or less social interactions as well as changes in social interactions over time. Second, we discuss possible time scales on which the regulation of social behavior could occur. Third, we incorporate our findings in current integrative frameworks of personality and social relationships to advance the understanding of their interplay.

4.6.1 Trait Effects and Situational Effects on Social Desires and Social Interactions

We assumed that individual differences in the affiliation motive would highlight how social desires and social interactions change over time. In general, we observed that with a higher affiliation motive, people reported a stronger desire to be in contact (in Study 1[21]) and a weaker desire to be alone (in both studies). More importantly, when people were in contact for about the last hour (Study 1), they reported a stronger desire to be alone, with lower affiliation motive. Likewise, when people were alone the hour before (Study 1) or had little contact on a certain day (Study 2), they reported an increased desire for social interactions, with a higher affiliation motive.

Despite these associations with social desires, and contrary to expectations, the affiliation motive hardly mattered for transitions from being alone to being in contact, or vice versa on an approximately hourly basis (Study 1) or for dynamic changes from day to day (Study 2). Instead, people seemed to be attuned to situational affordances, for example, whether contact was possible and how pleasant the previous contact was, which predicted both social desires and future contacts. Furthermore, we generally observed auto-regressive effects, even for social interactions detected through conversation-based mobile sensing. This indicates that when people were currently in contact, they were more likely to be in contact subsequently, which coheres with other studies focusing on a similar time scale (e.g., Hall, 2017; Wrzus et

[21] The difference between studies could be attributed to the timing and phrasing of how social desires were assessed. In Study 1, people reported at a specific moment whether they would like to have more (or less) contact; in Study 2, they reported at the end of the day whether they would have liked to have had more contact. Thus, in Study 2, desires could have been largely fulfilled, or alternatively, people adjusted the report of unfulfilled desires to the situational possibilities during that day.

al., 2016). Conversely, desiring more contact played less of a role in predicting social interactions in both studies. Still, people actively reduced contact and reported less subsequent contact when they desired to be alone more strongly—at least on a short time scale of about one hour. The sensitivity analyses showed that extraversion generally did not predict social desires or changes in social interactions, except for a moderation effect regarding desires to be alone in Study 2.

The results seem to indicate that individual differences in the affiliation motive play a smaller role than theoretically predicted for the temporal dynamics of established social relationships in daily life – at least, when the affiliation motive is assessed with self-report questionnaires. Reliable contingencies between situational characteristics and behavior (e.g., possible contact and socializing) or between social desires and social behaviors might, however, themselves be considered expressions of personality characteristics (Back, 2021; Kuper et al., 2022). Reliable differences in the examined temporal dynamics and differences in the self-concept of affiliation motive might, thus, represent distinct aspects of personality, not necessarily overlapping to a large degree (see Kroencke, Kuper, et al., 2023) for a similar argument). In addition, capturing meaningful associations between daily contingencies and questionnaire-measured personality characteristics might also be challenging methodologically because both would need sufficiently high reliability and temporal stability (Back, 2021; Kuper et al., 2022).

In addition, social traits might indeed play a smaller role than theoretically assumed for daily temporal dynamics, when most social interactions might be prearranged or routine (Hall et al., 2021; Nezlek, 2001). Therefore, prearrangements and routines would leave less room to alter social interactions in line with one’s social desires and preferences on relatively short time scales of a few hours or even the next day. Still, people seem to arrange their social environment according to their dispositional preferences, for example, by arranging a more or less contact-intense daily life (Buss, 1987; Mehl et al., 2006; Rauthmann, 2021a). For instance, people high in extraversion establish friendships and larger social networks more easily (Harris & Vazire, 2016; Selfhout et al., 2010), and they more often work in jobs that demand high levels of sociable behavior (Denissen et al., 2014). Thus, the affiliation motive and extraversion likely contribute to people’s daily social lives to different extents on different time scales, which are not yet clearly defined in personality theories.

4.6.2 Time Scale of Dynamic Regulation of Social Relationships

Based on theoretical work on the affiliative self-regulation (Carver & Scheier, 1998; Hall & Davis, 2017; O'Connor & Rosenblood, 1996), we assumed that people differ in how fast social interactions become “too much” and lead to leaving further contact, and likewise, how quickly being alone becomes undesirable and social interaction is sought. For some people, this might occur rather rapidly, in less than one hour, whereas others might enjoy hour-long or even day-long stretches of contact or solitude. For example, in a daily life study, adults spent on average 40 min in interaction before transitioning into solitude and 5 hours alone before contact occurred again, although individual differences were not addressed (Luo, Pauly, et al., 2022). Also, longer-than-typical contact was followed by even longer solitude, and vice versa, demonstrating an adaptive variation of contact and solitude (Luo, Pauly, et al., 2022). These patterns can be interpreted as social oversatiation and social deprivation (e.g., Krämer et al., 2024; Luo, Macdonald, et al., 2022; for an overview, see Wrzus, Roos, Krämer, & Richter, 2024).

A few studies have addressed individual differences in social oversatiation and examined how low extraversion predicts decreased well-being, increased fatigue, and greater desire for solitude after more-than-typical social behavior with mixed results (Leikas & Ilmarinen, 2017; Zelenski et al., 2012). The mixed findings might be explained by accounting for time: During or briefly after social interactions, some participants experienced higher well-being compared to being alone, irrespective of their extraversion level; however, well-being decreased in the hours to follow (Leikas & Ilmarinen, 2017; Pickett et al., 2020).

While research on the short-term satiation of social needs is scarce, even fewer studies have focused on day-to-day dynamics (e.g., Neubauer et al., 2018). For example, a higher relatedness motivation on one day predicted the satisfaction of social needs through social interactions the following day, whereas social need dissatisfaction did not predict the next day’s relatedness motivation (Neubauer et al., 2018). The present findings from Study 2 extend these results and demonstrate that people had more contact on days when contact was pleasant, and in the evening their desire seemed met as they did not wish to have had more contact. When only little contact had occurred during the day, the desire to have had more contact was stronger for people with a higher affiliation motive.

In the current studies, we examined fixed time periods of 1 to 3 hours (Study 1), as well as day-to-day changes (Study 2). Ideally, we would begin assessments as soon as a social interaction starts, and then again when it ends. However, real life is more complicated: For example, most people would agree that a social interaction does not stop when somebody leaves the room for a few seconds to fetch something from another room. Yet, how much time must pass to count this break as solitude? Theoretically, similar to social satiation continuously increasing over time (and perhaps faster in unpleasant interactions), increases in the need for social interaction are also assumed to accumulate over time (Luo, Pauly, et al., 2022). Overall, the current and previous studies (Hall, 2017; O'Connor & Rosenblood, 1996) suggest that the regulation of temporal dynamics (i.e., the effects of previous contact on later contact) generally happens within a day, and effects then dissipate over longer time spans, such as days or weeks. Still, these are open research questions and potentially fruitful avenues for enhancing theory on personality differences regarding the temporal dynamics of social interactions and social relationships.

4.6.3 Theoretical and Practical Implications

The current findings possess substantial theoretical and practical implications. Concerning theoretical advancements, our studies heeded the call for more integrative research on the interplay of personality and social relationships (e.g., Back et al., 2023; Back & Vazire, 2015), instead of pursuing research on affiliation and extraversion or on different relationship types separately and in parallel. The current findings demonstrate similarities, but also substantial differences, regarding both different traits and different relationships. Again, both the affiliation motive and (parts of) extraversion belong to the overarching personality domain of “communion” (Back et al., 2023) and predict the engagement in and enjoyment of social interactions. Yet, the concepts differ in their emphasis on kinds of social interaction (e.g., extraversion) or contact with closer others to form and maintain satisfying social relationships (affiliation motive). In addition, some research traditions emphasize the descriptive versus motivational aspects of extraversion and the affiliation motive (Back & Vazire, 2015; McCrae & Costa, 2008), whereas the motivational aspects of Big Five traits have also been described (Denissen & Penke, 2008; Denissen et al., 2013; Dweck, 2017). Thus, the affiliation motive and extraversion are often strongly correlated, yet not identical, as also demonstrated in their associations with social relationship characteristics (Krämer et al., 2022; Schönbrodt & Gerstenberg, 2012; Wrzus, Roos, Krämer, & Richter, 2024). A comprehensive analysis of social personality dispositions should, thus, move beyond broad descriptive personality traits (i.e., the “Big Few”, Mõttus et al., 2020) and distinguish individual differences in process-domains (e.g., interpersonal behavioral styles), necessarily implying more specific content facets (e.g., affiliation/sociability; Back et al., 2023; Back & Vazire, 2015).

Similarly, although romantic relationships, family, and friendships are all considered close social ties that fulfill social needs (Argyle & Henderson, 1985; Hofer & Hagemeyer, 2018; Neyer et al., 2011), they differ in multiple aspects (e.g., duration, formality, societal norms, quality) which can modify the personality-relationship interplay together with situational and contextual affordances (cf. Back et al., 2023). In the current studies, neither the affiliation motive nor extraversion were meaningfully linked to the amount of contact reported over 2 or 14 days on a bivariate level, accounting for contact with all kinds of social relationships. This was partly explained by associations being only evident in relationships with friends or colleagues, but not with family. These results indicate that individual differences in both the affiliation motive and extraversion can be acted out better in relationships with more lenience. As friendships are voluntary relationships, weaker social norms and expectations exist around whether and how to maintain these relationships, compared to family relationships (Neyer et al., 2011). We assume that having contact with family was more shaped by demands of the situation and specific relationships, and therefore individual differences were less important. This reasoning is in line with the *Nonlinear Interaction of Person and Situation Model* (Blum et al., 2018; Schmitt et al., 2013), proposing that personality differences are most visible when situational affordances are moderately strong.

Finally, the current studies extend previous theoretical accounts by addressing multiple time scales of relationship dynamics (i.e., within days over several hours to across days). Often, time lags between assessments and in analyses are chosen for pragmatic rather than theoretical reasons. However, social relationships likely unfold differently in daily life, with repeated and long interactions with some relationship partners during the day (e.g., household members, colleagues), versus infrequent or brief interactions with others (e.g., seeing certain family or friends only once a month). The studies that focused on some temporal aspects (e.g., Human et al., 2018; van Zalk et al., 2019) often focused on specific relationships (and traits) and, therefore, lost the sought generalizability from integration. Accordingly, a truly comprehensive approach toward the interplay of personality and social relationships would furthermore take different temporal dynamics into account to shed further light on the underlying processes. Although not all results confirmed the current hypotheses, it is too early to abandon research on personality effects on temporal relationship dynamics because convincing theoretical approaches exist for how structures (i.e., traits) shape processes, as well as how processes contribute to structure through development (Back et al., 2023; Back & Vazire, 2015; Baumert et al., 2017; Wrzus & Roberts, 2017).

The practical implications for further research arising from the aforementioned theoretical considerations are straightforward: To comprehensively understand the interplay of personality and social relationships, personality characteristics, social relationships, and contextual affordances must be assessed comprehensively: This concerns (a) the selection of content (i.e., multiple personality characteristics, multiple relationships, multiple context characteristics) and (b) study designs that encompass multiple perspectives and multi-method assessments, while using direct assessments and indirect observations across a multitude of situations (e.g., Breil et al., 2022; Harari et al., 2020; Schoedel, Kunz et al., 2023). Such enhanced efforts are likely repaid with vast theoretical advancements that will be gained from the results; even or especially when differences between perspectives, measures, and traits arise.

4.6.4 Strengths, Limitations, and Future Directions

We combined findings from two studies that examined how personality traits (i.e., the affiliation motive, extraversion) and situational affordances contribute to the temporal dynamics of social relationships in people's daily lives. Both samples were gender-balanced, diverse in educational backgrounds, and covered a broad age range from young adulthood to old age. This heterogeneity was a strength, and at the same time a limitation. On the one hand, the results are not confined to student samples or young adults, and potentially generalize across the adult lifespan. This is plausible since the affiliation motive constitutes a fundamental need across the entire lifespan (Carstensen, 1991; McClelland, 1987), and therefore people should be inclined to regulate their social interactions in line with their needs also across the entire lifespan. Only the source of satisfaction (e.g., parents, large groups of peers, a small number of confidants) and the possibilities to actively initiate or end contact might change across the lifespan (Antonucci et al., 2014; Carstensen, 1991; Wrzus et al., 2013). Conversely, the daily lives of the participants might have been relatively unique (e.g., attending college, working full-time, taking care of children, or being retired). These differences create quite heterogeneous contexts for daily social interactions, and these contexts might also shape relationship dynamics (Huxhold et al., 2022; Roos, Krämer, Schoedel et al., 2023), together with cultural differences (Nguyen et al., 2023). Future studies could complement the current approach through focusing on homogeneous subgroups (e.g., retired people without work and care-giving responsibilities), specific minority groups, who might require different recruitment strategies, and other cultural groups that differ in social norms regarding family and friends (Fischer et al., 2022; Nguyen et al., 2023).

Assessments in daily life generally rely on EMAs (ecological momentary assessments), which have the advantage of reducing memory biases and reporting biases (Neubauer et al., 2019; Schwarz, 2012), yet largely still focus on self-reported thoughts, feelings, and behaviors (for alternative examples see Breil et al., 2022; van Zalk et al., 2019). Mobile sensing offers the advantage of unobtrusively assessing social interactions if they occur through the phone or the phone is close by and great progress has been achieved recently in preparing algorithms to detect social interactions (Harari et al., 2017, 2020; Hebbar et al., 2021). Still, some measurement problems especially regarding data coverage exist, for example, when other apps on the phone interfere with sensing or when the phone cannot sense the interaction when it is not close by (Niemeijer et al., 2023; Roos, Krämer, Schoedel, et al., 2023). Some previous studies and the current studies still found insightful results using this novel method; furthermore, the reliability of assessments will improve soon, leading to hopefully even more robust findings. Even the quality of social interactions might be reliably measurable though algorithms (e.g., using vocal and linguistic features, Horn & Timmons, 2023; Lee et al., 2023). Still, some subjective evaluations of interactions or interaction partners will be assessed best with EMA, leading to future study designs that combine both EMA and mobile sensing (Ebner-Priemer & Santangelo, 2023; Schoedel & Mehl, 2024).

Finally, the current studies did not examine momentary well-being in social interactions or situations without social interactions. Ample evidence exists that, on average, people feel better when they are with other people, compared to being alone, as most contact is rather pleasant (Kroencke, Harari, et al., 2023; Liu et al., 2019). Simultaneously, people's well-being varies intra-individually, depending on the kind of contact, with higher well-being in face-to-face interactions compared to digital contact (Kroencke, Harari, et al., 2023), and in contact with friends compared to family or other relationships (Buijs et al., 2023; Kroencke, Harari, et al., 2023). Still, the satisfaction of social needs can be achieved with different social interaction partners (Baumeister & Leary, 1995; Krämer et al., 2024; Kroencke, Harari, et al., 2023), yet potentially to a different extent as relationship characteristics such as the quality of the interaction or the closeness within the relationship likely contribute to need satisfaction.

While we focused on social traits and situational differences in changes in social desires and social interactions, future studies could aim to address the entire regulatory process outlined theoretically: Mismatches between momentary contact and social desires should lead to changes in well-being, which then motivate changes in contact (Carver & Scheier, 1998; Hall & Davis, 2017). For example, a mismatch between desired and current contact was indeed associated with decreased momentary well-being in the case of social oversatiation (i.e., experiencing more contact than desired; Krämer et al., 2024). Similarly, in romantic relationships, a current desire for closeness with the partner and corresponding behavior predicted momentary relationship well-being (Zygar et al., 2018), yet neither study addressed whether decreased momentary well-being in turn motivated behavioral changes as theoretically proposed (Carver & Scheier, 1998; Hall & Davis, 2017). The current studies also demonstrated the difficulties in modelling such process chains, as multiple person and situational affordances (i.e., traits, situational constraints) contribute concurrently to each link of the chain, and especially since several parts of the chain can vary between individuals per their time scale (e.g., Back et al., 2023). Imminent technological advancements will likely facilitate the idiographic modelling of such complex regulatory processes—if researchers are able to effectively measure these processes that occur as a continuous stream in people's daily lives.

4.7 Conclusion

People differ in maintaining social relationships—relative to others and within themselves over time. Whereas social traits, such as the affiliation motive and extraversion, have been repeatedly linked to structural aspects or averages of relationship characteristics (e.g., network size, relationship quality), confirming the theoretically proposed links of these traits with temporal dynamics within relationships has proven to be more difficult. For one, situational affordances, routines, and longer-term arrangements might better explain the flow of contacts and periods of solitude in daily life. Also, social traits might shape situational affordances indirectly by creating specific social environments. Overall, the present findings emphasize that research on the dynamics between personality and social relationships benefits greatly from integrating different perspectives on social traits and the variety of social relationships simultaneously and ideally using multi-method approaches instead of focusing on single traits or relationship types.

Chapter 5: Persons in Contexts: The Role of Social Networks and Social Density for the Dynamic Regulation of Face-to-face Interactions in Daily Life

Yannick Roos[1], Michael D. Krämer[2,3,4], David Richter[4,5] & Cornelia Wrzus[1]

[1] Heidelberg University, Heidelberg, Germany [2] German Institute for Economic Research, Berlin, Germany

[3] University of Zurich, Zurich, Switzerland [4] Freie Universität Berlin, Berlin, Germany

[5] SHARE BERLIN Institute GmbH, Berlin, Germany

Abstract

Current psychological theories on daily social interactions emphasize individual differences yet are underspecified regarding contextual factors. We aim to extend this research by examining how two context factors shape social interactions in daily life: how many relationships people maintain and how densely people live together. In Study 1, 307 German participants (age M = 39.44 years, SD = 14.14) answered up to 20 experience sampling questionnaires regarding their social interactions over two days. In Study 2, 313 German participants (age M = 48.96 years, SD = 15.54) summarized their daily interactions in daily diaries for 14 days. Participants reported on their social network size and the social density (i.e., household and neighborhood density) of their living situation. Mobile sensing provided additional measures of social interactions and network size. The results showed that participants living in densely populated households transitioned faster from solitude to social interactions but slower from social interactions to solitude. Participants living in dwellings with more homes also transitioned slower from solitude to social interactions. Contrary to the hypothesis, social network size was inconsistently linked with transitions from solitude to social interactions and vice versa. Furthermore, current social desires predicted subsequent social interactions within days, but not across days—irrespective of individuals' social network size or social density. Together the results point out that people live their daily life in social contexts, which contribute to how they engage in social interactions. The findings thus call for a greater integration of contextual factors in personality theories of social interactions.

Roos, Y., Krämer, M. D., Richter, D., & Wrzus, C. (2024). Persons in contexts: The role of social networks and social density for the dynamic regulation of face-to-face interactions in daily life. *Journal of Personality and Social Psychology.* Advance online publication. https://doi.org/10.1037/pspp0000512

5.1 Introduction

Social relationships play a crucial role in people's lives (Baumeister & Leary, 1995; Dweck, 2017) and people who are deprived of social interactions experience substantial declines in well-being and health (Berkman et al., 2000; Holt-Lunstad et al., 2017). Whereas earlier research focused mostly on static differences between people and on the detrimental effects of unmet affiliative needs (e.g., loneliness; Berkman et al., 2000; Holt-Lunstad et al., 2017), more recent research emphasized the dynamic nature of social relationships and the importance of assessing social interactions as they occur in daily life (Back et al., 2011; Hall & Davis, 2017; Huxhold et al., 2022).

Despite the attention given to individuals' personality, such as affiliative motives and personality traits in social relationship research (Back et al., 2023; Hall, 2017), relatively little attention has been paid to the social contexts in which social relationships are embedded (Huxhold et al., 2022; Meagher, 2020). To account for the role of context in shaping social relationships, the concept of the social opportunity structure—the availability of social ties as well as the costs of engaging with them—has been proposed (Fiori et al., 2020; Lang & Carstensen, 1994). Yet, empirical research on the link between social context and social relationships mainly focused on specific situations and samples, such as university students or high-rise building residents (Churchman & Ginsberg, 1984; Easterbrook & Vignoles, 2015). Therefore, larger scale investigations of how social contexts shape social interactions in the diverse daily lives of participants from more heterogenous samples are still missing.

We aim to address this research gap by examining how the social context contributes to dynamic short- and medium-term relationship processes using two sizeable age- and gender-heterogenous samples. Specifically, we address how two factors that are central to the availability of interaction partners are associated with the dynamic regulation of face-to-face social interactions in daily life: the size of people's social networks and the social density of people's living environments.

The current study focuses on face-to face (i.e., in-person) interactions as central building blocks of social relationships (Back et al., 2011, 2023). While acknowledging the increasing prevalence of technology-mediated communication (i.e., texting, calling, and video-calling; Harari et al., 2020), processes regulating technology-mediated interactions might be somewhat different from processes regulating face-to-face interactions (e.g., differences in availability of interaction partners or costs of interactions), as also indicated through distinct effects on well-being (Kroencke, Harari et al., 2023). For now, face-to-face interactions remain the most prevalent and most important form of social interaction for most people. Therefore, to maintain focus and manage scope, we excluded texting, calling, video-calling, and social media use from the current analysis. Two research questions guide the present study:

RQ1: How does the regulation of everyday social interactions relate to the social network characteristics?

RQ2: How does the regulation of everyday social interactions relate to the social density of the living environment?

5.1.1 How Are Social Interactions Regulated in Daily Life?

Most theoretical accounts of how social interactions are regulated in daily life can be traced back to control theory (Ashby, 1957; Carver & Scheier, 1982; Revelle & Wilt, 2021). Control-theory approaches argue that the dynamic regulation of social relationships in daily life is best viewed as a negative feedback loop, where the momentary desire to interact with other people is compared to the actual social situation, and any discrepancy between both is then reduced (Hall, 2017; Hall & Davis, 2017). For example, a student who spends most of the day learning alone in a library might, as the day goes on, develop a growing desire to interact with other people, and then invite friends over for dinner. In contrast, a teacher might notice a growing desire to spend time alone throughout the day or week after lots of interactions with students, and decide to decline an invitation for another social activity on the weekend and rather stay alone. The terms "alone" or "solitude" refer to states without social interaction, not necessarily implying the physical absence of other people (see Long et al., 2003). For instance, solitude includes activities like walking by oneself in a populated neighborhood, even if other people are physically nearby.

Accordingly, in their everyday lives, people monitor how their social interactions satisfy their momentary social desires. On the one hand, if people have fewer or less positive social interactions than desired, social deprivation occurs, and people are motivated to reach out for social interactions. On the other hand, if people continue to be involved in social interactions, although their affiliative desire is already satisfied, social oversatiation occurs and people are motivated to disengage from further social interactions (Hall, 2017; Krämer et al., 2024; Wrzus, Roos, Krämer, & Richter, 2024). Yet, control theory approaches do not specify the exact timeframes in which these processes are expected to unfold. Recent studies showed some support for within-day regulation of social contacts (Hall, 2017; Luo, Pauly et al., 2022) but these studies do not exclude the possibility of slower processes occurring in parallel (e.g., social deprivation building up over days or weeks, see Baumeister & Leary, 1995; Holt-Lunstad et al., 2017; Neubauer et al., 2018). For example, some people might need solitude after a socially busy week.

Overall, control theory models have proven helpful to explain individual differences between persons and some within-person variation in daily social interactions (Back et al., 2023; Hall, 2017; O'Connor & Rosenblood, 1996), yet substantial variation remained unexplained. Critically, these models hardly account for contextual factors influencing the availability of social interaction partners. Therefore, the models cannot explain why people may find themselves in (prolonged) states where their social desires and actual social situation disagree. Hence, a sole focus on individual dispositions limits the comprehensive understanding of relationship processes, and contextual factors could be an important addition (Huxhold et al., 2022; Meagher, 2020).

5.1.2 Social Networks Facilitate Social Interactions

People entertain various social relationships differing in emotional closeness and time investment (Antonucci et al., 2014; Huxhold et al., 2022). Depending on the definition of who should be included in a person's social network (i.e., what the minimum requirement for a meaningful interpersonal connection is) most people maintain networks with several dozen people (Wrzus et al., 2013), know more than 250 people (McCarty et al., 2001), and have access to more than 500 people in their online social networks (Hampton et al., 2011). Interaction partners can vary from romantic partners, family, and friends to acquaintances and strangers.

To give some structure to people's networks, social network researchers differentiate between two broad categories of network members, so-called strong ties and weak ties (Granovetter, 1973). Most people feel very close only to a handful of people (Antonucci et al., 2014; Roberts et al., 2009). These relationships are *strong ties* and are characterized by a considerable time investment, high emotional closeness, and reciprocal acts of support (Granovetter, 1973). Examples of very close relationships could be a romantic partner, close friends, and close family members. In addition to romantic partners, close friends, and family, people also interact with plenty of other people.

Weak ties are all relationships that are less close and less important than strong ties, but have some substantial significance (Granovetter, 1973). For example, weak ties may include relationships with co-workers, neighbors, extended family, or acquaintances one meets regularly. Although people are often more reluctant to interact with weak ties and strangers compared to strong ties (Sandstrom et al., 2022), such interactions can contribute to well-being and satisfy belongingness needs (J. L. Hirsch & Clark, 2019; Sandstrom & Dunn, 2014; Van

Lange & Columbus, 2021). Importantly, people not only have more weak than strong ties in their social network, but they also interact with weak ties frequently. For example, social interactions with weak ties accounted for the majority of social interactions in adults' daily lives (Sandstrom & Dunn, 2014).

Overall, people tend to prefer interacting with people whom they also interacted with in the past (Meijerink-Bosman et al., 2023; Sandstrom et al., 2022). Accordingly, the availability of strong and weak ties in peoples's social networks is anticipated to influence their day-to-day social interactions, as interactions with familiar individuals are viewed as more easily available, less risky, and requiring less energy than interactions with strangers (Huxhold et al., 2022; Sandstrom et al., 2022). Conversely, compared to people with larger social networks, people with smaller social networks have access to a smaller pool of interaction partners, may receive fewer offers for social interactions, and may find themselves for longer periods of time in situations where they cannot immediately find available interaction partners. Therefore, we expected that both strong and weak ties contribute to people's social interactions in daily life and derived the following hypothesis:

H1: People with larger social networks transition faster from solitude to social interactions.

In detail, we predicted that the higher the number of strong and weak ties in the social network, the higher the probability to transition from periods of being alone to subsequent social interactions (H1a), from days with little contact to subsequent days with more contact (H1b), and the less people report that they would have liked to spend more time with other people (H1c).[22] Because it was unclear whether the availability of strong and weak ties would be equally linked to daily social interactions (e.g., strong ties may be more easily available for interaction), we examined both kinds of ties separately.

Although social oversatiation may occur in situations where social interactions are difficult to avoid (as argued in the following section), having access to a bigger social network should usually still allow a person to spend time alone. Consequently, we expected no

[22] This manuscript combines two studies with separate preregistrations. H1 and H2 were identical in both preregistrations and are presented in their original wording. For a clearer presentation, we changed the labeling of the superordinate hypotheses from the two different preregistrations and split some compound hypotheses. A comparison with the original formatting can be found in the deviations from preregistration at https://osf.io/z4jqs.

association between the number of strong and weak ties and transitions from periods of interactions to subsequent periods of being alone (H1d), nor with transitions from days with a lot of contact to subsequent days with less contact (H1e). Nonetheless, we expected other context factors to constrain people's ability to transition from social interactions to solitude, which we will discuss in the next section.

5.1.3 Social Interactions are Situated in Environments: Social Density and Crowding

Empirical accounts of how social interactions in everyday live are facilitated or constrained by contextual factors date back to early ecological psychology (Barker, 1975; Festinger et al., 1950). One environmental characteristic that has been found to be crucial for social interactions is social density (Festinger et al., 1950; Sng et al., 2017; Stokols, 1972). Social density refers to the ratio between the number of people occupying a space and the size of the space (Altman, 1975; Stokols, 1972). Social density may be examined on different levels: *household density* refers to the ratio between apartment size and people living in the apartment, and *neighborhood density* refers to the social density in or around people's dwelling (Regoeczi, 2003). For example, two parents sharing a small apartment with three children in a high-rise building could be considered living in a dense environment on both indicators (i.e., their living situation is characterized by a high household density and a high neighborhood density).

Overall, higher household and higher neighborhood density both seem to promote social interactions in daily live. For example, neighbors who lived closer together met more often and were more likely to develop friendships (Festinger et al., 1950). Similarly, women living in high-rise buildings in Israel reported that this form of housing promotes social interaction (Churchman & Ginsberg, 1984). In another study, students living in apartments with shared areas such as a lounge, dining area, or communal bathroom unintentionally met their roommates more often than students living in apartments without such shared areas (Easterbrook & Vignoles, 2015). Likewise, research on college dormitories, hospitals, and nursing homes found associations between the design (e.g., suite or apartment layouts) and the frequency of social interaction or feelings of belonging (Bronkema & Bowman, 2017; Devlin et al., 2008; Dijkstra et al., 2006; Ullán et al., 2012).

However, higher social densities may also promote undesired social interactions and impede people's ability to withdraw from social interactions. Still, having too little time alone can diminish well-being (Coplan et al., 2019; Krämer et al., 2024). Accordingly, being unable to avoid social interactions, for example because of space constraints, may lead to the subjective experience of crowding, which refers to psychological stress resulting from a high ratio of people to the amount of space in the surrounding environment (Altman, 1975; Stokols, 1972). For example, insufficient space may lead to frustration, less self-disclosure, and eventually motivate people to socially withdraw (Sundstrom, 1975). As such, being unable to regulate social interactions due to environmental constraints (e.g., not enough space to retreat) may ultimately lead to increased anonymity, and reduced social support (McCarthy & Saegert, 1978; Skjaeveland & Gärling, 1997).

To summarize, living together with other people in the same household or living in a densely populated neighborhood provides people with ample opportunities for social interactions. At the same time, sharing space with many other people may reduce opportunities to be alone and thus occasionally lead to prolonged undesired interactions. Here, we assumed a qualitative difference between the effects of social network size and social density on transitions from social interaction to solitude. While both a larger social network and higher social density may offer increased opportunities for social interaction, we expected the actual physical closeness of other people in the environment to be more constraining (i.e., limiting availability of personal space and perhaps increasing demands to interact) than having access to a bigger social network. To summarize, we expected the following effects of social density:

H2: People living in high-density environments transition faster from solitude to social interactions but transition slower from interactions to solitude.

In detail, we predicted: the higher the density of the environment, the higher is the probability to transition from a period of being alone to subsequent social interactions (H2a), from days with little contact to subsequent days with more contact (H2b), and the less people report that they would have liked to spend more time with other people (H2c). Because of the increased presence of other people in high-density environments, we further predicted: the higher the density of the environment, the lower is the probability to transition from a period of interactions to spending time alone (H2d), from days with a lot of contact to subsequent days with less contact (H2e), and the more people report that they would have liked to spend more time alone (H2f).

5.1.4 Social Context and Desire-Situation Mismatch

So far, we argued that the social context may either facilitate or constrain social interactions. Yet, how constraining or facilitating people perceive a situation may depend on whether they want to change their current situation. If people are currently in a social interaction and want to remain in a social interaction, the availability of space to withdraw may be of little relevance for them. Likewise, if people are currently alone and wish to remain alone, the availability of potential interaction partners may be less relevant for them compared to when they desire social interactions. Accordingly, effects of the social context (e.g., the availability of social network partners or the effect of high social densities) on social interactions should be especially pronounced in situations where people want to change their social situation (also see Schmitt et al., 2013). Accordingly, we hypothesized:

H3: Both effects specified in H1 and H2 are more pronounced if people's desire (to be alone or to interact with others) does not match their actual social situation.

5.1.5 Present Study

The present study aims to extend theories of social interaction regulation by examining how social interactions in daily life are shaped by two context factors contributing to the social opportunity structure: how many relationships people maintain (i.e., number of weak and strong ties in the social network) and how densely people live together (i.e., household and neighborhood density). We argue that large social networks and high-density environments provide plenty of easily available opportunities for social interactions and therefore are expected to facilitate transitions from solitude to social interactions. Further, transitions from social interactions to solitude are expected to be unrelated to network size, but to be facilitated by low-density environments.

To test these hypotheses, two studies focusing on different timescales were conducted. Study 1 addressed short-term processes, that is the regulation of social interactions within days. Accordingly, in Study 1, participants answered experience sampling questionnaires about every 80 minutes (from 9:00 a.m. to 9:00 p.m.) for two consecutive days. Study 2 addressed medium-term processes, that is, how social interactions are regulated over multiple days. In Study 2, participants summarized their daily interactions in daily diaries for 14 days. Additionally, in both studies, mobile sensing (Harari et al., 2016; Schoedel, Kunz et al., 2023) was used to passively measure the amount of conversation occurring in participants' immediate surroundings and to derive an alternative measure of social network size to probe the robustness of our findings in exploratory analyses.

5.2 Study 1

5.2.1 Transparency and Openness

We report all manipulations and data exclusions. We report all preregistered analyses in the main text, and we clearly indicate all deviations from the preregistration. The preregistration of Study 1 is available at https://osf.io/shbdz. A documentation of all measures, anonymized data sets, data analysis scripts, preprocessing scripts, a list of used software packages, and deviations from the preregistration are available at https://osf.io/z4jqs. The study adhered to the principles of the Declaration of Helsinki for research involving human subjects and was given IRB approval by Johannes Gutenberg University Mainz (process number: 2018-JGU-psychEK-002).

5.2.2 Participants

Data collection for Study 1 occurred in Germany from September 2021 to mid-December 2021 and from March 2022 to April 2022.[23] Germany is a country with a comparatively high population density of about 238 inhabitants per square kilometer and a high degree of urbanization with 77.5 % of the population living in cities with at least 150 inhabitants per square kilometer (Destatis, 2024; World Bank, 2024). We further elaborate on the cultural context of the sample in the limitations section. Overall, 307 participants (51% female, M_{age} = 39.44 years, SD_{age} = 14.14, range 18-80 years) answered at least one experience sampling questionnaire (sample size rationale and power analyses are reported in the preregistration). The sample of Study 1 can be described as an age- and gender-heterogenous convenience sample. Older people, people with low levels of education, and parents were somewhat underrepresented compared to the general population. An overview of the sample characteristics of Study 1 and Study 2 is presented in Table 5.1.

[23] Study enrolment was paused between January and March 2022 due to increased COVID-19 infections and associated governmental regulations on social events (Appendix A). However, there were no broad restrictions on everyday face-to-face interactions during the study period.

Table 5.1

Demographic Characteristics of the Study Samples

Characteristic		Study 1 (N = 307)		Study 2 (N = 313)	
		n	%	n	%
Gender	Female	156	51	153	49
	Male	149	49	160	51
	Gender-diverse (e.g., non-binary)	2	1	N/A	N/A
Age[a]		39.44	14.14	48.96	15.54
Relationship Status	Stable romantic relationship	184	60	250	80
	Single	101	33	37	12
	Divorced	22	7	19	6
	Widowed	0	0	7	2
Children	Yes	107	35	194	62
	No	200	65	110	35
	Missing data	0	0	9	1
Highest Education	College or university	142	46	97	31
	High school	107	35	51	16
	Other schools	56	18	154	49
	Still attending school or no degree	2	1	8	3
	Missing data	0	0	3	1
Occupation	Working full-time	101	33	135	43
	Working part-time	44	14	52	17
	Student / Apprentice	99	32	35	11
	Retired	30	10	69	22
	Unemployed	17	6	22	7
	Missing data	16	5	0	0

[a] Mean and standard deviation are displayed for age.

5.2.3 Procedure

Participants were recruited via online advertisements, email lists, flyers, news articles, and word of mouth. They signed up on the study website for an introductory video call, which always occurred on Thursdays. During the video call, participants received information about the study, provided informed consent, and installed the PhoneStudy research app (Schoedel, Kunz et al., 2023).[24] Participants then completed a baseline questionnaire on demographics, personality traits, and their social network. Over the next two days (Friday and Saturday), participants were prompted via the app to answer 10 experience sampling questionnaires per day. A random sampling schedule was used to capture not only states and circumstances surrounding social interactions but also characteristics of solitude periods. For example, the random sampling approach allowed us to assess the desire for interaction during solitude periods. The prompts were delivered roughly every 80 min between 9:00 a.m. and 9:00 p.m. to avoid participants knowing exactly when the next assessment would occur (for details see Appendix B). Mobile sensing ran continuously in the background on participants' phones until Sunday. Participants received €40 (~40 USD) for participating and a bonus of €10 if they filled out 17 or more experience sampling questionnaires.

5.2.4 Measures

The following presentation of measures is limited to the measures used in subsequent analyses. A full documentation of all variables assessed in the context of Study 1 is available at https://osf.io/z4jqs.

Social Interactions

Participants reported whether they were in a face-to-face interaction at the time of each experience sampling questionnaire. Participants were instructed that being around other people without any direct interaction (e.g., in a waiting room) is insufficient to count as a face-to-face interaction.

Furthermore, a privacy-sensitive conversation detection algorithm sampled ambient noise through the smartphone's microphone and inferred whether conversation occurred around the participants' phone (AWARE-Conversations plug-in; Ferreira & Mulukutla, 2020). The algorithm was set to follow a cycle of 1-min sampling and 3-min pause to strike a balance between comprehensive measurement and battery conservation. In the field, differences in the number of samplings per episode occurred on different smartphone models (for the distribution of AWARE-Conversations samplings, see Appendix C). For each experience sampling

[24] The Phonestudy app (Schoedel, Kunz et al., 2023) runs on Android OS and collects data on phone usage and surroundings. About 65% of the German population were estimated to use Android phones around the time of the study (Keusch et al., 2020).

measurement, we calculated the *proportion of conversation* in the next 80 minutes. The proportion of conversation was calculated as the number of AWARE-Conversation samplings indicating conversation divided by the total number of samplings in the respective timeframe. If less than five samplings were available in a given timeframe, we set the proportion of voice to missing. Multiple studies have demonstrated the validity of the AWARE-Conversations plug-in and found high accuracies of more than 85% correct classification using hip-worn audio sampling devices (Lane et al., 2012; Rabbi et al., 2011). Although the accuracy in the field using participants' smartphones is probably lower, proportion of conversation measures showed substantial agreement with other assessments of social interactions (Roos et al., 2023).

Social Desires: Desire to be Alone and Desire to Interact

Social desires were assessed counterfactual to the current social situation of participants. That is, if participants were currently interacting with others, they were asked if they would prefer to be alone at the moment. Conversely, if participants were alone, they were asked if they would prefer to be in the company of others and whether they would like to have personal contact with someone at the moment. Social desires were measured with a 7-point rating scale from 1 = *not at all* to 7 = *very much so*. Desire to be alone was inferred from the single item and desire to interact was calculated by taking the mean of the two desire to interact items.

Social Network Size: Number of Strong and Weak Ties

Social network size was assessed with an adaptation of the summation approach (McCarty et al., 2001). Participants were provided with a list of 10 relationship types (e.g., children, neighbors, co-workers) and asked to count or estimate how many people they knew from those categories. Within each category, participants were asked to differentiate between strong ties (i.e., "very close people: people you talk with about important matters, you are regularly in contact with or who are there for you if you need any help") and weak ties (i.e., "somewhat close people: people who are more than casual acquaintances but are not very close").[25] Two indices were derived: the number of strong ties was calculated by summing up the number of all "very close" contacts, and the number of weak ties was calculated by summing up the number of all "somewhat close" contacts. Additionally, for exploratory analyses, we

[25] To assess the social network, we chose a different approach than a name generator task because name generators are demanding for participants and thus may limit the number of contacts participant mention (e.g., due to design, time restraints, or convenience; Kogovšek & Hlebec, 2019).

used the number of contacts with a unique phone number saved in participants' smartphone contact lists as an objective indicator for network size.

Household Density

In an open-answer format, participants reported the number of people living in their apartment and the size of their apartment in square meters. To calculate household density, the number of persons living in the apartment was divided by the size of the apartment. Hence, higher values on household density indicate more persons per square meter, which is equivalent to fewer square meters per person.

Dwelling Density

As a measure of neighborhood density, participants were asked to select the best description of their current accommodation from a list of options, including "agricultural dwelling", "1–2 families house", "1–2 families house, row house", "dwelling with 3–4 apartments", "dwelling with 5–8 apartments", "dwelling with 9 or more apartments", and "high-rise building with 9 and more floors" (coded 1 to 7 prior to scaling). Higher scores on dwelling density indicate that people were living together with more people in the same dwelling.

5.2.5 Analytical Strategy

As preregistered, outliers with scores outside $M \pm 3$ *SD* were winsorized. This affected eight observations of strong ties, five observations of weak ties, seven observations of phone numbers, and two observations of household density. Almost identical results were obtained if analyses were repeated without outlier correction. Because observations (level 1) were nested in participants (level 2), we used logistic multilevel models with random intercepts and random slopes for the confirmatory analyses (Hoffman, 2015). All models were estimated with the lme4-package (version 1.1–29; Bates et al., 2015) in R (version 4.2.3; R Core Team, 2022) using maximum likelihood (Laplace approximation).

Two models were computed: the first model ("alone") predicted transitions from being alone to interaction, and the second model ("in contact") predicted transitions from social interaction to being alone. In both models, social interaction at the next measurement was predicted by social context factors (i.e., the number of strong and weak ties, and household and dwelling density) and social desire (i.e., desire to be alone if currently in contact or desire to interact if currently alone), as well as interactions between social desire and the social context factors. Age and gender were included as control variables. Social desires were split into a between-person component and a within-person component by calculating each person's mean (between-person) and centering single observations on the person's mean (within-person, Hoffman, 2015). The within-person components of social desire were scaled using each person's within-person standard deviation. Level two variables (i.e., number of strong and weak ties, household and dwelling density, gender, age, and the between-person components of social desire) were scaled and grand-mean centered. The model formulae with random slopes for within-person social desire were:

Level 1

$$interactions_{(t+1)i} = \beta_{0i} + \beta_{1i} socialdesireWP_{ti} + e_{ti}$$

Level 2

$$\begin{aligned}\beta_{0i} = \gamma_{00} &+ \gamma_{01} strongties_i + \gamma_{02} weakties_i + \gamma_{03} socialdesireBP_i \\ &+ \gamma_{04} householddensity_i + \gamma_{05} dwellingdensity_i \\ &+ \gamma_{06} gender_i + \gamma_{07} age_i + \gamma_{08} strongties_i socialdesireBP_i \\ &+ \gamma_{09} weakties_i socialdesireBP_i \\ &+ \gamma_{010} householddensity_i socialdesireBP_i \\ &+ \gamma_{011} dwellingdensity_i socialdesireBP_i + \upsilon_{0i}\end{aligned}$$

$$\begin{aligned}\beta_{1j} = \gamma_{10} &+ \gamma_{11} strongties_i + \gamma_{12} weakties_i + \gamma_{13} householddensity_i \\ &+ \gamma_{14} dwellingdensity_i + \upsilon_{1i}\end{aligned}$$

where at time t for participant i $e_{ti} \sim N(0, \sigma_e^2)$ and $\begin{bmatrix}\upsilon_{0i} \\ \upsilon_{1i}\end{bmatrix} \sim MVN\left(\begin{bmatrix}0 \\ 0\end{bmatrix}, \begin{bmatrix}\tau_{00} & \\ \tau_{10} & \tau_{11}\end{bmatrix}\right)$.

Deviating from the preregistered analyses plan, we were unable to compute the elapsed time since the last interaction, because of missing values and missing information on when social interactions ended. However, time is still included in our models because of the time-lagged design. That is, higher probabilities to transition from one state to another in the current time-lagged design can be interpreted as faster transitions, whereas lower probabilities are interpreted as slower transitions. To keep the results section concise, we report models that incorporated social network size and social density variables at the same time in the main text. Models including either social network size or social density variables as predictors showed almost identical results. We conducted further exploratory analyses with mobile sensing indicators for network size and face-to-face interactions.

5.2.6 Results

Participants answered on average 74% out of 20 experience sampling questionnaires. The means, standard deviations, and ranges of the main variables are reported in Table 5.2, and their between-person correlations are reported in Table 5.3.

Table 5.2

Means, Standard Deviations, ICCs, and Range of Main Variables in Study 1 and Study 2

	Variable	*M*		*SD*		*iSD*		*ICC*		*Range*	
		Study 1	Study 2	Study 1	Study 2	Study 1	Study 2	Study 1	Study 2	Study 1	Study 2
1	Strong ties[a]	11.19	6.36	7.89	3.49	/	/	/	/	0–37	0–18
2	Weak ties	32.99	/	32.37	/	/	/	/	/	0–194	/
3	Phone numbers	211.52	212.85	170.01	174.15	/	/	/	/	2–775	6–951
4	Household density	0.03	0.03	0.01	0.01	/	/	/	/	0.01–0.09	0.00–0.06
5	Dwelling density	4.46	3.69	1.53	1.65	/	/	/	/	2-7	1–7
6	Population per residence	/	5.23	/	2.36	/	/	/	/	/	1.56–11.08
7	Gender	0.49	0.51	/	/	/	/	/	/	0–1	0–1
8	Age	39.44	48.96	14.14	15.54	/	/	/	/	18–80	19–84
9	Desire alone[a]	3.24	2.99	1.15	1.33	1.34	1.17	0.32	0.49	1–7	1–7
10	Desire interact[a]	3.28	3.03	1.06	1.29	0.97	1.3	0.44	0.43	1–7	1–7
11	Contact[a,b]	0.57	0.49	0.26	0.38	0.42	0.28	0.21	0.52	0–1	0–1
12	Conversation[a,c]	0.11	0.13	0.10	0.10	0.12	0.10	0.28	0.32	0.00–0.96	0.00–0.78

Note. The table is based on unstandardized, winsorized variables. Range was rounded to integers for social network variables and refers to the within-person ranges for Desires, Contact, and Conversation. *M* = mean, *SD* = standard deviation, *iSD* = mean of intraindividual standard deviations, *ICC* = intra-class correlation (i.e., proportion of variance on between-person level).

[a] The assessment of these variables differed between Study 1 and Study 2.

[b] In Study 1, a zero on Contact indicates solitude and a one indicates face-to-face interaction. In Study 2, a zero on Contact indicates less and a one indicates more face-to-face contact than the sample median.

[c] In Study 1, Conversation indicates the proportion of conversation over 80 minutes, while in Study 2, Conversation indicates the proportion of conversation calculated over daily intervals.

Table 5.3

Between-Person Correlations of Main Variables in Study 1 and Study 2

	Variable	1	2	3	4	5	6	7	8	9	10	11	12
1	Strong ties[a]		/	.07 [-.04,.18]	-0.03 [-.14,.08]	-.07 [-.18,.04]	-.02 [-.13,.09]	.00 [-.11,.11]	.29 [.18,.38]	-.05 [-.16,.06]	-.08 [-.19,.03]	.11 [.00,.22]	.09 [-.02,.21]
2	Weak ties	.47 [.38,.55]		/	/	/	/	/	/	/	/	/	/
3	Phone numbers	.19 [.08,.29]	.21 [.10,.32]		.10 [.-01,.22]	-.18 [-.29,-.07]	-.07 [-.18,.04]	-.08 [-.19,.03]	-.19 [-.29,-.08]	.09 [-.02,.20]	.04 [-.07,.15]	.09 [-.02,.20]	.16 [.05,.27]
4	Household density	.10 [-.02,.21]	-.02 [-.13,.09]	-.03 [-.15,.08]		.30 [.19,.40]	.14 [.03,.25]	-.02 [-.13,.10]	-.41 [-.50,-.32]	.22 [.11,.33]	.02 [-.09,.13]	.19 [.08,.30]	.02 [-.09,.14]
5	Dwelling density	-.09 [-.20,.02]	-.09 [-.20,.02]	-.02 [-.13,.09]	.26 [.15,.36]		.61 [.53,.68]	-.02 [-.13,.09]	-.10 [-.21,.01]	.04 [-.08,.15]	.05 [-.06,.16]	-.17 [-.27,-.06]	-.18 [-.29,-.07]
6	Population per residence	/	/	/	/	/		-.03 [-.14,.08]	-.10 [-.21,.01]	.01 [-.10,.12]	-.03 [-.14,.08]	-.13 [-.24,-.02]	-.19 [-.30,-.08]
7	Gender	-.02 [-.13,.09]	-.04 [-.15,.07]	.13 [.02,.24]	-.01 [-.12,.10]	.00 [-.11,.11]	/		-.07 [-.17,.05]	.03 [-.08,.14]	-.11 [-.21,.01]	.05 [-.06,.16]	.08 [-.03,.19]
8	Age	-.12 [-.23,-.01]	-.03 [-.14,.09]	-.05 [-.16,.06]	-.44 [-.53,-.35]	-.12 [-.23,-.01]	/	-.02 [-.13,.09]		-.17 [-.28,-.06]	-.10 [-.20,.02]	.05 [-.06,.16]	-.11 [-.22,.01]
9	Desire alone[a]	-.07 [-.19,.04]	-.06 [-.17,.06]	-.07 [-.19,.04]	-.09 [-.20,.03]	-.03 [-.14,.09]	/	.07 [-.05,.18]	.12 [.01,.23]		.13 [.02,.24]	.08 [-.03,.19]	.09 [-.02,.20]
10	Desire interact[a]	.13 [.02,.24]	.00 [-.11,.12]	.07 [-.05,.18]	.00 [-.11,.12]	.06 [-.05,.17]	/	.18 [.06,.28]	-.02 [-.14,.09]	-.22 [-.33,-.11]		-.16 [-.27,-.06]	-.01 [-.12,.11]
11	Contact[a,b]	.12 [.01,.23]	.04 [-.07,.15]	.08 [-.03,.19]	.10 [-.01,.21]	-.14 [-.25,-.03]	/	-.05 [-.16,.06]	.08 [-.03,.19]	-.08 [-.19,.04]	-.03 [-.14,.08]		.19 [.08,.30]
12	Conversation[a,c]	.01 [-.11,.13]	.03 [-.09,.15]	.22 [.11,.33]	.06 [-.06,.17]	.04 [-.08,.15]	/	-.03 [-.15,.09]	-.15 [-.26,-.03]	-.06 [-.18,.06]	.10 [-.02,.21]	.07 [-.05,.19]	

Note. The table is based on unstandardized, winsorized variables. Between-person correlations from Study 1 are displayed below the diagonal and between-person correlations from Study 2 are displayed above the diagonal. For the time varying variables, between-person correlations refer to correlations with the person mean. M = mean, SD = standard deviation, iSD = mean of intraindividual standard deviations, ICC = intra-class correlation (i.e., proportion of variance on between-person level).

[a] The assessment of these variables differed between Study 1 and Study 2.

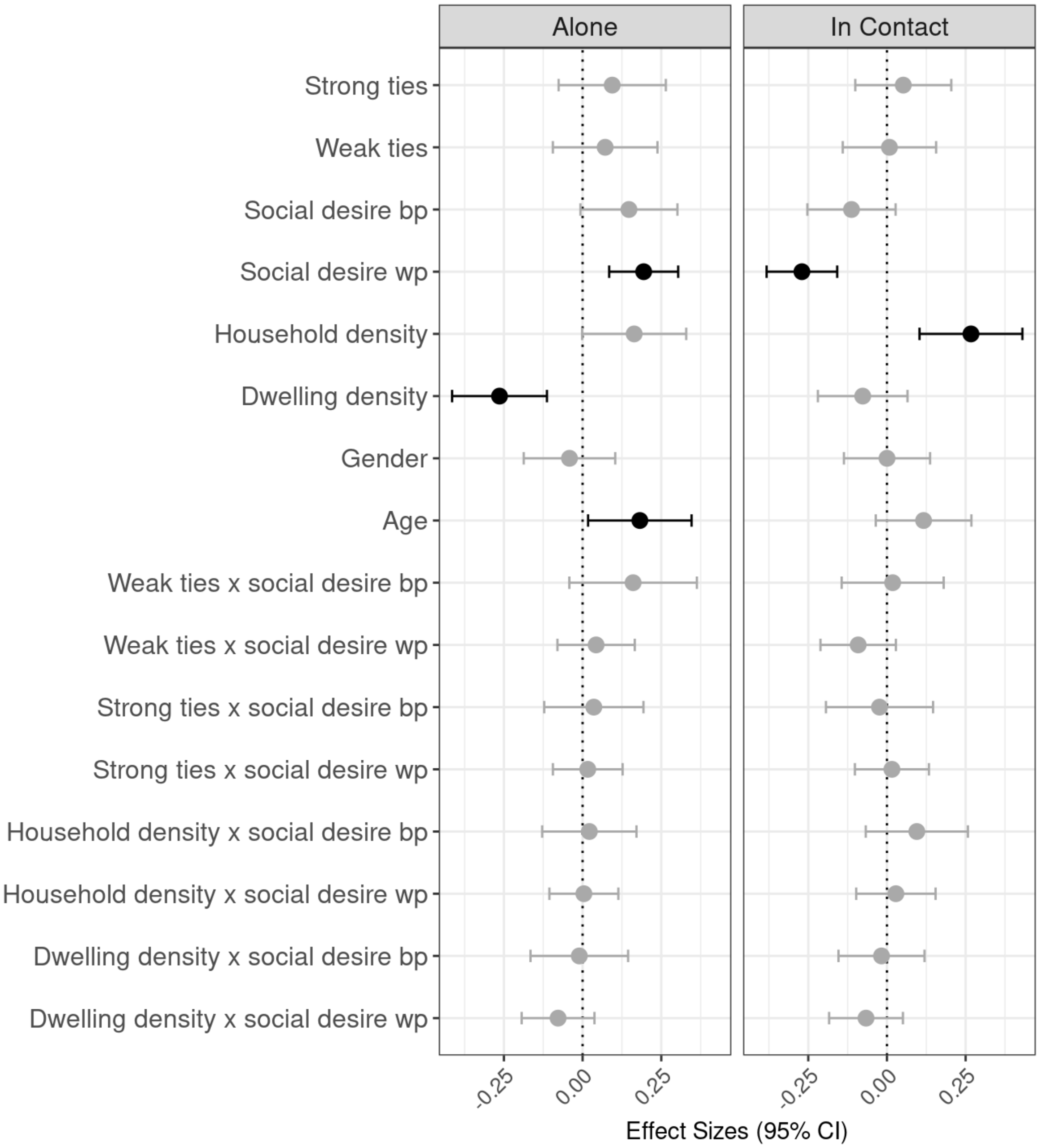
[b] In Study 1, a zero on Contact indicates solitude and a one indicates face-to-face interaction. In Study 2, a zero on Contact indicates less and a one indicates more face-to-face contact than the sample median.

[c] In Study 1, Conversation indicates the proportion of conversation over 80 minutes, while in Study 2, Conversation indicates the proportion of conversation calculated over daily intervals.

To test the hypotheses, social interaction at the next measurement was predicted by social context factors (network size and social densities), social desires (i.e., desire to be alone or desire to interact), and interactions between desires and context factors, with gender and age included as control variables (Figure 5.1).

Figure 5.1

Study 1: Social Interaction at Next Episode Predicted by Social Desires and Social Context When People were Currently Alone or in Social Contact



Note. Effects with CIs that included zero are displayed in grey. Social desires indicate desires counterfactual to the current situation of participants. That is, in the left panel, based on all measurements during which participants were currently alone, higher social desire indicates a higher desire to interact with others. Conversely, in the right panel, based on measurements during which participants reported to be in a social interaction, higher social desire indicates a higher desire to be alone. Positive effect sizes indicate a higher probability of being in face-to-face interactions during the next measurement. The left panel was based on 1,832 observations from 291 participants, and the right panel was based on 2,377 observations from 297 participants. bp = between person component (i.e., person mean); wp = within-person component (i.e., within person deviation from the person mean).

Contrary to Hypothesis 1, neither the number of strong ties, nor the number of weak ties predicted interactions at the next measurement—irrespective of whether participants were currently alone (strong ties: $b = 0.09$, 95% CI [-0.08, 0.26], $p = .279$; weak ties: $b = 0.07$, [-0.09, 0.24], $p = .398$) or in a social interaction (strong ties: $b = 0.05$, [-0.10, 0.20], $p = .505$; weak ties: $b = 0.01$, [-0.14, 0.16], $p = .917$). Partly supporting Hypothesis 2, a higher household density did not predict transitions from being alone to social interaction ($b = 0.16$, [0.00, 0.33], $p = .052$), but predicted remaining in social interaction at the next measurement, $b = 0.27$, [0.10, 0.43], $p = .001$. Contrary to Hypothesis 2, living in a residential building with more apartments was associated with a higher probability of staying alone ($b = -0.26$, [-0.41, -0.11], $p < .001$), and did not predict remaining in social interaction ($b = -0.08$, [-0.22, 0.07], $p = .289$).

Regarding social desires, the within-person components of desire to be alone and desire to interact were both associated with desire-consistent changes in the social situation. Participants who were currently alone and had a stronger than usual desire for interaction were more likely to be in a social interaction at the next measurement ($b = 0.19$, 95% CI [0.08, 0.30], $p < .001$). Likewise, participants who were in a social interaction and reported a stronger than usual desire to be alone were more likely to be alone at the next measurement ($b = -0.27$, [-0.38, -0.16], $p < .001$). Contrary to Hypothesis 3, no substantial interactions between the social desire variables and any social context variables were observed.

In a series of robustness checks, we examined whether these effects replicated in models with lead-two and lead-three social interaction as an outcome (i.e., social interactions occurring about 160 min or 240 min later, Appendix D). To summarize, the effects of both weak and strong ties remained non-significant throughout all models. The effects of household density on transitioning from being alone to social interaction were significant in lead-two and lead-three models. All other effects of household and neighborhood density, as well as the within-person effects of the social desires, could be replicated across the different time specifications, with the exception of desire to interact, which was non-significant in lead-three analyses (Appendix D).

In further exploratory analyses, we examined how social network, social density, and social desire variables were associated with the proportion of conversation detected within the next 80 minutes. Again, the robustness of the findings across different timeframes was probed by running lead-two (conversation occurring 80 min to 160 min after ending the questionnaire) and lead-three analyses (conversation occurring 160 min to 240 min after ending the questionnaire). In the following, we report effects on conversation in the next 80 minutes that replicated in at least one other specification of the timeframes: when people were in an interaction right before answering the questionnaire, higher age was associated with less conversation in the next 80 minutes (b = -0.03, 95% CI [-0.04, -0.01], p = .003, Figure E1, Appendix E). A higher within-person desire to interact predicted more conversation in the next 80 minutes (b = 0.02, [0.01, 0.03], p < .001, Figure E1, Appendix E). There were multiple significant interactions between context variables and social desires across the different time specifications, but no clear pattern emerged (Appendix E).

Furthermore, in another series of exploratory models, we used similar models as those reported in Figure 5.1 but substituted the self-report measures of weak and strong ties with the number of phone numbers saved in people's smartphones as an alternative indicator of network size. In line with Hypothesis 1, the number of phone numbers was associated with a higher probability of transitioning from solitude to social interaction (b = 0.21, 95% CI [0.06, 0.36], p = .005), and did not predict remaining in social interaction (b = -.00, [-0.15, 0.11], p = .792, Figure E4, Appendix E).

5.3 Study 2

5.3.1 Transparency and Openness

We report all manipulations and data exclusions and clearly indicate all deviations from the preregistration, which is available at https://osf.io/tf69m. A documentation of all measures, anonymized data sets, data analysis scripts, preprocessing scripts, a list of used software packages, and deviations from the preregistration are available at https://osf.io/z4jqs. The study adhered to the principles of the Declaration of Helsinki for research involving human subjects and was given IRB approval by Johannes Gutenberg University Mainz (process number: 2018-JGU-psychEK-002).

5.3.2 Participants

Study 2 was part of the Socio-Economic Panel Innovation Sample (SOEP-IS; Richter & Schupp, 2015), which is a nationwide yearly panel study on socio-economic and psychological topics. The data collection for Study 2 occurred in Germany from July 2022 to January 2023. The SOEP-IS as a whole is based on regionally clustered multi-stage random samples. In 2022, 2,507 participants took part in the SOEP-IS study of which 1,322 (53%) reported initial interest in the smartphone-study and 844 (34%) fulfilled all requirements (i.e., regularly using a smartphone running on Android version 6.1 or higher). Finally, 12% of the 2022 SOEP-IS sample, that is N = 313 participants, took part in the 14-day smartphone study and answered at least one daily diary.[26] The sample of Study 2 is characterized by considerable diversity in demographics and living situations. Compared to the German population, participants in the sample tended to be somewhat younger, had higher levels of education, and had higher incomes. The selectivity and biases of the smartphone study subsample are examined in further detail in Schoedel, Bühner, et al. (2023). An overview of the sample characteristics is reported in Table 5.1.

5.3.3 Procedure

The 2022 SOEP-IS interviews were mostly conducted using computer-assisted telephone or web interviews and included questions pertaining to participants' social network and social context factors (a full documentation is available at https://osf.io/z4jqs). At the end of the interview, participants were asked if they owned a smartphone running on Android OS version 6.1 or higher and if they were interested in participating in an additional 14-day smartphone study. Those who agreed to participate were sent a postal invitation to take part in the study along with instructions on how to install and set up the PhoneStudy app.[27] Similar to Study 1, participants were thoroughly informed multiple times during the onboarding process about the study procedure and data protection, and informed consent was obtained during the setup of the app.

After installation of the app, participants received daily notifications to fill out a brief questionnaire on their mood and social contact each evening for 14 days. Questionnaires were

[26] Initially, 385 participants took part in the 14-day smartphone study, but 72 participants installed an outdated app version with different item wordings and were therefore excluded (see Appendix F).

[27] For Study 2, the experience sampling part of the PhoneStudy app was changed, while the mobile sensing part was identical to the version of the app that was used in Study 1.

available each day from 8:00 p.m. to 4:00 a.m. of the following day. Participants were instructed to answer the questionnaire right before going to bed and received up to two reminders between 8:00 p.m. and 12:00 a.m. Additionally, smartphone sensing ran on the participants' phones, passively gathering data on anonymized social interactions and stored contacts (see Measures). Participants received €40 (~40 USD) for participation.

5.3.4 Measures

Social Interactions

Participants answered, "How much face-to-face contact did you have with your partner/friends/colleagues/family/children/other persons today?" and estimated the total amount of time spent with people from each of the corresponding categories in minutes (indicated on a scroll wheel with anchors 5 min, 15 min, and 30 min, followed by steps of 30 min up to a max duration of 24 hr). Participants could select a "Had no contact with…" option if they had no contact with people from a given category on this day. First, we winsorized (i.e., fixed to $M \pm 3$ SD) the contact duration within each relationship type. Second, daily social contact was estimated by adding up the time in contact with all relationship types. We calculated the *proportion of conversation* the same way as in Study 1, but aggregated on a daily level, from 4:00 a.m. until completion of the questionnaire (usually between 8:00 p.m. the same day and 1:00 a.m. of the following day).

Desire for More or Less Social Interactions

To measure social desire, at the end of each day, participants indicated how much they agreed to the following statements: "I would rather have spent more time in the company of others today" and "I would rather have spent more time alone today", using a scale of 1 = "*does not apply*" to 7 = "*does apply*".[28]

Social Network Size (Strong Ties)

Participants answered, "How many close friends would you say that you have?" in an open-answer format. Furthermore, the SOEP-IS contained information on the size of the

---

[28] In the context of German-language surveys, a scale with the anchors 1 = *trifft nicht zu* to 1 = *trifft zu* is commonly understood as asking for gradual agreement to the presented statements.

immediate family (relationship status and number of children).[29] As an indicator for the number of strong ties in the social network, we added the number of close friends and immediate family members.

Household Density

As in Study 1, household density indicates the number of people living in the participant's apartment divided by the size of the apartment.

Dwelling Density and Population per Residence

The same measure as in Study 1 was used for dwelling density. Additionally, as another indicator of neighborhood density, an estimate for population per residence was obtained in Study 2. Using Destatis census data (Destatis, 2022a, 2022b), population per residence was calculated for each participant by dividing the total population living in their municipality by the number of residential buildings in that municipality.

5.3.5 Analytical Strategy

Regarding outliers, seven observations of strong ties, four observations of phone numbers, and one observation of household density were winsorized (i.e., fixed to $M \pm 3$ *SD*). To test the hypotheses, we used logistic multilevel models with random intercepts and random slopes, using similar specifications as in Study 1.

Two models were computed. The first model ("Less") predicted transitions from days with less contact (below sample median, i.e., summed duration across all relationship type categories < 12 hr) to days with more contact (i.e., above sample median, summed duration across all categories > 12 hr). The second model ("More") predicted transitions from days with more contact to days with less contact.[30] The general setup of models followed the analytic procedure of Study 1.

---

[29] Deviating from the preregistration, we could not include the number of parents alive because this information was missing for most participants.

[30] Please note that using a different cut-off value for each participant (i.e., using a within-person criteria to split the outcome variable) would render the prediction of the outcome by between-person social context variables largely meaningless. By using the sample median, we decided to focus on an observer's viewpoint on what could be considered little or a lot of contact. Other studies using an alternative analytical framework and focusing more on the subjective perceptions of the participants could complement the current approach.

5.3.6 Results

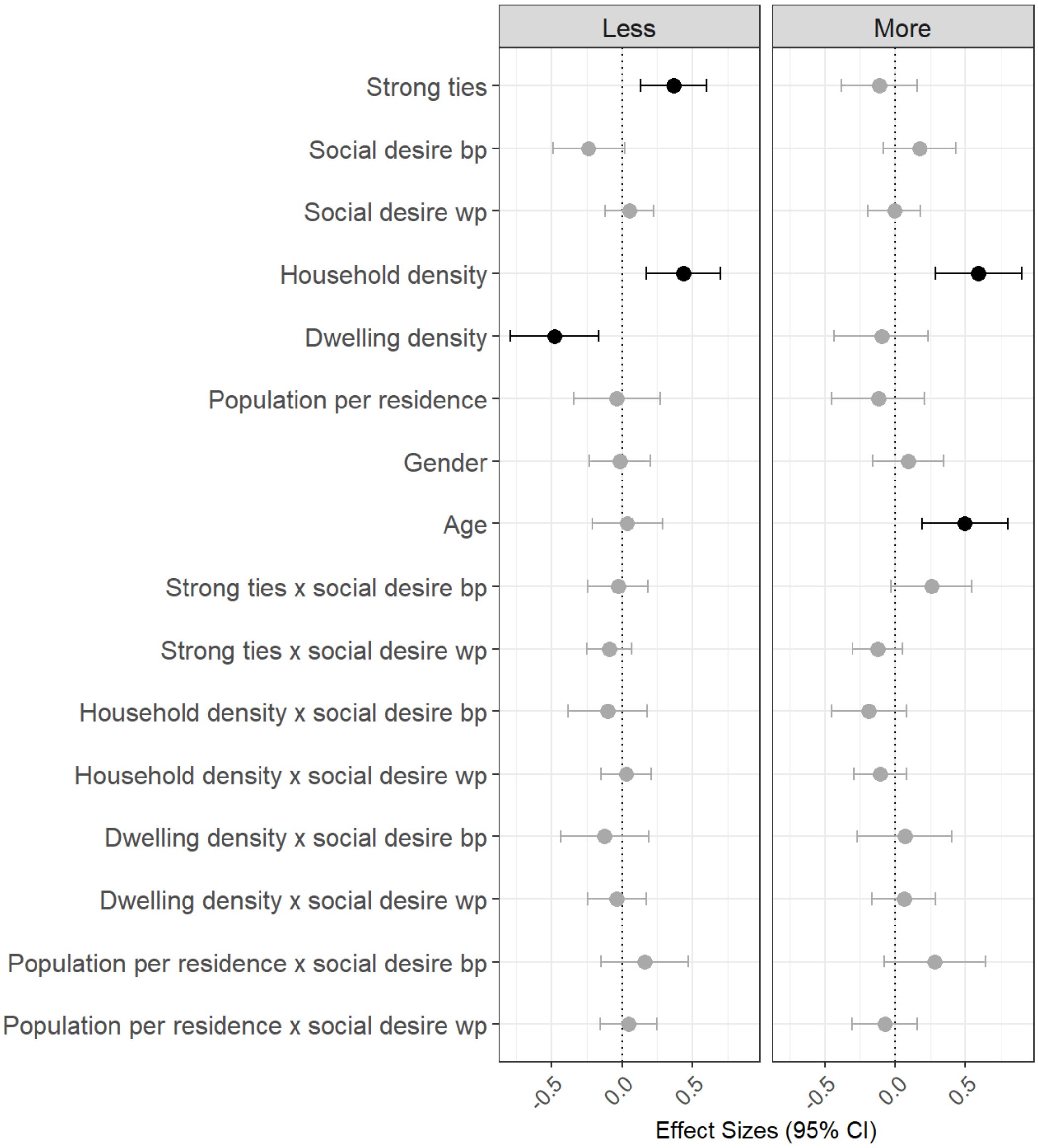
Participants answered on average 85% out of 14 daily diary questionnaires. To test the hypotheses, a binary variable indicating whether the next day had less (i.e., below sample median) or more (i.e., above sample median) social contact was predicted by social context factors (i.e., network size and social densities), social desires (i.e., desire to be alone or desire to interact), and interactions between desires and context factors, with gender and age included as control variables (Figure 5.2). To test Hypotheses 1c, 2c, and 2f, social desire was predicted by social context factors with age and gender as control variables in two additional models. In the following, we present results of the main effects of social network size, social density and social desire variables first, followed by interaction effects and exploratory analyses with mobile sensing.

Supporting Hypothesis 1, the number of strong ties predicted transitioning from days with less social contact to days with more contact (b = 0.37, [0.13, 0.60], p = .002) but was unrelated to transitions from days with a lot of contact to days with less contact (b = -0.12, [-0.39, 0.15], p = .392). Furthermore, as predicted in Hypothesis 2, a higher household density predicted both transitions from days with less contact to days with more contact (b = 0.44, [0.17, 0.70], p = .001) and sustained high levels of social contact after days with a lot of social contact (b = 0.59, [0.28, 0.90], p < .001). Contrary to Hypothesis 2, living in a residential building with more apartments was associated with experiencing consecutive days with little contact (b = -0.48, [-0.79, -0.16], p = .003) and was unrelated to transitions to less contact after days with a lot of contact (b = -0.10, [-0.43, 0.24], p = .562). When entered simultaneously in the models including dwelling density, population per residence predicted neither consecutive days with little contact (b = -0.04, [-0.34, 0.27], p = 0.815), nor transitions to less contact after days with a lot of contact (b = -0.12, [-0.45, 0.20], p = 0.459). Higher age was associated with sustained high levels of contact after days with a lot of contact (b = 0.49, [0.19, 0.80], p < .001). The effects of strong ties, household density, dwelling density, and age remained significant in lead-two and lead-three models (Appendix G).

Regarding social desires, desire to be alone and desire to interact were largely unrelated to transitioning to days with more or less social contact (all p > .05, Figure 5.2). Contrary to Hypothesis 3, no significant interactions between the social desire variables and the social context variables were observed. Also contrary to the hypotheses, in models with the social desires as outcome, desire to interact was largely unrelated to the social context variables (all p > .05). As predicted, desire to be alone was increased for participants living in high-density households *(b* = 0.25, 95% CI [0.09, 0.41], *p* = .003) but dwelling density and population per residence were not significantly associated with the desire to be alone (all *p* > .05).

Figure 5.2

Study 2: Social Contact at the Next Day Predicted by Social Desires and Social Context on Days with Less or More Social Contact Than Typical



Note. Effects with CIs that included zero are displayed in grey. In the left panel, based on all days during which participants had less contact than typical, social desire refers to the desire to interact. Conversely, in the right panel, based on days during which participants had more contact, higher values on social desire indicate a higher desire to be alone. Positive effect sizes indicate a higher probability of having more social contact than the sample median on the next day. The left panel was based on 1,615 observations from 241 participants, and the right panel was based on 1,551 observations from 252 participants.

We further probed the robustness of the findings using mobile sensing data obtained from the conversation detection algorithm. We divided the dataset into days with more (above sample median) and less (below sample median) conversation and predicted the proportion of conversation on the subsequent day. Contrary to Hypothesis 1, people with more strong ties in their network were more likely to be around a lot of conversation after days with a lot of conversation (b = 0.02 [0.01, 0.04], p = .001). Following days with less conversation, people with a generally higher desire for interaction were less likely to be around conversation the next day if they also lived in a dwelling with more apartments (b = 0.01, [0.00, 0.02], p = .019). Following days with a lot of conversation, higher age was related to less conversations on the next day (b = -0.01, [-0.03,0.00], p = .014). This pattern of results was consistent across time specifications, with the exception of strong ties, which was non-significant in lead-three analyses (Appendix H). In additional exploratory models, the main effects of phone numbers on social contact during the next day were non-significant (but there was a significant interaction with the between-person component of the desire for less contact, see Appendix H, Figure H4).

5.4 General Discussion

Engaging in social interactions is vital for maintaining health and well-being (Holt-Lunstad et al., 2017). Still, in people's daily lives, time and energy for investment in various social interactions is limited (Hall & Davis, 2017; Huxhold et al., 2022) and must be balanced with other needs, such as time for oneself or work (Coplan et al., 2019; Grund et al., 2014). To better understand the regulation of social interactions beyond individual differences in dispositions (Back et al., 2023), it is crucial to examine contextual factors that represent opportunities or constraints, and either facilitate or hinder interactions (Huxhold et al., 2022; Meagher, 2020). To this end, two multi-method studies using diverse samples examined associations between social interactions in everyday life and different operationalizations of two context factors, namely social network size and social density.

5.4.1 Mixed Findings for Social Network Size

Regarding social network size, we expected people with larger social networks to transition faster from solitude to social interactions and found mixed evidence for this hypothesis. In Study 1, no substantial associations between self-reported social network size and the regulation of social interactions within days were found. However, in exploratory analyses, the number of contacts saved on participants' smartphones was associated with transitions from being alone to subsequent interaction being more likely. In Study 2, the self-reported number of strong ties was linked with having more contact after days with little contact, yet no associations were observed with the number of phone contacts. As assumed, we found no associations between social network size and transitions from social interactions to solitude, or from days with a lot of contact to days with less contact, in the confirmatory analyses (but some effects of strong ties on conversations the next day were found in exploratory analyses).

Although different operationalizations of social network size were employed, the number of relationships people maintain may be less influential in shaping dynamics of social interactions than initially hypothesized. It is plausible that, in a given situation, nobody from one's social network is currently available, for example because of physical distance or time constraints. Accordingly, future studies could delve further into links between more stable structural characteristics (e.g., social network characteristics such as composition or residential proximity) and how they unfold in concrete situations (e.g., momentary availability of interaction partners). Furthermore, it could be interesting to expand the scope of investigation beyond (the sheer number of) face-to-face interactions. For example, unfulfilled social desires might prompt people to seek technology-mediated social contact (Krämer et al., 2022; Kroencke, Harari et al., 2023). Moreover, unfulfilled social desires might not directly influence subsequent social interaction but rather prompt people to arrange future appointments with people from their social network a few days or weeks later (van den Berg et al., 2010). These social planning behaviors were not addressed in the current study, but as daily social interactions are partly routine or pre-arranged, social planning might be one avenue for research on the regulation of everyday social interactions (Nezlek, 2001; van den Berg et al., 2010).

5.4.2 Dense Households Facilitate but Dense Dwellings Inhibit Social Interactions

Regarding social densities, our hypothesis posited that people living in high-density environments would transition faster from solitude to social interactions but slower from interactions to solitude. When high-density environments were operationalized as household density (i.e., persons per square meter) the results strongly supported this hypothesis across both studies and hence various timeframes. This aligns well with prior research suggesting that living spaces with shared areas and dwelling designs incorporating suites (versus apartments) facilitate social interaction (Bronkema & Bowman, 2017; Devlin et al., 2008; Dijkstra et al., 2006; Easterbrook & Vignoles, 2015; Ullán et al., 2012).

Yet, when high-density environments were operationalized as dwelling density (i.e., an indicator of the number of apartments within people's dwelling), no facilitation of social interactions was observed. Instead, living in dwellings with more apartments was associated with a lower probability of transitioning out of solitude (Study 1) or little contact (Study 2). Although contrary to our initial expectations, this finding concurs with literature suggesting that overly dense social environments may impede individuals' regulation of their need for solitude, eventually promoting anonymity and a tendency to withdraw socially (Altman, 1975; McCarthy & Saegert, 1978; Skjaeveland & Gärling, 1997; Stokols, 1972). The type of dwelling people lived in was highly correlated with another measure for neighborhood density: population per residence. The results showed no incremental effects of population per residence on the prediction of social interaction dynamics. Perhaps, the more immediate context variables (i.e., characteristics of people's apartment or dwelling) might be better indicators of an individual's social opportunity structure and thus more relevant for everyday social interaction dynamics than population per residence (Rosenberg, 1982). Integrating such aspects would enrich current psychological theories on social relationships substantially.

5.4.3 Social Desires Influence Social Interactions Within Days

Regarding the role of social desires, the results provided strong evidence for associations between momentary desires and subsequent social interactions within days, as observed in Study 1. This finding further supports the scarce prior studies on social dynamics, which showed that desire to be alone reduced the likelihood of subsequent social interaction within days (Hall, 2017), and that communal motivations increased the likelihood of subsequently showing affection to one's partner (Zygar et al., 2018). However, in Study 2, no substantial associations between social desires and social interactions on the next days were found, contrasting with a study that found that relatedness need motivation predicted relatedness need satisfaction across days (Neubauer et al., 2018). One possible explanation could lie in the different operationalizations of the outcomes as amount of social contact vs. affective consequences (i.e., relatedness need satisfaction).

Contrary to Hypothesis 3, the effects of social networks and social densities were largely independent from momentary social desires. In deriving Hypothesis 3, we emphasized people's agency in regulating their social interactions, which aligns with current psychological theories on social relationships (Back et al., 2011; Hall & Davis, 2017; Huxhold et al., 2022). Although the main effects of social desire in Study 1 provided some support for this notion of agency, it is important to recognize that social desires alone were insufficient to explain the temporal dynamics of everyday social interactions. This aligns well with the literature demonstrating that personal preferences for social interaction or solitude may be overridden by competing needs or situational characteristics (Coplan et al., 2019; Emmons et al., 1986; Grund et al., 2014; Krämer et al., 2022). That is, the strong and independent effects of the social context variables on social interactions underscore the importance of contextual factors and challenge the assumption that most aspects of social interactions are solely within people's agency.

Consequently, psychologists interested in social interactions may benefit from more actively embracing perspectives from other disciplines concerned with people's social contexts. For example, social scientists use diverse approaches for measuring neighborhoods or for integrating spatial aspects into analyses of social networks (for overviews see Hipp et al., 2012; Neal, 2020). One such approach is the measurement of activity spaces—personalized collections of locations people visit in their daily routines—with GPS sensors (e.g., J. A. Hirsch et al., 2016). Personalized activity spaces offer opportunities to explore how the regulation of social interactions is linked to characteristics of those social contexts that individuals spend most of their time in. Thus, activity spaces could help to personalize measures of social density, overcoming some limitations of neighborhood density measures based on administrative boundaries (e.g., population per residence in a municipality). Alternatively, activity spaces may provide the option to restrict social networks to those people who live in reasonable proximity using objective criteria, addressing some limitations of self-reported social networks. Still, we believe such approaches unfold their full potential only when integrated with psychological insights obtained through (repeatedly) questioning people (Roos et al., 2023; Wrzus & Mehl, 2015).

To summarize, future investigations on when, and how, and which situational demands, social obligations, or other external constraints prevail over individual preferences seem promising to provide deeper insights on the complex dynamics of social interaction regulation in daily life.

5.4.4 Limitations

Using two sizeable studies with age- and gender-heterogenous samples and combining ecological momentary assessment, mobile sensing, and questionnaires, we found compelling evidence for effects of social context variables on the regulation of everyday social interactions. Still, several limitations need to be mentioned.

First, despite the temporal ordering in the analyses (i.e., momentary data predicted social contact at the next measurement), conclusions regarding the directionality of effects and the influences of third variables remain open. We argued that different context factors do not directly influence everyday social interactions but together create a social opportunity structure, which then either facilitates or constrains social interactions (Fiori et al., 2020). Beyond social network characteristics and social densities, other variables may influence both the contexts in which people live in and their everyday social interactions. For example, socioeconomic status was identified as an important variable in mobility behavior (van den Berg et al., 2010) and might partly explain negative effects of higher dwelling density on social interactions.

Second, the results were obtained in two German samples, which might limit the generalizability to other cultural contexts. In a comparison of 39 countries, Germany exhibited a position close to the median regarding relational mobility (i.e., a measure of how fluid and open interpersonal relationships are in a culture; Thomson et al., 2018). Accordingly, because different cultures organize living closely together in very different ways, effects of context variables might differ between cultures (Rosenberg, 1982). For example, perspectives of Israelis on living in high-rise buildings were remarkably different from perspectives of US Americans or Norwegians (Churchman & Ginsberg, 1984; McCarthy & Saegert, 1978; Skjaeveland & Gärling, 1997).

Third, the measurement of social interactions still poses challenges to researchers in general and also in this study (Harari et al., 2016; Roos et al., 2023). On the one hand, questionnaire methods currently often lack a precise definition of social interaction because only brief explanations are provided and certain interactions such as working together silently might not be specified. Furthermore, uncertainty about the exact timing of the underlying processes poses challenges for determining the optimal spacing for questionnaire measurements. On the other hand, focusing on conversation behavior, which—to a certain degree—can be measured continuously and objectively with sensors, poses technical challenges, and might miss meaningful social interactions without (constant) conversation (Roos et al., 2023). Another debate revolves around the amount of social interaction necessary to be considered meaningful. How much time needs to be spent in a social interaction to interrupt a period of solitude? Should researchers opt for an observation-based approach or is the subjective of perception of people concerning what is little or much social interaction for them more important? How can both approaches be reconciled?

With these challenges in mind, we propose two complementary approaches for future research. First, although broad generalizable theories are desirable, the concept of social interactions incorporates very different experiences with very different interaction partners. Thus, future research could consider further characteristics of social interactions such as the valence of the social interaction, the kind of interaction partner, or the type of activity. Second, we advocate for continued use of multi-method approaches to study social interactions. Apart from providing a more comprehensive basis for any content-related claims, this also enables a comparison of measurement methods and consequently allows a deeper insight not only about social interactions but also about the measurements that are used to study them (Roos et al., 2023; Wrzus & Mehl, 2015).

5.5 Conclusion

Current theories on the regulation of social interactions emphasize the role of agentic social desires and individual differences therein in the regulation of everyday social interactions (Back et al., 2011; Hall & Davis, 2017; Huxhold et al., 2022). While some theories include broad statements that context plays an important role, they lack specificity regarding which context factors influence social interactions. Across two multi-method studies using two sizeable heterogenous samples, we found consistent evidence that the social density of the living environment contributes to the dynamic regulation of social interactions in daily life, while the interplay of social network characteristics and everyday social interactions warrants further investigation. Together, the results point out that people live their daily life in social contexts, which contribute to how people engage in social interactions. The findings thus call for a greater integration of contextual factors in personality theories of social interactions.

Chapter 6: Resuming Social Contact After Months of Contact Restrictions: Social Traits Moderate Associations Between Changes in Social Contact and Well-being

Michael D. Krämer[1,2,3], Yannick Roos[4], David Richter[1,2,3], & Cornelia Wrzus[4]

[1] German Institute for Economic Research, Germany [2] International Max Planck Research School on the Life Course (LIFE), Max Planck Institute for Human Development, Germany [3] Freie Universität Berlin, Germany [4] Ruprecht Karls University Heidelberg, Germany

Abstract

Humans possess a need for social contact. Satisfaction of this need benefits well-being, whereas deprivation is detrimental. However, how much contact people desire is not universal, and evidence is mixed on individual differences in the association between contact and well-being. This preregistered longitudinal study (*N* = 190) examined changes in social contact and well-being (life satisfaction, depressivity/anxiety) in Germany during pervasive contact restrictions, which exceed lab-based social deprivation. We analyzed how changes in personal and indirect contact and well-being during the first COVID-19 lockdown varied with social traits (e.g., affiliation, extraversion). Results showed that affiliation motive, need to be alone, and social anxiety moderated the resumption of personal contact under loosened restrictions as well as associated changes in life satisfaction and depressivity/anxiety.

Krämer, M. D., Roos, Y., Richter, D., & Wrzus, C. (2022). Resuming social contact after months of contact restrictions: Social traits moderate associations between changes in social contact and well-being. *Journal of Research in Personality, 98*, 104223. https://doi.org/10.1016/j.jrp.2022.104223

6.1 Introduction

Humans have an innate need to seek social contact and form relationships (Baumeister & Leary, 1995; Hofer & Hagemeyer, 2018). At the same time, people differ in how they satisfy this need in daily life: Some enjoy being around others a lot and feel unwell in ongoing solitude, whereas others seek less social contact and are less affected in well-being by little contact.

Our study examines social contact and well-being as part of a dynamic need regulation in the context of the COVID-19 pandemic, which required a population-wide reduction in personal contact to curtail virus transmission (Flaxman et al., 2020). Harnessing the unique situation of a gradual reboot of social contact over three months, our study provides insights into social need regulation and individual differences in social behavior during the pandemic. The contact restrictions introduced to reduce the spread of COVID-19 provide an unprecedented opportunity to study social need regulation outside the laboratory. We investigate longitudinally (a) how social contact changes in relation to social traits, and (b) how well-being changes with increased social contact depending on social traits. Under a broad conceptualization of well-being, we examine both life satisfaction and depressivity/anxiety as potential markers of social need satisfaction.

6.1.1 Social Need Regulation

Social need regulation is conceptualized as continuous internal comparisons between a person’s ideal level of social contact and the level currently experienced (i.e., both amount and quality; Hall & Davis, 2017; Nezlek, 2001; Sheldon, 2011). Deviations from the ideal level in both directions are theorized to reduce well-being and motivate individuals to align social behavior towards need satisfaction (Hall & Davis, 2017; Sheldon, 2011). For example, experience sampling studies have shown that higher momentary need motivation leads to higher need satisfaction through need-relevant behavior (Neubauer et al., 2018; Zygar et al., 2018). Social need regulation therefore represents a dynamic process in which past social contact influences future contact through need satisfaction or dissatisfaction (Carver & Scheier, 1998). Satisfying one’s social needs is linked to higher well-being (Demir & Özdemir, 2010; J. Sun et al., 2020; Tay & Diener, 2011). Early motive theories (e.g., McClelland, 1987) and recent empirical work suggest that, depending on social need strength, people’s well-being is differently affected by need satisfaction (Dufner et al., 2015; Zygar et al., 2018).

Evidence on the extent to which indirect contact (e.g., texting, videocalls) satisfies social needs remains inconclusive (Kushlev et al., 2019; Orben & Przybylski, 2019, 2020). Indirect contact might substitute personal contact during the pandemic lockdown (Gabbiadini et al., 2020). Daily diary data indicate, however, that only personal contact is robustly related to well-being (Lades et al., 2020; R. Sun et al., 2020). In terms of mental health, the prevalence of depression and anxiety symptoms increased during the COVID-19 pandemic (Ettman et al., 2020; Twenge & Joiner, 2020), and there is associative evidence that being alone due to contact restrictions—thereby unable to satisfy social needs—negatively affects mental health (Benke et al., 2020; Fried et al., 2022).

6.1.2 Social Traits

People differ in the ideal level of social contact to which they compare their current experiences (Sheldon, 2011). Thus, the same situation such as being alone for several days can elicit either an appetitive (i.e., enjoying and maintaining solitude) or an aversive response (i. e., disliking solitude and seeking social contact; Hagemeyer et al., 2013) depending on the individual's ideal level, which is captured in social traits.

Of the Big Five traits (Soto & John, 2017), extraversion is closely related to interpersonal behavior (DeYoung et al., 2013). Extraversion predicts, among other things, how much someone likes the company of others (Breil et al., 2019), and whether someone leaves situations when they are alone (Wrzus et al., 2016).

The affiliation motive describes the need to initiate and maintain close relationships (Hofer & Hagemeyer, 2018). With a higher affiliation motive, people partake in more social interactions such as visiting friends or phone calls and are more likely to crave social contact when alone (Hill, 2009).

Although humans have social needs, they also seek solitude, for example, to pursue a hobby or wind down after a long day of meetings (Lay et al., 2019). Individuals vary in the strength of this need to be alone (Coplan et al., 2019; Hagemeyer et al., 2013). A higher need to be alone reduces the likelihood of social contact (Hall, 2017).

Another reason why people avoid others is that they experience anxiety when anticipating social contact. Subclinically low to moderate anxiety about social contact is prevalent in the general population (Peters et al., 2012). Higher social anxiety is associated with smaller social networks (Van Zalk et al., 2011), being disliked by interaction partners more frequently (Tissera et al., 2020), and lower momentary well-being (Brown et al., 2007).

6.1.3 Current Study

In this longitudinal study, we assessed social contact and well-being four times over three months—beginning during most rigorous contact restrictions and continuing during gradual resumption of social contact. Governmental restrictions limiting personal contact for several weeks in early 2020 constitute a strong situation with limited room to express social traits (Cooper & Withey, 2009). In contrast, person effects of social traits are presumably more pronounced in weak situations that do not constrain social activity and allow behavioral expression of traits (Blum et al., 2018; Schmitt et al., 2013). Successively eased restrictions therefore represent a transition from a strong situation curbing the person-situation interaction into a more normal interplay of the two (Schmitt et al., 2013). However, as Cooper and Withey (2009) state, the "personality-dampening effect of strong situations" (p. 62) has not been shown convincingly because truly strong situations are difficult to induce in laboratory settings or to observe under regular situational circumstances. The first COVID-19 lockdown, thus, represents a unique opportunity to study social need regulation because it caused long-lasting and pervasive restrictions of social contact with widespread deprivation of social needs, which considerably exceed laboratory-based deprivation.

The "lockdown" to manage the COVID-19 pandemic in Germany in early 2020 initially created strong situational constraints severely restricting everyday mobility in all age groups and regions (Becher et al., 2021; Bönisch et al., 2020). Compared to pre-pandemic levels, social contact frequency was estimated to have decreased by 61–90%, reaching a nadir in April 2020 (Del Fava et al., 2021; Tomori et al., 2021). This time period, during which our longitudinal study started, also represents the maximum extent of governmental contact restrictions in all German federal states during the first COVID-19 wave (Aravindakshan et al., 2020). Following federal decrees on 6 May 2020 (Bundesregierung, 2020), restrictions were gradually eased (until the second wave of infections in the fall of 2020), and people in Germany resumed social contact accordingly, although not yet to pre-pandemic levels by late June 2020 (Tomori et al., 2021). In addition to these mean-level increases of social contact frequency, its variance had substantially increased over this period of eased restrictions (Tomori et al., 2021). This is consistent with evidence that personality traits were associated with differences in precautionary behavior and adherence to contact restrictions (Aschwanden et al., 2021; Götz et al., 2021; Zajenkowski et al., 2020; Zettler et al., 2022).

Although contact restrictions undoubtedly presented a strong situation unprecedented in the second half of the 20th century, evidence is ambiguous regarding resiliency and well-being during this period (Luchetti et al., 2020; Zacher & Rudolph, 2021). German population-representative panel data indicate stability in well-being but an increase in loneliness during contact restrictions, which affects extraverted people more severely (Entringer & Gosling, 2021; Entringer et al., 2020). In contrast, providing preliminary support for the strong situation hypothesis, the association between extraversion and well-being was lower during lockdown than before the pandemic in a cross-sectional study (Anglim & Horwood, 2021). We go beyond previous work by considering multiple social traits, distinguishing personal and indirect social contact, and making use of the strong situation of the COVID-19 pandemic.

Specifically, we address how social traits influence two steps of social need regulation: First, we investigate whether individual differences in social traits were associated with diverging trends in pursuing social contact when restrictions were gradually being eased. Second, we probe the well-being consequences of increased social contact and differences therein related to social traits.

We preregistered the following hypotheses[31] (https://osf.io/n8jrv):

H1a: Social contact will increase over time more strongly for people higher in extraversion and affiliation motive.

H1b: Social contact will increase less over time for people higher in the need to be alone and social anxiety.

H2a: Social contact and personality (extraversion, affiliation motive) will moderate effects of time on well-being, that is, well-being will be lowest for people with low social contact and high extraversion or affiliation motive.

H2b: With higher need to be alone and social anxiety[32], well-being will be less strongly related to social contact.

6.2 Methods

We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study. The preregistration (and deviations from it), data, documentation of assessed variables, and R-scripts to reproduce this manuscript are available at https://osf.io/8xubm/. The current data stem from a project aimed at developing a questionnaire on social dynamics.

6.2.1 Participants

Our preregistered sample size rationale of $N = 195$ relied on an a-priori power estimation based on a repeated measures ANOVA with $\alpha = .05$, $(1 - \beta) = .90$ and a small effect size of $f = .10$ which we performed when we were uncertain about the ultimate temporal progression of the study (see document Deviations_preregistration.pdf on the OSF). Anticipating attrition, we

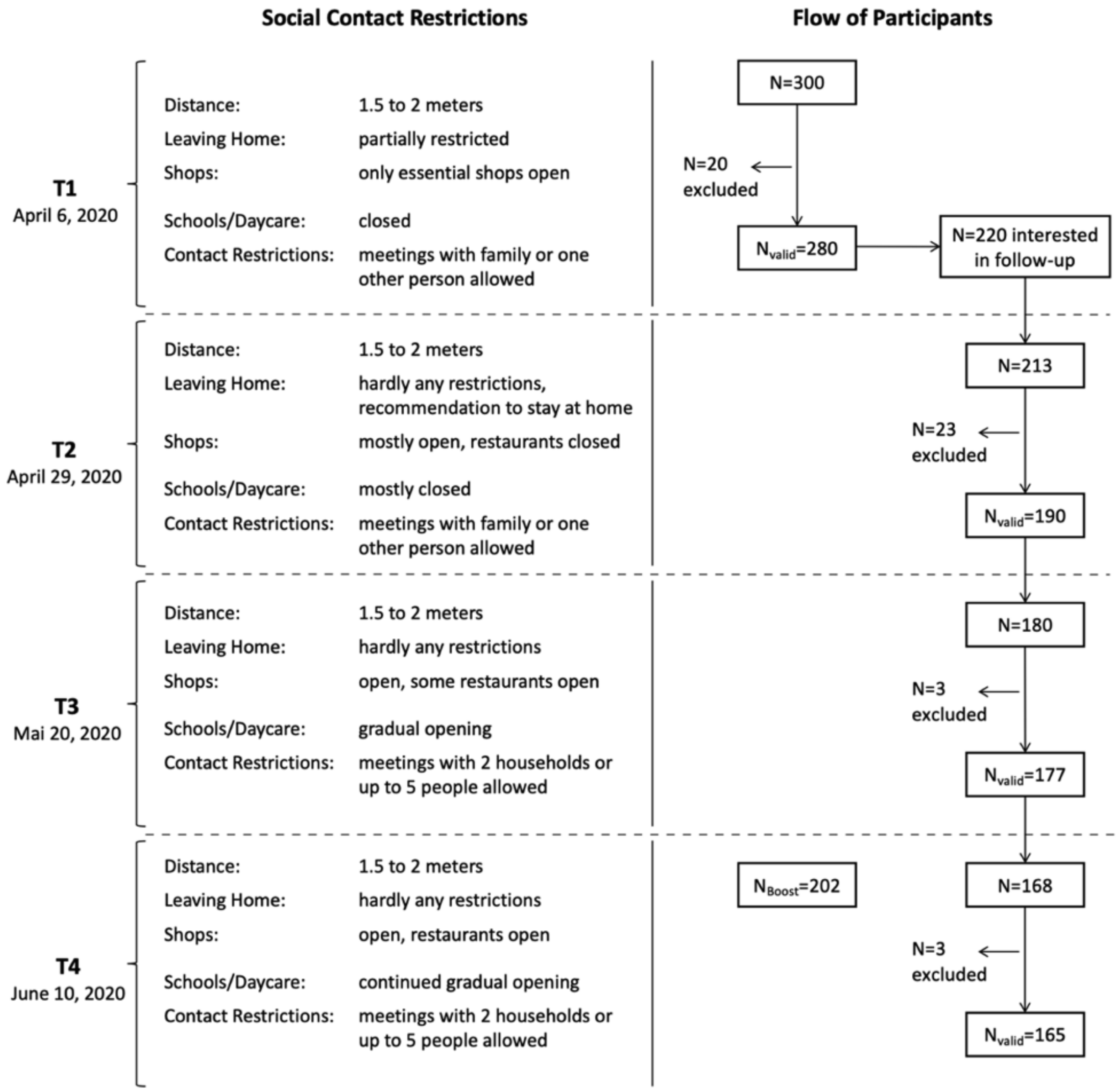
[31] In the preregistration, H1 = H2 and H2 = H3.

[32] We intended H2a/H2b to mirror H1a/H1b in constructs but forgot to include social anxiety in H2b in our preregistration. Deviations from our pre-registration are listed at https://osf.io/8xubm/.

recruited 300 German-speaking participants balanced by gender and five age groups (18–29, 30–39, 40–49, 50–59, 60–75) via the crowdsourcing service https://www.clickworker.com. Of these, 220 initially agreed to participate in up to three longitudinal follow-ups (see Figure 6.1).

Figure 6.1

Participant Flowchart With Information on COVID-19 Contact Restrictions in Germany During the Four Assessment Waves.



Note: The start date of each wave is shown on the left. For the analyses in this article we included N = 190 participants with valid responses at least for the first and second wave. We did not include the refreshment sample (N_{Boost} at T4). We also provide a detailed timeline of contact restrictions for two exemplary federal states on the OSF (see document *Time-line_restrictions.pdf*).

We screened participants for non-compliant response behavior (Meade & Craig, 2012) and—out of the 220 interested in follow-ups—excluded those with unrealistically short response times for the longest page of the online survey (<70s for a 39-item scale on social dynamics; n = 9 at T2, n = 3 each at T3/T4). We did not need to exclude further participants solely based on other signs of non-compliant responding (unusual response patterns, failed attention check). Additionally, a few participants gave invalid identifiers for follow-up preventing matching to the previous wave (n = 8) or opted out of the longitudinal part of the study (n = 5).

For longitudinal analyses, we included N = 190 participants who provided valid responses at least for the first and second wave. Participants ranged in age from 16 to 70 (M = 44.24, SD = 14.18) and 47% were women. Most participants were married (34%) or in a romantic relationship (31%); 42% were parents and 23% had children living in their household. Regarding occupational status, 39% of participants were employed full-time, 9% part-time, 21% were self-employed, 9% were students, 11% were pensioners, and the remaining were marginally employed or not employed. About 46% of participants held a university degree, and 43% came from urban areas.

At the first measurement, 85% of participants reported that they currently stayed at home most of the time, either as a voluntary precaution for themselves and others (52%), because they were working from home (32%), because of closed (pre-)schools (11%), illness (6%), short-time work (6%), unemployment (5%), or compulsory quarantine (1%; multiple answers allowed). 32% indicated that they or someone in their household belonged to an at-risk group for COVID-19. Over three further assessment waves, the proportion of participants staying at home most of the time decreased: 83% at the second (50% as a voluntary precaution; 10% due to closed schools), 76% at the third (38% as a voluntary precaution; 5% due to closed schools), and 67% at the fourth wave (27% as a voluntary precaution; 4% due to closed schools). The proportion of participants staying at home most of the time due to work-related reasons remained roughly the same. Overall, this progression is in line with contact survey data demonstrating that contact frequency had substantially increased by June 2020, though not yet to pre-pandemic levels (Tomori et al., 2021). Note that the phrasing of the item asking whether participants stayed home most of the time includes the possibility that changes in social contact occurred even if answered in the affirmative, as we see in the measurement of personal contact frequency (see Table S1).

6.2.2 Attrition Analysis

We performed two kinds of attrition analyses: First, we compared participants who provided valid responses in all four waves (165) with participants who initially expressed interest in participating in follow-ups but later dropped out (55). Those who provided valid responses in all waves had a lower affiliation motive, $d = 0.39$, $p = .013$, were on average 5.82 years younger, $p = .010$, and had a lower indirect contact frequency, $d = 0.42$, $p = .008$. All other variables included in analyses did not differ significantly between the two groups (all $p > .05$). Second, in the final longitudinal analysis sample ($N = 190$), we compared participants who provided valid responses in all four waves (165) with those who dropped out (25), and found no significant group differences (all $p > .05$) as well as smaller mean differences than in the first comparison (in 8 out of 10 variables).

6.2.3 Procedure

Participants answered four online surveys approximately every three weeks—starting on April 6, 2020, and ending on June 14, 2020 (722 longitudinal observations). At the first assessment, to reduce COVID-19 transmissions in Germany, all (pre-)schools, leisure activities, and shops besides supermarkets and drug stores were closed, and people were only allowed to meet with one other person (but were discouraged from doing so). Over the course of the two and a half months of the study, contact restrictions were gradually eased (see Aravindakshan et al., 2020; Tomori et al., 2021). At the time of the last assessment, shops, restaurants, and schools had reopened, recreational activities were again allowed, and warmer weather attracted people to meet outdoors (Yakubenko, 2021). Figure 6.1 summarizes the progression of the main contact restrictions in Germany. On the OSF, we provide a detailed timeline of restrictions for two exemplary federal states along with federal decrees (document *Timeline_restrictions.pdf*). Participants gave informed consent and received 4.50 to 5.00 euros per wave as compensation. The study adhered to the principles of the Declaration of Helsinki for research involving human subjects and was declared exempt from IRB evaluation.

6.2.4 Measures

Extraversion. Extraversion was assessed at the first wave as part of the Big Five Inventory-2 (BFI-2; Soto & John, 2017; German version: Danner et al., 2016) consisting of 60 items, 12 of which measure extraversion (ω = 0.88). A sample item reads "I am someone who is outgoing, sociable". Items were answered on a 5-point Likert-scale (1 = *disagree strongly*, 2 = *disagree a little*, 3 = *neutral*, 4 = *agree a little*, 5 = *agree strongly*).

Affiliation motive. We used the six-item version of the affiliation subscale of the Unified Motive Scales (Schönbrodt & Gerstenberg, 2012) at the first measurement occasion (ω = 0.87). A sample item is "I try to be in company of friends as much as possible". The Unified Motive Scales include items formulated as statements, which require an agreement rating (1 = *strongly disagree*, 2 = *disagree*, 3 = *rather disagree*, 4 = *rather agree*, 5 = *agree*, 6 = *strongly agree*), and items formulated as goals, which require an importance rating (1 = *not important to me*, 2 = *of little importance to me*, 3 = *of some importance to me*, 4 = *important to me*, 5 = *very important to me*, 6 = *extremely important to me*).

Need to be alone. The need to be alone was assessed at the first wave using the four-item appetence subscale of the desire for being alone (ω = 0.74) included in the ABC model of social desires (Hagemeyer et al., 2013). A sample item is "I like to be completely alone". Items were answered on a 7-point frequency scale ranging from 1 to 7 (1 = *never*, 4 = *sometimes*, 7 = *always*).

Social anxiety. We measured social anxiety at the first wave using the Social Interaction Anxiety Scale (SIAS-6; Peters et al., 2012; German version: Stangier et al., 1999). One of the items reads "I have difficulty talking with other people". The six items were answered on a 5-point scale (1 = *not at all*, 2 = *slightly*, 3 = *moderately*, 4 = *very*, 5 = *extremely*) and showed high internal consistency, ω = 0.85.

Social contact. At each wave, participants were asked "How often did you engage in social interactions during the last week?" for three different relationship categories (family, friends, coworkers) and four channels of social contact (personal contact, calls, video calls, texts). Personal contact referred to in-person interactions. These 12 items were answered on a 5-point scale (1 = *not at all*, 2 = *once*, 3 = *multiple days*, 4 = *daily*, 5 = *multiple times a day*). Personal contact frequency was computed as the average of personal contact from all relationship categories. To calculate indirect contact frequency, we averaged the frequency ratings of calls, video calls, and texts from all relationship categories.

Well-Being. To capture several aspects of the broad construct well-being, we measured both life satisfaction, representing a general, cognitive appraisal of well-being, and depressivity/anxiety, representing negative affect, which we deemed likely to have been affected by the pandemic lockdown. We measured life satisfaction at each wave with an 11-point Likert scale item adapted from the Socio-Economic Panel (SOEP; see Richter et al., 2017): "How satisfied are you with your life, all things considered?" (0 = *completely* *dissatisfied*, 10 = *completely satisfied*). This single-item measure has been shown to perform very similarly to longer scales in terms of criterion validity (Cheung & Lucas, 2014; Lucas & Donnellan, 2012). We used the four-item screening tool Patient Health Questionnaire for Depression and Anxiety (PHQ–4; Kroenke et al., 2009; Löwe et al., 2010) to assess depressivity and generalized anxiety symptoms at each wave. We asked "Over the last week, how often have you been bothered by any of the following problems?" The four items "Little interest or pleasure in doing things", "Feeling down, depressed, or hopeless", "Feeling nervous, anxious, or on edge", and "Not being able to stop or control worrying" were each answered on a 4-point scale (1 = *not at all*, 2 = *several days*, 3 = *more than half the days*, 4 = *nearly every day*). Internal consistency was high, $\omega = 0.81$. A raw correlation plot of the constructs analyzed is shown in Figure S1.

6.2.5 Analytical Strategy

As preregistered, we winsorized outliers with scores outside $M \pm 3 \times SD$ to the respective upper or lower bound. This procedure was used for eleven observations of depressivity/anxiety, eight observations of social anxiety, two and five observations of personal and indirect contact frequency, respectively.

We employed multilevel modeling (Hoffman, 2015) with observations (Level 1) nested in participants (Level 2). Intra-class correlations for all time-varying variables along with means and standard deviations over time can be found in Table S1. All models were estimated using maximum likelihood with random intercepts. We included random slopes of the Level 1 predictors of interest in those instances where likelihood ratio tests indicated that the addition of the random slope significantly improved model fit (Hoffman & Walters, 2022). If this was the case, we report the results of the random slope model herein and of the fixed slope model in the Supplemental Material (Tables S2–S6), and vice versa. As Level 2 variables, all social traits were grand-mean centered and, thus, represent the between-person effect of deviation from the average trait level in the sample. To test our hypotheses, we estimated two different types of models. First, to predict personal and indirect contact frequency (H1a, H1b), we estimated models with a cross-level interaction of time (linear effect, zero at the first wave) and each trait:

$$contact_{ti} = \gamma_{00} + \gamma_{01} trait_i + \gamma_{10} time_{ti} + \gamma_{11} time_{ti} trait_i + \upsilon_{0i} + e_{ti} \,,$$

where at time t for person i $e_{ti} \sim N(0, \sigma_e^2)$ and $\upsilon_{ti} \sim N(0, \tau_{00})$ (for a fixed slope model). We estimated separate models for the two dependent variables personal and indirect contact and each of the four traits, extraversion, affiliation motive, need to be alone, and social anxiety.

Second, we predicted variation in well-being over time (life satisfaction and depressivity/anxiety) with contact frequency as a time-varying predictor (either personal or indirect contact) and each social trait as a Level 2 predictor (person level):

$$wellbeing_{ti} = \gamma_{00} + \gamma_{01}trait_i + \gamma_{02}contactBP_i + \gamma_{03}trait_i contactBP_i + \gamma_{10}time_{ti} + \gamma_{20}contactWP_{ti} + \gamma_{21}trait_i contactWP_{ti} + v_{0i} + e_{ti} \,,$$

where $e_{ti} \sim N(0, \sigma_e^2)$ and $v_{ti} \sim N(0, \tau_{00})$ (for a fixed slope model). We included *time* as a linear predictor centered at the first assessment wave to detrend the effects (Wang & Maxwell, 2015). Contact was centered on the person-specific baseline (T1) to distinguish between-person from within-person variation in contact (Hoffman, 2015, 2020): With baseline-centering, the between-person component ($contactBP_i$) was each person's contact frequency at the first assessment, from which the grand mean was subtracted. The within-person component ($contactWP_{ti}$) was the baseline-centered contact frequency, that is, a person's contact frequency at each wave, from which their contact frequency at the first wave was subtracted. Thus, $contactWP_{ti}$ represented the within-person effect of a higher contact frequency at that wave than at the first wave. To test H2a and H2b, we estimated a cross-level interaction between contact frequency (personal or indirect) and each social trait ($trait_i contactWP_{ti}$).

To probe significant cross-level interactions, we utilized simple-slopes plots at conditional values and regions-of-significance plots via the Johnson-Neyman technique (McCabe et al., 2018; Preacher et al., 2006). To compare the models' predictive power, we computed R^2 for the proportion of total variance explained by the model fixed effects (Hoffman, 2015), which is the squared Pearson correlation between the actual outcome and the outcome predicted by the model fixed effects. To gauge how robust the multilevel models were to violated assumptions regarding multivariate normality and contamination by outliers, we re-estimated all models with robust linear mixed-effects models (see Supplemental Material and Tables S7 to S11; Koller, 2016).

We used R (Version 4.0.4; R Core Team, 2020) and the R-packages *lme4* (Version 1.1.26; Bates et al., 2015), and *lmerTest* (Version 3.1.3; Kuznetsova et al., 2017) for multilevel modeling, as well as *tidyverse* (Wickham, Averick, Bryan, Chang, McGowan, François, et al., 2019) for data wrangling, and *papaja* (Aust & Barth, 2020) for reproducible manuscript production. A complete list of software we used and full model equations are provided in the Supplemental Material.

6.3 Results

6.3.1 Social Contact

At the first assessment, that is, when shops, restaurants, and schools were closed and people were only allowed to meet with one other person, participants reported on average less frequent personal contact, $\hat{\gamma}_{00} = 1.82$, 95% CI $[1.71, 1.93]$, than indirect contact, $\hat{\gamma}_{00} = 2.30$, 95% CI $[2.21, 2.39]$. Notably, social traits were not associated with personal contact during the week of the strictest contact restrictions but predicted the level of indirect contact at this time (see Table 6.1): with higher extraversion, $\hat{\gamma}_{01} = 0.39$, 95% CI $[0.26, 0.52]$, higher affiliation motive, $\hat{\gamma}_{01} = 0.26$, 95% CI $[0.17, 0.36]$, or lower social anxiety, $\hat{\gamma}_{01} = -0.16$, 95% CI $[-0.29, -0.04]$, people reported more frequent indirect contact at the first assessment during the strictest contact restrictions.

As restrictions were eased over time, personal contact frequency rose, $\hat{\gamma}_{10} = 0.14$, 95% CI $[0.11, 0.18]$, while indirect contact frequency decreased, $\hat{\gamma}_{10} = -0.06$, 95% CI $[-0.08, -0.03]$ (see Table 6.1). Partly supporting H1a, social traits moderated changes in social contact over time: With higher extraversion, decreases in indirect contact frequency were more pronounced, $\hat{\gamma}_{11} = -0.04$, 95% CI $[-0.07, -0.01]$ (see Figures 6.2a and 6.2b). The regions-of-significance analysis reveals that this interaction was significant for values of extraversion above 2.33 (i.e., above -0.70 for the centered variable). In addition, with a higher affiliation motive, the increase in personal contact frequency was more pronounced, $\hat{\gamma}_{11} = 0.04$, 95% CI $[0.00, 0.07]$. This interaction was significant for values of affiliation motive above 1.28 (i.e., above -1.95 for the centered variable), nearly the complete range of observed values (see Figures 6.2c and 6.2d). In partial support of H1b, with a higher need to be alone, increases in personal contact frequency were less pronounced, $\hat{\gamma}_{11} = -0.05$, 95% CI $[-0.08, -0.01]$ (see Table 6.1 and Figures 6.2e and 6.2f). This interaction was significant for the whole range of observed values in the need to be alone. We did not observe social anxiety to be related to rates of change in personal or indirect social contact.

Table 6.1

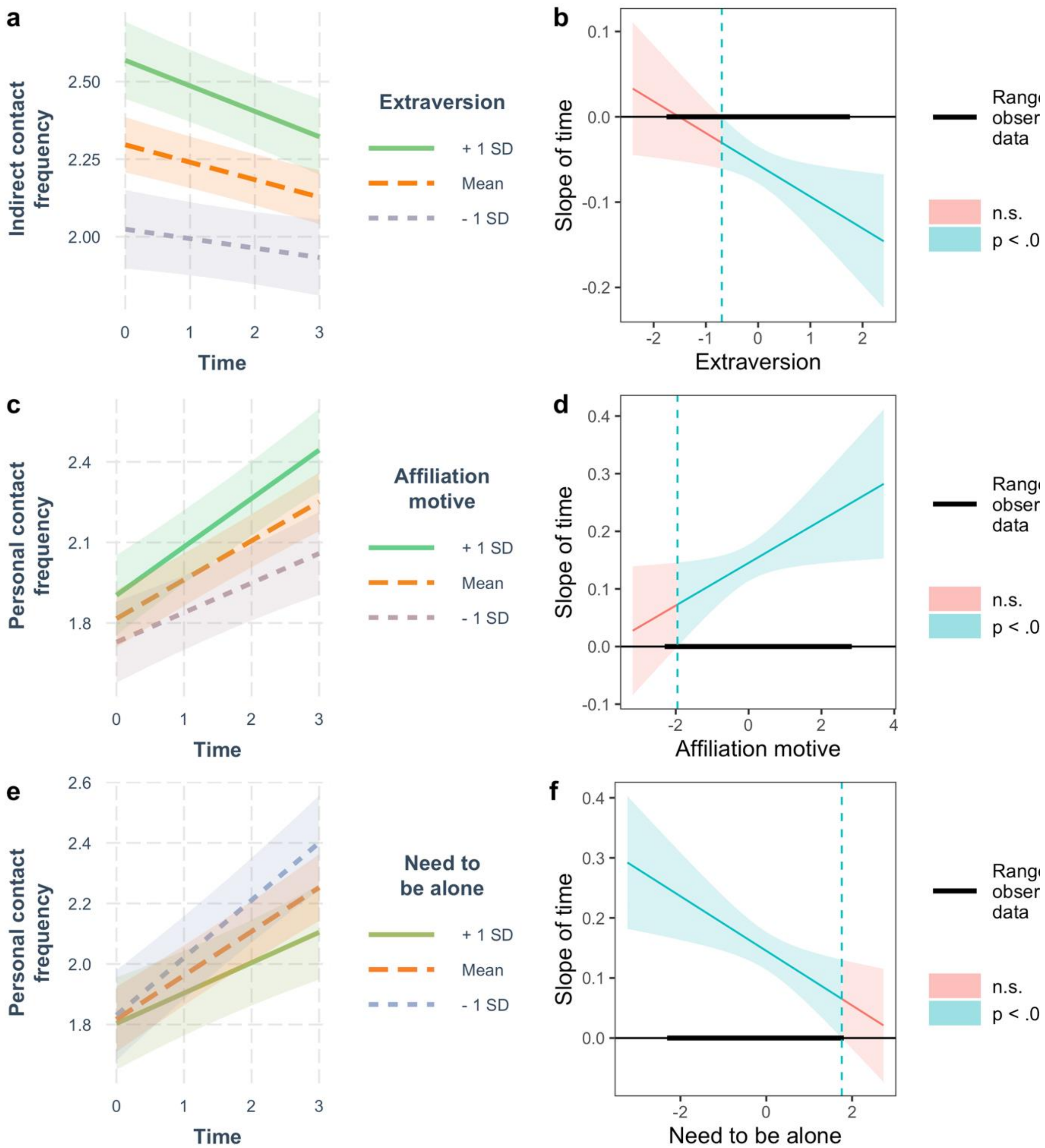
Fixed Effects of Social Contact Frequency Predicted by Time and Social Traits

	Personal contact				Indirect contact			
Parameter	$\hat{\gamma}$	95% CI	t	p	$\hat{\gamma}$	95% CI	t	p
Extraversion (M1a, M1b)								
Intercept, $\hat{\gamma}_{00}$	1.82	[1.71, 1.93]	32.87	< .001	2.30	[2.21, 2.39]	50.59	< .001
Time, $\hat{\gamma}_{10}$	0.14	[0.11, 0.18]	8.94	< .001	-0.06	[-0.08, -0.03]	-5.11	< .001
Extraversion, $\hat{\gamma}_{01}$	0.05	[-0.11, 0.20]	0.59	.557	0.39	[0.26, 0.52]	6.02	< .001
Time * Extraversion, $\hat{\gamma}_{11}$	0.01	[-0.03, 0.06]	0.51	.611	-0.04	[-0.07, -0.01]	-2.34	.020
Affiliation motive (M2a, M2b)								
Intercept, $\hat{\gamma}_{00}$	1.82	[1.71, 1.92]	33.39	< .001	2.30	[2.21, 2.39]	49.92	< .001
Time, $\hat{\gamma}_{10}$	0.15	[0.11, 0.18]	9.01	< .001	-0.06	[-0.08, -0.03]	-5.03	< .001
Affiliation motive, $\hat{\gamma}_{01}$	0.09	[-0.02, 0.20]	1.63	.105	0.26	[0.17, 0.36]	5.49	< .001
Time * Affiliation motive, $\hat{\gamma}_{11}$	0.04	[0.00, 0.07]	2.15	.032	-0.01	[-0.03, 0.01]	-0.80	.425
Need to be alone (M3a, M3b)								
Intercept, $\hat{\gamma}_{00}$	1.82	[1.71, 1.92]	33.10	< .001	2.30	[2.20, 2.40]	46.83	< .001
Time, $\hat{\gamma}_{10}$	0.15	[0.11, 0.18]	9.02	< .001	-0.06	[-0.08, -0.03]	-5.03	< .001
Need to be alone, $\hat{\gamma}_{01}$	-0.01	[-0.12, 0.09]	-0.25	.799	-0.09	[-0.19, 0.00]	-1.86	.064
Time * Need to be alone, $\hat{\gamma}_{11}$	-0.05	[-0.08, -0.01]	-2.73	.006	0.00	[-0.03, 0.02]	-0.39	.695
Social anxiety (M4a, M4b)								
Intercept, $\hat{\gamma}_{00}$	1.82	[1.71, 1.93]	32.87	< .001	2.30	[2.21, 2.40]	47.25	< .001
Time, $\hat{\gamma}_{10}$	0.14	[0.11, 0.18]	8.94	< .001	-0.06	[-0.08, -0.03]	-5.08	< .001
Social anxiety, $\hat{\gamma}_{01}$	0.01	[-0.13, 0.15]	0.16	.876	-0.16	[-0.29, -0.04]	-2.53	.012
Time * Social anxiety, $\hat{\gamma}_{11}$	-0.04	[-0.08, 0.01]	-1.71	.088	0.02	[-0.01, 0.05]	1.09	.277

Note. Two models were computed for each social trait: as predictors of personal contact frequency (models MXa) and of indirect contact frequency (models MXb). Models MXb feature random slopes of time. CI = confidence interval. $R^2_{M1a} = 0.04$, $R^2_{M1b} = 0.13$, $R^2_{M2a} = 0.07$, $R^2_{M2b} = 0.13$, $R^2_{M3a} = 0.05$, $R^2_{M3b} = 0.03$, $R^2_{M4a} = 0.04$, $R^2_{M4b} = 0.04$.

Figure 6.2

Simple-slopes Plots (a, c, e) and Neyman-Johnson regions-of-significance Plots (b, d, f) for Significant Cross-level Interaction Effects Predicting Contact Frequency



Note. Confidence bands represent 95% confidence intervals. Variables presented on the X-axis (b, d, f) are grand-mean centered; original scale values can be computed by adding the mean of the respective variable reported in Table S1.

The practical significance and size of the effects can be inferred from the scaling of personal contact on the y-axis in Figure 6.2. For example, in Figure 6.2c, participants low (-1 SD) and high (+1 SD) in affiliation motive reported roughly the same amount of personal contact at the first assessment, which was a little less than "once" during the last week (corresponding to 2 on the 5-point scale). At the last assessment, participants low in affiliation motive reported on average 0.33 scale points more personal contact just passing 2 on the 5-point scale (i.e, "once" during the last week). In contrast, participants high in affiliation motive reported 0.54 higher personal contact, which corresponded to 2.44 on the 5-point scale (i.e., in between "once" and "multiple days" during the last week).

6.3.2 Well-Being

Over time, life satisfaction declined linearly, $\hat{\gamma}_{10} = -0.11$, 95% CI $[-0.20, -0.03]$, whereas depressivity/anxiety remained stable on average (see Tables 6.2 to 6.5). During strict contact restrictions at the first assessment, life satisfaction was higher with higher extraversion, $\hat{\gamma}_{01} = 1.18$, 95% CI $[0.76, 1.60]$, higher affiliation motive, $\hat{\gamma}_{01} = 0.40$, 95% CI $[0.08, 0.73]$, and lower social anxiety, $\hat{\gamma}_{01} = -0.85$, 95% CI $[-1.22, -0.47]$. At the same time, the lower the participants' extraversion, $\hat{\gamma}_{01} = -0.26$, 95% CI $[-0.38, -0.15]$, and the higher their social anxiety, $\hat{\gamma}_{01} = 0.38$, 95% CI $[0.29, 0.47]$, the higher their depressivity/anxiety. More frequent initial personal and indirect contact (i.e., between-person differences at T1) was associated with higher life satisfaction, although these effects were significant in only five out of eight models (see Tables 6.2 to 6.5).

Having more indirect contact as compared to the baseline (i.e., during the strictest contact restrictions) was associated with higher life satisfaction for people with a higher affiliation motive, $\hat{\gamma}_{21} = 0.41$, 95% CI $[0.07, 0.74]$ (see Table 6.3). As Figures 6.3a and 6.3b show, life satisfaction increased with more frequent indirect contact for those with a higher affiliation motive, whereas it decreased for those with a lower affiliation motive. The regions-of-significance plot shows that the within-person association between indirect contact and life satisfaction was significant for values of affiliation motive below 2.26 (i.e., below -0.97 for the centered variable) and above 5.18 (i.e., above 1.95 for the centered variable), albeit in opposite directions. Although non-significant at p = .050, we found a similar pattern for the cross-level interaction of affiliation motive and more frequent personal contact as compared to the baseline, which we present in Figure S2 for the sake of completeness.

Conversely, more frequent personal contact as compared to the first assessment was associated with higher life satisfaction for people with a lower need to be alone, $\hat{\gamma}_{21} = -0.20$, 95% CI $[-0.39, -0.02]$ (see Table 6.4 and Figures 6.3c and 6.3d), the slope being significant for people scoring below 5.15 (i.e., below -0.10 for the centered variable) in the need to be alone. Participants' depressivity/anxiety increased with more frequent personal or indirect contact as compared to the baseline among people higher in social anxiety, $\hat{\gamma}_{21} = 0.08$, 95% CI $[0.00, 0.15]$, $\hat{\gamma}_{21} = 0.14$, 95% CI $[0.00, 0.27]$ (see Table 6.5). Figures 6.3e to 6.3h emphasize the nature of these associations via simple-slopes and regions-of-significance plots: More frequent social contact than at the first wave was associated with higher depressivity/anxiety among people higher in social anxiety (above 3.23 in social anxiety for personal contact, i.e., above 1.47 for the centered variable; and above 3.78 for indirect contact, i.e., above 2.02 for the centered variable).

Overall, we found partial empirical support for H2a and H2b such that affiliation motive, need to be alone, and social anxiety moderated the effects of increased social contact on well-being over the course of our study as contact restrictions were being eased.

6.3.3 Exploratory Analyses

Following an anonymous reviewer's suggestion to investigate overlap between the social trait constructs, we specified multilevel structural equation models in *Mplus* (Muthén & Muthén, 2019, Version 8.4), in which a latent social trait factor moderated the effects of time and of social contact. This latent factor represented the shared variance of the four social traits. The exploratory analyses suggested significant moderation of the resumption of personal contact by the latent social trait factor (see Table S12). For predicting well-being changes, we did not find significant moderation of the effects of increased contact by the latent social trait factor (see Table S13). This could indicate that the effects for well-being reported in the main manuscript are specific to each social trait.

Table 6.2

Fixed Effects of Well-Being Predicted by Time, Contact Frequencies, and Extraversion

	Life satisfaction				Depressivity/anxiety			
Parameter	$\hat{\gamma}$	95% CI	t	p	$\hat{\gamma}$	95% CI	t	p
Personal contact frequency (M1a, M1b)								
Intercept, $\hat{\gamma}_{00}$	6.72	[6.41, 7.03]	42.72	< .001	1.66	[1.57, 1.75]	38.07	< .001
Time, $\hat{\gamma}_{10}$	-0.11	[-0.20, -0.03]	-2.56	.011	0.00	[-0.03, 0.02]	-0.36	.717
Personal contact (BP), $\hat{\gamma}_{02}$	0.33	[-0.04, 0.70]	1.77	.078	-0.02	[-0.12, 0.09]	-0.31	.756
Personal contact (WP), $\hat{\gamma}_{20}$	0.19	[-0.02, 0.40]	1.81	.071	0.01	[-0.05, 0.06]	0.24	.810
Extraversion, $\hat{\gamma}_{01}$	1.18	[0.76, 1.60]	5.56	.001	-0.26	[-0.38, -0.15]	-4.50	< .001
Personal contact (BP) * Extraversion, $\hat{\gamma}_{03}$	-0.05	[-0.59, 0.49]	-0.19	.847	0.01	[-0.14, 0.16]	0.12	.901
Personal contact (WP) * Extraversion, $\hat{\gamma}_{21}$	-0.03	[-0.30, 0.24]	-0.21	.830	-0.02	[-0.10, 0.05]	-0.63	.530
Indirect contact frequency (M2a, M2b)								
Intercept, $\hat{\gamma}_{00}$	6.68	[6.36, 7.00]	40.78	< .001	1.66	[1.57, 1.74]	38.19	< .001
Time, $\hat{\gamma}_{10}$	-0.08	[-0.17, 0.00]	-1.99	.047	-0.01	[-0.03, 0.02]	-0.55	.583
Indirect contact (BP), $\hat{\gamma}_{02}$	0.22	[-0.22, 0.67]	0.98	.329	0.13	[0.01, 0.25]	2.12	.035
Indirect contact (WP), $\hat{\gamma}_{20}$	-0.06	[-0.41, 0.29]	-0.35	.730	0.03	[-0.09, 0.14]	0.46	.645
Extraversion, $\hat{\gamma}_{01}$	1.17	[0.73, 1.61]	5.21	< .001	-0.32	[-0.44, -0.20]	-5.31	< .001
Indirect contact (BP) * Extraversion, $\hat{\gamma}_{03}$	-0.27	[-0.85, 0.32]	-0.90	.368	-0.04	[-0.19, 0.12]	-0.49	.628
Indirect contact (WP) * Extraversion, $\hat{\gamma}_{21}$	0.20	[-0.22, 0.63]	0.94	.350	-0.07	[-0.22, 0.08]	-0.95	.343

Note. Two models were computed for each personal and indirect contact frequency: predicting life satisfaction (models MXa) and depressivity/anxiety (models MXb). Model M2b features a random slope of within-person contact. CI = confidence interval; BP = between-person effect; WP = within-person effect. $R^2_{M1a} = 0.14$, $R^2_{M1b} = 0.08$, $R^2_{M2a} = 0.13$, $R^2_{M2b} = 0.10$.

Table 6.3

Fixed Effects of Well-Being Predicted by Time, Contact Frequencies, and Affiliation Motive

	Life satisfaction				Depressivity/anxiety			
Parameter	$\hat{\gamma}$	95% CI	t	p	$\hat{\gamma}$	95% CI	t	p
Personal contact frequency (M1a, M1b)								
Intercept, $\hat{\gamma}_{00}$	6.71	[6.38, 7.04]	39.95	< .001	1.66	[1.57, 1.75]	35.89	< .001
Time, $\hat{\gamma}_{10}$	-0.11	[-0.20, -0.03]	-2.59	.010	0.00	[-0.03, 0.02]	-0.33	.744
Personal contact (BP), $\hat{\gamma}_{02}$	0.31	[-0.09, 0.71]	1.53	.128	-0.02	[-0.13, 0.09]	-0.36	.720
Personal contact (WP), $\hat{\gamma}_{20}$	0.15	[-0.06, 0.36]	1.35	.176	0.01	[-0.05, 0.07]	0.38	.707
Affiliation motive, $\hat{\gamma}_{01}$	0.40	[0.08, 0.73]	2.43	.016	-0.05	[-0.14, 0.04]	-1.08	.280
Personal contact (BP) * Affiliation motive, $\hat{\gamma}_{03}$	0.12	[-0.31, 0.54]	0.53	.596	-0.02	[-0.13, 0.10]	-0.29	.774
Personal contact (WP) * Affiliation motive, $\hat{\gamma}_{21}$	0.22	[0.00, 0.43]	1.96	.050	-0.02	[-0.08, 0.04]	-0.70	.481
Indirect contact frequency (M2a, M2b)								
Intercept, $\hat{\gamma}_{00}$	6.68	[6.35, 7.01]	39.85	< .001	1.66	[1.57, 1.75]	36.42	< .001
Time, $\hat{\gamma}_{10}$	-0.09	[-0.17, -0.01]	-2.13	.034	-0.01	[-0.03, 0.02]	0.50	.619
Indirect contact (BP), $\hat{\gamma}_{02}$	0.48	[0.03, 0.94]	2.08	.039	0.03	[-0.10, 0.15]	0.45	.652
Indirect contact (WP), $\hat{\gamma}_{20}$	-0.14	[-0.49, 0.21]	-0.79	.432	0.02	[-0.09, 0.14]	0.39	.700
Affiliation motive, $\hat{\gamma}_{01}$	0.41	[0.08, 0.74]	2.46	.015	-0.06	[-0.15, 0.03]	-1.34	.183
Indirect contact (BP) * Affiliation motive, $\hat{\gamma}_{03}$	-0.29	[-0.70, 0.13]	-1.36	.175	-0.01	[-0.13, 0.10]	-0.21	.830
Indirect contact (WP) * Affiliation motive, $\hat{\gamma}_{21}$	0.41	[0.07, 0.74]	2.39	.017	-0.04	[-0.16, 0.07]	-0.72	.476

Note. Two models were computed for each personal and indirect contact frequency: predicting life satisfaction (models MXa) and depressivity/anxiety (models MXb). Model M2b features a random slope of within-person contact. CI = confidence interval; BP = between-person effect; WP = within-person effect. $R^2_{M1a} = 0.06$, $R^2_{M1b} = 0.01$, $R^2_{M2a} = 0.08$, $R^2_{M2b} = 0.01$.

Table 6.4

Fixed Effects of Well-Being Predicted by Time, Contact Frequencies, and Need to be Alone

	Life satisfaction				Depressivity/anxiety			
Parameter	$\hat{\gamma}$	95% CI	t	p	$\hat{\gamma}$	95% CI	t	p
Personal contact frequency (M1a, M1b)								
Intercept, $\hat{\gamma}_{00}$	6.75	[6.42, 7.07]	40.64	< .001	1.65	[1.57, 1.74]	36.60	< .001
Time, $\hat{\gamma}_{10}$	-0.12	[-0.21, -0.04]	-2.80	.005	0.00	[-0.03, 0.02]	-0.23	.816
Personal contact (BP), $\hat{\gamma}_{02}$	0.42	[0.03, 0.80]	2.11	.037	-0.04	[-0.14, 0.07]	-0.66	.513
Personal contact (WP), $\hat{\gamma}_{20}$	0.19	[-0.02, 0.40]	1.77	.077	0.01	[-0.05, 0.06]	0.21	.836
Need to be alone, $\hat{\gamma}_{01}$	0.28	[-0.03, 0.58]	1.75	.082	-0.04	[-0.13, 0.04]	-1.05	.295
Personal contact (BP) * Need to be alone, $\hat{\gamma}_{03}$	-0.26	[-0.70, 0.18]	-1.15	.252	0.08	[-0.04, 0.20]	1.26	.210
Personal contact (WP) * Need to be alone, $\hat{\gamma}_{21}$	-0.20	[-0.39, -0.02]	-2.17	.030	0.02	[-0.03, 0.07]	0.67	.502
Indirect contact frequency (M2a, M2b)								
Intercept, $\hat{\gamma}_{00}$	6.61	[6.29, 6.93]	40.68	< .001	1.66	[1.57, 1.74]	37.85	< .001
Time, $\hat{\gamma}_{10}$	-0.09	[-0.17, -0.01]	-2.08	.038	-0.01	[-0.03, 0.02]	-0.52	.602
Indirect contact (BP), $\hat{\gamma}_{02}$	0.71	[0.27, 1.14]	3.20	.002	-0.01	[-0.13, 0.11]	-0.15	.877
Indirect contact (WP), $\hat{\gamma}_{20}$	-0.01	[-0.35, 0.33]	-0.04	.965	0.01	[-0.11, 0.13]	0.19	.848
Need to be alone, $\hat{\gamma}_{01}$	0.29	[-0.03, 0.60]	1.80	.074	-0.05	[-0.14, 0.03]	-1.20	.231
Indirect contact (BP) * Need to be alone, $\hat{\gamma}_{03}$	0.07	[-0.36, 0.50]	0.32	.751	-0.02	[-0.13, 0.10]	-0.30	.767
Indirect contact (WP) * Need to be alone, $\hat{\gamma}_{21}$	-0.18	[-0.49, 0.14]	-1.10	.270	-0.01	[-0.13, 0.10]	-0.24	.808

Note. Two models were computed for each personal and indirect contact frequency: predicting life satisfaction (models MXa) and depressivity/anxiety (models MXb). Model M2b features a random slope of within-person contact. CI = confidence interval; BP = between-person effect; WP = within-person effect. $R^2_{M1a} = 0.04$, $R^2_{M1b} = 0.02$, $R^2_{M2a} = 0.06$, $R^2_{M2b} = 0.01$.

Table 6.5

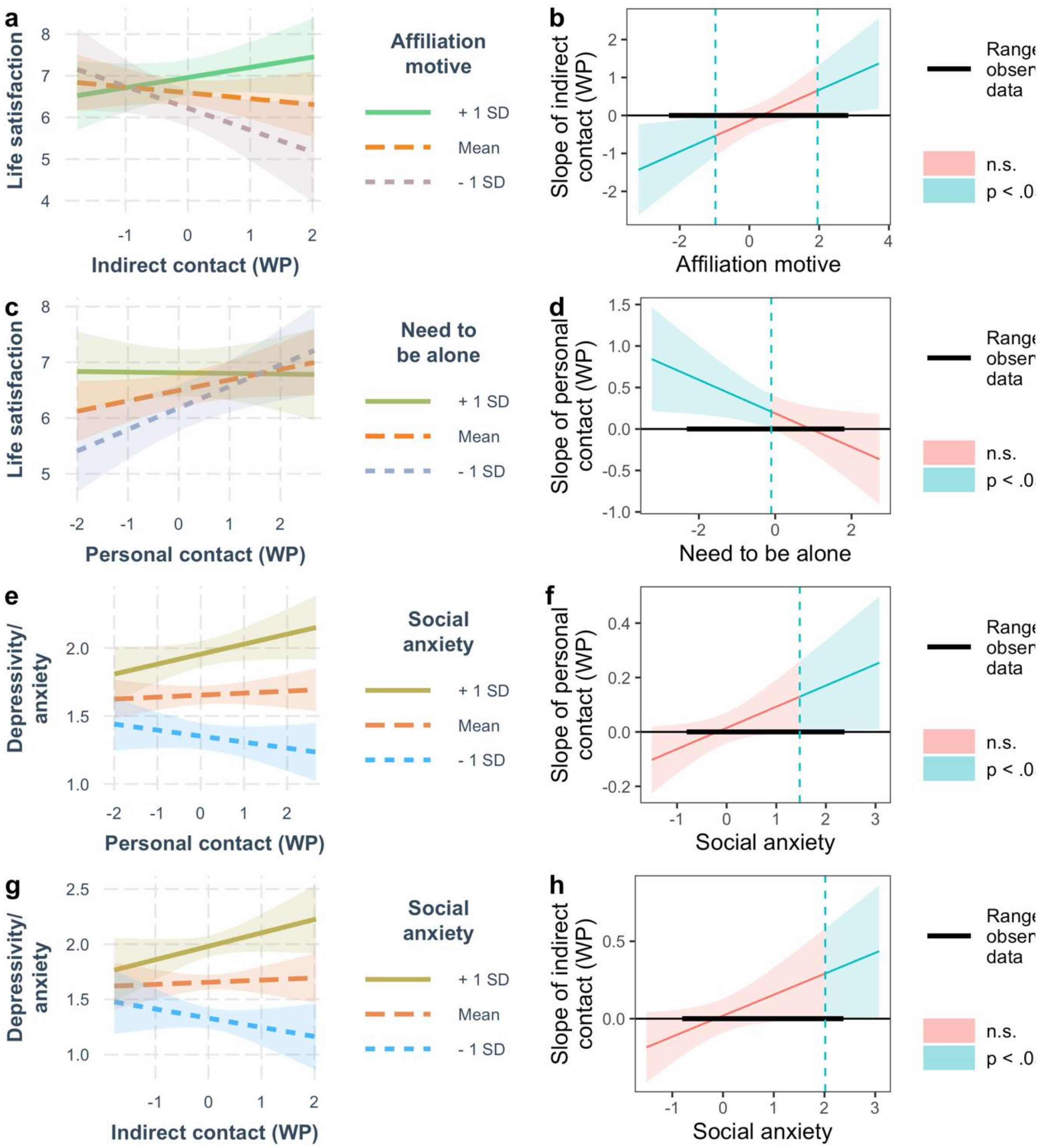
Fixed Effects of Well-Being Predicted by Time, Contact Frequencies, and Social Anxiety

	Life satisfaction				Depressivity/anxiety			
Parameter	$\hat{\gamma}$	95% CI	t	p	$\hat{\gamma}$	95% CI	t	p
Personal contact frequency (M1a, M1b)								
Intercept, $\hat{\gamma}_{00}$	6.76	[6.45, 7.07]	42.89	< .001	1.65	[1.57, 1.73]	42.23	< .001
Time, $\hat{\gamma}_{10}$	-0.11	[-0.20, -0.03]	-2.57	.011	0.00	[-0.03, 0.02]	-0.27	.786
Personal contact (BP), $\hat{\gamma}_{02}$	0.48	[0.11, 0.85]	2.54	.012	-0.05	[-0.14, 0.04]	-1.04	.299
Personal contact (WP), $\hat{\gamma}_{20}$	0.18	[-0.02, 0.39]	1.73	.085	0.01	[-0.04, 0.07]	0.51	.613
Social anxiety, $\hat{\gamma}_{01}$	-0.85	[-1.22, -0.47]	-4.37	.001	0.38	[0.29, 0.47]	8.07	.001
Personal contact (BP) * Social anxiety, $\hat{\gamma}_{03}$	0.62	[0.08, 1.16]	2.27	.024	-0.11	[-0.24, 0.02]	-1.67	.097
Personal contact (WP) * Social anxiety, $\hat{\gamma}_{21}$	0.07	[-0.20, 0.35]	0.52	.602	0.08	[0.00, 0.15]	2.02	.044
Indirect contact frequency (M2a, M2b)								
Intercept, $\hat{\gamma}_{00}$	6.65	[6.34, 6.96]	42.07	< .001	1.66	[1.58, 1.73]	44.18	< .001
Time, $\hat{\gamma}_{10}$	-0.09	[-0.17, -0.01]	-2.09	.037	-0.01	[-0.03, 0.02]	-0.44	.660
Indirect contact (BP), $\hat{\gamma}_{02}$	0.50	[0.08, 0.92]	2.34	.020	0.08	[-0.02, 0.18]	1.60	.112
Indirect contact (WP), $\hat{\gamma}_{20}$	0.00	[-0.34, 0.33]	-0.03	.978	0.02	[-0.09, 0.13]	0.35	.731
Social anxiety, $\hat{\gamma}_{01}$	-0.86	[-1.24, -0.48]	-4.49	< .001	0.43	[0.34, 0.51]	9.42	< .001
Indirect contact (BP) * Social anxiety, $\hat{\gamma}_{03}$	0.27	[-0.28, 0.83]	0.97	.331	0.07	[-0.05, 0.20]	1.15	.252
Indirect contact (WP) * Social anxiety, $\hat{\gamma}_{21}$	0.14	[-0.28, 0.55]	0.65	.519	0.14	[0.00, 0.27]	2.00	.048

Note. Two models were computed for each personal and indirect contact frequency: predicting life satisfaction (models MXa) and depressivity/anxiety (models MXb). Model M2b features a random slope of within-person contact. CI = confidence interval; BP = between-person effect; WP = within-person effect. $R^2_{M1a} = 0.12$, $R^2_{M1b} = 0.23$, $R^2_{M2a} = 0.11$, $R^2_{M2b} = 0.23$.

Figure 6.3

Simple-slopes Plots (a, c, e, g) and Neyman-Johnson regions-of-significance Plots (b, d, f, h) for Significant Cross-level Interaction Effects Predicting Well-being



Note. Confidence bands represent 95% confidence intervals. Variables presented on the X-axis (b, d, f, h) are grand-mean centered; original scale values can be computed by adding the mean of the respective variable reported in Table S1.

6.4 Discussion

Based on the assumption that people differ in the need to maintain social relationships (Hall & Davis, 2017; Nezlek, 2001; Sheldon, 2011), we investigated how four social traits predicted changes in both contact frequency and well-being during successively eased contact restrictions.

At the first assessment when personal contact was severely restricted (Aravindakshan et al., 2020; Becher et al., 2021; Bönisch et al., 2020; Del Fava et al., 2021; Tomori et al., 2021), only indirect but not personal contact varied with individual differences in social traits: Extraversion and affiliation motive were associated with more frequent indirect contact (Harari et al., 2020), and higher social anxiety with less frequent indirect contact. These results are especially noteworthy given robust associations between higher extraversion or affiliation motive and more frequent social contact under unrestricted circumstances (Breil et al., 2019; Hall, 2017; Wrzus et al., 2016). The difference between personal and indirect contact further suggests that governmental contact restrictions created a strong situation overriding individual differences (Cooper & Withey, 2009). As restrictions were eased, social traits predicted the resumption of personal contact. People with a higher affiliation motive increased their personal contact more, whereas people with a higher need to be alone increased their personal contact less. This supports our preregistered hypotheses and theoretical considerations of social need regulation (Hall & Davis, 2017; Sheldon, 2011): People experienced contact restrictions—on average—as deviations from their ideal level of social contact (Entringer & Gosling, 2021). With increasing situational opportunities to pursue their social needs, people resumed personal contact. The intensity of this increase varied depending on people's affiliation motive and need to be alone. Likewise, recent studies have found personality traits to be associated with differences in self-reported pandemic precautions and adherence to governmental contact restrictions (Aschwanden et al., 2021; Götz et al., 2021; Zajenkowski et al., 2020; Zettler et al., 2022).

The results for well-being offer further insights into how social traits shape the response to this strong situation: Well-being was still higher with higher extraversion when social contact was severely restricted during lockdown, yet extraverts' well-being did not benefit more from resumed social activity. This is in line with research that extraverts' higher well-being is due primarily to the energy level facet and not to being more active socially (Anglim et al., 2020; Lucas et al., 2008; Margolis et al., 2020). Instead, differences in affiliation motive, need to be alone, and social anxiety moderated how well-being changed with increased contact: As predicted, more frequent indirect or personal contact compared to the first assessment during strict contact restrictions was associated with higher life satisfaction among people with a higher affiliation motive or a lower need to be alone, respectively—in line with previous research on romantic relationships (Zygar et al., 2018). In addition, people high in social anxiety increased in depressivity/anxiety as their social contact increased. Possibly, unwanted social contact amid an ongoing pandemic increased worries and fears among socially anxious people (Brown et al., 2007; Olivera-La Rosa et al., 2020). Results for indirect contact further emphasize the importance of individual differences in social need regulation: Affiliation motive and social anxiety moderated effects of changes in indirect contact frequency on well-being. This could explain divergent results on the role of digital technologies regarding well-being and coping with COVID-19-related distress (Boursier et al., 2020; Gabbiadini et al., 2020). The moderating effects of social traits on well-being, however, only occurred with certain trait manifestations (see Figure 6.3) and, thus, warrant further investigation. It is possible that the regulation of life satisfaction, a cognitive component of well-being, is more closely linked to affiliation motive and need to be alone, whereas the regulation of depressivity/anxiety, an affective component of well-being, is linked to social anxiety.

Together, these results provide novel, real-life evidence of differential regulation of social needs (Hall & Davis, 2017; McClelland, 1987) under unique nationwide external constraints on social contact that would not be possible in laboratory experiments or in observational studies under regular circumstances. After initial social deprivation during strict contact restrictions, people resumed personal contact to differing degrees, and increases in social contact were differentially associated with changes in well-being—with both effects depending on people's social traits.

6.4.1 Limitations

Despite following an age- and gender-stratified sample longitudinally during governmental contact restrictions, some limitations need to be addressed. First, we did not measure participants' pre-pandemic traits, contact frequency, and well-being. We assume that personal contact was at a nadir in Germany in early April 2020 (see mobility and social contact survey data, Becher et al., 2021; Bönisch et al., 2020; Del Fava et al., 2021; Tomori et al., 2021) and social need satisfaction thwarted at the first measurement. Relatedly, we assessed experiences during the previous week instead of moment to moment. Combined with an average time lag of 22 days between assessments, our design may have missed more short-term fluctuations in social contact and well-being as well as reciprocal links. For example, unmet social needs presumably reduce well-being within the next hours, and low well-being likely initiates seeking social contact (Zygar et al., 2018). Instead, the present study's timing and reference frame of contact measurements allowed for an examination of a particular person-situation interaction, with changes to the strong situation unfolding over the course of weeks.

Second, more culturally diverse samples would have allowed us to test effects of contact restrictions in different countries. Given previous cross-cultural work on social relationships and need satisfaction (Chen et al., 2015; Tay & Diener, 2011), however, we assume that the current results generalize relatively broadly to cultures other than Germany, when they underwent similar contact restrictions. Third, we focused on life satisfaction and depressivity/anxiety, yet did not measure positive affect, which was also affected in the COVID-19 pandemic (e.g., Anglim & Horwood, 2021; Lades et al., 2020), and is important to social need satisfaction (Tay & Diener, 2011).

Fourth, we cannot completely rule out nonrandom attrition over ime. Attrition analyses indicate differences in affiliation motive and indirect contact frequency between participants completing the study and those initially indicating interest in participating in follow-ups but not taking part in all waves. There are no meaningful differences if only attrition in the longitudinal analysis sample is considered. Still, attrition might have led us to underestimate effects involving affiliation motive and indirect contact frequency. Finally, relying on self-reports, our results are subject to common method bias (Podsakoff et al., 2003). Future studies could incorporate experience sampling and smartphone sensing data (Harari et al., 2020; Zygar et al., 2018), for which we expect similar results.

6.4.2 Conclusions

Our study demonstrates that social traits such as affiliation motive and need to be alone play an important role in the regulation of social contact. Experiencing a situation that imposed strict constraints on the expression of social traits, people nonetheless demonstrated trait differences in their levels of indirect contact and well-being. Afterwards—as the situation opened up—social traits moderated both the resumption of personal contact and changes in well-being associated with more frequent contact. This illuminates the regulation of social needs and also provides support to the theoretical assumption that social need satisfaction feels different depending on someone's traits. The COVID-19 pandemic has restricted many people in their satisfaction of social needs with little leeway to evade. Our study adds further evidence that the ways in which people react or adapt to this restricted situation differ depending on their personality traits, in this case their affiliation motive, need to be alone, and social anxiety.

Chapter 7: General Discussion

The aims of this dissertation were twofold: First, this dissertation compared different approaches to the measurement of social interactions, social traits, and environmental aspects central to social interaction dynamics. Second, this dissertation extended control theory models of social interaction regulation by incorporating aspects of the social opportunity structure, that is, situational affordances and the embeddedness of social interactions in larger contexts. To this end, the five chapters of this dissertation described findings from three studies with more than 1,000 adult participants sampled from a broad age range and diverse living circumstances.

Following the structure of the chapters in this dissertation, I will first discuss methodological implications before diving deeper into theoretical implications. Accordingly, the general discussion will start with key takeaways regarding the measurement of social interactions, social traits, and relevant context factors. Then, in the second part of the discussion, I will reflect on control theory approaches to social interaction regulation in light of the results of this dissertation and other recent research and discuss theoretical implications. Finally, in the future directions section, I discuss important topics relating to processes of social interaction regulation that were beyond the scope of this dissertation.

7.1 Methodological Implications

As demonstrated throughout this dissertation, daily life studies offer valuable insights into human functioning in real life (Wrzus & Mehl, 2015). Still, measuring complex within-person processes in changing contexts poses many challenges (Kuper et al., 2022; Roos et al., 2023; Yarkoni, 2022). Such measurement challenges were touched upon in all chapters of this dissertation and were the focus of Chapters 2 and 3. Further reflecting on previous chapters, I want to discuss two main methodological takeaways.

Firstly, repeated measurements of psychological states and social interactions on daily, hourly, or even finer time resolutions are essential to understanding short-term dynamic processes of social interactions and complement approaches using only aggregated (trait) measures. Still, carefully considering measurement spacing remains important, which will be further discussed in the *Measurement Spacing and Suitability for Hypotheses Testing* section below.

Secondly, there are numerous approaches to measuring social interactions, social traits, and relevant context factors surrounding social interactions. Although each method has unique limitations and benefits, there is considerable overlap in constructs, suggesting that a further harmonization of measurements is possible. While methodological diversity is in principle desired (Fiedler, 2017), this diversity could be even better leveraged by an increased focus on multi-method studies. Multi-method studies such as the ones described in this dissertation help to validate methods and to bridge between still in large parts separate research programs. Furthermore, multi-method studies protect against the inflation of content-based correlations due to common method variance (Huang et al., 2015; Shaw et al., 2020). In general, combining different methods to assess both objective (e.g., mobile sensing) and subjective aspects (introspective questionnaires) appears most promising (see also Struminskaya et al., 2020; Schoedel & Mehl, 2024).

7.1.1 Measurement Spacing and Suitability for Hypotheses Testing

For now, it remains unclear at what exact time frames different processes of the dynamic regulation of social interaction occur (Back et al., 2023; Wrzus, Roos, Krämer, Schoedel et al., 2024). Some first insights suggest that relatively high time resolution measurements are needed to understand these processes better. For example, a study that assessed the start and end of conversations or social interactions demonstrated that many interactions were rather short (e.g., shorter than an hour, Luo, Pauly et al., 2022). Yet, achieving such high time resolutions with traditional questionnaire measurements is difficult, mainly because of the disruptiveness of questionnaires and participant burden (Roos et al., 2023; Wrzus & Neubauer, 2022).

Despite these challenges, it is crucial to aim for a high time resolution to capture underlying processes accurately and to be able to choose appropriate aggregation windows (Langener et al., 2024). If the spacing of measurements is not tight enough, the signal frequency might be misidentified (i.e., aliasing might occur, Tukey & Hamming, 1949). According to the Nyquist-Shannon sampling theorem, the sampling frequency of discrete samples should be more than twice the frequency of the highest frequency component to capture the information from a continuous-time signal (Shannon, 1949; Voelkle & Oud, 2013). Applied to social interactions, this indicates that to accurately capture the fluctuations in social behavior or desires, measurements should be taken at intervals less than half the duration of the shortest social interaction a researcher is interested in. For instance, if the shortest meaningful social interaction lasts around 10 minutes, then according to the Nyquist-Shannon sampling theorem, measurements should be taken at least every 5 minutes to avoid aliasing.

Evidently, repeated experience sampling questions, when delivered according to a fixed sampling protocol, are unsuitable for achieving the necessary time resolution. In the previous chapters, we therefore used items with retrospective item content (e.g., asked participants to list social interactions that happened since the last measurement). One resulting challenge was the inability to extract the exact start and end times of social interactions, which would have been desirable for even more accurately estimating the time spent in social interactions.

An alternative to experience sampling with fixed sampling protocols could be event-contingent sampling. However, this method comes with its own drawbacks. Validation studies for comprehensive event-contingent sampling of social interactions are still largely missing (although some studies are moving in this direction, see Himmelstein et al., 2019; Stadel et al., 2024). Whereas with a fixed sampling protocol, researchers would know exactly how many questionnaires were missed, the number of missed social interactions in event-contingent sampling is still difficult to estimate without thorough validation studies. Consequently, it currently remains unclear how comprehensively event-contingent sampling assesses social interactions. Furthermore, a fixed sampling approach seems more suitable to also assess the states and circumstances that accompany solitude.

Another promising solution to achieve higher time resolutions is mobile sensing, which imposes less participant burden during data collection (Chapter 2). The chapters in this dissertation suggest that mobile sensing methods will continue to be a cornerstone in psychologists' toolkits, offering high-resolution access to exciting new data types. Some further developments are needed to address technical challenges and to measure more qualitative aspects of social interactions (Harari et al., 2020; Hebbar et al., 2021; Niemeijer et al., 2023; Roos et al., 2023). Still, to truly understand personality processes as they occur in daily life, fine-grained extensive assessments are necessary, making the advancement of mobile sensing methods a clear path forward (Harari et al., 2020; Schoedel & Mehl, 2024).

Further advancing mobile sensing methods might also help tremendously with another challenge daily life studies face: appropriate sample sizes. Overall, the inability of previous daily life studies to find expected interaction effects (e.g., Kuper et al., 2022) and arguments related to the generalizability of findings (Yarkoni, 2022) stress the importance of taking sample size considerations very seriously. We made considerable efforts to gather sizeable heterogenous samples for the studies described in this dissertation. Still, to capture interindividual differences in within-person processes, even bigger sample sizes might be needed. This is hardly possible for small research groups with limited funds using traditional experience sampling methods. Consequently, the sheer amount of data gained from mobile sensing or other methods (e.g., virtual or augmented reality) will enable further exploration of how various underutilized analytical advancements can be best applied to enhance our understanding of social interaction dynamics. Promising candidates are time-series analyses like the damped oscillator model (e.g., Bisconti et al., 2004; Chow et al., 2005), dynamic network models (Beck & Jackson, 2020; Epskamp, 2020), multilevel and multistate survival analysis (Elmer et al., 2023), or a diverse range of machine learning techniques (e.g., Beck & Jackson, 2022; Stachl et al., 2020).

In summary, researchers should aim to measure social interaction processes as close as possible to real-time, ideally using a mix of more subjective and objective measurement approaches (Roos et al., 2023; Struminskaya et al., 2020; Wrzus, Roos, Krämer, Schoedel et al., 2024). Ultimately, scientific progress depends on embracing diverse approaches, acknowledging their strengths and limitations, and continuously refining theories and measurement methods (Fiedler, 2017). Based on different types of high time-resolution data from different measurement approaches, further technological developments and new analyses may allow for even better modeling of complex regulatory processes—offering huge potential to better understand these processes (Wrzus, Roos, Krämer, Schoedel et al., 2024).

7.1.2 Assessing Social Interactions

In Chapter 2, three different methods to assess social interactions were compared. Each of these methods involves more or less explicit assumptions about what concretely constitutes a social interaction (e.g., conversation vs. doing an activity together). Likewise, researchers in psychology, communication studies, and sociology have for a long time argued what constitutes meaningful information about social interactions (Hall, 2018; Montgomery & Duck, 1991; Wheeler & Nezlek, 1977). These arguments include debates on the benefits and drawbacks of interpretative vs. more objectivist approaches, the value of the participant, peer and observer perspective, as well as questions about the appropriate social unit: individual, dyad, or group (Montgomery & Duck, 1991). Regularly revisiting these foundational assumptions and definitions is crucial for theoretical advancements.

Many previous studies that relied on subjective reports of participants either did not provide a definition for social interaction at all or used somewhat vague definitions (Goffman, 1963; Hall, 2018). In contrast, more objective measures, for example proportion of conversation as used in the present studies, are clearly defined, but may not capture all kinds of phenomena that could pass as social interaction (Roos et al., 2023). Additionally, the personal interpretation of seemingly identical acts (e.g., a 30 min social interaction) can vary strongly among people. Thus, considering societal and personal meanings alongside physical reality as measured by sensors is essential for accurately modeling social interactions (Rauthmann et al., 2015).

Both questionnaire approaches and mobile sensing are complementary, useful in the circumstances of certain research questions, and may lead to interesting insights. However, opting for further development and use of more objective approaches seems much more promising than relying solely on questionnaires when pursuing the goal of better understanding the interplay of personality, situation, and behavior. This is because using more objective measurements alongside subjective reports allows to better separate aspects of personality, situation, and behavior, and thus decreases common method variance. Hence, measuring social interactions using innovative technologies, such as mobile sensing (Harari et al., 2020), eye-tracking in daily life (Aschwanden et al., 2019), or the electronically activated recorder (Mehl, 2017) continues to hold significant yet not fully captured potential. Besides aspects regarding the quantity of social contact, further research is needed to explore methods to assess the quality of social interactions. First research suggests that in the future, advanced algorithms may even offer reliable ways to measure qualitative aspects of social interactions, for example by analyzing vocal and linguistic features (Horn & Timmons, 2023; Lee et al., 2023).

7.1.3 Assessing Social Traits

Previous chapters (especially Chapters 3 and 4) have shown and discussed different approaches to assess relatively stable tendencies of people to act, think, and feel socially. Many personality psychologists think that population-level variation in personality is best represented as a hierarchy of traits with differing specificity, and that no level of description uniquely represents “true” underlying processes (Back et al., 2023; Baumert et al., 2017; Mõttus et al., 2020). Although the Big Five, including extraversion, are useful for conveniently summarizing how people differ with a manageable number of dimensions, there is little evidence that constructs at the level of the Big Five are particularly suitable units for explaining personality processes in concrete daily life situations (Jonas & Markon, 2016; Mõttus et al., 2020).

Accordingly, in the studies described in this dissertation, we mostly focused on affiliation motive and the need to be alone. Additionally, next to trait measures, we also included state measures (e.g., desire to interact or desire to be alone), which seems to have been a good decision: In Chapter 3, affiliation motive and the need to be alone were closely connected with the measurement of stable tendencies for social deprivation and social oversatiation. In Chapter 4, the more process oriented theoretical background of the affiliation motive provided a good foundation to explore the effects of social desires on social behaviors. Moreover, in Chapter 4, affiliation motive was overall better suited to predict social interactions than extraversion.

One takeaway from Chapters 4 and 5 was that I would not recommend assessing social desires in an aggregated fashion over the whole day. Participants often reported that they would have liked to spend more time alone and more time in social interaction within the same day, in essence wishing that their day had more hours. This resulted in unexpectedly low correlations between the two items, although a negative association was expected. Rather than measuring aggregates across the day, measuring social desires in concrete situations remained the more useful approach, and provided us with interesting insights into how social desires influence social interaction (see Chapters 3, 4, 5, and 6).

To summarize, the previous chapters showed the added benefits of including state measures on social desires, and not only measuring social traits as decontextualized aggregates. Such aggregates do not adequately capture boundary conditions, instead they generalize over contexts, relationship types, and types of activities. For some research questions, being able to generalize so broadly is a strength. However, for understanding processes in daily life, social desires need to be measured in concrete situations, along with the measurement of relevant context factors (Wrzus, Roos, Krämer, Schoedel et al., 2024).

7.1.4 Assessing Context Factors

The previous chapters investigated context factors that can be sorted from more proximal (i.e., micro-context, Chapter 4) to more distal (meso-context, Chapter 5; macro-context, Chapter 6). Thereby, Chapter 4 and 5 found slight evidence suggesting that more immediate contexts might be more suitable to predict individual behavior than more distal contexts. Specifically, in Chapter 5, more immediate context variables (i.e., characteristics of people's apartments or dwellings) were more relevant for everyday social interaction dynamics than population per residence. However, an analysis considering multiple context levels concurrently may contribute to an even better understanding, as immediate situations are also shaped by broader contexts. For example, Chapter 6 showed that the macro-context (e.g., governmental restrictions on social behavior due to a global pandemic) may create very strong situations that strongly influence social behavior (Blum et al., 2018; Schmitt et al., 2013).

Thus, it appears fruitful to continue to assess context at various levels and to consider different aspects of contexts. For example, situations may be described in terms of cues (physical and objectively quantifiable information, e.g., presence of other people), characteristics (psychological representations of meanings of situations, e.g., friendly conversation), and classes (types of situations, e.g., intimacy and interpersonal relations, Rauthmann et al., 2015). For assessing contexts in various ways, it is worth looking out for new technologies and neighboring disciplines attempts to measure different aspects of contexts at different levels of proximity (Roos et al., 2024; Sharmeen et al., 2014).

An increased emphasis on context effects is pivotal for a deeper understanding of social interactions in everyday life (Huxhold et al., 2022; Roos et al., 2024). As I will discuss in more depth next, the social opportunity structure more generally, or situational affordances more specifically, helped tremendously to understand social interactions in daily life better.

7.2 Theoretical Implications

Social Interaction dynamics in daily life were the focus of Chapters 4, 5, and 6. These chapters were arranged to follow a progression from more proximal to more distal contexts: Chapter 4 focused on aspects of the micro-context, Chapter 5 on aspects of the meso-context, and Chapter 6 on aspects of the macro-context surrounding social interactions. Overall, the results showed that social desires were associated with desire-consistent changes in social situations (Chapters 4 and 5) and that individual living conditions were associated with how people regulated social interactions in their daily lives (Chapter 5). Whereas personality traits were clearly associated with longer-term processes of social interaction regulation (i.e., the reuptake of social interactions over several weeks after contact restrictions, Chapter 6), the role of personality traits in shaping daily social interactions remained less clear (Chapter 4). Together, the results emphasize that social interactions are shaped by a combination of personal desires, as well as situational constraints and opportunities.

7.2.1 Social Interaction Regulation Depends on Personality and Context Factors

Overall, as demonstrated in the previous chapters, the extension of the control theory model by social context and situational affordances was successful and offered new insights (see Figure 1.2, Chapters 4–6): Contexts measured at different proximity to the individual affected social interactions (Chapters 4–6). For example, the availability of interaction partners as approximated by social densities influenced transitions from solitude to social interaction, and vice versa (Chapter 5). Features of the environment shape how functional people's behaviors are, i.e., determine how instrumental certain actions are in achieving desired outcomes and thereby provide regularity to people's behavior (Barker, 1975). Still, a better understanding is needed on how different context aspects integrate to create a social opportunity structure (Huxhold et al., 2022; Roos et al., 2024). For example, it could be interesting to assess people's objective as well as subjective representations of interaction partner availability. These representations could then be connected with comprehensive assessments of living conditions or situational aspects for even more insights.

Chapter 6 presented a rare empirical demonstration of a very strong situation. At wave 1 of the measurement, none of the usually present personality-related differences in the amount of face-to-face interactions could be found. The question of when the effects of persons or situations are stronger is important for understanding the interplay between individuals and their environments (Lewin, 1936; Schmitt et al., 2013). It has been suggested that personality effects come into play more strongly when the situation is weaker, meaning there is less restriction and individuals have more freedom to behave according to their needs (Blum et al., 2018; Schmitt et al., 2013). This is because individuals with certain personality traits are more likely to seek out and create situations that are in line with their needs and preferences (i.e., selection effects, Bühler et al., 2023; Buss, 1987; Mehl et al., 2006; Rauthmann, 2021a). For example, extraverted individuals may seek out more social situations, whereas introverted individuals may prefer more solitary activities.

Throughout the chapters of this dissertation, there were fewer moderations of shorter-term processes by social traits or desires than initially expected (but see Chapter 6 for how social traits moderated longer-term processes). Yet, most chapters focused on personality effects on social interactions in relatively short timeframes and might have missed selection effects of personality that had already happened weeks, months, or years before. Therefore, further research could more strongly consider the personal histories that led people to their current social situations. It could also be interesting for future research to better understand when, how, and for how long people get caught up in contexts they initially self-selected in, but after some time, they decide they would rather leave. Such research could also consider socioeconomical factors and constellations of obligations (e.g., childcare arrangements, work obligations), to further explore who has—when and how—opportunities to fluidly change situations or even move out of certain larger contexts to fulfil social needs best.

7.2.2 Further Reflections on the Dynamic Regulation of Social Interactions

One central—and until now little discussed—assumption in the design of the studies included in this dissertation was the assumption that social deprivation and social satiation are asymmetric processes. From a phenomenological perspective, transitioning from solitude to social interaction or transitioning out of social interaction are vastly different experiences. We considered this in the previous chapters when we split data depending on the current social situation, or assessed affiliation motive and the need to be alone separately. The results presented in previous chapters provide further support that such a distinction is not only valuable theoretically, but also necessary to adequately describe the differences between situations of solitude and social interaction episodes (see for example Chapter 5, Figure 5.1). Based on the results of Chapters 4 and 5, I strongly discourage conceptualizing the amount of contact as a unidimensional construct, assuming linear and equal processes on both ends of the continuum. Instead, this dissertation suggests that treating these processes as different (also potentially occurring on different timescales) fits the observed phenomena much better.

Meanwhile, recent research strongly supports the notion that desiring more interaction and desiring time alone are distinct processes and that the quality and content of the interaction matter. For example, people sought solitude after energy-draining interactions, but not necessarily after social interactions where they felt connected (Hall et al., 2023). Moreover, contrary to a simplistic interpretation of the homeostatic regulation principle, people desired even more social interaction after they had social interactions that made them feel connected (Hall et al., 2023; Reissmann et al., 2021). Thus, perhaps energy costs, and not necessarily belongingness need satisfaction, could be a better indicator of whether people desire and then actually are alone in the future. Perhaps, feelings of connection with others cannot reach a point of oversatiation and continually motivate further social connection. This assumption ties in nicely with the autocorrelational associations of social interaction described in Chapter 4. Still, social interactions require energy (and do not always lead to feelings of connection), and because of this, recovery is needed (Hall et al., 2023; Leikas & Ilmarinen, 2017). Factors that influenced how energy-draining social interactions were included the content of a conversation, volition, familiarity of partners, as well as feelings of connection or disconnection (Hall et al., 2023).

Thus, how energy-draining social interactions are also depends on the relationship between the actors. It remains likely that people, besides having a general state of being deprived, satisfied, or oversatiated with social interactions, may have more specific needs (e.g., for time spent with their partner or very intimate social encounters) that they cannot satisfy with every person. Accordingly, further differentiating who people interacted with, perhaps using even more detailed descriptions than relationship type, could be another avenue for future research. Still, the chapters of this dissertation demonstrated that much can be gained by assessing interdependencies of different relationship types. Consequently, for research on social interactions in daily life, paying more attention to characteristics of the interaction partners should not come at the cost of dropping entire relationship types from the analyses (i.e., focusing on only single relationship types). For some people, balancing time to appease people from different relationship types may feel like an obligation.

Obligations to interact made interactions more energy-draining (Hall et al., 2023) and when longer than usual social interactions originated from others or external demands, the desire to be alone became more pronounced over time (Chapter 4). What is still not considered much is that besides social interactions themselves requiring energy, considerable effort is involved in finding interaction partners, arranging meetings, and preparing one's home for visitors. Consequently, I argued that the total amount of energy needed for social interactions also depends on how constraining or facilitating the context is. Examining the activities that lead to or precede social interactions (e.g., social planning and preparations for social meetings) could be an interesting area for future research.

To summarize, the general notion of a homeostatic feedback loop provided good starting points to understand social interaction in daily life. Still, control theory models of social interaction regulation may be too unspecific and broad to be consistently applied over diverse relationship experiences with diverse interaction partners. Additionally, the asymmetry between social deprivation and social oversatiation processes needs to be targeted in future revisions of these models. Besides the negative feedback loop, control theory (Carver & Scheier, 1982) offers additional strong theoretical concepts that are still waiting to be fully integrated into control theory models of social interaction regulation. Next, I explore how control theory models of social interaction regulation integrate with other motivational and personality theories and where theoretical arguments can be reconciled with the findings of this dissertation to better bridge between social interaction, context factors, and personality theories.

7.2.3 Control Theory Models and Motivational Theories

Control theory approaches provide a simplified and mostly testable model for understanding how social interactions unfold. However, current applications of control theory to social interactions primarily concentrate on the negative feedback loop mechanism (Hall & Davis, 2017; Krämer et al., 2024; Sheldon, 2011; Wrzus, Roos, Krämer, Schoedel et al., 2024). Yet, in the foundational work of Carver and Scheier (1982), a second important mechanism for understanding the dynamic regulation of behavior was described: the expectancy loop. The expectancy loop suggests that individuals evaluate their environment regarding the likelihood that their behavior will satisfy their goals, that is, motivation is important (Carver & Scheier, 1982).

The dynamic regulation of social interactions can easily be described in motivational terms: Motivation can be seen as selective approach/avoidance of certain situations (Heckhausen & Heckhausen, 2018). People may engage in situation management strategies (e.g., maintaining or terminating; Asendorpf & Rauthmann, 2020; Rauthmann & Sherman, 2016), and the choice of situation management strategy aligns with the perceived rewards or punishments within the given situation (Wenzel et al., 2023). Thus, affiliative behavior can be considered motivated if the behavior has produced positive consequences in the past or is expected to have positive consequences in future, i.e. possesses a positive reinforcement value. This reinforcement value might depend on the current social deprivation or oversatiation, as well as on the structure of the environment. Additionally, motivational theories offer an easy explanation for why people sometimes act contrary to their current social desires: conflicts between social motives and other goals. Humans are thought to resolve such conflicts by comparing competing motive strengths, selecting the strongest and suppressing others or at least their behavioral expression (e.g., Read et al., 2010; Revelle & Condon, 2015).

It seems promising to reconcile specific control theory approaches to social interaction regulation with broader motivational theories, such as the Zurich model of motivation (Quirin et al., 2022) or general motivational architectures for personality (Del Giudice, 2023). These theories hold significant potential to bridge the gap between the processes of social interaction regulation and broader aspects of personality. Better understanding motivational systems underlying concrete behaviors and the structure of chosen as well as imposed environments could result in considerable progress towards explaining stability and structure of traits (Read, Droutman, & L. C. Miller, 2017). I will next discuss some ideas on how social interaction theories connect with broader personality theories.

7.2.4 Control Theory Models and Personality Theories

Recently, personality theories inspired by cybernetic frameworks have gained much renewed interest (e.g., Quirin et al., 2022; Safron & DeYoung; 2021; Sosnowska et al., 2020). Interestingly, control theory approaches to the dynamic regulation of social interactions and dynamic personality theories are remarkably similar in their basic constructs. For example, the dynamics systems approach to personality (Sosnowska et al., 2020) tries to reconcile more stable (trait) and more fluctuating aspects (personality states) of personality. The core of the model are the concepts of baseline personality (i.e., set point around which personality states fluctuate), personality variability (i.e., extend to which personality states fluctuate across time and situations), and personality attractor strength (i.e., how fast deviations from the baseline are pulled back). This is very similar to the homeostatic model of social interaction regulation, which also posits a momentary reference value, deviations from this value and the urge to minimize the gap (Hall & Davis, 2017; Krämer et al., 2024; Sheldon, 2011; Wrzus, Roos, Krämer, Schoedel et al., 2024).

The considerable overlap in concepts such as need-related situational features, need states, reference values or setpoints, activation, behavioral programs, and coping strategies within such personality approaches (e.g., Read, Smith et al., 2017; Revelle & Condon, 2015; Sosnowska et al., 2020) suggests that principles from the dynamic regulation of social interactions might offer high-level explanations for a broader range of personality phenomena. Further research is needed to explore what exactly is special about the regulation of social interactions, and what principles from social interaction research can also be transferred to other traits or personality processes more generally.

7.3 Future Directions

7.3.1 Exploring Emotional Processes as Steering Mechanisms

For understanding processes of the dynamic regulation of everyday social interactions, this dissertation drew heavily from control theory approaches and motivational theories. However, motivation does not work in isolation from emotion and cognition, which should also be considered to harness their combined explanatory power (Baumert et al., 2017). The associations of social interactions and momentary affect is complex and depends on a multitude of factors, among them the quantity and quality of previous and the current social interactions (Krämer et al., 2024; Liu et al., 2019), as well as situational factors (e.g., daSilva et al., 2021; Kroencke, Harari et al., 2023).

In general, both more social interactions (e.g., Lucas et al., 2008; Sandstrom & Dunn, 2014) as well as higher quality social interactions (e.g., Smillie et al., 2015) were associated with increased affective well-being (for a review, see Liu et al., 2019). Still, the positive effects of social interaction quantity showed diminishing returns. That is, beyond a certain point, further social interaction may lead to social oversatiation and harm well-being (Krämer et al., 2024; Luo, Macdonald, & Hülür, 2022; Ren et al., 2022). This could be explained by too many interactions depleting energy resources (Hall & Davis, 2017). Correspondingly, immediate increases in positive affect after extraverted behavior were followed by fatigue (Leikas & Ilmarinen, 2017).

Consequently, emotional processes may act as a steering mechanism, for example by acting as a discrepancy indicator or through energizing people, thus ensuring goal directedness of social behaviors (Baumert et al., 2017; Reissmann et al., 2021). Accordingly, people experienced being with others while wanting to be alone—a mismatch between their social desire and actual social contact—to be unpleasant, even if this mismatch lasted only a few hours (Krämer et al., 2024). Linking with previous arguments, context also plays a considerable role for emotional reactions and should be further considered. For example, people experienced more positive and less negative affect in chosen social situations, compared to unchosen solitude or social interactions (Nikitin et al., 2022; Tse et al., 2022; Uziel & Schmidt-Barad, 2022).

7.3.2 Considering Cognitive Processes in Daily Life Studies

Research on cognitive processes involved in social interactions has predominantly been focused on more controlled environments, and less on daily life studies (Osborne-Crowley, 2020). Still, cognitive processes would be interesting to understand better in the context of the dynamic regulation of social interactions in daily life. This could also help to better understand differences between people, because social traits likely come along with their own information processing signatures (Baumert et al., 2017). For example, people differing in sociability may also differ in how they selectively perceive, interpret, and remember not only social interactions themselves, but also the social affordances or constraints of situations.

A stronger focus on cognitive processes also highlights the importance of not rushing ahead and reconsidering fundamental theoretical distinctions between persons, situations, and behaviors. For example, people’s personality and history likely influences the perception of a situation's pleasantness. Therefore, it is essential to integrate measurements of personal, societal, and objective aspects of reality (Rauthmann et al., 2015). With the rise of eye-tracking, virtual reality, and augmented reality technologies there is significant potential for advancing research on attention processes related to interpersonal encounters, and cognitive processes involved in the regulation of social interactions in daily life (Aschwanden et al., 2019; Brunyé et al., 2019; M. R. Miller et al., 2019).

7.3.3 Perspectives for Aging and Development Research

Affiliation is important over the whole lifespan (Baumeister & Leary, 1995; Carstensen, 1991; Dweck, 2017; McClelland, 1987). Still, it remains unclear how exactly affiliation motivation changes longitudinally, as dedicated measures for affiliation motivation are not yet included in large, long-running panel studies—although some predictions could be derived from the personality development literature (e.g., normative changes in affiliation motive might be similar to normative changes in extraversion). While this dissertation focused on social interaction patterns of adults with a broad age range, it would also be interesting to further explore how social desires and social opportunity structures change over the lifespan, further adding to research on the co-development of personality and social relationships (Wrzus & Neyer, 2016).

In general, changing situational patterns likely do not immediately translate to changes in personality, because individual motives and habits provide some consistency even in changing surroundings (Baumert et al., 2017; Wrzus & Roberts, 2017) Still, structural change might be coupled with changing constraints and opportunities for behaviors. For example, throughout development, biological maturation or decline, the uptake of new social roles and obligations, historical innovations, crises (e.g., pandemics, Chapter 6), or individual changes in living conditions may lead to changes in the reward structure of the surroundings.

Furthermore, sources of how people satisfy their need to belong change for many people as they age (Antonucci et al., 2014; Carstensen, 1991; Wrzus et al., 2013). For example, much research shows that people become more selective and choose to spend their time with a decreasing number of close ties as they age (Carstensen, 1991). Furthermore, age also plays a major role in how (much) people use technology to interact with others (Hampton et al., 2011; Roos & Wrzus, 2023). To sum up, many exciting opportunities for research on aging effects in regulation of online and offline social interactions await further exploration (Huxhold et al., 2022; Wrzus, Roos, Krämer, Schoedel et al., 2024).

7.4 General Conclusion

Through three studies concerned with the daily lives of more than 1,000 adult participants from heterogenous backgrounds, this dissertation explored how personality and context jointly contribute to social interactions in daily life. Overall, the previous chapters serve as a humbling reminder of the complexities inherent in understanding people’s social interactions in everyday life. While psychologists tend to emphasize the role of individual choice in the regulation of social interactions (Back et al., 2023; Baumert et al., 2017; Hall & Davis, 2017), this dissertation provided evidence that the micro-, meso-, and macro-context are also important to consider. Accordingly, this dissertation showed that social behavior can be shaped by the current situation (Chapter 4), people’s living conditions (e.g., social density, Chapter 5), and larger historical contexts (e.g., pandemics, Chapter 6).

Finally, I want to call attention to measurement issues inherent in the assessment of social interactions as well as relevant person and context aspects (see Chapters 2 and 3). Rapid technological developments—both regarding measurement devices as well as statistical analyses—will allow personality researchers to push the boundaries of what we know even further. Still, any meaningful theoretical advances depend on the sound observation of phenomena (see also Bringmann et al., 2022). I want to close with Cronbach (1975), who wrote: "The theorist performs a dramatist's function; if a plot with a few characters will tell the story, it is more satisfying than one with a crowded stage. But the observer should be a journalist, not a dramatist." (p. 124). Therefore, I encourage consideration of both researchers' roles, the theorist role as well as the observer role. To make sure we are not leaving the stage causing perplexed expressions of our fellow researchers, investing in the further development of methods to assess and model social phenomena as they occur in their natural contexts seems advisable.

References

Aharony, N., Pan, W., Ip, C., Khayal, I., & Pentland, A. (2011). Social fMRI: Investigating and shaping social mechanisms in the real world. *Pervasive and Mobile Computing, 7*(6), 643–659. https://doi.org/10.1016/j.pmcj.2011.09.004

Altman, I. (1975). *The environment and social behavior: Privacy, personal space, territory, and crowding.* Monterey, California: Brooks/Cole Publishing Company.

American Psychological Association. (n.d.-a). Social interaction. In *APA dictionary of psychology*. Retrieved September 27, 2023, from https://dictionary.apa.org/social-interaction

American Psychological Association. (n.d.-b). Social relationship. In *APA dictionary of psychology*. Retrieved September 27, 2023, from https://dictionary.apa.org/social-relationship

Anglim, J., & Horwood, S. (2021). Effect of the COVID-19 pandemic and big five personality on subjective and psychological well-being. *Social Psychological and Personality Science, 12*(8), 1527–1537. https://doi.org/10.1177/1948550620983047

Anglim, J., Horwood, S., Smillie, L. D., Marrero, R. J., & Wood, J. K. (2020). Predicting psychological and subjective well-being from personality: A meta-analysis. *Psychological Bulletin, 146*(4), 279–323. https://doi.org/10.1037/bul0000226

Antonucci, T. C., Ajrouch, K. J., & Birditt, K. S. (2014). The convoy model: Explaining social relations from a multidisciplinary perspective. *The Gerontologist, 54*(1), 82–92. https://doi.org/10.1093/geront/gnt118

Anusic, I., Lucas, R. E., & Donnellan, M. B. (2017). The validity of the day reconstruction method in the German socio-economic panel study. *Social Indicators Research, 130*(1), 213–232. https://doi.org/10.1007/s11205-015-1172-6

Appelbaum, M., Cooper, H., Kline, R. B., Mayo-Wilson, E., Nezu, A. M., & Rao, S. M. (2018). Journal article reporting standards for quantitative research in psychology: The

APA Publications and Communications Board task force report. *American Psychologist*, *73*(1), 3–25. https://doi.org/10.1037/amp0000191

Aravindakshan, A., Boehnke, J., Gholami, E., & Nayak, A. (2020). Preparing for a future COVID-19 wave: Insights and limitations from a data-driven evaluation of non-pharmaceutical interventions in Germany. *Scientific Reports, 10*(1), 20084. https://doi.org/10.1038/s41598-020-76244-6

Argyle, M., & Henderson, M. (1985). *The anatomy of relationships: And the rules and skills needed to manage them successfully*. William Heinemann.

Aschwanden, D., Langer, N., & Allemand, M. (2019). Eye Tracking in the Wild: Piloting a Real-Life Assessment Paradigm for Older Adults. *Journal of eye movement research*, *12*(1). https://doi.org/10.16910/jemr.12.1.4

Aschwanden, D., Strickhouser, J. E., Sesker, A. A., Lee, J. H., Luchetti, M., Stephan, Y., Sutin, A. R., & Terracciano, A. (2021). Psychological and behavioural responses to Coronavirus disease 2019: The role of personality. *European Journal of Personality, 35*(1), 51–66. https://doi.org/10.1002/per.2281

Asendorpf, J. B. (1990). Beyond social withdrawal: Shyness, unsociability, and peer avoidance. *Human Development*, *33*(4-5), 250–259. https://doi.org/10.1159/000276522

Asendorpf, J. B., & Rauthmann, J. F. (2020). States and situations, traits and environments. In P. J. Corr & G. Matthews (Eds.), *The Cambridge handbook of personality psychology* (pp. 56–68). Cambridge University Press. https://doi.org/10.1017/9781108264822.007

Ashby, W. R. (1957). *An introduction to cybernetics.* London: Chapman and Hall.

Aust, F., & Barth, M. (2020). *papaja: Prepare reproducible APA journal articles with R Markdown* [R Package Version 0.1.0.9997].

Back, M. D. (2021). Social interaction processes and personality. In J. Rauthmann (Ed.), *The Handbook of Personality Dynamics and Processes* (pp. 185–227). Elsevier.

Back, M. D., Baumert, A., Denissen, J. J., Hartung, F. M., Penke, L., Schmukle, S. C., Schönbrodt, F. D., Schröder- Abé, M., Vollmann, M., Wagner, J., & Wrzus, C. (2011). PERSOC: A unified framework for understanding the dynamic interplay of personality and social relationships. *European Journal of Personality, 25*(2), 90–107. https://doi.org/10.1002/per.811

Back, M. D., Branje, S., Eastwick, P. W., Human, L. J., Penke, L., Sadikaj, G., Slatcher, R. B., Thielmann, I., von Zalk, M. H. W., & Wruz C. (2023). Personality and social relationships: What do we know and where do we go? *Personality Science, 4*: e7505, 1–32. https://doi.org/10.5964/ps.7505

Back, M. D., & Vazire, S. (2015). The social consequences of personality: Six suggestions for future research. *European Journal of Personality*, *29*(2), 296–307. https://doi.org/10.1002/per.1998

Bähr, S., Haas, G. C., Keusch, F., Kreuter, F., & Trappmann, M. (2022). Missing data and other measurement quality issues in mobile geolocation sensor data. *Social Science Computer Review*, *40*(1), 212–235. https://doi.org/10.1177/0894439320944118

Barker, R. G. (1975). *Ecological psychology: Concepts and methods for studying the environment of human behavior (1. Edition).* Stanford, California: Stanford University Press.

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software, 67*(1), 1–48. https://doi.org/10 .18637/jss.v067.i01

Baumeister, R. F., & Leary, M. R. (1995). The need to belong: Desire for interpersonal attachments as a fundamental human motivation. *Psychological Bulletin, 117*(3), 497–529. https://doi.org/10.1037/0033-2909.117.3.497

Baumert, A., Schmitt, M., Perugini, M., Johnson, W., Blum, G. S., Borkenau, P., Costantini, G., Denissen, J., Fleeson, W., Grafton, B., Jayawickreme, E., Kurzius, E., MacLeod, C., Miller, L. C., Read, S. J., Robinson, M. D., Roberts, B., Wood, D., & Wrzus, C. (2017). Integrating personality structure, personality process, and personality development. *European Journal of Personality*, *31*, 503–528. https://doi.org/10.1002/per.2115

Becher, H., Bönisch, S., & Wegscheider, K. (2021). Reduction of mobility during the COVID-19 pandemic in Germany according to age, sex, and federal state. *Deutsches Arzteblatt International*, *118*(31–32), 536–537. https://doi.org/10.3238/arztebl.m2021.0293

Beck, E. D., & Jackson, J. J. (2020). Consistency and change in idiographic personality: A longitudinal ESM network study. *Journal of Personality and Social Psychology, 118*(5), 1080–1100. https://doi.org/10.1037/pspp0000249

Beck, E. D., & Jackson, J. J. (2022). Personalized Prediction of Behaviors and Experiences: An Idiographic Person–Situation Test. *Psychological Science*, *33*(10), 1767–1782. https://doi.org/10.1177/09567976221093307

Bemmann, F., & Buschek, D. (2020). LanguageLogger: A mobile keyboard application for studying language use in everyday text communication in the wild. *Proceedings of the ACM on Human-Computer Interaction*, *4*(EICS), 1–24. https://doi.org/10.1145/3397872

Benke, C., Autenrieth, L. K., Asselmann, E., & Pané-Farré, C. A. (2020). Lockdown, quarantine measures, and social distancing: Associations with depression, anxiety and distress at the beginning of the COVID-19 pandemic among adults from Germany. *Psychiatry Research, 293*, 113462. https://doi.org/10.1016/j.psychres.2020.113462

Berk, L. (2015). *Child development*. Pearson Higher Education AU.

Berkman, L. F., Glass, T., Brissette, I., & Seeman, T. E. (2000). From social integration to health: Durkheim in the new millennium. *Social science & medicine, 51*(6), 843–857. https://doi.org/10.1016/S0277-9536(00)00065-4

Bischof, N. (1993). Untersuchungen zur Systemanalyse der sozialen Motivation. I: Die Regulation der sozialen Distanz - Von der Feldtheorie zur Systemtheorie [Social Distance Regulation - From „field" to „system"]. *Zeitschrift für Psychologie, 201,* 5–43.

Bisconti, T. L., Bergeman, C. S., & Boker, S. M. (2004). Emotional well-being in recently bereaved widows: A dynamical systems approach. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, *59*(4), 158–167. https://doi.org/10.1093/geronb/59.4.P158

Bland, J. M., & Altman, D. G. (1999). Measuring agreement in method comparison studies. *Statistical methods in medical research*, *8*(2), 135–160. https://doi.org/10.1177/096228029900800204

Blieszner, R. (2018). Close Relationships in Middle and Late Adulthood. In A. L. Vangelisti & D. Perlman (Eds.), *Cambridge Handbook of Personal Relationships* (pp. 211–227). Cambridge: University Press.

Blum, G. S., Rauthmann, J. F., Göllner, R., Lischetzke, T., & Schmitt, M. (2018). The Nonlinear Interaction of Person and Situation (NIPS) model: theory and empirical evidence. *European Journal of Personality, 32*(3), 286–305. https://doi.org/10.1002/per.2138

Boase, J., & Ling, R. (2013). Measuring mobile phone use: Self-report versus log data. *Journal of Computer-Mediated Communication, 18*(4), 508–519. https://doi.org/10.1111/jcc4.12021

Boateng, G. O., Neilands, T. B., Frongillo, E. A., Melgar-Quiñonez, H. R., & Young, S. L. (2018). Best practices for developing and validating scales for health, social, and behavioral research: a primer. *Frontiers in Public Health*, *6*, 149. https://doi.org/10.3389/fpubh.2018.00149

Bönisch, S., Wegscheider, K., Krause, L., Sehner, S., Wiegel, S., Zapf, A., Moser, S., & Becher, H. (2020). Effects of coronavirus disease (COVID-19) related contact restrictions in Germany, March to May 2020, on the mobility and relation to infection patterns. *Frontiers in Public Health, 8*, 619. https://doi.org/10.3389/fpubh.2020.568287

Bosch, O. J., & Revilla, M. (2022). When survey science met online tracking: Presenting an error framework for metered data. *Journal of the Royal Statistical Society: Series A (Statistics in Society), 185*(Suppl. 2), 408–436. https://doi.org/10.1111/rssa.12956

Boursier, V., Gioia, F., Musetti, A., & Schimmenti, A. (2020). Facing Loneliness and Anxiety During the COVID-19 Isolation: The Role of Excessive Social Media Use in a Sample of Italian Adults. *Frontiers in Psychiatry*, *11*, 586222–586222. https://doi.org/10.3389/fpsyt.2020.586222

Bowlby, J. (1991). Attachment and loss. Vol. 1. Attachment. New York: Basic Books.

Breil, S. M., Schweppe, P., Geukes, K., Biesanz, J. C., Quintus, M., Wagner, J., Wrzus, C., Nestler, S., & Back, M. D. (2022). The incremental validity of average states: A replication and extension of Finnigan and Vazire (2018). *Journal of Personality and Social Psychology*. https://doi.org/https://doi.org/10.1037/pspp0000408

Breil, S. M., Geukes, K., Wilson, R. E., Nestler, S., Vazire, S., & Back, M. D. (2019). Zooming into real-life extraversion how personality and situation shape sociability in social interactions. Collabra Psychology, *5*(7). https://doi.org/10.1525/collabra.170

Bronfenbrenner, U. (1994). Ecological models of human development. In *International Encyclopedia of Education, Vol. 3, 2nd Ed.* Oxford: Elsevier. Reprinted in: Gauvain, M. & Cole, M. (Eds.), *Readings on the development of children, 2nd Ed*. pp. 37–43 New York: Freeman.

Brown, L. H., Silvia, P. J., Myin-Germeys, I., & Kwapil, T. R. (2007). When the need to belong goes wrong: The expression of social anhedonia and social anxiety in daily life.

Psychological Science, *18*(9), 778–782. https://doi.org/10.1111/j.1467-9280.2007.01978.x

Bringmann, L. F., Elmer, T., & Eronen, M. I. (2022). Back to basics: The importance of conceptual clarification in psychological science. *Current Directions in Psychological Science*, *31*(4), 340–346. https://doi.org/10.1177/09637214221096485

Bronkema, R., & Bowman, N. A. (2017). A residential paradox? Residence hall attributes and college student outcomes. *Journal of College Student Development, 58*, 624–630. https://doi.org/10.1353/csd.2017.0047

Brunyé, T. T., Drew, T., Weaver, D. L., & Elmore, J. G. (2019). A review of eye tracking for understanding and improving diagnostic interpretation. *Cognitive research: principles and implications*, *4*, 1–16. https://doi.org/10.1186/s41235-019-0159-2

Bryant, C. M., Conger, R. D., & Meehan, J. M. (2004). The influence of in-laws on change in marital success. *Journal of Marriage and Family*, *63*(3), 614–626. https://doi.org/10.1111/j.1741-3737.2001.00614.x

Bühler, J. L., Orth, U., Bleidorn, W., Weber, E., Kretzschmar, A., Scheling, L., & Hopwood, C. J. (2023). Life Events and Personality Change: A Systematic Review and Meta-Analysis. *European Journal of Personality*, 08902070231190219. https://doi.org/10.1177/08902070231190219

Bühner, M. (2011). *Einführung in die Test-und Fragebogenkonstruktion* (Vol. 4033). Pearson Deutschland GmbH.

Buijs, V. L., Jeronimus, B. F., Lodder, G. M., Riediger, M., Luong, G., & Wrzus, C. (2023). Interdependencies between family and friends in daily life: Personality differences and associations with affective well-being across the lifespan. *European Journal of Personality*, *37*(2), 154–170. https://doi.org/10.1177/08902070211072745

Bundesregierung (2020). *Pressekonferenz von Bundeskanzlerin Merkel, Ministerpräsident Söder und dem Ersten Bürgermeister Tschentscher im Anschluss an das Gespräch mit* *den Regierungschefinnen und Regierungschefs der Länder [Press conference by Chancellor Merkel, Minister President Söder and First Mayor Tschentscher following the conversation with the heads of the federal states]*. https://www.bundesregierung.de/bregde/aktuelles/pressekonferenzen/pressekonferenz-von-bundeskanzlerin-merkel-ministerpraesident-soeder-und-dem-ersten-buergermeister-tschentscher-im-anschluss-an-das-gespraech-mit-den-regierungschefinnen-und-regierungschefs-der-laender-1751050

Buss, D. M. (1987). Selection, evocation, and manipulation. *Journal of Personality and Social Psychology*, *53*(6), 1214–1221. https://doi.org/10.1037/0022-3514.53.6.1214

Carstensen, L. L. (1991). Socioemotional selectivity theory: Social activity in life-span context. *Annual Review of Gerontology and Geriatrics*, *11*, 195–217.

Carstensen, L. L. (1992). Social and emotional patterns in adulthood: Support for socioemotional selectivity theory. *Psychology and Aging, 7*, 331–338. https://doi.org/10.1037/0882-7974.7.3.331

Carver, C. S., & Scheier, M. F. (1982). Control theory: A useful conceptual framework for personality–social, clinical, and health psychology. *Psychological Bulletin, 92*(1), 111–135. https://doi.org/10.1037/0033-2909.92.1.111

Carver, C. S., & Scheier, M. F. (1998). *On the self-regulation of behavior.* Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9781139174794.

Chen, B., Vansteenkiste, M., Beyers, W., Boone, L., Deci, E. L., Van der Kaap-Deeder, J., Duriez, B., Lens, W., Matos, L., Mouratidis, A., Ryan, R. M., Sheldon, K. M., Soenens, B., Van Petegem, S., & Verstuyf, J. (2015). Basic psychological need satisfaction, need frustration, and need strength across four cultures. *Motivation and Emotion, 39*(2), 216–236. https://doi.org/10.1007/s11031-014-9450-1

Cheng, C., Wang, H.-y., Sigerson, L., & Chau, C.-l. (2019). Do the socially rich get richer? A nuanced perspective on social network site use and online social capital accrual. *Psychological Bulletin*, NA. https://doi.org/10.1037/bul0000198

Cheung, F., & Lucas, R. (2014). Assessing the validity of single-item life satisfaction measures: Results from three large samples. *Quality of Life Research, 23*(10), 2809–2818. https://doi.org/10.1007/s11136-014-0726-4

Chow, S.-M., Ram, N., Boker, S. M., Fujita, F., & Clore, G. (2005). Emotion as a Thermostat: Representing Emotion Regulation Using a Damped Oscillator Model. *Emotion, 5*(2), 208–225. https://doi.org/10.1037/1528-3542.5.2.208

Churchman, A., & Ginsberg, Y. (1984). The image and experience of high rise housing in Israel. *Journal of Environmental Psychology, 4*, 27–41. https://doi.org/10.1016/S0272-4944(84)80017-1

Cooper, W. H., & Withey, M. J. (2009). The strong situation hypothesis. *Personality and Social Psychology Review, 13*(1), 62–72. https://doi.org/10.1177/1088868308329378

Coplan, R. J., Hipson, W. E., Archbell, K. A., Ooi, L. L., Baldwin, D., & Bowker, J. C. (2019). Seeking more solitude: Conceptualization, assessment, and implications of aloneliness. Personality and Individual Differences, 148, 17–26. https://doi.org/10.1016/j.paid.2019.05.020

Cronbach, L. J. (1975). Beyond the two disciplines of scientific psychology. *American Psychologist, 30*(2), 116–127. https://doi.org/10.1037/h0076829

Csikszentmihalyi, M., & Larson, R. (1987). Validity and reliability of the experience-sampling method. *The Journal of Nervous and Mental Disease, 175*(9), 526-536.

Danner, D., Rammstedt, B., Bluemke, M., Treiber, L., Berres, S., Soto, C., & John, O. (2016). *Die deutsche Version des Big Five Inventory 2 (BFI-2).* https://doi.org/ 10.6102/zis247

daSilva, A. W., Huckins, J. F., Wang, W., Wang, R., Campbell, A. T., & Meyer, M. L. (2021). Daily perceived stress predicts less next day social interaction: Evidence from a naturalistic mobile sensing study. *Emotion, 21*(8), 1760–1770. https://doi.org/10.1037/emo0000994

Deci, E. L., & Ryan, R. M. (2000). The" what" and" why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry, 11*(4), 227–268.

Del Fava, E., Cimentada, J., Perrotta, D., Grow, A., Rampazzo, F., Gil-Clavel, S., & Zagheni, E. (2021). Differential impact of physical distancing strategies on social contacts relevant for the spread of SARS-CoV-2: Evidence from a cross-national online survey, March April 2020. *BMJ Open*, *11*(10), e050651. https://doi.org/ 10.1136/bmjopen-2021-050651

Demir, M., & Özdemir, M. (2010). Friendship, need satisfaction and happiness. Journal of Happiness Studies, 11(2), 243–259. https://doi.org/10.1007/s10902-009-9138-5 DeYoung, C. G., Weisberg, Y., Quilty, L., & Peterson, J. (2013). Unifying the aspects of the big five, the interpersonal circumplex, and trait affiliation. *Journal of Personality, 81*, 465–475. https://doi.org/10.1111/jopy.12020

Denissen, J. J. A., & Penke, L. (2008). Motivational individual reaction norms underlying the Five-Factor model of personality: First steps towards a theory-based conceptual framework. *Journal of Research in Personality*, *42*(5), 1285–1302. https://doi.org/10.1016/j.jrp.2008.04.002

Denissen, J. J. A., Ulferts, H., Lüdtke, O., Muck, P. M., & Gerstorf, D. (2014). Longitudinal transactions between personality and occupational roles: A large and heterogeneous study of job beginners, stayers, and changers. *Developmental Psychology*, *50*(7), 1931–1192.

Denissen, J. J. A., van Aken, M. A. G., Penke, L., & Wood, D. (2013). Self-regulation underlies temperament and personality: An integrative developmental framework. *Child Development Perspectives, 7*, 55–60. https://doi.org/10.1111/cdep.12050

Destatis (2022a). Bevölkerung nach Geschlecht - Stichtag 31.12. - regionale Tiefe: Gemeinden [Dataset]. https://www.regionalstatistik.de/genesis//online?operation=table&code=12411-01-01-5&bypass=true&levelindex=1&levelid=1681401925995#abreadcrumb

Destatis (2022b). Bestand an Wohngebäuden und Wohnungen in Wohn- und Nichtwohngebäuden - Stichtag 31.12. - regionale Tiefe: Gemeinden [Dataset]. https://www.regionalstatistik.de/genesis//online?operation=table&code=31231-02-01-5&bypass=true&levelindex=1&levelid=1681401742899#abreadcrumb

Destatis (2024). Key table population density. [Data set]. https://www.destatis.de/EN/Themes/Countries-Regions/International-Statistics/Data-Topic/Tables/BasicData_PopulationDensity.html

Devlin, A. S., Donovan, S., Nicolov, A., Nold, O., & Zandan, G. (2008). Residence hall architecture and sense of community: Everything old is new again. *Environment & Behavior, 40*, 487–521. https://doi.org/10.1177/0013916507301128

Dijkstra, K., Pieterse, M., & Pruyn, A. (2006). Physical environmental stimuli that turn healthcare facilities into healing environments through psychologically mediated effects: Systematic review. *Journal of Advanced Nursing, 56*, 166–181. https://doi.org/10.1111/j.1365-2648.2006.03990.x

DeYoung, C. G., Weisberg, Y. J., Quilty, L. C., & Peterson, J. B. (2013). Unifying the aspects of the Big Five, the interpersonal circumplex, and trait affiliation. *Journal of Personality*, *81*, 465–475. https://doi.org/10.1111/jopy.12020

Dufner, M., Arslan, R. C., Hagemeyer, B., Schönbrodt, F. D., & Denissen, J. J. A. (2015). Affective contingencies in the affiliative domain: Physiological assessment, associations with the affiliation motive, and prediction of behavior. *Journal of Personality and Social Psychology, 109*(4), 662–676. https://doi.org/10.1037/pspp0000025

Dweck, C. S. (2017). From needs to goals and representations: Foundations for a unified theory of motivation, personality, and development. *Psychological Review, 124*(6), 689–719. https://doi.org/10.1037/rev0000082

Easterbrook, M. J., & Vignoles, V. L. (2015). When friendship formation goes down the toilet: Design features of shared accommodation influence interpersonal bonds and well-being. *British Journal of Social Psychology, 54*, 125–139. https://doi.org/10.1111/bjso.12062

Ebner-Priemer, U. W., & Santangelo, P. S. (2023). Viva Experience Sampling: Combining passive mobile sensing with active momentary assessments. In M. R. Mehl, M. Eid, C. Wrzus, G. M. Harari, & U. W. Ebner-Priemer (Eds.), *Mobile Sensing in Psychology: Methods and Applications* (pp. 53). Guilford.

Elmer, T., & Lodder, G. (2023). Modeling social interaction dynamics measured with smartphone sensors: An ambulatory assessment study on social interactions and loneliness. *Journal of Social and Personal Relationships*, *40*(2), 654–669.

Elmer, T., van Duijn, M. A. J., Ram, N., & Bringmann, L. F. (2023). Modeling categorical time-to-event data: The example of social interaction dynamics captured with event-contingent experience sampling methods. *Psychological Methods.* Advance online publication. https://doi.org/10.1037/met0000598

Emmons, R. A., Diener, E., & Larsen, R. J. (1986). Choice and avoidance of everyday situations and affect congruence: Two models of reciprocal interactionism. *Journal of Personality and Social Psychology, 51*(4), 815–826. https://doi.org/10.1037/0022-3514.51.4.815

Entringer, T. M., & Gosling, S. D. (2021). Loneliness during a nationwide lockdown and the moderating effect of extroversion. *Social Psychological and Personality Science.* https://doi.org/10.1177/19485506211037871

Entringer, T. M., Kröger, H., Schupp, J., Kühne, S., Liebig, S., Goebel, J., Grabka, M. M., Graeber, D., Kroh, M., Schröder, C., Seebauer, J., & Zinn, S. (2020). *Psychische Krise durch Covid-19? Sorgen sinken, Einsamkeit steigt, Lebenszufriedenheit bleibt stabil* (SOEPpapers on Multidisciplinary Panel Data Research Nos. 1087). Deutsches Institut für Wirtschaftsforschung (DIW). https://doi.org/http://hdl.handle.net/ 10419/222647

Epskamp, S. (2020). Psychometric network models from time-series and panel data. *Psychometrika, 85*(1), 206–231. https://doi.org/10.1007/s11336-020-09697-3

Epskamp, S., Cramer, A. O., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). qgraph: Network Visualizations of Relationships in Psychometric Data. *Journal of Statistical Software*, *48*(4), 1–18. https://doi.org/10.18637/jss.v048.i04

Ettman, C. K., Abdalla, S. M., Cohen, G. H., Sampson, L., Vivier, P. M., & Galea, S. (2020). Prevalence of Depression Symptoms in US Adults Before and During the COVID-19 Pandemic. *JAMA Network Open, 3*(9), Article e2019686–e2019686. https://doi.org/ 10.1001/jamanetworkopen.2020.19686

Flaxman, S., Mishra, S., Gandy, A., Unwin, H. J. T., Mellan, T. A., Coupland, H., Whittaker, C., Zhu, H., Berah, T., Eaton, J. W., Monod, M., Imperial College COVID-19 Response Team, Ghani, A. C., Donnelly, C. A., Riley, S., Vollmer, M. A. C., Ferguson, N. M., Okell, L. C., & Bhatt, S. (2020). Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe. *Nature*, *584*(7820), 257–261. https://doi.org/10.1038/s41586-020-2405-7

Ferreira, D., & Mulukutla, R. (2020). *AWARE Plugin: Conversations.* Retrieved from https://github.com/denzilferreira/com.aware.plugin.studentlife.audio_final

Festinger, L., Schachter, S., & Back, K. (1950). *Social pressures in informal groups: a study of human factors in housing*. Stanford, California: Stanford University Press.

Fiedler, K. (2017). What Constitutes Strong Psychological Science? The (Neglected) Role of Diagnosticity and A Priori Theorizing. *Perspectives on Psychological Science*, *12*(1), 46–61. https://doi.org/10.1177/1745691616654458

Fiedler, K., & Juslin, P. (Eds.). (2005). *Information sampling and adaptive cognition*. Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9780511614576

Fiori, K. L., Rauer, A. J., Birditt, K. S., Marini, C. M., Jager, J., Brown, E., & Orbuch, T. L. (2017). "I Love You, Not Your Friends": Links between partners' early disapproval of friends and divorce across 16 years. *Journal of Social and Personal Relationships, 35*(9), 1230–1250. https://doi.org/10.1177/0265407517707061

Fiori, K. L., Smith, J., & Antonucci, T. C. (2007). Social network types among older adults: A multidimensional approach. *Journals of Gerontology Series B: Psychological Sciences & Social Sciences, 62B*, 322–330.

Fiori, K. L., Windsor, T. D., & Huxhold, O. (2020). The increasing importance of friendship in late life: Understanding the role of sociohistorical context in social development. *Gerontology, 66*(3), 286–294. https://doi.org/10.1159/000505547

Fischer, M. M., Kroh, M., De Vries, L., Kasprowski, D., Kühne, S., Richter, D., & Zindel, Z. (2022). Sexual and gender minority (SGM) research meets household panel surveys: research potentials of the German Socio-Economic Panel and its boost sample of SGM households. *European Sociological Review, 38*(2), 321–335.

Fraley, C., & Roberts, B. W. (2005). Patterns of continuity: A dynamic model for conceptualizing the stability of individual differences in psychological constructs across the life course. *Psychological Review*, *112*, 60–74. https://doi.org/10.1037/0033-295X.112.1.60

Fried, E. I., Papanikolaou, F., & Epskamp, S. (2022). Mental Health and Social Contact During the COVID-19 Pandemic: An Ecological Momentary Assessment Study.

Clinical Psychological Science, *10*(2), 340–354. https://doi.org/10.1177/21677026211017839

Fung, H. H., Carstensen, L. L., & Lang, F. R. (2001). Age-related patterns in social networks among European Americans and African Americans: implications for socioemotional selectivity across the life span. *International Journal Of Aging & Human Development, 52*(3), 185–206.

Fung, H. H., Stoeber, F. S., Yuen-lan Yeung, D., & Lang, F. R. (2008). Cultural Specificity of Socioemotional Selectivity: Age Differences in Social Network Composition Among Germans and Hong Kong Chinese. *Journal of Gerontology: Psychological Sciences, 63*, 156–164.

Gabbiadini, A., Baldissarri, C., Durante, F., Valtorta, R. R., De Rosa, M., & Gallucci, M. (2020). Together apart: The mitigating role of digital communication technologies on negative affect during the COVID-19 outbreak in Italy. *Frontiers in Psychology, 11*, 2763. https://doi.org/10.3389/fpsyg.2020.554678

Gadassi Polack, R., Sened, H., Aubé, S., Zhang, A., Joormann, J., & Kober, H. (2021). Connections during crisis: Adolescents' social dynamics and mental health during COVID-19. *Developmental Psychology*, *57*(10), 1633–1647. doi: https://doi.org/10.1037/dev0001211

Goffman, E. (1963). *Behavior in public places: Notes on the social organization of gatherings*. New York: The Free Press.

Götz, F. M., Gvirtz, A., Galinsky, A. D., & Jachimowicz, J. M. (2021). How personality and policy predict pandemic behavior: Understanding sheltering-in-place in 55 countries at the onset of COVID-19. *American Psychologist, 76*(1), 39–49. https://doi.org/10.1037/amp0000740

Götz, F. M., Stieger, S., & Reips, U.-D. (2017). Users of the main smartphone operating systems (iOS, Android) differ only little in personality. *PLoS ONE, 12*(5), e0176921. https://doi.org/10.1371/journal.pone.0176921

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, *78*(6), 1360–1380. http://www.jstor.org/stable/2776392

Groves, R. M., & Lyberg, L. (2010). Total survey error: Past, present, and future. *Public Opinion Quarterly, 74*(5), 849–879. https://doi.org/10.1093/poq/nfq065

Grund, A., Brassler, N. K., & Fries, S. (2014). Torn between study and leisure: How motivational conflicts relate to students' academic and social adaptation. *Journal of Educational Psychology, 106*(1), 242–257. https://doi.org/10.1037/a0034400

Del Giudice, M. (2023). A general motivational architecture for human and animal personality. *Neuroscience and Biobehavioral Reviews, 144,* Article 104967. https://doi.org/10.1016/j.neubiorev.2022.104967

Hagemeyer, B., Neyer, F. J., Neberich, W., & Asendorpf, J. B. (2013). The ABC of social desires: Affiliation, being alone, and closeness to partner. European Journal of Personality, *27*(5), 442–457. https://doi.org/10.1002/per.1857

Hall, J. A. (2017). The regulation of social interaction in everyday life: A replication and extension of O'Connor and Rosenblood (1996). *Journal of Social and Personal Relationships*, *34*(5), 699–716. https://doi.org/10.1177/0265407516654580

Hall, J. A. (2018). When is social media use social interaction? Defining mediated social interaction. *New Media & Society*, *20*(1), 162–179. https://doi.org/10.1177/1461444816660782

Hall, J. A., & Davis, D. C. (2017). Proposing the communicate bond belong theory: Evolutionary intersections with episodic interpersonal communication. *Communication Theory, 27*(1), 21–47. https://doi.org/10.1111/comt.12106

Hall, J. A., Dominguez, J., Merolla, A. J., & Otmar, C. D. (2023). Social Bandwidth: When and Why Are Social Interactions Energy Intensive? *Journal of Social and Personal Relationships*, *40*(8), 2614–2636. https://doi.org/10.1177/02654075231154937

Hall, J. A., Mihailova, T., & Merolla, A. J. (2021). Typicality and volition as fundamental features of everyday relational communication. *Personal Relationships*, *28*(3), 607–626.

Hampton, K. N., Goulet, L. S., Rainie, L., & Purcell, K. (2011). *Social networking sites and our lives: How people's trust, personal relationships, and civic and political involvement are connected to their use of social networking sites and other technologies.* Pew Research Center. https://www.pewresearch.org/internet/wp-content/uploads/sites/9/media/Files/Reports/2011/PIP-Social-networking-sites-and-our-lives.pdf

Harari, G. M., Gosling, S. D., Wang, R., Chen, F., Chen, Z., & Campbell, A. T. (2017). Patterns of behavior change in students over an academic term: A preliminary study of activity and sociability behaviors using smartphone sensing methods. *Computers in Human Behavior*, *67*, 129–138. https://doi.org/10.1016/j.chb.2016.10.027

Harari, G. M., Lane, N. D., Wang, R., Crosier, B. S., Campbell, A. T., & Gosling, S. D. (2016). Using smartphones to collect behavioral data in psychological science: Opportunities, practical considerations, and challenges. *Perspectives on Psychological Science*, *11*(6), 838–854. https://doi.org/10.1177/1745691616650285

Harari, G. M., Müller, S. R., Stachl, C., Wang, R., Wang, W., Bühner, M., Rentfrow, P. J., Campbell, A. T., & Gosling, S. D. (2020). Sensing sociability: Individual differences in young adults' conversation, calling, texting, and app use behaviors in daily life. *Journal of Personality and Social Psychology, 119*(1), 204–228. https://doi.org/10.1037/pspp0000245

Harari, G. M., Soh, S. J., & Kroencke, L. (2023) How to conduct mobile sensing research.

In M. R. Mehl, M. Eid, C. Wrzus, G. Harari & U. W. Ebner-Priemer (Eds.), *Mobile sensing in psychology: Methods and applications*. New York: Guilford.

Harris, K., & Vazire, S. (2016). On friendship development and the Big Five personality traits. *Social and Personality Psychology Compass, 10*(11), 647–667. https://doi.org/10.1111/spc3.12287

Hartung, F. M., & Renner, B. (2014). The need to belong and the relationship between loneliness and health. *Zeitschrift für Gesundheitspsychologie, 22*(4), 194–201. https://doi.org/10.1026/0943-8149/a000129

Hartup, W. W., & Stevens, N. (1997). Friendships and adaptation in the life course. *Psychological Bulletin, 121*, 355–370.

Hebbar, R., Papadopoulos, P., Reyes, R., Danvers, A. F., Polsinelli, A. J., Moseley, S. A., Sbarra, D. A., Mehl, M. R., & Narayanan, S. (2021). Deep multiple instance learning for foreground speech localization in ambient audio from wearable devices. *EURASIP Journal on Audio, Speech, and Music Processing, 2021*(1), 1–8. https://doi.org/10.1186/s13636-020-00194-0

Heckhausen, J., & Heckhausen, H. (2018). *Motivation und Handeln* (5. Aufl.). Berlin, Heidelberg: Springer. http://doi.org/10.1007/978-3-662-53927-9

Hill, C. A. (2009). Affiliation motivation. In M. R. Leary, & R. H. Hoyle (Eds.), *Handbook of individual differences in social behavior* (pp. 410–425). The Guilford Press.

Himmelstein, P. H., Woods, W. C., & Wright, A. G. (2019). A comparison of signal-and event-contingent ambulatory assessment of interpersonal behavior and affect in social situations. *Psychological Assessment, 31*(7), 952. https://doi.org/10.1037/pas0000718

Hipp, J. R., Faris, R. W., & Boessen, A. (2012). Measuring ‘neighborhood’: Constructing network neighborhoods. *Social networks*, *34*(1), 128–140. https://doi.org/10.1016/j.socnet.2011.05.002

Hirsch, J. A., Winters, M., Ashe, M. C., Clarke, P., & McKay, H. (2016). Destinations That Older Adults Experience Within Their GPS Activity Spaces Relation to Objectively Measured Physical Activity. *Environment and behavior*, *48*(1), 55–77. https://doi.org/10.1177/0013916515607312

Hirsch, J. L., & Clark, M. S. (2019). Multiple paths to belonging that we should study together. *Perspectives on Psychological Science*, *14*(2), 238–255. https://doi.org/10.1177/1745691618803629

Hofer, J., & Hagemeyer, B. (2018). Social Bonding: Affiliation Motivation and Intimacy Motivation. In J. Heckhausen & H. Heckhausen (Eds.), *Motivation and Action* (pp.305–334). Springer International Publishing. https://doi.org/10.1007/978-3-319-65094-4_7

Hoffman, L. (2015). *Longitudinal analysis: Modeling within-person fluctuation and change.* Routledge/Taylor & Francis Group.

Hoffman, L. (2020). Disaggregating Between-Person Time Slope Effects from Within-Person Effects. *PsyArXiv*. https://doi.org/10.31234/osf.io/6q2sm.

Hoffman, L., & Walters, R. W. (2022). Catching Up on Multilevel Modeling. *Annual Review of Psychology*, *73*, 659–689. https://doi.org/10.1146/annurev-psych-020821-103525

Holt-Lunstad, J., Robles, T. F., & Sbarra, D. A. (2017). Advancing social connection as a public health priority in the United States. *American Psychologist*, *72*(6), 517–530. https://doi.org/10.1037/amp0000103

Hopwood, C. J., & Donnellan, M. B. (2010). How should the internal structure of personality inventories be evaluated?. *Personality and Social Psychology Review*, *14*(3), 332–346.

Horn, A. B., & Timmons, A. C. (2023). Mobile sensing in relationship research. In M. R. Mehl, M. Eid, C. Wrzus, G. M. Harari, & U. W. Ebner-Priemer (Eds.), *Mobile Sensing in Psychology: Methods and Applications* (pp. 53). Guilford.

Huang, J. L., Liu, M., & Bowling, N. A. (2015). Insufficient effort responding: Examining an insidious confound in survey data. *Journal of Applied Psychology*, *100*, 828–845. https://doi.org/10.1037/a0038510

Human, L. J., Carlson, E. N., Geukes, K., Nestler, S., & Back, M. D. (2018). Do accurate personality impressions benefit early relationship development? The bidirectional associations between accuracy and liking. *Journal of Personality and Social Psychology*, *118*(1), 199–212. https://doi.org/10.1037/pspp0000214

Huxhold, O., Fiori, K. L., & Windsor, T. (2022). Rethinking social relationships in adulthood: The differential investment of resources model. *Personality and Social Psychology Review*, *26*(1), 57–82. https://doi.org/10.1177/10888683211067035

Jacques-Hamilton, R., Sun, J., & Smillie, L. D. (2019). Costs and benefits of acting extraverted: A randomized controlled trial. *Journal of Experimental Psychology: General, 148*(9), 1538–1556. https://doi.org/10.1037/xge0000516

Jonas, K. G., & Markon, K. E. (2016). A descriptivist approach to trait conceptualization and inference. *Psychological Review, 123*, 90–96. https://doi.org/10.1037/0022-3514.74.6.1556

Kahneman, D., Krueger, A. B., Schkade, D. A., Schwarz, N., & Stone, A. A. (2004). A survey method for characterizing daily life experience: The day reconstruction method. *Science*, *306*(5702), 1776–1780. https://doi.org/10.1126/science.1103572

Kargl, F., van der Heijden, R. W., Erb, B., & Bösch, C. (2019). Privacy in mobile sensing. In H. Baumeister, & C. Montag (Eds.) *Digital Phenotyping and Mobile Sensing. Studies in Neuroscience, Psychology and Behavioral Economics.* Springer, Cham. https://doi.org/10.1007/978-3-030-31620-4_1

Keusch, F., Bähr, S., Haas, G.-C., Kreuter, F., & Trappmann, M. (2020). Coverage error in data collection combining mobile surveys with passive measurement using apps: Data from a German national survey. *Sociological Methods & Research*. Advance online publication. https://doi.org/10.1177/0049124120914924

Keusch, F., Struminskaya, B., Antoun, C., Couper, M. P., & Kreuter, F. (2019). Willingness to participate in passive mobile data collection. *Public Opinion Quarterly, 83,* 210–235. https://doi.org/10.1093/poq/nfz007

Keusch, F., Wenz, A., & Conrad, F. (2022). Do you have your smartphone with you? Behavioral barriers for measuring everyday activities with smartphone sensors. *Computers in Human Behavior, 127,* 107054. https://doi.org/10.1016/j.chb.2021.107054

Kersten, P., Borschel, E., Neyer, F. J., & Mund, M. (2023). The social side of personality: Do affiliation and intimacy motives moderate associations of personal relationships with well-being? *Journal of Personality, 91*(4), 992–1011.

Klärner, A., Keim, S., & von der Lippe, H. (2016). Social network dynamics in the course of family formation: Results from a mixed-methods longitudinal study. *International Review of Social Research, 6*(4), 245–255. https://doi.org/10.1515/irsr-2016-0026

Kogovšek, T., & Hlebec, V. (2019). Measuring personal networks with surveys. *Advances in Methodology and Statistics, 16*(2), 41–55. https://doi.org/10.51936/tvlq6671

Koller, M. (2016). robustlmm: An R package for robust estimation of linear mixed-effects models. *Journal of Statistical Software, 75*(6), 1–24. https://doi.org/10.18637/jss.v075.i06

Krämer, M. D., Roos, Y., Richter, D., & Wrzus, C. (2022). Resuming social contact after months of contact restrictions: Social traits moderate associations between changes in social contact and well-being. *Journal of Research in Personality, 98,* 104223. https://doi.org/10.1016/j.jrp.2022.104223

Krämer, M. D., Roos, Y., Schoedel, R., Wrzus, C., & Richter, D. (2024). Social dynamics and affect: Investigating within-person associations in daily life using experience sampling and mobile sensing. *Emotion*, *24*(3), 878–893. https://doi.org/10.1037/emo0001309

Kroencke, L., Harari, G. M., Back, M. D., & Wagner, J. (2023). Well-being in social interactions: Examining personality-situation dynamics in face-to-face and computer-mediated communication. *Journal of Personality and Social Psychology*, *124*(2), 437–460. https://doi.org/10.1037/pspp0000422

Kroencke, L., Humberg, S., Breil, S. M., Geukes, K., Zoppolat, G., Balzarini, R. N., Alonso-Ferres, M., Slatcher, R. B., & Back, M. D. (2023). Extraversion, social interactions, and well-being during the COVID-19 pandemic: Did extraverts really suffer more than introverts? *Journal of Personality and Social Psychology*, *125*(3), 649–679. https://doi.org/10.1037/pspp0000468

Kroencke, L., Kuper, N., Mota, S., Geukes, K., Zeigler-Hill, V., & Back, M. D. (2023). Narcissistic status pursuit in everyday social life: A within-person process approach to the behavioral and emotional dynamics of narcissism. *Journal of Personality and Social Psychology, 125*(6), 1519–1541. https://doi.org/10.1037/pspp0000467

Kroenke, K., Spitzer, R. L., Williams, J. B. W., & Löwe, B. (2009). An ultra-brief screening scale for anxiety and depression: The PHQ4. *Psychosomatics, 50*(6), 613–621. https://doi.org/10.1016/S0033-3182(09)70864-3

Kuper, N., Breil, S. M., Horstmann, K. T., Roemer, L., Lischetzke, T., Sherman, R. A., Back, M. D., Denissen, J. J., & Rauthmann, J. F. (2022). Individual differences in contingencies between situation characteristics and personality states. *Journal of Personality and Social Psychology*, *123*(5), 1166–1198. https://doi.org/10.1037/pspp0000435

Kuper, N., Modersitzki, N., Phan, L. V., & Rauthmann, J. F. (2021). The dynamics, processes, mechanisms, and functioning of personality: An overview of the field. *British Journal of Psychology*, *112*(1), 1–51. https://doi.org/10.1111/bjop.12486

Kuper, N., von Garrel, A. S., Wiernik, B. M., Phan, L. V., Modersitzki, N., & Rauthmann, J. F. (2023). Distinguishing four types of Person× Situation interactions: An integrative framework and empirical examination. *Journal of Personality and Social Psychology, 126*(2), 282–311. https://doi.org/10.1037/pspp0000473

Kushlev, K., Dwyer, R., & Dunn, E. W. (2019). The social price of constant connectivity: Smartphones impose subtle costs on well-being. *Current Directions in Psychological Science, 28*(4), 347–352. https://doi.org/10.1177/0963721419847200

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest package: Tests in linear mixed effects models. *Journal of Statistical Software, 82*(13), 1–26. https://doi.org/10.18637/jss.v082.i13

Lades, L. K., Laffan, K., Daly, M., & Delaney, L. (2020). Daily emotional well-being during the COVID-19 pandemic. *British Journal of Health Psychology, 25*(4), 902–911. https://doi.org/10.1111/bjhp.12450

Lane, N. D., Mohammod, M., Lin, M., Yang, X., Lu, H., Ali, S., Doryab, A., Berke, E., Choudhury, T., & Campbell, A. (2012). Bewell: A smartphone application to monitor, model and promote wellbeing. In *Proceedings of the 5th international ICST conference on pervasive computing technologies for healthcare* (p. 23e26) New York: IEEE. http://dx.doi.org/10.4108/icst.pervasivehealth.2011.246161

Lang, F. R., & Carstensen, L. L. (1994). Close emotional relationships in late life: Further support for proactive aging in the social domain. *Psychology and Aging, 9*, 315–324. https://doi.org/10.1037/0882-7974.9.2.315

Lang, F. R., John, D., Lüdtke, O., Schupp, J., & Wagner, G. G. (2011). Short assessment of the Big Five: robust across survey methods except telephone interviewing. *Behavior Research Methods, 43*(2), 548–567. https://doi.org/10.3758/s13428-011-0066-z

Langener, A. M., Stulp, G., Jacobson, N. C., Costanzo, A., Jagesar, R. R., Kas, M. J., & Bringmann, L. F. (2024). It’s All About Timing: Exploring Different Temporal

Resolutions for Analyzing Digital-Phenotyping Data. *Advances in Methods and Practices in Psychological Science*, *7*(1), 25152459231202677. https://doi.org/10.1177/251524592312026

Lay, J. C., Pauly, T., Graf, P., Biesanz, J. C., & Hoppmann, C. A. (2019). By myself and liking it? Predictors of distinct types of solitude experiences in daily life. *Journal of Personality, 87*(3), 633–647. https://doi.org/10.1111/jopy.12421

Leary, M. R., Kelly, K. M., Cottrell, C. A., & Schreindorfer, L. S. (2013). Construct Validity of the Need to Belong Scale: Mapping the Nomological Network. *Journal of Personality Assessment*, *95*(6), 610–624. https://doi.org/10.1080/00223891.2013.819511

Lee, C.-C., Chaspari, T., Provost, E. M., & Narayanan, S. S. (2023). An engineering view on emotions and speech: From analysis and predictive models to responsible human-centered applications. *Proceedings of the IEEE*.

Leikas, S., & Ilmarinen, V. J. (2017). Happy now, tired later? Extraverted and conscientious behavior are related to immediate mood gains, but to later fatigue. *Journal of Personality*, *85*(5), 603–615. https://doi.org/10.1111/jopy.12264

Lewin, K. (1936). *Principles of topological psychology*. New York [u.a.]: MacGraw-Hill.

Lewin, K. (1939). Field theory and experiment in social psychology: Concepts and methods. *American Journal of Sociology*, *44*, 868–896. https://doi.org/10.1086/218177

Liu, H., Xie, Q. W., & Lou, V. W. (2019). Everyday social interactions and intra-individual variability in affect: A systematic review and meta-analysis of ecological momentary assessment studies. *Motivation and Emotion*, *43*, 339–353.

Long, C. R., Seburn, M., Averill, J. R., & More, T. A. (2003). Solitude experiences: Varieties, settings, and individual differences. *Personality and Social Psychology Bulletin*, *29*(5), 578–583. https://doi.org/10.1177/0146167203029005003

Löwe, B., Wahl, I., Rose, M., Spitzer, C., Glaesmer, H., Wingenfeld, K., Schneider, A., & Brähler, E. (2010). A 4-item measure of depression and anxiety: Validation and standardization of the Patient Health Questionnaire-4 (PHQ-4) in the general population. *Journal of Affective Disorders, 122*(1), 86–95. https://doi.org/10.1016/j.jad.2009.06.019

Lucas, R. E., & Donnellan, M. B. (2012). Estimating the reliability of single-item life satisfaction measures: Results from four national panel studies. *Social Indicators Research, 105*(3), 323–331. https://doi.org/10.1007/s11205-011-9783-z

Lucas, R. E., Le, K., & Dyrenforth, P. S. (2008). Explaining the extraversion/positive affect relation: Sociability cannot account for extraverts' greater happiness. *Journal of Personality, 76*(3), 385–414. https://doi.org/10.1111/j.1467-6494.2008.00490.x

Lucas, R. E., Wallsworth, C., Anusic, I., & Donnellan, M. B. (2021). A direct comparison of the day reconstruction method (DRM) and the experience sampling method (ESM). *Journal of Personality and Social Psychology, 120*(3), 816. https://doi.org/10.1037/pspp0000289

Luchetti, M., Lee, J. H., Aschwanden, D., Sesker, A., Strickhouser, J. E., Terracciano, A., & Sutin, A. R. (2020). The trajectory of loneliness in response to COVID-19. *American Psychologist, 75*(7), 897–908. https://doi.org/10.1037/amp0000690

Luo, M., Macdonald, B., & Hülür, G. (2022). Not "the more the merrier": Diminishing returns to daily face-to-face social interaction frequency for well-being in older age. *The Journals of Gerontology: Series B, 77*(8), 1431–1441. https://doi.org/10.1093/geronb/gbac010

Luo, M., Pauly, T., Röcke, C., & Hülür, G. (2022). Alternating time spent on social interactions and solitude in healthy older adults. *British Journal of Psychology, 113*(4), 987–1008. https://doi.org/10.1111/bjop.12586

Makowski, D., Wiernik, B. M., Patil, I., Lüdecke, D., & Ben-Shachar, M. S. (2022). *correlation*: Methods for correlation analysis [R package]. https://CRAN.R-project.org/package=correlation (Original work published 2020)

Maner, J. K., DeWall, C. N., Baumeister, R. F., & Schaller, M. (2007). Does social exclusion motivate interpersonal reconnection? Resolving the ‘‘porcupine problem”. *Journal of Personality and Social Psychology, 92*, 42–55. https://doi.org/10.1037/0022-3514.92.1.42

Margolis, S., Stapley, A. L., & Lyubomirsky, S. (2020). The association between extraversion and well-being is limited to one facet. *Journal of Personality, 88*(3), 478–484. https://doi.org/10.1111/jopy.12504

McCabe, C. J., Kim, D. S., & King, K. M. (2018). Improving present practices in the visual display of interactions. *Advances in Methods and Practices in Psychological Science, 1*(2), 147–165. https://doi.org/10.1177/2515245917746792

McCarthy, D., & Saegert, S. (1978). Residential density, social overload, and social withdrawal. *Human Ecology, 6*, 253–272. https://doi.org/10.1007/BF00889026

McCarty, C., Killworth, P. D., Bernard, H. R., Johnsen, E. C., & Shelley, G. A. (2001). Comparing two methods for estimating network size. *Human Organization, 60*(1), 28–39. http://www.jstor.org/stable/44126693

McClelland, D. C. (1987). *Human motivation*. Cambridge: Cambridge University Press.

McCrae, R. R., & Costa, P. T. (2008). The Five-Factor Theory of personality. In O. P. John, R. W. Robins & L. A. Pervin (Eds.), *Handbook of personality: Theory and research* (pp. 159-181). New York: Guilford Press.

Meade, A. W., & Craig, S. B. (2012). Identifying careless responses in survey data. *Psychological Methods, 17*(3), 437–455. https://doi.org/10.1037/a0028085

Meagher, B. R. (2020). Ecologizing social psychology: The physical environment as a necessary constituent of social processes. *Personality and Social Psychology Review,24*(1), 3–23. https://doi.org/10.1177/1088868319845938

Mehl, M. R. (2017). The electronically activated recorder (EAR): A method for the naturalistic observation of daily social behavior. *Current Directions in Psychological Science, 26*(2), 184–190. https://doi.org/10.1177/0963721416680611

Mehl, M. R., Gosling, S. D., & Pennebaker, J. W. (2006). Personality in its natural habitat: Manifestations and implicit folk theories of personality in daily life. *Journal of Personality and Social Psychology, 90*, 862–877. https://doi.org/10.1037/0022-3514.90.5.862

Meijerink-Bosman, M., Back, M., Geukes, K., Leenders, R., & Mulder, J. (2023). Discovering trends of social interaction behavior over time: An introduction to relational event modeling: Trends of social interaction. *Behavior Research Methods, 55*, 997–1023. https://doi.org/10.3758/s13428-022-01821-8

Miller, G. (2012). The smartphone psychology manifesto. *Perspectives on Psychological Science, 7*(3), 221–237. https://doi.org/10.1177/1745691612441215

Miller, M. R., Jun, H., Herrera, F., Yu Villa, J., Welch, G., & Bailenson, J. N. (2019). Social interaction in augmented reality. *PloS one, 14*(5), e0216290. https://doi.org/10.1371/journal.pone.0216290

Miller-Slough, R. L., & Dunsmore, J. C. (2019). Longitudinal patterns in parent and friend emotion socialization: Associations with adolescent emotion regulation. *Journal of Research on Adolescence, 29*(4), 953–966. https://doi.org/10.1111/jora.12434

Miller-Slough, R. L., & Dunsmore, J. C. (2023). Parents' and friends' socialization of positive emotions: Associations with adolescent emotion regulation. *Journal of Applied Developmental Psychology, 88*, 101579. https://doi.org/10.1016/j.appdev.2023.101579

Montgomery, B. M., & Duck, S. (Eds.). (1991). *Studying interpersonal interaction.* Guilford Press.

Mõttus, R., Wood, D., Condon, D. M., Back, M. D., Baumert, A., Costantini, G., Epskamp, S., Greiff, S., Johnson, W., & Lukaszewski, A. (2020). Descriptive, predictive and explanatory personality research: Different goals, different approaches, but a shared need to move beyond the Big Few traits. *European Journal of Personality*, *34*(6), 1175–1201. https://doi.org/10.1002/per.2311

Mueller, S., Ram, N., Conroy, D. E., Pincus, A. L., Gerstorf, D., & Wagner, J. (2019). Happy like a fish in water? The role of personality–situation fit for momentary happiness in social interactions across the adult lifespan. *European Journal of Personality, 33*(3), 298-316. doi: 10.1002/per.2198

Mund, M., & Neyer, F. J. (2014). Treating personality-relationship transactions with respect: Narrow facets, advanced models, and extended time frames. *Journal of Personality and Social Psychology, 107,* 352-368. doi: 10.1037/a0036719

Muthén, L. K., & Muthén, B. O. (2019). *Mplus (Version 8.4)*. Muthén & Muthén.

Neal, Z. P. (2020). The spatial dimensions of social networks. In R. Light & J. Moody (Eds.), *The Oxford handbook of social networks* (pp. 368–383). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780190251765.001.0001

Nestler, S., Back, M. D., & Egloff, B. (2011). Psychometrische Eigenschaften zweier Skalen zur Erfassung interindividueller Unterschiede in der Präferenz zum Alleinsein [Psychometric properties of the two scales for assessing individual differences in preference for solitude]. *Diagnostica, 57*, 57–67. https://doi.org/10.1026/0012-1924/a000032

Neubauer, A. B., Scott, S. B., Sliwinski, M. J., & Smyth, J. M. (2019). How was your day? Convergence of aggregated momentary and retrospective end-of-day affect ratings across the adult life span. *Journal of Personality and Social Psychology*, *119*(1), 185–203. https://doi.org/10.1037/pspp0000248

Neubauer, A. B., Voss, A., & Ditzen, B. (2018). Exploring need dynamics within and across days in everyday life: A three-level analysis. *Journal of Research in Personality*, *77*, 101–112. https://doi.org/10.1016/j.jrp.2018.10.001

Newzoo. (2021). *Newzoo Global Mobile Market Report 2021 | Free Version* Retrieved from https://newzoo.com/insights/trend-reports/newzoo-global-mobile-market-report-2021-free-version/

Neyer, F. J., Wrzus, C., Wagner, J., & Lang, F. R. (2011). Principles of relationship differentiation. *European Psychologist*, *16*, 267–277. https://doi.org/10.1027/1016-9040/a000055

Nezlek, J. B. (2001). The motivational and cognitive dynamics of day-to-day social life. In J. P. Forgas, K. D. Williams, & L. Wheeler (Eds.), *The social mind: Cognitive and motivational aspects of interpersonal behavior* (p. 92–111). Cambridge: Cambridge University Press.

Nguyen, T. T., Taylor-Bower, E., & Yau, K. (2023). Solitude in context: A systematic review of how societal norms and physical environment shape perceptions of solitary experiences *PsyArXiv*. https://doi.org/10.31234/osf.io/xb8gd

Niemeijer, K., Mestdagh, M., Verdonck, S., Meers, K., & Kuppens, P. (2023). Combining Experience Sampling and Mobile Sensing for Digital Phenotyping With m-Path Sense: Performance Study. *JMIR formative research*, *7*, e43296. https://doi.org/10.2196/43296

Nikitin, J., Rupprecht, F. S., & Ristl, C. (2022). Experiences of solitude in adulthood and old age: The role of autonomy. *International Journal of Behavioral Development*, *46*(6), 510–519. https://doi.org/10.1177/01650254221117498

O'Connor, S. C., & Rosenblood, L. K. (1996). Affiliation motivation in everyday experience: A theoretical comparison. *Journal of Personality and Social Psychology, 70*, 513–522. https://doi.org/10.1037/0022-3514.70.3.513

Olaru, G., Schroeders, U., Wilhelm, O., & Ostendorf, F. (2018). A confirmatory examination of age-associated personality differences: Deriving age-related measurement-invariant solutions using ant colony optimization. *Journal of Personality*, *86*(6), 1037–1049. https://doi.org/10.1111/jopy.12373

Olivera-La Rosa, A., Chuquichambi, E. G., & Ingram, G. P. D. (2020). Keep your (social) distance: Pathogen concerns and social perception in the time of COVID-19. *Personality and Individual Differences, 166*, 110200. https://doi.org/10.1016/j.paid.2020.110200

Orben, A., & Przybylski, A. K. (2019). Screens, teens, and psychological well-being: Evidence from three time-use-diary studies. *Psychological Science, 30*(5), 682–696. https://doi.org/10.1177/0956797619830329

Orben, A., & Przybylski, A. K. (2020). Reply to: Underestimating digital media harm. *Nature Human Behaviour*, *4*(4), 349–351. https://doi.org/10.1038/s41562-020- 0840-y

Ortiz-Ospina, E., Giattino, C., & Roser, M. (2024). *Time Use: How do people across the world spend their time? How do daily activities differ across countries, and how do these differences matter for people's lives? Explore data and research on time use.* Our World in Data. https://ourworldindata.org/time-use

Osborne-Crowley, K. (2020). Social cognition in the real world: Reconnecting the study of social cognition with social reality. *Review of General Psychology*, *24*(2), 144–158. https://doi.org/10.1177/1089268020906483

Peters, L., Sunderland, M., Andrews, G., Rapee, R. M., & Mattick, R. P. (2012). Development of a short form Social Interaction Anxiety (SIAS) and Social Phobia

Scale (SPS) using nonparametric item response theory: The SIAS-6 and the SPS-6. *Psychological Assessment*, *24*(1), 66–76. https://doi.org/10.1037/a0024544

Pickett, J., Hofmans, J., Feldt, T., & De Fruyt, F. (2020). Concurrent and lagged effects of counterdispositional extraversion on vitality. *Journal of Research in Personality*, *87*, 103965. https://doi.org/https://doi.org/10.1016/j.jrp.2020.103965

Podsakoff, P. M., MacKenzie, S. B., Jeong-Yeon, L., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Poole, K. L., Van Lieshout, R. J., & Schmidt, L. A. (2017). Exploring relations between shyness and social anxiety disorder: The role of sociability. *Personality and Individual Differences, 110*, 55–59. https://doi.org/10.1016/j.paid.2017.01.020

Preacher, K. J., Curran, P. J., & Bauer, D. J. (2006). Computational tools for probing interactions in multiple linear regression, multilevel modeling, and latent curve analysis. *Journal of Educational and Behavioral Statistics, 31*(4), 437–448. https://doi.org/10.3102/10769986031004437

Quintus, M., Egloff, B., & Wrzus, C. (2021). Momentary processes predict long-term development in explicit and implicit representations of Big Five traits: An empirical test of the TESSERA framework. *Journal of Personality and Social Psychology, 120*(4), 1049–1073. doi: http://dx.doi.org/10.1037/pspp0000361

Quirin, M., Malekzad, F., Paudel, D., Knoll, A. C., & Mirolli, M. (2022). Dynamics of personality: The Zurich model of motivation revived, extended, and applied to personality. *Journal of Personality, 91*(4), 928–946. https://doi.org/10.1111/jopy.12805

R Core Team. (2020). *R: A language and environment for statistical computing.* R Foundation for Statistical Computing. https://www.R-project.org/.

R Core Team. (2022). *R: A language and environment for statistical computing.* R Foundation for Statistical Computing. https://www.R-project.org/.

Rabbi, M., Ali, S., Choudhury, T., & Berke, E. (2011). Passive and In-Situ assessment of mental and physical well-being using mobile sensors. *Proceedings of the 13th International Conference on Ubiquitous Computing - UbiComp '11*, 385–394. https://doi.org/10.1145/2030112.2030164

Rauthmann, J. F. (2021a). Capturing interactions, correlations, fits, and transactions: A Person-Environment Relations Model. In J. F. Rauthmann (Ed.), *The Handbook of Personality Dynamics and Processes* (pp. 427–522). Elsevier.

Rauthmann, J. F. (2021b). *The Handbook of Personality Dynamics and Processes*. Elsevier.

Rauthmann, J. F., & Sherman, R. A. (2016). Situation change: Stability and change of situation variables between and within persons. *Frontiers in Psychology, 6*, Article 1938. https://doi.org/10.3389/fpsyg.2015.01938

Rauthmann, J. F., Sherman, R. A., & Funder, D. C. (2015). Principles of situation research: Towards a better understanding of psychological situations. *European Journal of Personality, 29*(3), 363–381. https://doi.org/10.1002/per.1994

Read, S. J., Droutman, V., & Miller, L. C. (2017). Virtual personalities: A neural network model of the structure and dynamics of personality. In R. R. Vallacher, S. J. Read, & A. Nowak (Eds.), *Computational social psychology* (pp. 15-37). New York: Routledge.

Read, S. J., Monroe, B. M., Brownstein, A. L., Yang, Y., Chopra, G., & Miller, L. C. (2010). A neural network model of the structure and dynamics of human personality. *Psychological Review, 117*(1), 61–92. https://doi.org/10.1037/a0018131

Read, S. J., Smith, B. J., Droutman, V., & Miller, L. C. (2017). Virtual personalities: Using computational modeling to understand within- person variability. *Journal of Research in Personality, 69*, 237– 249. https://doi.org/10.1016/j.jrp.2016.10.005

Regoeczi, W. C. (2003). When context matters: A multilevel analysis of household and neighbourhood crowding on aggression and withdrawal. *Journal of Environmental Psychology, 23*(4), 457–470. https://doi.org/10.1016/S0272-4944(02)00106-8

Reissmann, A., Stollberg, E., Hauser, J., Kaunzinger, I., & Lange, K. W. (2021). The role of state feelings of loneliness in the situational regulation of social affiliative behavior: Exploring the regulatory relations within a multilevel framework. *Plos One, 16*(6), e0252775. https://doi.org/10.1371/journal.pone.0252775

Reitz, A. K., Zimmermann, J., Hutteman, R., Specht, J., & Neyer, F. J. (2014). How peers make a difference: The role of peer groups and peer relationships in personality development. *European Journal of Personality, 28*(3), 279–288. https:/doi.org/10.1002/per.1965

Ren, D., Stavrova, O., & Loh, W. W. (2022). Nonlinear effect of social interaction quantity on psychological well-being: Diminishing returns or inverted U? *Journal of Personality and Social Psychology*, *122*(6), 1056–1074. https://doi.org/10.1037/pspi0000373

Revelle, W., & Condon, D. M. (2015). A model for personality at three levels. *Journal of Research in Personality*, *56*, 70–81. https://doi.org/10.1016/j.jrp.2014.12.006

Revelle, W., & Wilt, J. (2021). The history of dynamic approaches to personality. In J. F.Rauthmann (Ed.), *The handbook of personality dynamics and processes* (pp. 3–31). Elsevier Academic Press. https://doi.org/10.1016/B978-0-12-813995-0.00001-7

Richter, D., Rohrer, J., Metzing, M., Nestler, W., Weinhardt, M., & Schupp, J. (2017). *SOEP scales manual (updated for SOEP-Core v32.1)* (SOEP Survey Papers Nos. 423). Deutsches Institut für Wirtschaftsforschung (DIW).

Richter, D., & Schupp, J. (2015). The SOEP Innovation Sample (SOEP IS). *Schmollers Jahrbuch: Journal of Applied Social Science Studies/Zeitschrift für Wirtschafts-und Sozialwissenschaften, 135*(3), 389–400. https://doi.org/10.3790/schm.135.3.389

Roberts, S. G., Dunbar, R. I., Pollet, T. V., & Kuppens, T. (2009). Exploring variation in active network size: Constraints and ego characteristics. *Social Networks, 31*(2), 138–146. https://doi.org/10.1016/j.socnet.2008.12.002

Roos, Y., & Wrzus, C. (2023). Is the Smartphone Friend and Foe? Benefits and Costs of Self-reported Smartphone Use for Important Life Domains in a Representative German Sample. *Current Psycholog*y, 42, 24717–24731. https://doi.org/10.1007/s12144-022-03593-y

Roos, Y., Krämer, M. D., Richter, D., Schoedel, R., & Wrzus, C. (2023). Does Your Smartphone “Know” Your Social Life? A Methodological Comparison of Day Reconstruction, Experience Sampling, and Mobile Sensing. *Advances in Methods and Practices in Psychological Science*, *6*(3), 1–12. https://doi.org/10.1177/25152459231178738

Roos, Y., Krämer, M. D., Richter, D., & Wrzus, C. (2024). Persons in contexts: The role of social networks and social density for the dynamic regulation of face-to-face interactions in daily life. *Journal of Personality and Social Psychology.* Advance online publication. https://doi.org/10.1037/pspp0000512

Rosenberg, G. (1982). High population densities in relation to social behavior. *Ekistics; reviews on the problems and science of human settlements*, *49*(296), 400–404. http://www.jstor.org/stable/43620596

Rözer, J., Mollenhorst, G., & Poortman, A.-R. (2016). Family and friends: Which types of personal relationships go together in a network? *Social Indicators Research, 127*(2), 809–826. https://doi.org/10.1007/s11205-015-0987-5

Russell, J. J., Moskowitz, D. S., Zuroff, D. C., Bleau, P., Pinard, G., & Young, S. (2011). Anxiety, emotional security and the interpersonal behavior of individuals with social anxiety disorder. *Psychological medicine, 41*(3), 545–554. https://doi.org/10.1017/S0033291710000863

Safron, A., & DeYoung, C. G. (2021). Integrating Cybernetic Big Five Theory with the Free Energy Principle: A new strategy for modeling personalities as complex systems. In *Measuring and modeling persons and situations* (pp. 617–649). Academic Press.

Sander, J., Schupp, J., & Richter, D. (2017). Getting together: Social contact frequency across the life span. *Developmental Psychology*, *53*(8), 1571. https://doi.org/10.1037/dev0000349

Sandstrom, G. M., & Dunn, E. W. (2014). Social interactions and well-being: The surprising power of weak ties. *Personality and Social Psychology Bulletin*, *40* (7), 910–922. https://doi.org/10.1177/0146167214529799

Sandstrom, G. M., Boothby, E. J., & Cooney, G. (2022). Talking to strangers: A week-long intervention reduces psychological barriers to social connection. *Journal of Experimental Social Psychology, 102*, 104356. https://doi.org/10.1016/j.jesp.2022.104356

Shannon, C. E. (1949). Communication in the presence of noise. *Proceedings of the IRE, 37*(1), 10–21. https://doi.org/10.1109/jrproc.1949.232969

Sharmeen, F., Arentze, T., & Timmermans, H. (2014). Dynamics of face-to-face social interaction frequency: role of accessibility, urbanization, changes in geographical distance and path dependence. *Journal of Transport Geography*, *34*, 211–220. https://doi.org/10.1016/j.jtrangeo.2013.12.011

Schmitt, M., Gollwitzer, M., Baumert, A., Blum, G., Gschwendner, T., Hofmann, W., & Rothmund, T. (2013). Proposal of a Nonlinear Interaction of Person and Situation (NIPS) model. *Frontiers in Psychology*, *4*, 499. https://doi.org/10.3389/fpsyg.2013.00499

Schoedel, R., Bühner, M., Krämer, M. D., Mehl, M., Reiter, T., Richter, D., Roos, Y., & Wrzus, C. (2023). *Selectivity biases in mobile sensing studies: Empirical lessons from* *two panel studies* [Manuscript in preparation]. Department of Psychology, LMU Munich; Charlotte Fresenius University.

Schoedel, R., Kunz, F., Bergmann, M., Bemmann, F., Buehner, M., & Sust, L. (2023). Snapshots of daily life: Situations investigated through the lens of smartphone sensing. *Journal of Personality and Social Psychology,* Advance online publication. https://doi.org/10.1037/pspp0000469

Schoedel, R., & Mehl, M. R. (2024). Mobile sensing methods. In H. T. Reis, T. West, & C. M. Judd (Eds.), *Handbook of research methods in social and personality psychology (3rd Ed)*.

Schoedel, R., Oldemeier, M., Bonauer, L., & Sust, L. (2022). *Dataset for: Systematic categorisation of 3091 smartphone applications from a large-scale smartphone sensing dataset* [Data set]. PsychArchives. https://doi.org/10.23668/psycharchives.5680

Schönbrodt, F. D., & Gerstenberg, F. X. R. (2012). An IRT analysis of motive questionnaires: The Unified Motive Scales. Journal of Research in Personality, 46(6), 725–742. https://doi.org/10.1016/j.jrp.2012.08.010 Sheldon, K. M. (2011). Integrating behavioral-motive and experiential-requirement perspectives on psychological needs: A two process model. *Psychological Review, 118*(4), 552–569. https://doi.org/10.1037/a0024758

Schwarz, N. (2012). Why researchers should think "real-time": A cognitive rationale. In M. R. Mehl & T. Conner (Eds.), *Handbook of research methods for studying daily life* (pp. 22–42). Guilford Press.

Selfhout, M., Burk, W., Branje, S., Denissen, J., Van Aken, M., & Meeus, W. (2010). Emerging late adolescent friendship networks and Big Five personality traits: A social network approach. *Journal of Personality, 78*(2), 509–538. https://doi.org/10.1111/j.1467-6494.2010.00625.x

Sellbom, M., & Tellegen, A. (2019). Factor analysis in psychological assessment research: Common pitfalls and recommendations. *Psychological Assessment*, *31*(12), 1428–1441. https://doi.org/10.1037/pas0000623

Shaw, H., Ellis, D. A., Geyer, K., Davidson, B. I., Ziegler, F. V., & Smith, A. (2020). Quantifying smartphone "use": Choice of measurement impacts relationships between "usage" and health. *Technology, Mind, and Behavior, 1*, 1–15. https://doi.org/10.1037/tmb0000022

Sheeran, P., & Webb, T. L. (2016). The intention–behavior gap. *Social and personality psychology compass*, *10*(9), 503–518. https://doi.org/10.1111/spc3.12265

Sheldon, K. M. (2011). Integrating behavioral-motive and experiential-requirement perspectives on psychological needs: A two process model. *Psychological Review, 118*(4), 552–569. doi: 10.1037/a0024758

Simons, D. J., Shoda, Y., & Lindsay, D. S. (2017). Constraints on Generality (COG): A proposed addition to all empirical papers. *Perspectives on Psychological Science, 12*(6), 1123–1128. https://doi.org/10.1177/1745691617708630

Skjaeveland, O., & Gärling, T. (1997). Effects of interactional space on neighboring. *Journal of Environmental Psychology, 17*, 181–198. https://doi.org/10.1006/jevp.1997.0054

Smillie, L. D., DeYoung, C. G., & Hall, P. J. (2015). Clarifying the relation between extraversion and positive affect. *Journal of Personality*, *83*(5), 564–574. https://doi.org/10.1111/jopy.12138

Sng, O., Neuberg, S. L., Varnum, M. E. W., & Kenrick, D. T. (2017). The crowded life is a slow life: Population density and life history strategy. *Journal of Personality and Social Psychology*, *112*(5), 736–754. https://doi.org/10.1037/pspi0000086

Sosnowska, J., Kuppens, P., De Fruyt, F., & Hofmans, J. (2020). New Directions in the Conceptualization and Assessment of Personality—A Dynamic Systems Approach. *European Journal of Personality, 34*(6), 988–998. https://doi.org/10.1002/per.2233

Soto, C. J., & John, O. P. (2017). The next Big Five Inventory (BFI-2): Developing and assessing a hierarchical model with 15 facets to enhance bandwidth, fidelity, and predictive power. *Journal of Personality and Social Psychology, 113*(1), 117–143. https://doi.org/10.1037/pspp0000096

Srivastava, S., Angelo, K. M., & Vallereux, S. R. (2008). Extraversion and positive affect: A day reconstruction study of person–environment transactions. *Journal of Research in Personality, 42*(6), 1613–1618.

Stachl, C., Au, Q., Schoedel, R., Gosling, S. D., Harari, G. M., Buschek, D., Völkel, S. T., Schuwerk, T., Oldemeier, M., Ullmann, T., Hussmann, H., Bischl, B., & Bühner, M. (2020). Predicting personality from patterns of behavior collected with smartphones. *Proceedings of the National Academy of Sciences, 117*(30), 17680–17687. https://doi.org/10.1073/pnas.1920484117

Stachl, C., Hilbert, S., Au, J. Q., Buschek, D., De Luca, A., Bischl, B., Hussmann, H., & Bühner, M. (2017). Personality traits predict smartphone usage. *European Journal of Personality, 31*, 701–722. https://doi.org/10.1002/per.2113

Stadel, M., van Duijn, M. A., Wright, A. G., Bringmann, L. F., & Elmer, T. (2024). Considering the ‘With Whom’: Differences between event-and signal-contingent ESM data of person-specific social interactions. *Multivariate Behavioral Research*, 1–18. https://doi.org/10.1080/00273171.2024.2335405

Stangier, U., Heidenreich, T., Berardi, A., Golbs, U., & Hoyer, J. (1999). Die Erfassung sozialer Phobie durch die Social Interaction Anxiety Scale (SIAS) und die Social Phobia Scale (SPS). *Zeitschrift Für Klinische Psychologie Und Psychotherapie, 28*(1), 28–36. https://doi.org/10.1026//0084-5345.28.1.28

Stokols, D. (1972). On the distinction between density and crowding: Some implications for future research. *Psychological Review, 79*, 275–277. https://doi.org/10.1037/h0032706

Struminskaya, B., Lugtig, P., Keusch, F., & Höhne, J. K. (2020). Augmenting surveys with data from sensors and apps: Opportunities and challenges. *Social Science Computer Review*, 0894439320979951. https://doi.org/10.1177/0894439320979951

Sun, J., Harris, K., & Vazire, S. (2020). Is well-being associated with the quantity and quality of social interactions? *Journal of Personality and Social Psychology, 119*(6), 1478–1496. https://doi.org/10.1037/pspp0000272

Sun, R., Rieble, C., Liu, Y., & Sauter, D. (2020). Connected despite lockdown: The role of social interactions and social media use in wellbeing. *PsyArXiv*. https://doi.org/10.31234/osf.io/x5k8u.

Sundstrom, E. (1975). An experimental study of crowding: Effects of room size, intrusion, and goal blocking on nonverbal behavior, self-disclosure, and self-reported stress. *Journal of Personality and Social Psychology*, *32*, 645–654. https://doi.org/10.1037/0022-3514.32.4.645

Tay, L., & Diener, E. (2011). Needs and subjective well-being around the world. *Journal of Personality and Social Psychology, 101*(2), 354–365. https://doi.org/10.1037/a0023779

Thomson, R., Yuki, M., Talhelm T., Schug J., Kito M., Ayanian A. H., Becker J. C., Becker M., Chiu C.-Y., Choi H.-S., Ferreira C. M., Fülöp M., Gul P., Houghton-Illera A. M., Joasoo M., Jong J., Kavanagh C. M., Khutkyy D., Manzi C., … Visserman M. L. (2018). Relational mobility predicts social behaviors in 39 countries and is tied to historical farming and threat. *Proceedings of the National Academy of Sciences*, 115, 7521–7526. https://doi.org/10.1073/pnas.1713191115

Tissera, H., Gazzard Kerr, L., Carlson, E. N., & Human, L. J. (2020). Social anxiety and liking: Towards understanding the role of metaperceptions in first impressions.

Journal of Personality and Social Psychology, *121*(4), 948–968. https://doi.org/10.1037/pspp0000363

Tomori, D. V., Rübsamen, N., Berger, T., Scholz, S., Walde, J., Wittenberg, I., Lange, B., Kuhlmann, A., Horn, J., Mikolajczyk, R., Jaeger, V. K., & Karch, A. (2021). Individual social contact data and population mobility data as early markers of SARS-CoV-2 transmission dynamics during the first wave in Germany an analysis based on the COVIMOD study. *BMC Medicine, 19*(1), 271. https://doi.org/10.1186/s12916-021- 02139-6

Tse, D. C. K., Lay, J. C., & Nakamura, J. (2022). Autonomy matters: Experiential and individual differences in chosen and unchosen solitary activities from three Experience Sampling studies. *Social Psychological and Personality Science*, *13*(5), 946–956. https://doi.org/10.1177/19485506211048066

Tukey, J. W., & Hamming, R. H. (1949). Measuring noise color. In D. R. Brillinger (Ed.), *The collected works of John W. Tukey: Time Series, 1949-1964 (Vol. 1).* Belmont, CA: Wadsworth Advanced Books and Software.

Twenge, J. M., & Joiner, T. E. (2020). U.S. Census Bureau-assessed prevalence of anxiety and depressive symptoms in 2019 and during the 2020 COVID-19 pandemic. *Depression and Anxiety, 37*(10), 954–956. https://doi.org/10.1002/da.23077

Ullán, A. M., Belver, M. H., Fernández, E., Serrano, I., Delgado, J., & Herrero, C. (2012). Hospital designs for patients of different ages: Preferences of hospitalized adolescents, nonhospitalized adolescents, parents, and clinical staff. *Environment & Behavior, 44*, 668–694. https://doi.org/10.1177/0013916511403802

Uziel, L., & Schmidt-Barad, T. (2022). Choice matters more with others: Choosing to be with other people is more consequential to well-being than choosing to be alone. *Journal of Happiness Studies*, *23*(6), 2469–2489. https://doi.org/10.1007/s10902-022-00506-5

Valtorta, N. K., Kanaan, M., Gilbody, S., & Hanratty, B. (2016). Loneliness, social isolation and social relationships: what are we measuring? A novel framework for classifying and comparing tools. *BMJ open, 6*(4), e010799. https://doi.org/10.1136/bmjopen-2015-010799

van den Berg, P., Arentze, T., & Timmermans, H. (2010). Factors influencing the planning of social activities: Empirical analysis of data from social interaction diaries. *Transportation research record, 2157*(1), 63–70. https://doi.org/10.3141/2157-08

van Zalk, M., Nestler, S., Geukes, K., Hutteman, R., & Back, M. (2019). The codevelopment of extraversion and friendships: Bonding and behavioral interaction mechanisms in friendship networks. *Journal of Personality and Social Psychology*, *118*(6), 1269–1290. https://doi.org/10.1037/pspp0000253

Van Zalk, N., Van Zalk, M. H. W., Kerr, M., & Stattin, H. (2011). Social anxiety as a basis for friendship selection and socialization in adolescents' social networks. *Journal of Personality, 79*(3), 499–526. https://doi.org/10.1111/j.1467-6494.2011.00682.x

Van Lange, P. A. M., & Columbus, S. (2021). Vitamin S: Why is social contact, even with strangers, so important to well-being? *Current Directions in Psychological Science, 30*(3), 267–273. https://doi.org/10.1177/09637214211002538

Vangelisti, A. L., & Perlman, D. (2018). *The Cambridge handbook of personal relationships*. Cambridge University Press. https://doi.org/10.1017/9781316417867

Vazire, S. (2010). Who knows what about a person? The self-other knowledge asymmetry (SOKA) model. *Journal of Personality and Social Psychology, 98*(2), 281–300. https://doi.org/10.1037/a0017908

Vega, J., Li, M., Aguillera, K., Goel, N., Joshi, E., Khandekar, K., Durica, K. C., Kunta, A. R., & Low, C. A. (2021). Reproducible analysis pipeline for data streams: Open-source software to process data collected with mobile devices. *Frontiers in Digital Health*, 3. https://doi.org/10.3389/fdgth.2021.769823

Voelkle, M. C., & Oud, J. H. (2013). Continuous time modelling with individually varying time intervals for oscillating and non-oscillating processes. *British Journal of Mathematical and Statistical Psychology, 66*(1), 103–126. https://doi.org/10.1111/j.2044-8317.2012.02043.x

Wagner, J., Lüdtke, O., Roberts, B. W., & Trautwein, U. (2014). Who belongs to me? Social relationship and personality characteristics in the transition to young adulthood. *European Journal of Personality, 28,* 586–603. https://doi.org/10.1002/per.1974

Wang, L., & Maxwell, S. E. (2015). On disaggregating between-person and within-person effects with longitudinal data using multilevel models. *Psychological Methods, 20*(1), 63–83. https://doi.org/10.1037/met0000030

Weber, C., Quintus, M., Egloff, B., Luong, G., Riediger, M., & Wrzus, C. (2020). Same old, same old: Age differences in the diversity of daily life. *Psychology & Aging, 35*, 434–448. doi: https://doi.org/10.1037/pag0000407

Wenzel, M., Bürgler, S., Brandstätter, V., Kreibich, A., & Hennecke, M. (2023). Self-regulatory strategy use, efficacy, and strategy-situation-fit in self-control conflicts of initiation, persistence, and inhibition. *European Journal of Personality.* https://doi.org/10.1177/08902070221150478

Wheeler, L., & Nezlek, J. (1977). Sex differences in social participation. *Journal of Personality and Social Psychology*. 35, 742–754. https://doi.org/10.1037/0022-3514.35.10.742

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T. L., Miller, E., Bache, S. M., Müller, K., Ooms, J., Robinson, D., Seidel, D. P., Spinu, V., … Yutani, H. (2019). Welcome to the tidyverse. *Journal of Open Source Software, 4*(43), 1686. https://doi.org/10.21105/joss.01686

Winterheld, H. A., & Simpson, J. A. (2018). Personality in close relationships. In A. L. Vangelisti & D. Perlman (Eds.), *The Cambridge handbook of personal relationships* (pp. 163–174). Cambridge: Cambridge University Press. https://doi.org/10.1017/9781316417867.014

World Bank. (2024). World Development Indicators. [Data set]. World Bank Databank. https://databank.worldbank.org/reports.aspx?source=world-development-indicators

Wrzus, C. (2021). Processes of personality development: An update of the TESSERA framework. In J. Rauthmann (Ed.), *The Handbook of Personality Dynamics and Processes* (pp. 101–123). London, UK: Elsevier.

Wrzus, C., Hänel, M., Wagner, J., & Neyer, F. J. (2013). Social network changes and life events across the life span: a meta-analysis. *Psychological bulletin*, *139*(1), 53–80. https://doi.org/10.1037/a0028601

Wrzus, C., & Mehl, M. R. (2015). Lab and/or field? Measuring personality processes and their social consequences. *European Journal of Personality, 29*(2), 250–271. https://doi.org/10.1002/per.1986

Wrzus, C., & Neyer, F. J. (2016). Co-development of personality and friendships across the lifespan: An empirical review on selection and socialization. *European Psychologist, 21*, 254–273. doi: 10.1027/1016-9040/a000277

Wrzus, C., & Neubauer, A. B. (2022). Ecological momentary assessment: A meta-analysis on designs, samples, and compliance across research fields. *Assessment*, 10731911211067538. Advance online publication. https://doi.org/10.1177/10731911211067538

Wrzus, C., & Roberts, B. W. (2017). Processes of personality development in adulthood: The TESSERA framework. *Personality and Social Psychology Review*, *21*, 253–277. https://doi.org/10.1177/1088868316652279

Wrzus, C., Roos, Y., Krämer, M., & Richter, D. (2024). Individual differences in short-term social dynamics: Theoretical perspective and empirical development of the Social Dynamics Scale. *Current Psychology*. Advance online publication. https://doi.org/10.1007/s12144-024-05868-y

Wrzus, C., & Schoedel, R. (2023). Transparency and reproducibility in mobile sensing research. In M. R. Mehl, M. Eid, C. Wrzus, G. Harari, & U. W. Ebner-Priemer (Eds.), *Mobile Sensing in Psychology: Methods and Applications*. New York: Guilford.

Wrzus, C., Wagner, G. G., & Riediger, M. (2016). Personality-situation transactions from adolescence to old age. *Journal of Personality and Social Psychology, 110*(5), 782–799. https://doi.org/10.1037/pspp0000054

Wrzus, C., Wagner, J., & Neyer, F. J. (2012). The interdependence of horizontal family relationships and friendships relates to higher well-being. *Personal Relationships, 19*, 465–482. doi: 10.1111/j.1475-6811.2011.01373.x

Wrzus, C., Roos, Y., Krämer, M. D., Schoedel, R., Back, M. D., & Richter, D. (2024). *Affiliation Motive and Social Interactions in People's Daily Life: A Temporal Processes Approach Using Ecological Momentary Assessment and Mobile Sensing*.[Manuscript submitted for publication] Department of Psychological Aging Research, Institute of Psychology, Heidelberg University.

Yakubenko, S. (2021). Home alone? Effect of weather-induced behaviour on spread of SARS-CoV-2 in Germany. *Economics & Human Biology, 42*, 100998. https://doi.org/ 10.1016/j.ehb.2021.100998

Yarkoni, T. (2022). The generalizability crisis. *Behavioral and Brain Sciences, 45*, e1: 1–78. https://doi.org/10.1017/S0140525X20001685

Zacher, H., & Rudolph, C. W. (2021). Individual differences and changes in subjective wellbeing during the early stages of the COVID-19 pandemic. *American Psychologist, 76*(1), 50–62. https://doi.org/10.1037/amp0000702

Zajenkowski, M., Jonason, P. K., Leniarska, M., & Kozakiewicz, Z. (2020). Who complies with the restrictions to reduce the spread of COVID-19?: Personality and perceptions of the COVID-19 situation. *Personality and Individual Differences, 166*, 110199. https://doi.org/10.1016/j.paid.2020.110199

Zelenski, J. M., Santoro, M. S., & Whelan, D. C. (2012). Would introverts be better off if they acted more like extraverts? Exploring emotional and cognitive consequences of counterdispositional behavior. *Emotion*, *12*(2), 290–303. https://doi.org/10.1037/a0025169

Zettler, I., Schild, C., Lilleholt, L., Kroencke, L., Utesch, T., Moshagen, M., & Geukes, K. (2022). The role of personality in COVID-19-related perceptions, evaluations, and behaviors: Findings across five samples, nine traits, and 17 criteria. *Social Psychological and Personality Science, 13*(1), 299–310. https://doi.org/10.1177/19485506211001680

Zygar, C., Hagemeyer, B., Pusch, S., & Schönbrodt, F. D. (2018). From motive dispositions to states to outcomes: An intensive experience sampling study on communal motivational dynamics in couples. *European Journal of Personality*, *32*(3), 306–324. https://doi.org/10.1002/per.2145

Appendices and Supplements

Supplement for Chapter 2 refers to pages 11–29.

Supplement for Chapter 3: refers to pages 30–62.

Supplementary Information Chapter 4 refers to pages 63–94.

Appendix for Chapter 5 refers to pages 95–125.

Supplemental Material for Chapter 6 refers to pages 126–149.

Supplement for Chapter 2: Does Your Smartphone "Know" Your Social Life? A Methodological Comparison of Day Reconstruction, Experience Sampling, and Mobile Sensing

Yannick Roos, Michael D. Krämer, & David Richter, Ramona Schoedel & Cornelia Wrzus

Appendix A

Timeline of National Minimum Standards of Restrictive Measures during the COVID-19 Pandemic

<table>
<tr><th>Effective from</th><th>Life domain</th><th>Vaccinated/recovered</th><th>Unvaccinated</th></tr>
<tr><td>2021-08-23</td><td>Private gatherings</td><td>no restrictions</td><td>no restrictions</td></tr>
<tr><td></td><td>Major events</td><td>capacity restrictions</td><td>capacity restrictions</td></tr>
<tr><td></td><td></td><td colspan="2">negative test mandatory</td></tr>
<tr><td></td><td>Indoor activities</td><td>no restrictions</td><td>often negative tests required</td></tr>
<tr><td>2021-11-18</td><td>Private gatherings</td><td>no restrictions</td><td>no restrictions</td></tr>
<tr><td></td><td>Major events</td><td>capacity restrictions</td><td>capacity restrictions</td></tr>
<tr><td></td><td></td><td colspan="2">negative test mandatory</td></tr>
<tr><td></td><td>Indoor activities</td><td colspan="2">low hospitalization rate:</td></tr>
<tr><td></td><td></td><td>no restrictions</td><td>negative test required</td></tr>
<tr><td></td><td></td><td colspan="2">high hospitalization rate:</td></tr>
<tr><td></td><td></td><td>negative test required if risk of infection is high (e.g., in clubs).</td><td>negative test required to access workplaces, and public transportation.
no access to other indoor activities (except retail for daily needs).</td></tr>
<tr><td>2021-12-02</td><td>Private gatherings</td><td>low incidence: no restrictions.
high incidence: maximum of 50 persons (indoors)/ 200 persons (outdoors).</td><td>own household and up to 2 other persons</td></tr>
</table>

Effective from	Life domain	Vaccinated/recovered	Unvaccinated
	Major events	low incidence: negative test required in some cases. capacity restrictions high incidence: no sporting events. Most major events were canceled.	no access
	Indoor activities	low incidence: sometimes negative test required. high incidence: sometimes negative test required. no dancing activities and no access to clubs/discos.	negative test required to access workplaces, and public transportation. no access to other indoor activities (except retail for daily needs).
2021-12-28	Private gatherings	**maximum of 10 persons**	**own household and up to 2 other persons**
	Major events	no access	no access
	Indoor activities	sometimes negative test required. no access to clubs/discos.	negative test required to access workplaces, and public transportation. no access to other kinds of indoor activities (except retail for daily needs).
2022-01-07	Private gatherings	maximum of 10 persons	own household and up to 2 other persons
	Major events	no access	no access
	Indoor activities	negative test or booster vaccination required to access restaurants. no access to clubs/discos.	negative test required to access workplaces, and public transportation. no access to other kinds of indoor activities (except retail for daily needs).
2022-02-16	Private gatherings	no restrictions	own household and up to 2 other persons
	Major events	no access	no access

Effective from	Life domain	Vaccinated/recovered	Unvaccinated
	Indoor activities	negative test or booster vaccination required to access restaurants. no access to clubs/discos.	unrestricted access to retail outlets. negative test required to access workplaces, and public transportation. no access to other kinds of indoor activities.
2022-03-04	Private gatherings	no restrictions	own household and up to 2 other persons
	Major events	sometimes negative test required. capacity restrictions.	no access
	Indoor activities	negative test or booster vaccination required to access clubs/discos.	unrestricted access to retail outlets. negative test required to access restaurants, overnight accommodation, workplaces, and public transportation. no access to other kinds of indoor activities.
2022-03-20	Private gatherings	no restrictions	no restrictions
	Major events	no restrictions	no restrictions
	Indoor activities	no restrictions	no restrictions
2022-03-20	A new Infection Protection Act (Infektionsschutzgesetz) comes into effect. All far-reaching restrictions on social, cultural, and economic life are to be lifted. Under a transitional arrangement, the federal states are permitted to uphold both existing testing requirements and existing obligations to provide proof of vaccination or recovery until 2022-04-02.		

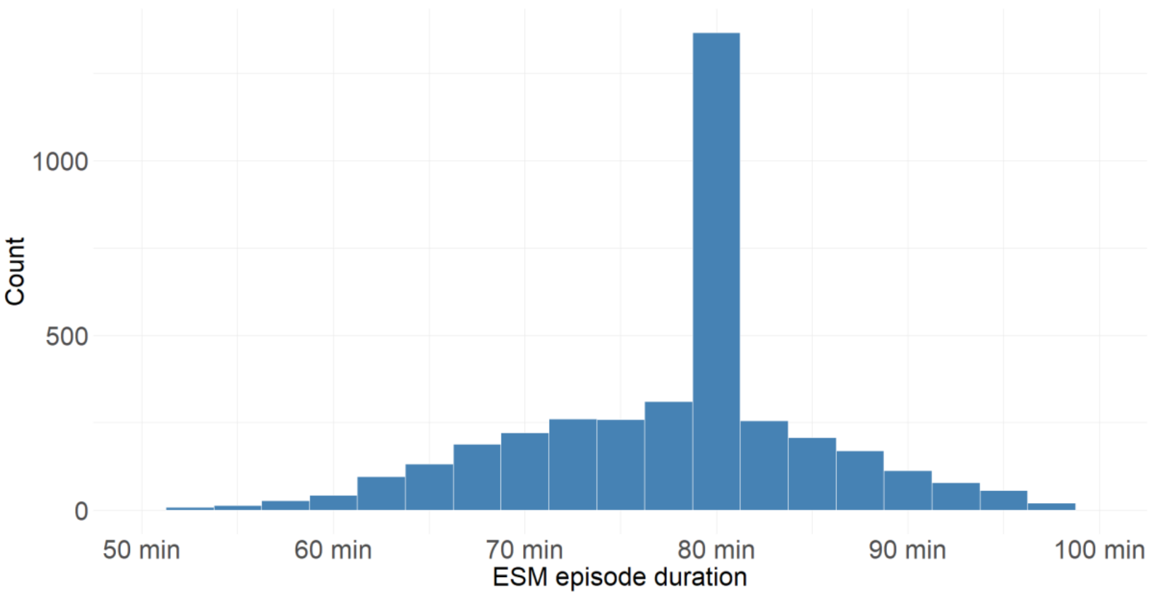
Note. All restrictive measures were national minimum standards that were agreed between the Federal Government and the State Governments. The federal states particularly affected by the pandemic acted beyond these minimum standards by means of state regulations. Data for this table was retrieved from the website of the German Government: https://www.bundesregierung.de/breg-de/themen/coronavirus/corona-regeln-und-einschrankungen-1734724

Appendix B: Details on the Distribution of ESM questionnaires

The PhoneStudy app was programmed to distribute experience sampling questionnaires every 80 minutes, with some jitter which resulted from drawing a random number from the interval [-10 min, +10 min]. During the study, other (background) processes running on participants' smartphones sometimes hindered the triggering of some experience sampling notifications (which is expected and is common to all comparable research apps we know). In those cases, the app rescheduled the notification and tried to push it to the foreground at a later time, resulting in some delayed notifications. The notification through which the ESM questionnaire was available was programmed to disappear after 15 minutes. The distribution of ESM episode duration is shown in Figure B1.

Figure B1

Distribution of ESM Episode Duration



Note. ESM episode duration indicates the time since the previously answered ESM questionnaire was completed. If no ESM questionnaire was answered within the last 100 min, the episode duration of the current ESM episode was set to 80 min.

Appendix C: Details on the PhoneStudy app logging modes

The PhoneStudy app (Schoedel et al., preprint) used three different logging modes:

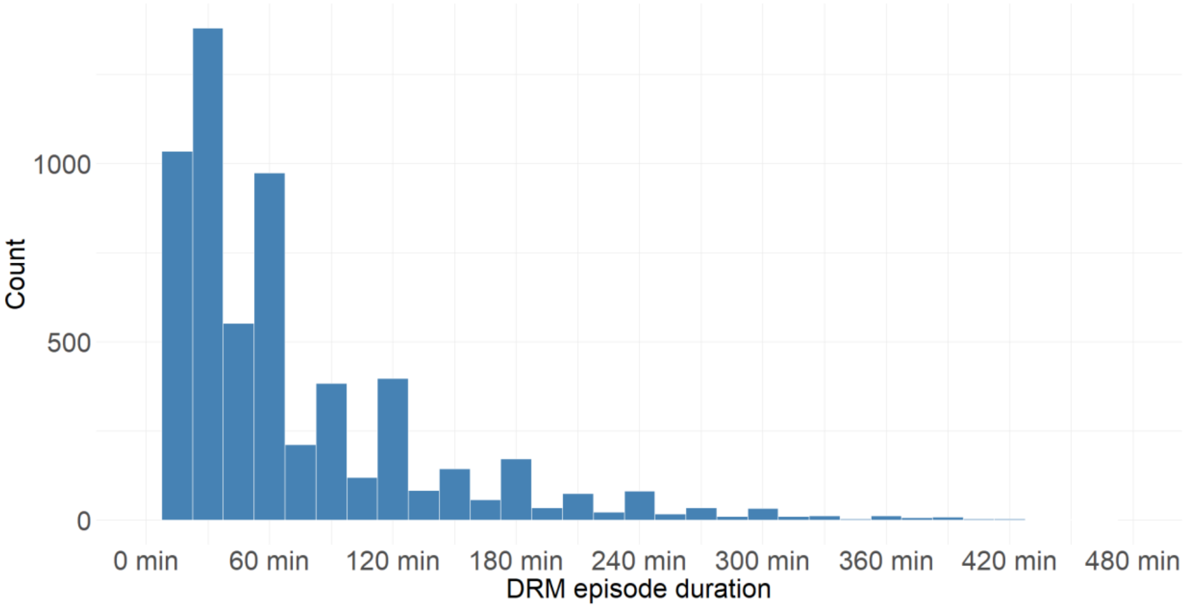
Event-based: For user-smartphone interactions (i.e., phone usage, app usage, keyboard usage) time-stamped data points were stored, and—depending on the data type—saved with different specifications (e.g., app usage logs with the app name; keyboard usage sessions with the number of characters typed).

Interval-based: Logging of face-to-face interactions (i.e., the presence of conversation) occurred at certain intervals, that is, the AWARE Conversations plug-in was programmed to follow a cycle of 1-min sampling and 3-min pause (Ferreira & Mulukutla, 2020). This sampling-pause ratio was implemented to strike a balance between measuring as often as possible and conserving battery life. In practice, differences in the number of samplings per episode occurred on different smartphone models, and the actual sampling rates from the current study are shown in Appendix E.

Trigger-based: ESM notifications were distributed based on intervals (Appendix B), but the ESM data itself were saved through ESM questionnaire-triggered logging, that is in the moment it was "produced". Thus, ESM data were stored whenever participants interacted with an ESM questionnaire (e.g., logs were created if participants opened or closed an ESM questionnaire, but also for every answered question). In addition, we used event-triggered sampling to assess interaction partner and valence of calls. That means, after sensing a call, a short questionnaire was triggered. Whenever participants interacted with the questionnaire, the data were logged. The event-triggered ESM questionnaire was triggered only after calls that lasted ten seconds or longer, mainly to prevent the detection of artefacts. We determined this ten second duration from a pilot study to prevent inappropriately triggered questions (e.g., when people called and nobody picked up).

Appendix D

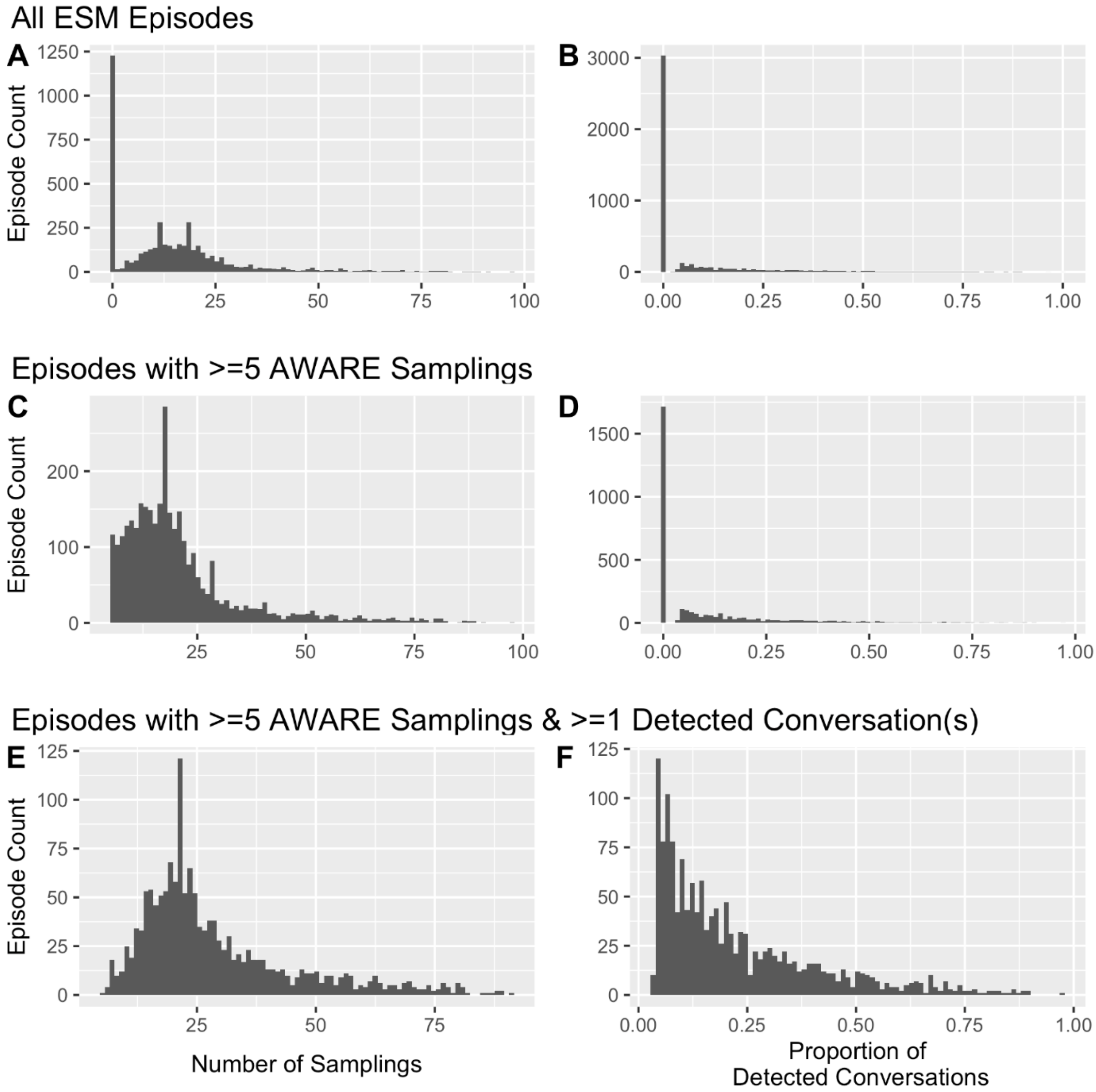
Distribution of DRM Episode Duration



Note. Participants were instructed that most people report episodes with durations between 15 min and 2 hr, but chose freely on how to divide their days into episodes.

Appendix E

Distribution of AWARE-Conversations Samplings and the Proportion of Detected Voices



Note. The figure is based on experience sampling episodes from n = 306 participants. The median duration of experience sampling episodes was 80 min, with a standard deviation of 8.01 min.

Appendix F: Details on the analytical procedure

Matching of face-to-face episodes

The raw data were collected at different sampling rates depending on the used method. For comparisons between these methods, we aligned their temporal resolution in a first step which we describe in the following section.

We aligned the DRM measurements with the ESM episodes using the following procedure:

1) For each ESM episode we searched the DRM dataset for all DRM episodes that had some temporal overlap with the ESM episode and indicated that people were in a face-to-face interaction.
2) If the whole ESM episode was embedded in a DRM episode with face-to-face interaction, the interaction duration measured by DRM was set to the duration of the ESM episode.
3) Else, the face-to-face interaction duration measured by DRM was calculated as the sum of all parts of the duration of DRM-episodes that indicated face-to-face interactions and fell within the period of the corresponding ESM episode.

Example: Given are

- a DRM episode indicating face-to-face interaction that started at 9:00 a.m. and ended at 11:00 a.m.
- another DRM episode indicating no face-to-face interaction that started at 11:00 a.m. and ended at 12:00 a.m.
- an ESM episode that started at 10:20 a.m. and ended 11:40 a.m. and included reports of social interactions that summed up to 50 minutes.

With this information we created a new entry in the aggregated dataset that has the following values: DRM_face-to-face_duration = 2400 sec (10:20 a.m. up to 11:00 a.m.), ESM_face-to-face_duration = 3000 sec.

We aligned DRM with the MS episodes, using the following procedure:

(1) For each DRM episode, we searched the MS data for any samplings of the AWARE-conversation plug-in.
(2) If less than five AWARE samplings were available for an episode, we set the MS measurement of face-to-face interactions for that episode to missing.
(3) For each DRM episode with five or more AWARE samplings, we calculated the proportion of conversation, that is, we divided all samplings indicating conversation

by the total number of samplings found within the period of the corresponding DRM-episode.

Example: Given are

- a DRM episode indicating face-to-face interaction that started at 9:00 a.m. and ended at 11:00 a.m.
- 10 Aware samplings that occurred between 9:00 a.m. and 11:00 a.m., of which 4 indicated “conversation” and 6 indicated “no conversation”.

With this information we created a new entry in the aggregated dataset that has the following values: DRM_face-to-face_duration = 7200 sec, MS_face-to-face_proportion = 0.40.

We aligned ESM with MS using the same procedure as outlined above.

Example: Given are

- an ESM episode that started at 10:20 a.m. and ended 11:40 a.m.
- the ESM measurement indicated 50 minutes of face-to-face interactions.
- 6 Aware samplings that occurred between 9:00 a.m. and 11:00 a.m. of which 3 indicated “conversation” and 3 indicated “no conversation”.

With this information we created a new entry in the aggregated dataset that has the following values: ESM_face-to-face_duration = 3000 sec, MS_face-to-face_proportion = 0.50.

Matching of calls

The current study compared the assessment of calls between DRM, ESM, and MS. Previous studies have often aggregated call-characteristics across episodes, but this leads to inaccuracies and problems with categorical variables (e.g., type of interaction partner). Instead, in the current study, we matched the calls one by one using the following procedure:

1) For each call reported in ESM, we searched the smartphone app activity log for sensed calls in the corresponding timeframe.
2) If no call was found in the app activity logs, no matching between ESM and MS occurred.

   If one call was found in the app activity logs that occurred in the corresponding timeframe, then this call was matched with the corresponding ESM call.

If more than one potentially matching call was found, then the match-score (described in the section below) was calculated for each MS-call and the MS-call with the highest match-score was matched with the ESM call.

3) Next, this procedure was repeated to match ESM-calls and DRM-calls (instead of searching the smartphone activity log, the DRM data were searched in the corresponding timeframes).
4) Lastly, DRM-calls and MS-calls were matched. For this matching, the smartphone app activity logs were searched for calls using a time window of +/- 15 minutes around the corresponding DRM episode. This time window was introduced to account for small inaccuracies in participants reports of episode start and end and to make the matching procedure between DRM and MS more comparable to the matching of ESM and MS (as most DRM-episodes were shorter than the median ESM-episode).

Match score formula for calls

If multiple calls were candidates for matching (e.g., multiple calls occurring in the same ESM-episode), we aimed to match calls with the most similar characteristics. An index for similarity was calculated using duration, relationship type, and valence from the two methods to be matched.

match_scores = (1 - dur_dif/max_dur) * 1/3 + who_agreement * 1/3 + (1 - val_dif /6) * 1/3

dur_dif, who_agreement and val_dif: vectors with one value for each call-matching candidate:

dur_dif: absolute value of the duration difference between calls from two methods.

max_dur: maximum value obtained for call duration.

who_agreement: 0 if relationship type does not agree, 1 if relationship type agrees. val_dif: absolute value of the valence difference between calls from two methods. The maximum possible difference was 6.

Table F1

Three Examples for the Matching of ESM and MS Calls

	ESM Dur	MS Dur	ESM who	MS who	ESMval	MS val	Rating	Match Score
Example 1	300 sec	244 sec	other family	others	6	5	undecided	0.49
Example 2	300 sec	694 sec	friends	strangers	5	4	not same call	0.32
Example 3	600 sec	652 sec	friends	friends	7	7	same call	0.97

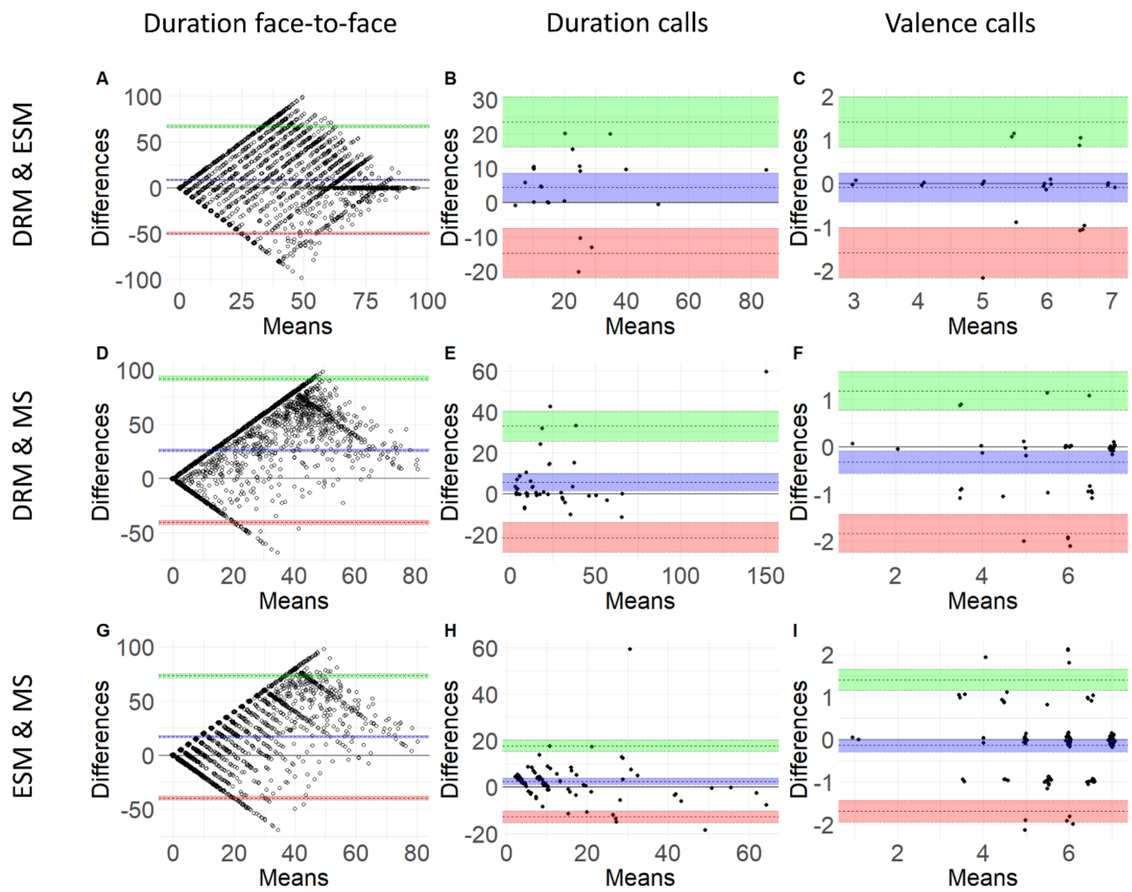
Note. ESM Dur = duration reported in ESM; MS Dur = duration extracted from app activity log; ESM who = relationship category of the interaction partner reported in ESM; MS who = relationship category of the interaction partner reported in event-triggered sampling; ESM val = valence of the call reported in ESM; MS val = valence reported in event-triggered sampling. Patterns as shown in Example 1 were rare in the data. Most calls followed patterns more similar to Example 2 and Example 3. In analyses with strict matching, calls like Example 1 and Example 2 were excluded prior to calculating correlations or agreement.

Matching of messages

In MS, messaging data were processed via logging keyboard sessions. A keyboard session was defined as the time period between opening and closing the keyboard (Bemmann & Buschek, 2020). Both start and end timestamps of the keyboard sessions were logged. Each timestamp entry additionally included data on the number of characters added or altered, the name of the app in which the text has been entered, and—if available—data on the function of the text field (e.g., “search”, “write a message…”). First, we reduced the dataset to messages that were typed in communication apps (which includes SMS and emails send from the phone; for the used app categorization see Schoedel et al., 2022). Next, we excluded messages that were typed into search or navigation text fields. For the comparison of messages assessed via ESM and MS, we then aggregated the MS data to match the ESM episodes: We summed the number of keyboard usage sessions occurring in the respective ESM episode.

Appendix G

Bland-Altman Plots for Continuous Variables



Note. All durations are in minutes. MS face-to-face duration was calculated by multiplying the proportion of conversation in an episode with the corresponding episode duration. The x-axis indicates the mean between both methods that are compared. Data are jittered to improve visibility of overlapping dots (uniform random jitter of 30 sec for durations, and of 0.1 rating points for valence). The call data shown in the plot are from calls matched with the strict matching procedure. DRM indicated longer durations for face-to-face interactions than ESM and MS (Panel A, D), ESM indicated longer durations for face-to-face interactions than MS (Panel G); and both DRM and ESM indicated longer call durations than MS (Panel E, H). DRM indicated slightly more negative valence ratings than MS (Panel F). Please note that any conclusions from these plots should be drawn very carefully, because the nested data structure is not accounted for.

Appendix H

Face-to-face Multilevel Correlations using different Cut-off Values for the Minimum Number of MS Samplings

Cut-off	DRM & MS			ESM & MS		
	n	r_{ml}	95% CI	*n*	r_{ml}	95% CI
>= 1 sampling	4708	.22	[.20,.25]	3085	.24	[.20,.27]
>= 5 samplings	3576	.20	[.17,.23]	2993	.24	[.20,.27]
>= 10 samplings	2457	.17	[.13,.21]	2548	.25	[.21,.28]
>= 15 samplings	1795	.16	[.11,.20]	1875	.27	[.23,.31]
>= 20 samplings	1350	.14	[.09,.19]	1204	.24	[.19,.30]
>= 25 samplings	1015	.14	[.08,.20]	693	.21	[.14,.28]
>= 30 samplings	827	.15	[.09,.22]	478	.18	[.09,.26]

Note. The multilevel correlation between DRM or ESM measurements of face-to-face interaction duration and the proportion of conversation assessed with MS was mostly unaffected by the choice of minimum number of AWARE samplings required to qualify an episode as a valid measurement.

References

Bemmann, F., & Buschek, D. (2020). LanguageLogger: A Mobile Keyboard Application for Studying Language Use in Everyday Text Communication in the Wild. *Proceedings of the ACM on Human-Computer Interaction, 4*(EICS), 1-24. https://doi.org/10.1145/3397872

Ferreira, D., & Mulukutla, R. (2020). AWARE Plugin: Conversations. Retrieved from https://github.com/denzilferreira/com.aware.plugin.studentlife.audio_final

Makowski, D., Wiernik, B. M., Patil, I., Lüdecke, D., & Ben-Shachar, M. S. (2022). *correlation*: Methods for correlation analysis [R package]. https://CRAN.R-project.org/package=correlation (Original work published 2020)

Schoedel, R., Kunz, F., Bergmann, M., Bemmann, F., Bühner, M., & Sust, L. (2022, August 10). Snapshots of Daily Life: Situations Investigated Through the Lens of Smartphone Sensing. https://doi.org/10.31234/osf.io/f3htz

Schoedel, R., Oldemeier, M., Bonauer, L., & Sust, L. (2022). *Dataset for: Systematic categorisation of 3091 smartphone applications from a large-scale smartphone sensing dataset* [Data set]. PsychArchives. https://doi.org/10.23668/psycharchives.5680

Supplement for Chapter 3: Individual Differences in Social Dynamics: Theoretical Perspective and Empirical Development of the Social Dynamics Scale

Cornelia Wrzus, Yannick Roos, Michael D. Krämer, & David Richter

Complete List of Initial Social Dynamics Scale Items

Table S1

Wordings and Psychometric Properties of all Items from initial SDS-item Pool at T1 (n = 280)

Subscale		Original German item	English version	*M*	*SD*	Skew	riic	α	SDS 5	SDS 4	SDS 3
SDS FFI	1	Ich bin ein Familienmensch.[#]	I am a family person.	3.28	1.74	0.41	0.50	0.923	*	*	
	2	Meine Freunde sind mir wichtiger als meine Familie.	My friends are more important to me than my family.	2.77	1.56	0.67	0.54	0.922	*	*	*
	3	Ich mache lieber mit meiner Familie einen Ausflug als mit Freunden.[#]	I would rather go on an excursion with my family than with friends.	3.95	1.73	0.06	0.53	0.922	*	*	*
	4	Ich verlasse mich eher auf meine Familie als auf meine Freunde.[#]	I rely more on my family than on my friends.	3.24	1.68	0.48	0.53	0.922	*	*	*
	5	Ich bin sehr familienorientiert.[#]	I am very family-oriented.	3.40	1.76	0.36	0.52	0.922	*		
	6	Meinen Geburtstag feiere ich lieber mit meiner Familie als mit Freunden.[#]	I prefer to celebrate my birthday with my family rather than with friends.	3.86	1.74	0.06	0.50	0.923			
	7	Ich fahre lieber mit Freunden weg als mit meiner Familie.	I prefer to go on vacations with my friends rather than with my family.	3.46	1.81	0.24	0.49	0.923			
	8	Wenn ich Probleme habe, wende ich mich zuerst an meine Freunde.	When I have problems, I turn to my friends first.	3.60	1.57	0.15	0.33	0.930			

	9	Ich kann meinen Freunden eher vertrauen als meiner Familie.	I can trust my friends more than my family.	2.91	1.48	0.52	0.47	0.925			
	10	Ich vertraue meinen Freunden mehr als meiner Familie.	I trust my friends more than my family.	2.91	1.54	0.55	0.48	0.924			
	11	Auf meine Familie kann ich mich eher verlassen als auf meine Freunde.#	I can rely more on my family than on my friends	3.28	1.71	0.55	0.51	0.923			
	12	Den Austausch mit meiner Familie empfinde ich oft als erfüllender als den mit meinen Freunden.#	I often find interactions with my family more fulfilling than those with my friends.	3.87	1.60	0.05	0.51	0.923			
	13	Meine Familie nur an Feiertagen und Geburtstagen zu sehen würde mir völlig ausreichen.	Seeing my family only on holidays and birthdays would be quite enough for me.	3.16	1.98	0.61	0.42	0.927			
	14	Ich habe das Gefühl, meiner Familie alles anvertrauen zu können.#	I feel like I can trust my family with anything.	3.32	1.89	0.44	0.49	0.924			
SDS SoS	15	Wenn ich den ganzen Tag unter Menschen war, bin ich abends lieber allein.	When I have been with people all day, I prefer to spend the evening alone.	4.92	1.67	-0.60	0.52	0.900	*	*	*
	16	Ich kann den ganzen Tag unter Menschen sein, ohne dass es mir zu viel wird.#	I can be around other people all day without it getting to be too much for me.	4.51	1.74	-0.45	0.50	0.901	*	*	*
	17	Ich treffe mich mit möglichst oft mit jemandem ohne dass ich Zeit für mich brauche.#	I get together with other people as often as I can, without needing time for myself.	5.34	1.45	-0.77	0.43	0.908	*	*	

18	Ich bin schnell erschöpft, wenn ich mit vielen Menschen zusammen bin.	I become exhausted quickly when I am around a lot of people.	4.01	1.88	-0.12	0.54	0.898	*	*	*
19	Ich bin am liebsten andauernd mit anderen zusammen.#	I prefer to be with others all the time.	5.55	1.44	-0.91	0.45	0.906	*		
20	Nach einer Feier oder einem Treffen mit vielen Menschen ziehe ich mich oft zurück und bin allein.	After a party or a meeting with many people, I often withdraw and spend time alone.	4.45	1.77	-0.34	0.49	0.902			
21	Ständig unter Menschen zu sein geht mir auf die Nerven.	Being around people all the time gets on my nerves.	4.73	1.85	-0.55	0.52	0.900			
22	Nach Tagen mit vielen Terminen oder Verabredungen brauche ich etwas Ruhe.	After days with many appointments, I need some rest.	5.65	1.47	-1.26	0.45	0.906			
23	Auch wenn ich den ganzen Tag schon viel Kontakt zu anderen Menschen hatte, treffe ich mich abends gerne mit Leuten.#	Even if I have had a lot of contact with other people all day, I like to meet people in the evening.	4.62	1.62	-0.20	0.50	0.902			
24	Wenn ich den ganzen Tag unter Menschen war, dann sage ich manchmal weitere Treffen mit Freunden ab.	When I've been around people all day, I sometimes cancel further meetings with friends.	3.98	1.87	-0.09	0.40	0.910			
25	Nach langen Unterhaltungen habe ich das Gefühl, erst meine Batterien aufladen zu müssen, bevor ich wieder mit jemandem sprechen will.	After long conversations, I feel like I need to recharge my batteries before I want to talk to someone again.	4.29	1.78	-0.24	0.52	0.900			

SDS SD	26	Wenn ich den ganzen Tag allein bin, fehlt mir der Kontakt mit anderen.	When I am alone all day, I miss being around people.	3.46	1.77	0.20	0.49	0.877	*	*	*
	27	Nach wenigen Stunden allein sein fühle ich mich unwohl.	After spending just a few hours alone, I feel uncomfortable.	2.16	1.48	1.40	0.43	0.882	*	*	*
	28	Wenn ich den ganzen Tag allein war, muss ich abends jemanden sehen oder anrufen. (initial item)	If I have spent all day alone, I have to get together with someone or call someone in the evening.	3.21	1.82	0.43	0.45	0.880			
		Wenn ich den ganzen Tag allein war, versuche ich abends jemanden zu sehen oder anzurufen. (final Item)	If I have spent all day alone, I try to get together with someone or call someone in the evening.	/	/	/	/	/	*	*	*
	29	Allein zu sein macht mir auch über einen längeren Zeitraum nichts aus.[#] (initial item)	I have no problem spending time by myself for a long period of time.	2.95	1.91	-0.26	0.39	0.885			
		Es macht mir nichts aus, ein paar Tage für mich allein zu sein.[#] (final item)	I have no problem spending a few days by myself.	/	/	/	/	/	*	*	
	30	Ich bin gern auch mal ein bis zwei Tage allein ohne den Kontakt mit anderen zu vermissen.[#]	I like to be alone for a day or two without missing contact with others.	2.64	1.62	0.83	0.43	0.882	*		
	31	Wenn ich den ganzen Tag allein war, versuche ich abends oder am nächsten Tag jemanden zu treffen.	If I've been alone all day, I try to meet someone in the evening or the next day.	3.56	1.71	0.06	0.42	0.882			
	32	Ich fahre gern allein weg.[#]	I like to go on vacations on my own.	4.37	1.89	-0.14	0.28	0.892			

33	Ich bin gern allein unterwegs.#	I like to travel alone.	3.72	1.78	0.25	0.32	0.889
34	Ich bin gern ein paar Stunden allein ohne den Kontakt mit anderen zu vermissen.#	I like to be alone for a few hours without missing contact with others.	2.03	1.29	1.57	0.34	0.888
35	Nach wenigen Stunden allein sein brauche ich wieder Kontakt mit jemandem.	After being alone for a few hours, I need contact with someone.	2.85	1.67	0.58	0.46	0.880
36	Nachdem ich eine Zeit alleine war, sehne ich mich nach Kontakt mit anderen Menschen.	After being alone for a while, I long for contact with other people.	4.37	1.63	-0.33	0.37	0.886
37	Meine Freunde eine Woche lang nicht zu sehen schlägt mir aufs Gemüt.	Not seeing my friends for a week wears me down.	2.95	1.71	0.56	0.30	0.891
38	Meine Freizeit verbringe ich am liebsten alleine.#	I prefer to spend my free time alone.	4.34	1.63	-0.18	0.39	0.884
39	Ich vermisse meine Familie, wenn ich mal für mehrere Tage von ihr getrennt bin.	I miss my family when I am away from them for several days.	4.15	2.05	-0.14	0.26	0.896

Note. There were improvements of item language for item 28 and 29 (initial wordings in grey). α = Cronbach's Alpha if item deleted. r_{iic} = average inter-item correlation. SDS 5 = five item version of the SDS-Scale. SDS 4 = four item version. SDS 3 = three item version. Reverse coded items are marked with a #.

Confirmatory Factor Analysis and Reliability of 15, 12, and 9-item versions of the Social Dynamic Scale

Table S2

Confirmatory Factor Analysis Results for Social Dynamics Scale (15, 12, and 9-item version)

Items	df	X^2	*p*	CFI	TLI	RMSEA
15	105	1759.23	0.000	0.873	0.847	0.104
12	51	147.32	0.000	0.915	0.890	0.088
9	24	40.26	0.020	0.979	0.969	0.052

Note. Data from the first measurement wave, *N* = 280.

Table S3

Internal Consistency and Retest Correlations of the Social Dynamics Scale (15,12. and 9-items)

Scale	Items	ω		$r_{3\text{-week}}$	$r_{6\text{-week}}$
		T1	T4		
FFI	5	0.87	0.83	0.89	0.86
	4	0.81	0.79	0.88	0.84
	3	0.78	0.79	0.85	0.78
SS	5	0.84	0.84	0.82	0.82
	4	0.81	0.82	0.79	0.85
	3	0.81	0.82	0.77	0.82
SD	5	0.86	0.87	0.85	0.85
	4	0.84	0.85	0.83	0.85
	3	0.84	0.85	0.80	0.79

Note. ω = omega total, internal consistency of items (McNeish, 2018). $r_{3\text{-week}}$ = six-week retest correlation. $r_{6\text{-week}}$ = three-week retest correlation.

Predictive Validity: Results for Contact with Colleagues

Table S4

Model Parameters for Changes in Personal and Indirect Contact with Colleagues

Effect	Colleagues Personal		Colleagues Indirect	
	b	95% CI	*b*	95% CI
Social Deprivation Models: Fixed effects				
Intercept	**1.71**	[1.54,1.88]	**2.09**	[1.95,2.23]
Time	**0.18**	[0.10,0.26]	**-0.06**	[-0.11,-0.01]
SD	0.05	[-0.06,0.16]	**0.11**	[0.01,0.21]
SD*Time	0.01	[-0.11,0.14]	-0.05	[-0.10,0.01]
Social Oversatiation Models: Fixed effects				
Intercept	**1.71**	[1.54,1.88]	**2.09**	[1.95,2.23]
Time	**0.18**	[0.10,0.25]	**-0.06**	[-0.11,-0.01]
SoS	**-0.18**	[-0.30,-0.05]	**-0.13**	[-0.24,-0.03]
SoS*Time	0.02	[-0.10,0.15]	-0.04	[-0.10,0.02]
Family-Friends-Interdependence Models: Fixed effects				
Intercept	**1.71**	[1.54,1.88]	**2.09**	[1.95,2.23]
time	**0.17**	[0.10,0.25]	**-0.06**	[-0.11,-0.01]
FFI	-0.06	[-0.18,0.06]	0.02	[-0.08,0.13]
FFI*Time	0.01	[-0.12,0.14]	-0.05	[-0.10,0.01]

Note. SD = Social deprivation, SoS = Social oversatiation, FFI = Family-Friends-Interdependence, the scale of Time is months. In all models, intercept and slope were free to vary. Significant effects are in bold (p < .05).

Facet-Level Analysis: Social Dynamics Scale and Extraversion Facets

Table S5

Correlations of Social Dynamics Scale and Extraversion Facets at T1 (lower diagonal, n = 280) and T4 (upper diagonal, n=356)

		1	2	3	4	5	6	7
1	SDS FFI		**.17**	**-.11**	**-.11**	**-.11**	-.07	**-.11**
2	SDS SoS	.10		**-.53**	**-.49**	**-.46**	**-.28**	**-.50**
3	SDS SD	**-.21**	**-.44**		**.32**	**.31**	**.17**	**.33**
4	Extraversion	.04	**-.43**	**.27**		**.87**	**.83**	**.82**
5	Sociability	.04	**-.42**	**.29**	**.86**		**.60**	**.58**
6	Assertiveness	.06	**-.27**	.11	**.84**	**.57**		**.50**
7	Energy level	.00	**-.39**	**.29**	**.85**	**.60**	**.56**	

Note. SDS FFI = Family-friends-interdependence. SDS SoS = Social oversatiation. SDS SD = Social deprivation. Significant correlations (p < .05) are printed in bold.

Explanation and Formulae for Multilevel-Models

The time variable was zero-centered with the starting time of the first survey as zero, and scaled in months. All models were set up as conditional growth models, in which the trajectory of the outcome across time (slope of time) was allowed to vary between people and this variation was predicted by SDS-tendency. The SDS-tendencies were grand mean centered at level 2 (i.e., people) prior to estimating the models. We used separate models to predict personal, as well as indirect contact, each separately for family, friends and colleagues. For example, the models for social deprivation were specified as follows:

Level 1

$$y_{ij} = \beta_{0j} + \beta_{1j} \times Time_{ij} + \beta_{2j} + \varepsilon_{ij}$$

Level 2

$$\beta_{0j} \sim N(\mu_{\beta_0}, \delta^2_{\beta_0})$$

$$\beta_{1j} \sim N(\gamma_0 + \gamma_1 \times SocialDeprivation_j, \delta^2_{\beta_1})$$

$$\beta_{2j} = \gamma_2 \times SocialDeprivation$$

In the Level 1 model, y_{ij} is a measure of social contact for person j for measurement occasion i and β_{0j} is a random intercept representing the mean of y for person j collapsed across the i measurement occasions. The random slope β_{1j} allows for varying effects of time between persons. The fixed effect β_{2j} represents the main effect of social deprivation on contact frequency. The error associated with each measurement is represented by ε_{ij}, and the variance of ε_{ij} constitutes the within-person (Level 1) residual variance. At level 2, μ_{β_0} represents the mean of β_{0j} and the variance $\delta^2_{\beta_0}$ represents the between-person (Level 2) variance of this intercept. Each person j is allowed to have an own slope β_{1j} across time. This slope is determined by an intercept (main effect of time), and by social deprivation (interaction effect between time and social deprivation). The variance of the slope of *Time* is $\delta^2_{\beta_1}$.

Supplementary Information for Chapter 4: Affiliation Motive and Social Interactions in People's Daily Life: A Temporal Processes Approach Using Ecological Momentary Assessment and Mobile Sensing

Cornelia Wrzus, Yannick Roos, Michael D. Krämer, Ramona Schoedel, Mitja D. Back, & David Richter

Examples for Model Equations

Study 1

An exemplary model equation for the models used in Study 1 is given below. In this case, referring to situations where participants were currently alone, social interaction at the next assessment are predicted by affiliation motive, the contact ratio in the previous episode of about 80 min, the perceived possibility of social interactions, as well as interactions between the quantity of previous social interactions and (a) affiliation motive and (b) the possibility of social interactions. Level 1 variables are split in a within-person ("wp") and a between-person ("bp") component.

Level 1

$$\begin{aligned} interaction_{(t+1)i} &= \beta_{0i} + \beta_{1i} contact\ ratio\ wp_{ti} + \beta_{2i} contact\ possibility\ wp_{ti} \\ &+ \beta_{3i} contact\ ratio\ wp_{ti} * contact\ possibility\ wp_{ti} + e_{ti} \end{aligned}$$

Level 2

$$\begin{aligned} \beta_{0i} = \gamma_{00} &+ \gamma_{01} affiliation_i + \gamma_{02} contact\ ratio\ bp_i + \gamma_{03} contact\ possibility\ bp_i \\ &+ \gamma_{06} gender_i + \gamma_{07} age_i + \upsilon_{0i} \end{aligned}$$

$$\beta_{1i} = \gamma_{10} + \gamma_{11} affiliation_i + \upsilon_{1i}$$

$$\beta_{2i} = \gamma_{20} + \upsilon_{2i}$$

$$\beta_{3i} = \gamma_{30}$$

where at time t for participant i $e_{ti} \sim N(0, \sigma_e^2)$ and $\begin{bmatrix} \upsilon_{0i} \\ \upsilon_{1i} \\ \upsilon_{2i} \end{bmatrix} \sim MVN\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \tau_{00} & & \\ \tau_{10} & \tau_{11} & \\ \tau_{20} & \tau_{21} & \tau_{22} \end{bmatrix}\right)$

Study 2

An exemplary equation for the models used in Study 2 is given below. Here, the amount of contact during the next day is predicted by contact amount on the current day, affiliation motive, as well as the interaction of contact amount on the current day and affiliation. Gender and age were added as control variables. Level 1 variables are split in a within-person (“wp”) and a between-person (“bp”) component.

Level 1

$$\begin{aligned} contact\ amount_{(t+1)i} \\ &= \beta_{0i} + \beta_{1i} contact\ amount\ wp_{ti} + \beta_{2i} contact\ valence\ wp_{ti} \\ &+ \beta_{3i} contact\ amount\ wp_{ti} * contact\ valence\ wp_{ti} + e_{ti} \end{aligned}$$

Level 2

$$\begin{aligned} \beta_{0i} = {} & \gamma_{00} + \gamma_{01} affiliation_i + \gamma_{02} contact\ amount\ bp_i + \gamma_{03} contact\ valence\ bp_i \\ & + \gamma_{06} gender_i + \gamma_{07} age_i + \upsilon_{0i} \end{aligned}$$

$$\beta_{1i} = \gamma_{10} + \gamma_{11} affiliation_i + \upsilon_{1i}$$

$$\beta_{2i} = \gamma_{20} + \upsilon_{2i}$$

$$\beta_{3i} = \gamma_{30}$$

where at time t for participant i $e_{ti} \sim N(0, \sigma_e^2)$ and $\begin{bmatrix} \upsilon_{0i} \\ \upsilon_{1i} \\ \upsilon_{2i} \end{bmatrix} \sim MVN\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \tau_{00} & & \\ \tau_{10} & \tau_{11} & \\ \tau_{20} & \tau_{21} & \tau_{22} \end{bmatrix}\right)$.

Supplementary Tables

Table S1

Study 1: Between- and Within-Person Correlations Among Study Variables

	Variable	1	2	3	4	5	6	7	8	9	10
1	Affiliation		/	/	/	/	/	/	/	/	/
2	Extraversion	.43		/	/	/	/	/	/	/	/
3	Contact ratio	.00	.07		.24	.01	-.19	.14	.06	.03	/
4	Conversation ratio	.09	.08	.20		.06	-.09	.05	.03	.01	/
5	Desire interact	.44	.07	-.06	.04		/	.03	.13	-.11	/
6	Desire alone	-.33	-.17	-.28	-.07	-.23		-.40	/	.09	/
7	Contact valence	.16	.20	.14	.04	.07	-.31		0.1	-.08	/
8	Contact possible	.04	.01	.25	.05	-.04	-.02	.11		.06	/
9	Contact initiated	-.05	-.04	-.04	-.01	.02	.17	-.14	.07		/
10	Age	-.12	.02	-.05	-.15	-.02	.12	.06	.01	-.07	/
11	Gender	-.01	-.14	-.08	-.03	.18	.07	-.13	-.02	-.06	-.02

Note. Between-person correlations from Study 1 are displayed below the diagonal and within-person correlations are displayed above the diagonal.

Table S2

Study 1: Fixed Effects of Models Predicting Contact at Next Measurement or Desire to Interact

Variable	Contact t+1		Social desire	
	b	95% CI	*b*	95% CI
	Currently Alone			
Intercept	-0.20	[-0.47,0.07]	**3.28**	[3.12, 3.44]
Affiliation	0.03	[-0.16,0.22]	**0.47**	[0.32,0.61]
Contact ratio bp	**0.77**	[0.57,0.97]	-0.02	[-0.16,0.11]
Contact ratio wp	-0.09	[-0.37, 0.19]	-0.01	[-0.13,0.11]
Contact possible bp	**0.26**	[0.13,0.39]	-0.04	[-0.16,0.07]
Contact possible wp	**0.27**	[0.11,0.44]	**0.17**	[0.07,0.27]
Gender	0.01	[-0.11,0.13]	**0.19**	[0.08, 0.30]
Age	**0.18**	[0.06,0.30]	0.04	[-0.07, 0.15]
Contact ratio wp x affiliation	-0.07	[-0.28,0.15]	-0.01	[-0.12,0.09]
Contact ratio wp x contact possible wp	-0.03	[-0.21,0.15]	0.03	[-0.07,0.13]
	Currently in Contact			
Intercept	**0.74**	[0.62,0.87]	**3.43**	[3.31,3.54]
Affiliation	0.03	[-0.09,0.15]	**-0.34**	[-0.46,-0.23]
Contact ratio bp	**0.87**	[0.74,1.00]	**-0.30**	[-0.41,-0.19]
Contact ratio wp	0.04	[-0.07,0.16]	**-0.22**	[-0.29,-0.16]
Contact initiated bp	-0.03	[-0.13,0.08]	**0.13**	[0.02,0.23]
Contact initiated wp	0.03	[-0.08,0.15]	0.04	[-0.03,0.10]
Contact valence bp	**-0.12**	[-0.23,-0.01]	**-0.22**	[-0.33,-0.11]
Contact valence wp	0.01	[-0.09,0.12]	**-0.51**	[-0.57,-0.44]
Gender	-0.01	[-0.11,0.10]	0.03	[-0.08,0.14]
Age	0.06	[-0.05,0.17]	0.07	[-0.04,0.18]
Contact ratio wp x affiliation	-0.02	[-0.13,0.08]	0.03	[-0.03,0.09]
Contact ratio wp x contact initiated wp	0.02	[-0.09,0.13]	**0.09**	[0.03,0.15]
Contact ratio wp x contact valence wp	0.01	[-0.10,0.11]	**-0.08**	[-0.14,-0.03]

Note. bp = between-person component, wp = within-person components. When currently alone, social desire refers to the desire to interact and when currently in contact, social desire refers to the desire to be alone. The top left model (Contact t+1, when currently alone) is based on 1832 observations from 291 participants. The top right model is based on 1949 observations from 293 participants. The bottom left and right models are based on 2378 and 2571 observations from 297 and 299 participants, respectively. Significant effects are printed in bold ($p < .05$).

Table S3

Study 1 and 2: Fixed Effects of Models With Mobile Sensing

Variable	Study 1		Study 2	
	b	95% CI	*b*	95% CI
Intercept	**0.114**	[0.109,0.119]	**0.128**	[0.124,0.133]
Affiliation	**0.006**	[0.001,0.011]	-0.001	[-0.005,0.004]
Conversation proportion bp	**0.098**	[0.093,0.103]	**0.089**	[0.085,0.094]
Conversation proportion wp	**0.042**	[0.038,0.047]	-0.001	[-0.005,0.004]
Gender	-0.001	[-0.006,0.004]	0.000	[-0.004,0.004]
Age	-0.002	[-0.007,0.003]	0.000	[-0.004,0.005]
Conversation proportion wp x affiliation	0.004	[0.000,0.009]	-0.003	[-0.008,0.001]

Note. bp = between-person component, wp = within-person components. Conversation proportion was aggregated over different timeframes (i.e., in Study 1 approximately over the last 80 minutes, in Study 2 over the day). The model for Study 1 was based on 3076 observations from 274 participants, and the model for Study 2 was based on 2372 observations from 331 participants. Significant effects are printed in bold ($p < .05$).

Table S4

Study 1: Fixed Effects of Extraversion-Models Predicting Contact at Next Measurement or Desire to Interact

Variable	Contact t+1		Social desire	
	b	95% CI	*b*	95% CI
	Currently Alone			
Intercept	-0.20	[-0.47,0.07]	**3.28**	[3.12,3.45]
Extraversion	-0.02	[-0.21,0.18]	0.04	[-0.11,0.20]
Contact ratio bp	**0.76**	[0.56,0.96]	-0.05	[-0.19,0.10]
Contact ratio wp	-0.10	[-0.38,0.19]	0.00	[-0.12,0.12]
Contact possible bp	**0.26**	[0.14,0.39]	-0.02	[-0.15,0.11]
Contact possible wp	**0.27**	[0.10,0.43]	**0.12**	[0.05,0.20]
Gender	0.01	[-0.11,0.13]	**0.19**	[0.07,0.31]
Age	**0.17**	[0.05,0.29]	-0.03	[-0.15,0.10]
Contact ratio wp x extraversion	-0.08	[-0.28,0.13]	-0.05	[-0.14,0.05]
Contact ratio wp x contact possible wp	-0.04	[-0.22,0.15]	-0.01	[-0.09,0.08]
	Currently in Contact			
Intercept	**0.75**	[0.62,0.88]	**3.41**	[3.28,3.53]
Extraversion	-0.06	[-0.18,0.06]	-0.12	[-0.24,0.00]
Contact ratio bp	**0.87**	[0.74,1.00]	**-0.27**	[-0.39,-0.15]
Contact ratio wp	0.04	[-0.08,0.16]	**-0.22**	[-0.28,-0.16]
Contact initiated bp	-0.03	[-0.14,0.07]	**0.13**	[0.03,0.24]
Contact initiated wp	0.03	[-0.08,0.15]	0.04	[-0.02,0.11]
Contact valence bp	-0.10	[-0.21,0.00]	**-0.26**	[-0.37,-0.14]
Contact valence wp	0.02	[-0.09,0.12]	**-0.51**	[-0.58,-0.44]
Gender	-0.01	[-0.12,0.09]	0.01	[-0.10,0.13]
Age	0.06	[-0.05,0.17]	**0.12**	[0.01,0.24]
Contact ratio wp x extraversion	-0.01	[-0.12,0.10]	0.00	[-0.06,0.06]
Contact ratio wp x contact initiated wp	0.02	[-0.09,0.13]	**0.09**	[0.03,0.15]

Contact ratio wp x contact valence wp	0.00	[-0.10,0.11]	**-0.08**	[-0.14,-0.03]

Note. bp = between-person component, wp = within-person components. The top left model (Contact t+1, when currently alone) is based on 1832 observations from 291 participants. The top right model is based on 1949 observations from 293 participants. The bottom left and right models are based on 2378 and 2571 observations from 297 and 299 participants, respectively. Significant effects are printed in bold (p < .05).

Table S5

Study 1 and 2: Correlations of Affiliation and Extraversion with Contact Duration in Specific Relationship Types

Relationship Type	Study 1		Study 2	
	Affiliation	Extraversion	Affiliation	Extraversion
Partner	**-.16** [-.27,-.05]	-.01 [-.12, .10]	.06 [-.05,.17]	.07 [-.05, .18]
Kids	-.02 [-.14,.09]	.04 [-.07, .15]	-.04 [-.15,.07]	.06 [-.06, .17]
Family	.01 [-.11,.12]	-.09 [-.19,.03]	.05 [-.06,.16]	.02 [-.09,.14]
Friends	**.17** [.06,.27]	.10 [-.02,.20]	**.27** [.16,.37]	**.15** [.03,.26]
Colleagues	**.16** [.05,.27]	.14 [.03,.25]	.06 [-.05,.17]	.03 [-.09,.14]
Strangers	.05 [-.06,.16]	.06 [-.05,.17]	.11 [-.00,.22]	-.01 [-.13,.10]
All types, EMA	.02 [-.09,.13]	.09 [-.02,.20]	.09 [-.02,.19]	.10 [-.01,.21]
All types, MS	**.13** [.02,.24]	**.12** [.01, .23]	**.14** [.02,.25]	.05 [-.07, .17]

Note. In Study 1, social interactions with people from multiple relationship types were counted towards the total interaction duration for each relationship type. EMA = ecological momentary assessment (i.e., person mean of total winsorized contact duration). MS = mobile sensing (i.e., person mean of proportion of conversation). Estimates in bold indicate p < .05.

Table S6

Study 2: Between- and Within-Person Correlations Among Study Variables

	Variable	1	2	3	4	5	6	7	8
1	Affiliation		/	/	/	/	/	/	/
2	Extraversion	.44		/	/	/	/	/	/
3	Contact duration	.09	.10		.20	-.17	-.02	.14	/
4	Conversation ratio	.14	.05	.15		-.09	-.02	.06	/
5	Desire interact	.04	-.06	-.14	.00		-.04	-.04	/
6	Desire alone	-.13	-.07	.07	.10	.13		-.13	/
7	Contact valence	.25	.19	.21	.08	-.14	-.18		/
8	Age	.07	.10	-.03	-.09	-.10	-.17	.15	
9	Gender	.11	.12	.05	.08	-.11	.03	.13	-.07

Note. Between-person correlations from Study 2 are displayed below the diagonal and within-person correlations are displayed above the diagonal.

Table S7

Study 2: Fixed Effects of Models Predicting Contact during Next Day and Social Desires

Variable	Contact t+1		Desire more contact		Desire more alone	
	b	95% CI	*b*	95% CI	*b*	95% CI
Intercept	**14.00**	[13.77,14.23]	**3.03**	[2.89,3.17]	**3.03**	[2.88,3.17]
Affiliation	-0.09	[-0.33,0.14]	0.13	[-0.02,0.28]	-0.12	[-0.27,0.03]
Contact duration bp	**9.12**	[8.88,9.35]	-0.08	[-0.23,0.06]	0.10	[-0.05,0.25]
Contact duration wp	**1.46**	[1.15,1.76]	**-0.27**	[-0.35,-0.20]	0.02	[-0.04,0.08]
Contact valence bp	0.02	[-0.22,0.27]	**-0.19**	[-0.34,-0.04]	**-0.26**	[-0.41,-0.11]
Contact valence wp	-0.22	[-0.46,0.01]	-0.03	[-0.07,0.02]	**-0.19**	[-0.23,-0.14]
Gender	-0.03	[-0.25,0.20]	-0.13	[-0.28,0.01]	0.07	[-0.08,0.21]
Age	0.03	[-0.20,0.26]	-0.10	[-0.24,0.04]	**-0.20**	[-0.35,-0.06]
Contact duration wp x affiliation	-0.11	[-0.41,0.18]	**-0.13**	[-0.2,-0.05]	-0.03	[-0.09,0.02]
Contact duration wp x contact valence wp	-0.25	[-0.50,0.00]	**-0.08**	[-0.14,-0.03]	**-0.12**	[-0.17,-0.07]

Note. bp = between-person component, wp = within-person components. The model with Contact t+1 as outcome is based on 3124 observations from 292 participants, and both models with desires as outcomes are based on 3388 observations from 293 participants. Significant effects are printed in bold ($p < .05$).

Table S8

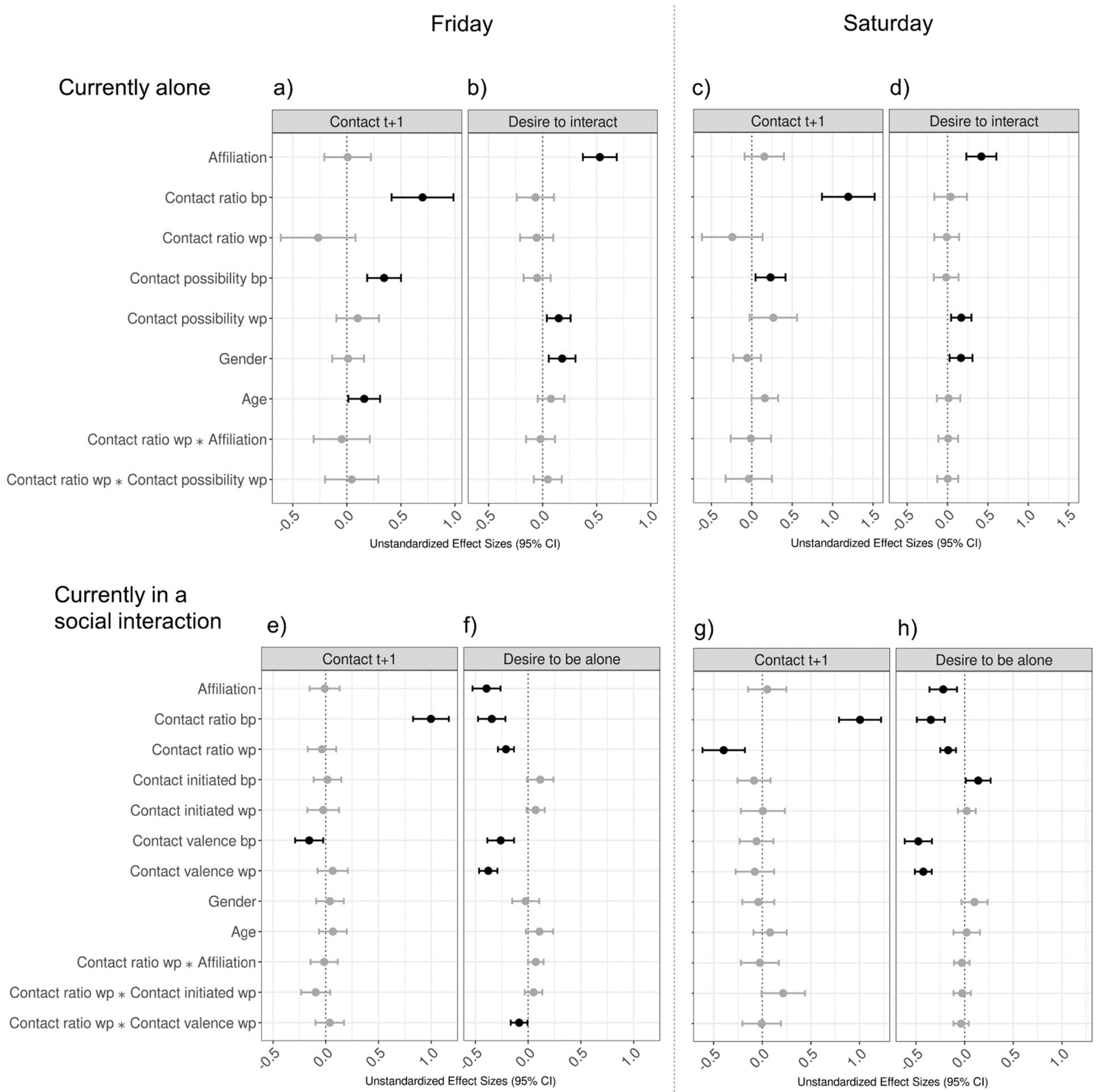
Study 2: Fixed Effects of Extraversion-Models Predicting Contact during Next Day and Social Desires

Variable	Contact t+1		Desire more contact		Desire more alone	
	b	95% CI	*b*	95% CI	*b*	95% CI
Intercept	**14.01**	[13.77,14.25]	**3.03**	[2.88,3.18]	**3.01**	[2.86,3.16]
Extraversion	-0.01	[-0.25,0.23]	-0.02	[-0.18,0.13]	-0.06	[-0.21,0.09]
Contact duration bp	**9.14**	[8.90,9.38]	-0.08	[-0.23,0.07]	0.11	[-0.04,0.26]
Contact duration wp	**1.72**	[1.48,1.96]	**-0.30**	[-0.38,-0.22]	0.01	[-0.05,0.07]
Contact valence bp	0.02	[-0.23,0.27]	-0.12	[-0.28,0.03]	**-0.28**	[-0.44,-0.13]
Contact valence wp	-0.22	[-0.46,0.02]	-0.02	[-0.06,0.03]	**-0.19**	[-0.24,-0.14]
Gender	-0.03	[-0.27,0.21]	-0.15	[-0.29,0.00]	0.04	[-0.11,0.19]
Age	0.03	[-0.21,0.27]	-0.11	[-0.26,0.03]	**-0.18**	[-0.33,-0.03]
Contact duration wp x extraversion	-0.06	[-0.31,0.20]	-0.05	[-0.13,0.04]	**-0.07**	[-0.13,0.00]
Contact duration wp x contact valence wp	-0.17	[-0.41,0.08]	**-0.08**	[-0.13,-0.02]	**-0.10**	[-0.15,-0.05]

Note. bp = between-person component, wp = within-person components. The model with Contact t+1 as outcome is based on 3124 observations from 292 participants, and both models with desires as outcomes are based on 3388 observations from 293 participants. Significant effects are printed in bold (p < .05).

Figure S1

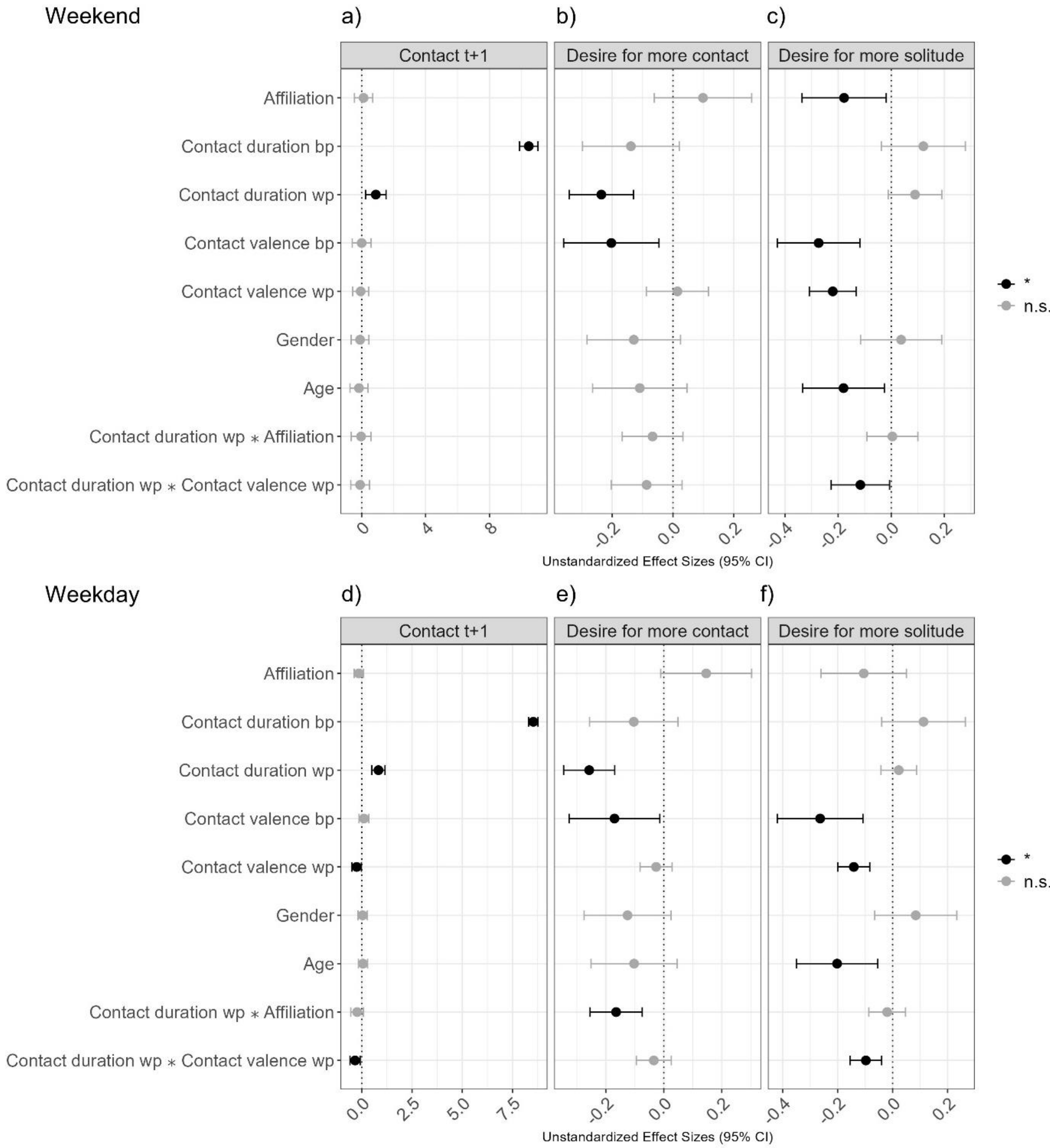
Study 1: Multilevel Regression Coefficients Predicting Future Contact and Current Social Desires as well as Interaction Effects Separately for Fridays and Saturdays.



Note. Effects with CIs that included zero are displayed in grey. Positive effect sizes indicate a higher probability of being in face-to-face interactions during the next measurement or a higher social desire. Sample sizes range from 841 observations from 246 participants to 1313 observations from 284 participants.

Figure S2

Study 2: Multilevel Regression Coefficients Predicting Future Contact and Current Social Desires as well as Interaction Effects Separately for Weekdays and Weekends.



Note. Effects with CIs that included zero are displayed in grey. Positive effect sizes indicate a higher probability of being in face-to-face interactions during the next measurement or a higher social desire. The data were split as follows: For panel a) the data was filtered to 938 observations from 299 participants, including only Fridays and Saturdays. Accordingly, Contact t+1 always refered to a weekend day in panel a). For panel b) and c), the data were filtered to 1018 observations from 302 participants, only including Saturdays and Sundays. For panel d), data were filtered to 2361 observations from 308 participants, including all days but Fridays and Saturdays. For panel e) and f) data were filtered to 2563 observations from 310 participants, only including days from Monday to Friday.

Appendix for Chapter 5: Persons in Contexts: The Role of Social Networks and Social Density for the Dynamic Regulation of Face-to-face Interactions in Daily Life

Yannick Roos, Michael D. Krämer, David Richter, & Cornelia Wrzus

Appendix A

Timeline of National Minimum Standards of Restrictive Measures during the COVID-19 Pandemic

Effective from	Life domain	Vaccinated/recovered	Unvaccinated
2021-08-23	Private gatherings	no restrictions	no restrictions
	Major events	capacity restrictions	capacity restrictions negative test mandatory
	Indoor activities	no restrictions	often negative tests required
2021-11-18	Private gatherings	no restrictions	no restrictions
	Major events	capacity restrictions	capacity restrictions negative test mandatory
	Indoor activities	low hospitalization rate:	
		no restrictions	negative test required
		high hospitalization rate:	
		negative test required if risk of infection is high (e.g., in clubs).	negative test required to access workplaces, and public transportation. no access to other indoor activities (except retail for daily needs).
2021-12-02	Private gatherings	low incidence: no restrictions. high incidence: maximum of 50 persons (indoors)/ 200 persons (outdoors).	own household and up to 2 other persons
	Major events	low incidence: negative test required in some cases. capacity restrictions high incidence: no sporting events. Most major events were canceled.	no access

Effective from	Life domain	Vaccinated/recovered	Unvaccinated
	Indoor activities	low incidence: sometimes negative test required. high incidence: sometimes negative test required. no dancing activities and no access to clubs/discos.	negative test required to access workplaces, and public transportation. no access to other indoor activities (except retail for daily needs).
2021-12-28	Private gatherings	**maximum of 10 persons**	**own household and up to 2 other persons**
	Major events	no access	no access
	Indoor activities	sometimes negative test required. no access to clubs/discos.	negative test required to access workplaces, and public transportation. no access to other kinds of indoor activities (except retail for daily needs).
2022-01-07	Private gatherings	maximum of 10 persons	own household and up to 2 other persons
	Major events	no access	no access
	Indoor activities	negative test or booster vaccination required to access restaurants. no access to clubs/discos.	negative test required to access workplaces, and public transportation. no access to other kinds of indoor activities (except retail for daily needs).
2022-02-16	Private gatherings	no restrictions	own household and up to 2 other persons
	Major events	no access	no access
	Indoor activities	negative test or booster vaccination required to access restaurants. no access to clubs/discos.	unrestricted access to retail outlets. negative test required to access workplaces, and public transportation. no access to other kinds of indoor activities.
2022-03-04	Private gatherings	no restrictions	own household and up to 2 other persons
	Major events	sometimes negative test required. capacity restrictions.	no access
	Indoor activities	negative test or booster vaccination required to access clubs/discos.	unrestricted access to retail outlets. negative test required to access restaurants, overnight

Effective from	Life domain	Vaccinated/recovered	Unvaccinated
			accommodation, workplaces, and public transportation. no access to other kinds of indoor activities.
2022-03-20	Private gatherings	no restrictions	no restrictions
	Major events	no restrictions	no restrictions
	Indoor activities	no restrictions	no restrictions
2022-03-20	A new Infection Protection Act (Infektionsschutzgesetz) comes into effect. All far-reaching restrictions on social, cultural, and economic life are to be lifted. Under a transitional arrangement, the federal states are permitted to uphold both existing testing requirements and existing obligations to provide proof of vaccination or recovery until 2022-04-02.		

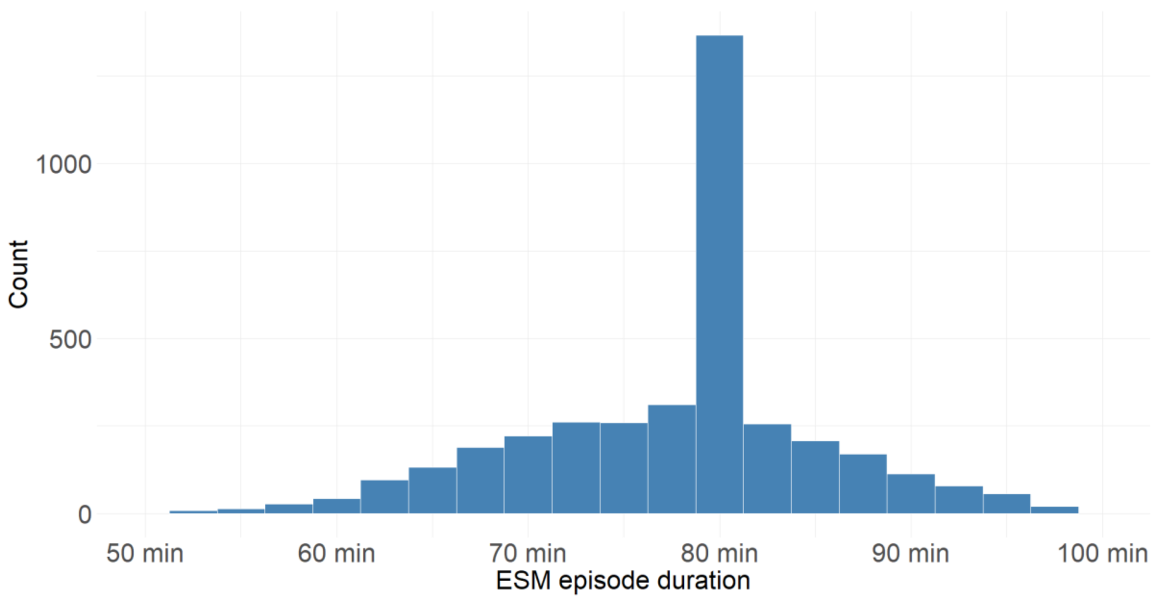
Note. All restrictive measures were national minimum standards that were agreed between the Federal Government and the State Governments. The federal states particularly affected by the pandemic acted beyond these minimum standards by means of state regulations. Data for this table was retrieved from the website of the German Government: https://www.bundesregierung.de/breg-de/themen/coronavirus/corona-regeln-und-einschrankungen-1734724

Appendix B: Details on the Distribution of ESM questionnaires in Study 1

In Study 1, the PhoneStudy app was programmed to distribute experience sampling questionnaires every 80 minutes, with some jitter which resulted from drawing a random number from the interval [-10 min, +10 min]. During the study, other (background) processes running on participants' smartphones sometimes hindered the triggering of some experience sampling notifications (which is expected and is common to all comparable research apps we know). In those cases, the app rescheduled the notification and tried to push it to the foreground at a later time, resulting in some delayed notifications. The notification through which the ESM questionnaire was available was programmed to disappear after 15 minutes. The distribution of ESM episode duration is shown in Figure B1.

Figure B1

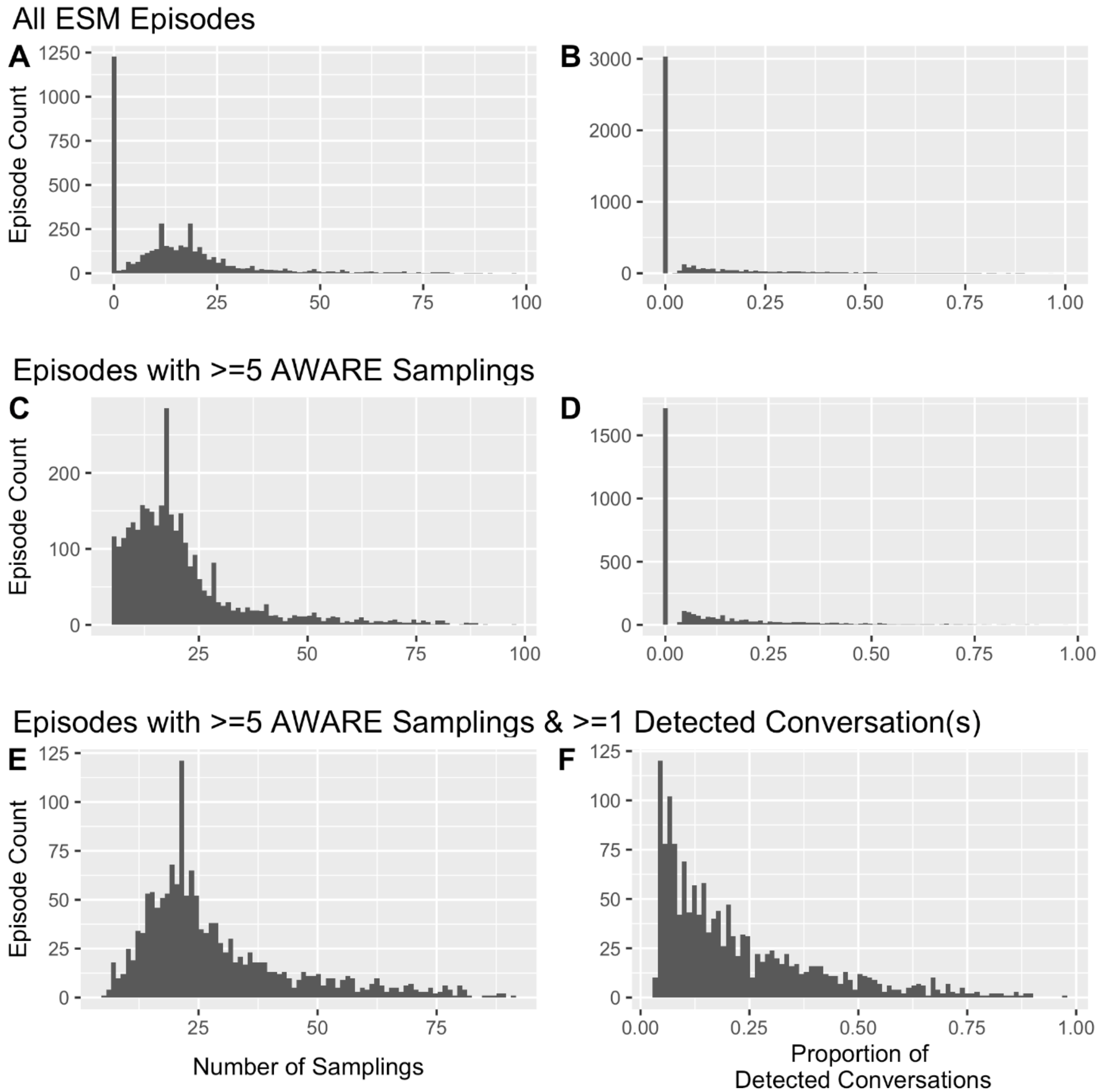
Study 1: Distribution of ESM Episode Duration in Study 1



Note. ESM episode duration indicates the time since the previously answered ESM questionnaire was completed. If no ESM questionnaire was answered within the last 100 min, the episode duration of the current ESM episode was set to 80 min.

Appendix C

Distribution of AWARE-Conversations Samplings and the Proportion of Detected Voices

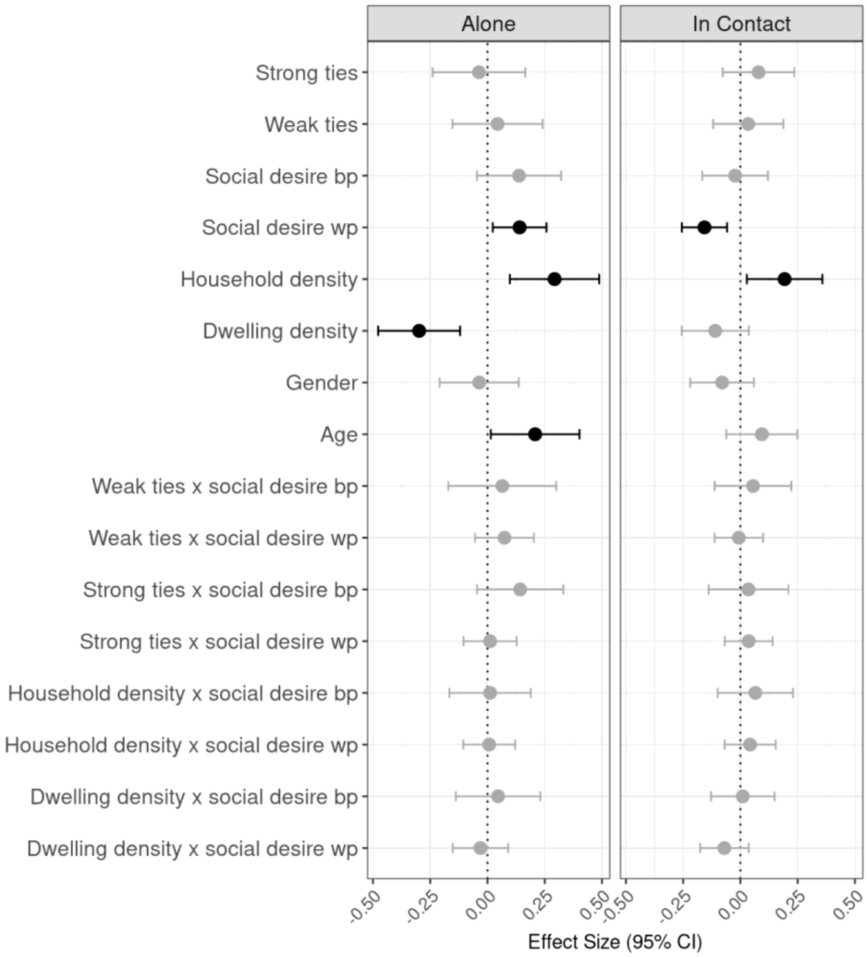


Note. The figure is based on experience sampling episodes from *n* = 306 participants from Study 1. The median duration of experience sampling episodes was 80 min, with a standard deviation of 8.01 min.

Appendix D

Figure D1

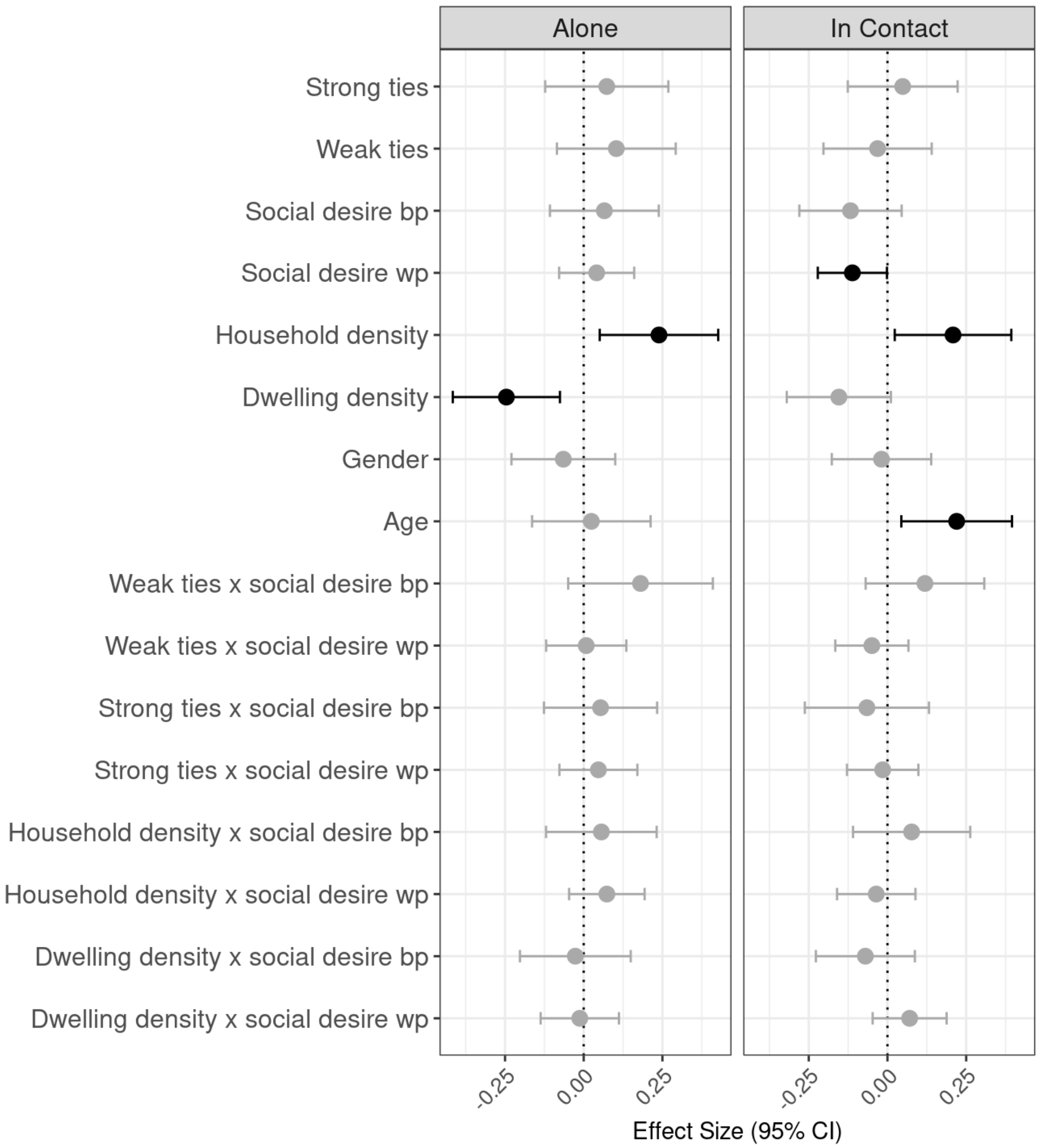
Study 1: Social Interaction Two Episodes Later (Lead 2) Predicted by Social Desires and Context Variables



Note. Effects with CIs that included zero are displayed in grey. Social desires indicate desires counterfactual to the current situation of participants. That is, in the left panel, based on all measurements during which participants were currently alone, higher social desire indicates a higher desire to interact with others. Conversely, in the right panel, based on measurements during which participants reported to be in a social interaction, higher social desire indicates a higher desire to be alone. Positive effect sizes indicate a higher probability of being in face-to-face interactions during the next measurement. The left panel was based on 1,713 observations from 288 participants, and the right panel was based on 2,192 observations from 294 participants. bp = between person component (i.e., person mean); wp = within-person component (i.e., within person deviation from the person mean).

Figure D2

Study 1: Social Interaction Three Episodes Later (Lead 3) Predicted by Social Desires and Context Variables

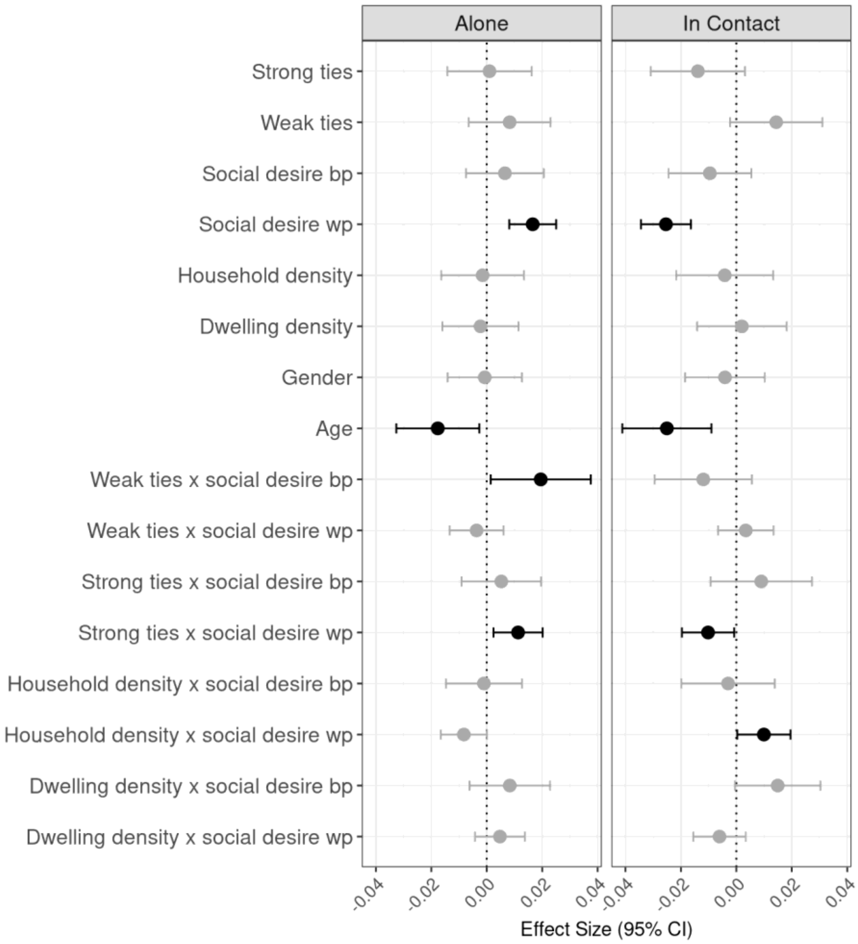


Note. Effects with CIs that included zero are displayed in grey. Social desires indicate desires counterfactual to the current situation of participants. That is, in the left panel, based on all measurements during which participants were currently alone, higher social desire indicates a higher desire to interact with others. Conversely, in the right panel, based on measurements during which participants reported to be in a social interaction, higher social desire indicates a higher desire to be alone. Positive effect sizes indicate a higher probability of being in face-to-face interactions during the next measurement. The left panel was based on 1,586 observations from 282 participants, and the right panel was based on 2,016 observations from 289 participants. bp = between person component (i.e., person mean); wp = within-person component (i.e., within person deviation from the person mean).

Appendix E

Figure E1

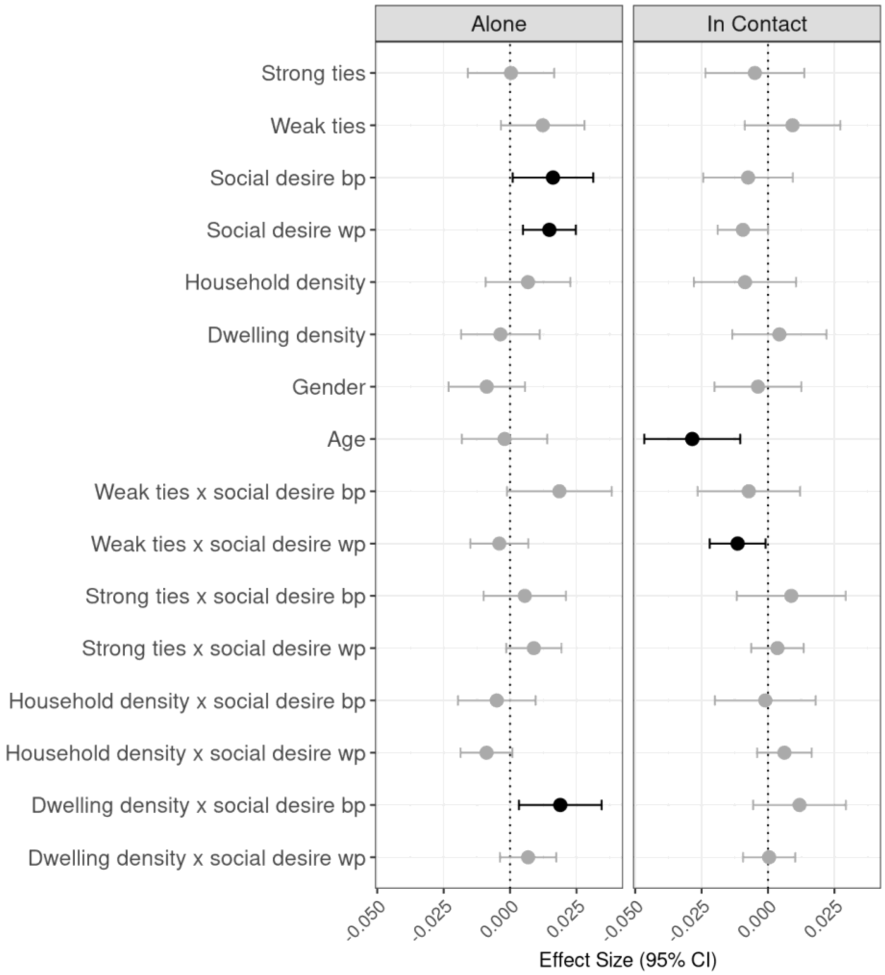
Study 1: Proportion of Conversation in the Next 80 Minutes Predicted by Social Desires and Context Variables



Note. Effects with CIs that included zero are displayed in grey. Social desires indicate desires counterfactual to the current situation of participants. That is, in the left panel, based on all measurements during which participants were currently alone, higher social desire indicates a higher desire to interact with others. Conversely, in the right panel, based on measurements during which participants reported to be in a social interaction, higher social desire indicates a higher desire to be alone. Positive effect sizes indicate a higher probability of being in face-to-face interactions during the next measurement. The left panel was based on 1,406 observations from 257 participants, and the right panel was based on 1,771 observations from 258 participants. bp = between person component (i.e., person mean); wp = within-person component (i.e., within person deviation from the person mean).

Figure E2

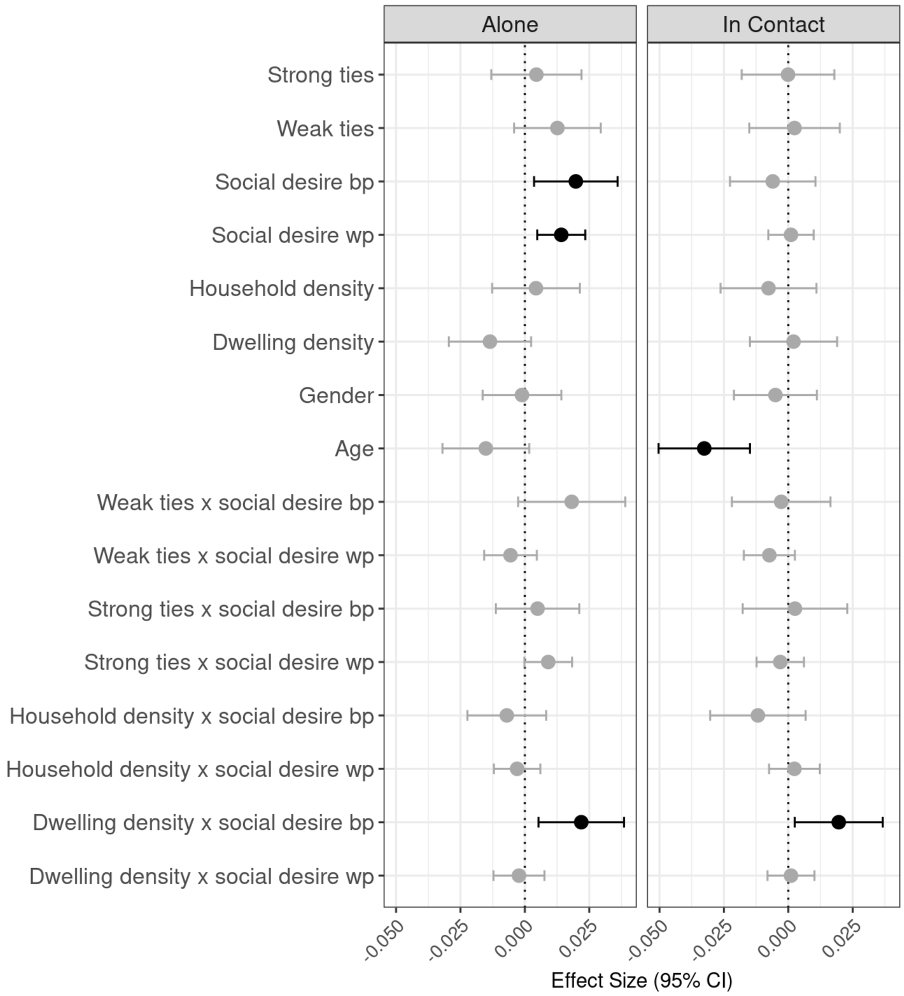
Study 1: Proportion of Conversation 80 to 160 Minutes Later (Lead 2) Predicted by Social Desires and Context Variable



Note. Effects with CIs that included zero are displayed in grey. Social desires indicate desires counterfactual to the current situation of participants. That is, in the left panel, based on all measurements during which participants were currently alone, higher social desire indicates a higher desire to interact with others. Conversely, in the right panel, based on measurements during which participants reported to be in a social interaction, higher social desire indicates a higher desire to be alone. Positive effect sizes indicate a higher probability of being in face-to-face interactions during the next measurement. The left panel was based on 1,363 observations from 256 participants, and the right panel was based on 1,693 observations from 257 participants. bp = between person component (i.e., person mean); wp = within-person component (i.e., within person deviation from the person mean).

Figure E3

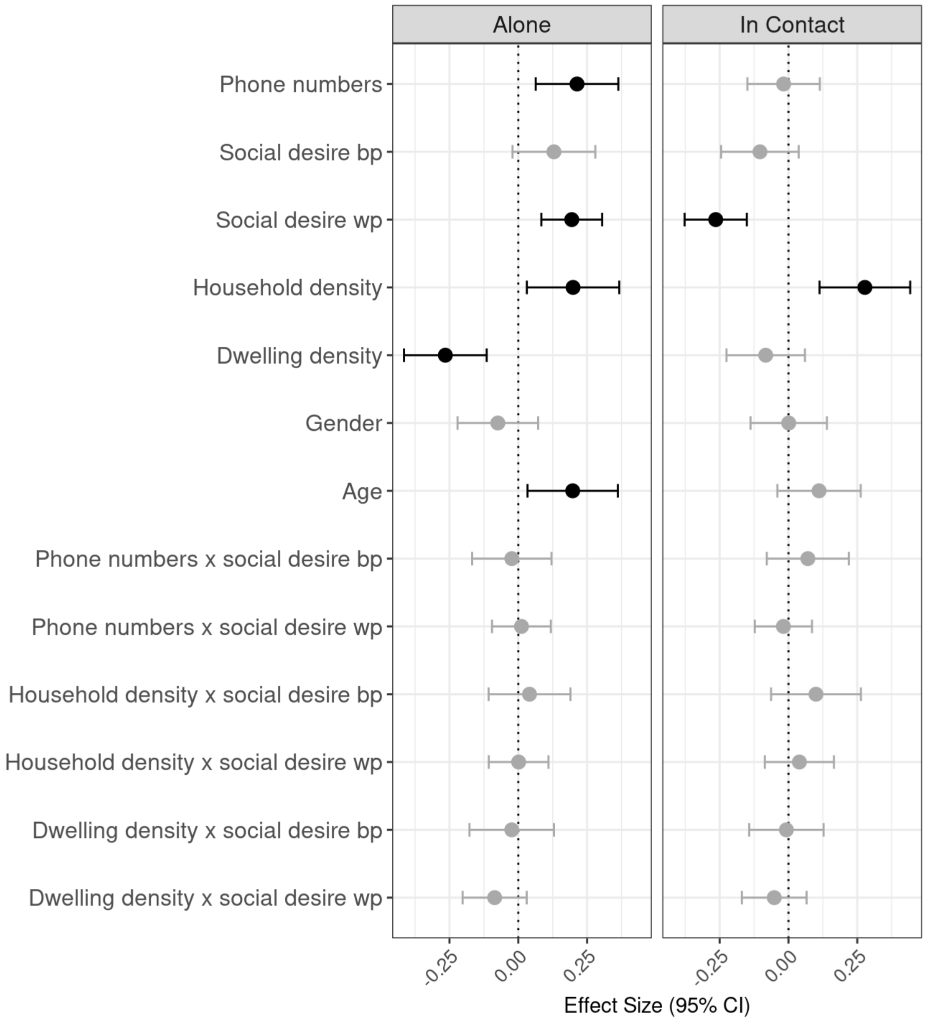
Study 1: Proportion of Conversation 160 to 240 Minutes Later (Lead 3) Predicted by Social Desires and Context Variables



Note. Effects with CIs that included zero are displayed in grey. Social desires indicate desires counterfactual to the current situation of participants. That is, in the left panel, based on all measurements during which participants were currently alone, higher social desire indicates a higher desire to interact with others. Conversely, in the right panel, based on measurements during which participants reported to be in a social interaction, higher social desire indicates a higher desire to be alone. Positive effect sizes indicate a higher probability of being in face-to-face interactions during the next measurement. The left panel was based on 1,276 observations from 246 participants, and the right panel was based on 1,596 observations from 258 participants. bp = between person component (i.e., person mean); wp = within-person component (i.e., within person deviation from the person mean).

Figure E4

Study 1: Social Interaction at Next Episode Predicted by Phone Numbers and Context Variables



Note. Effects with CIs that included zero are displayed in grey. Social desires indicate desires counterfactual to the current situation of participants. That is, in the left panel, based on all measurements during which participants were currently alone, higher social desire indicates a higher desire to interact with others. Conversely, in the right panel, based on measurements during which participants reported to be in a social interaction, higher social desire indicates a higher desire to be alone. Positive effect sizes indicate a higher probability of being in face-to-face interactions during the next measurement. The left panel was based on 1,818 observations from 289 participants, and the right panel was based on 2,360 observations from 295 participants. bp = between person component (i.e., person mean); wp = within-person component (i.e., within person deviation from the person mean).

Appendix F: Report on App Versions in Study 2

We suspended recruitment for a few weeks (14/10/2022 - 30/10/2022) during the changeover from daylight saving time to winter time (30/10/2022; recruitment location: Germany). We used a mobile sensing app that sets the timing for sending questionnaires for the experience sampling at the moment participants install the app. Thus, from a technical perspective, the app is not able to change the experience sampling time schedule independently once it was installed. Since the data collection period for each participant was 14 days, this would have resulted in different time intervals in which the evening questionnaires would have been available before and after the time shift (i.e., available from 8:00 p.m. to 4:00 a.m. on study days before 30/10/2022 and available from 7:00 p.m. to 3:00 a.m. study days after 30/10/2022). This was not a problem for the mobile sensing app if participants installed the app either 14 days before 30/10/2022 or after 30/10/2022. For the sake of comparability, we therefore decided to pause recruitment for the period over the time shift.

However, we made a mistake when resuming recruitment after the time shift and circulated an outdated app version. We noticed this mistake after about 14 days and again used the original app version for further data collection. Overall, this resulted in collecting data with an outdated app version for a small portion of our participants (N = 72, n = 818). With the original app version, we collected data of N = 313 participants (n = 3,737).[33] Passive data collection did not differ between app versions; however, there were some differences in the self-report questionnaire sent via experience sampling in the evening. The item variants of both app versions, as well as descriptive item analyses, are described in detail in Table F1.

In addition to the variations reported in Table F1, there was one discrepancy in the instruction. On the first page of the daily experience sampling questionnaire, participants were given a general instruction: "Please think briefly about whom you have had personal contact with today since you got up, i.e., meetings, conversations or appointments). In app version 1, the instruction was supplemented by the following subordinate clause: "but no (video) calls and text messages)". In app version 2, this subordinate clause was missing.

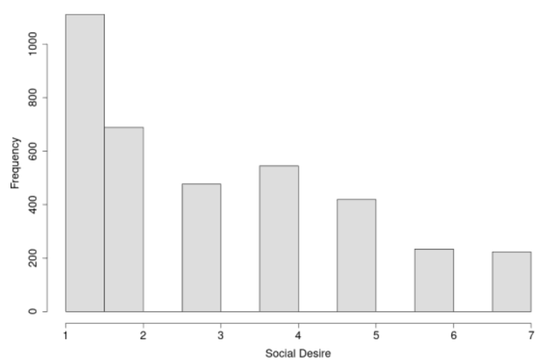
[33] Note that sample sizes refer to participants for whom survey, experience sampling, and sensing data were available.

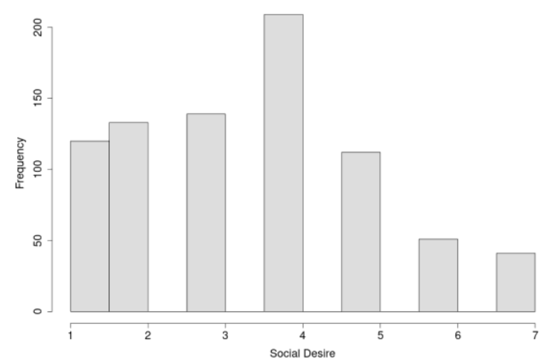
Based on the reported discrepancies between app versions, we conclude that item variations (especially #1 and #2 in Table F1) are not one-to-one comparable between the two app versions. Therefore, we decided to proceed as follows when analyzing our research questions: We reduced the dataset of Study 2 and only use data from participants collected via app version 1 (N = 313, n = 3,737).

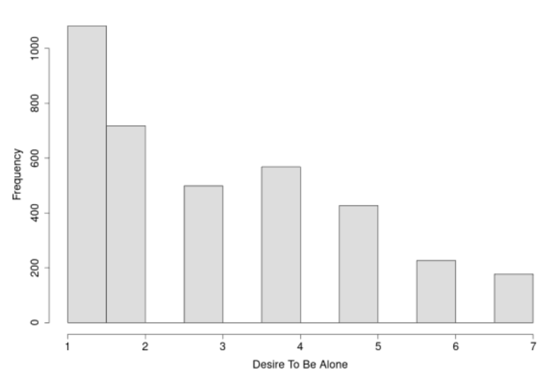
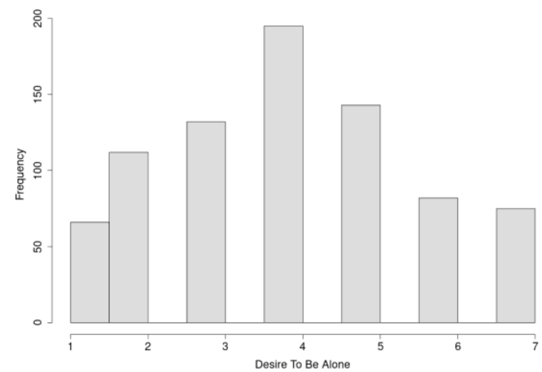
Table F1

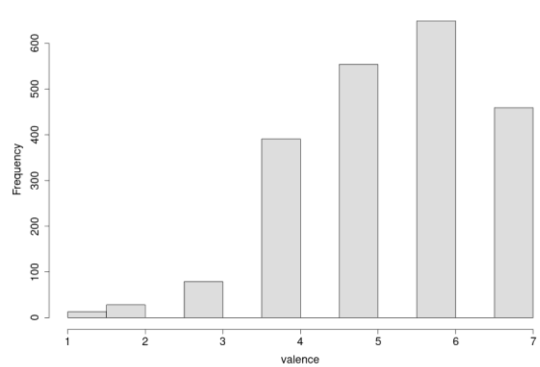
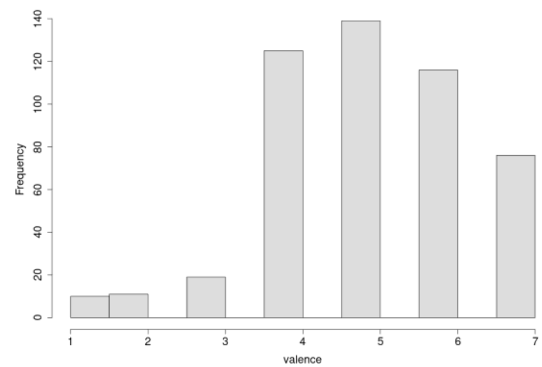
Description of Differences in Experience Sampling Items Between App Versions in Study 2

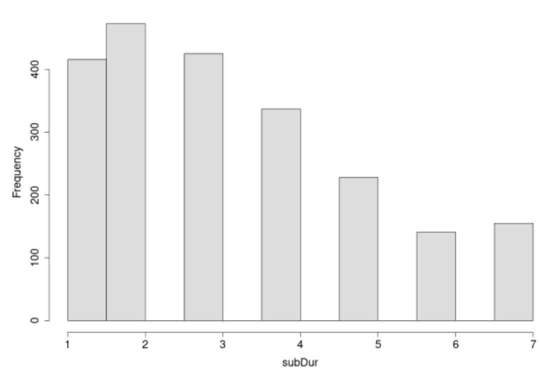
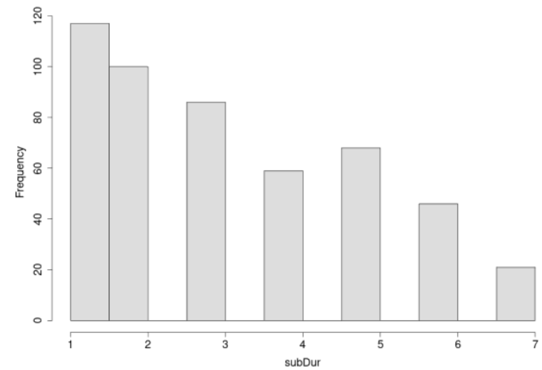
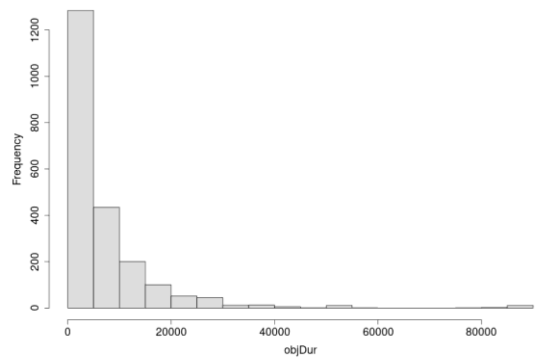
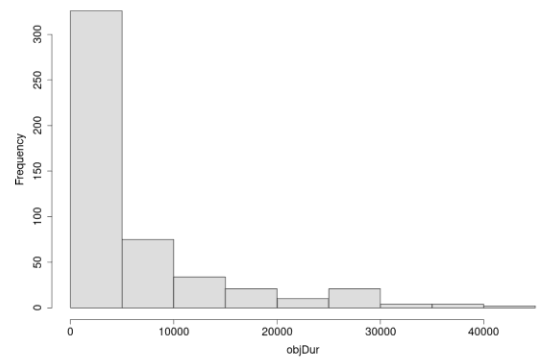
#	Item ID *	Difference	App Version 1 (*N* = 313, *n* = 3,737)	App Version 2 (*N* = 72, *n* = 818)
1	3006	Formulation of the *social desire* item and the anchors of the associated scale	***Item Formulation***	
			„Ich hätte heute gern mehr Zeit mit anderen Menschen verbracht“ [“I would have liked to spend more time with other people today”]	„Hätten Sie heute gern mehr Zeit mit anderen Menschen verbracht?“ [“Would you have liked to spend more time with other people today?”]
			Verbalized Anchors	
			trifft nicht zu (1) – trifft zu (7) [does not apply (1) – does apply (7)]	sehr ungern (1) – sehr gern (7) [very reluctantly (1) - very much (7)]
			Descriptives	
			M = 3.02, *SD* = 1.88	*M* = 3.47, *SD* = 1.66

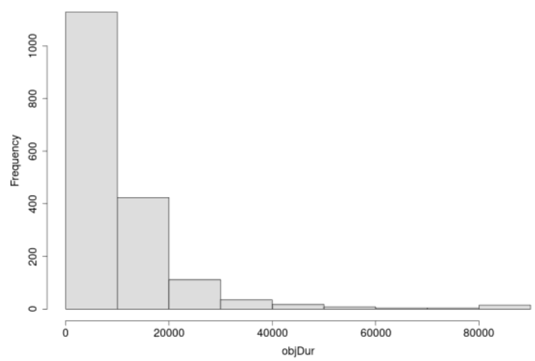
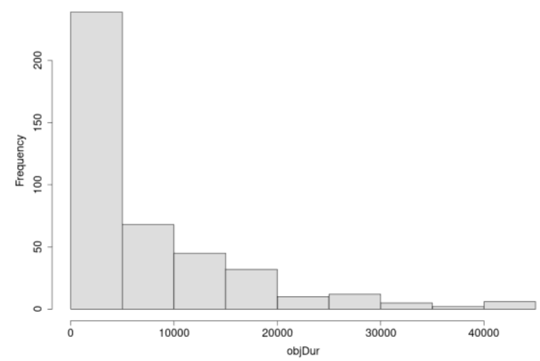




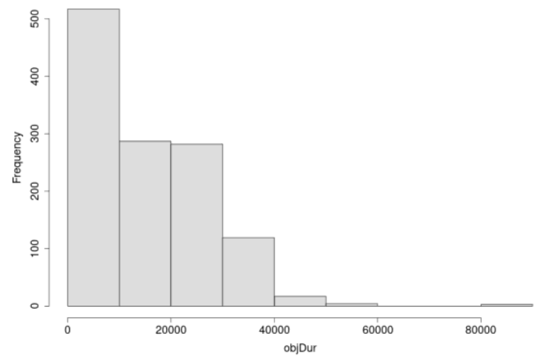
2	3006	Formulation of the *desire to be alone* item and the anchors of the associated scale	***Item Formulation***	
			„Ich hätte heute gern mehr Zeit alleine verbracht“ ["I would have liked to spend more time alone today"]	„Hätten Sie heute gern mehr Zeit alleine verbracht?“ ["Would you have liked to spend more time alone today?"]
			Verbalized Anchors	
			trifft nicht zu (1) – trifft zu (7) [does not apply (1) – does apply (7)]	sehr ungern (1) – sehr gern (7) [very reluctantly (1) - very much (7)]
			Descriptives	
			M = 2.98, *SD* = 1.82	*M* = 3.97, *SD* = 1.70
				

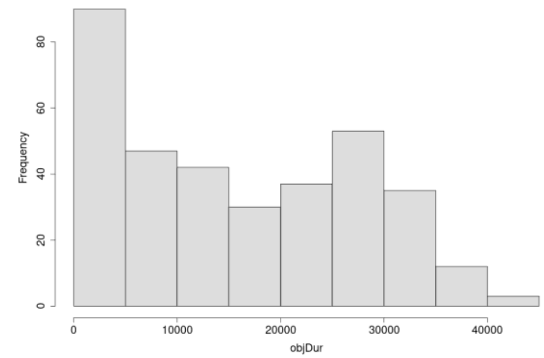
3	Item formulation to describe the contact with other people on the given day: used term "*other people*" versus "*strangers*"	***Item Formulation***	
		"Nun geht es um weitere Personen:" [“The following questions are about other people:”]	Nun geht es um Fremde: [“The following questions are about strangers:”]
		Descriptives (per dimension)	
30043		Valence of contact [unpleasant (1) – pleasant (7)]	
		M = 5.41, *SD* = 1.23  	*M* = 5.06, *SD* = 1.33 
2006		No contact (Number of times participants reported having no contact with other people/strangers on a given day)	
		n = 1,525 → in 40.8% of all observations	*n* = 309 → in 37.8% of all observations

30041	Perceived duration [very little (1) – very much (7)]	
	M = 3.24, *SD* = 1.79	*M* = 3.17, *SD* = 1.82
		
30042	Estimated duration	
	Possible range of value: 0-1440 [min]	Possible range of values: 0-720 [min]
	M = 112.80, *SD* = 170.12, *range* = 0.02 – 1,440.00	*M* = 99.19 min, *SD* = 136.85, *range* = 0.02 – 720.00
		

4	30042	Participants were asked to estimate the contact duration for different types of contact types (e.g., partners, family, children) on a given day; the possible maximum value for contact duration differed.	***Value range***	
			Min: 0; *Max*: 1440 [min]	*Min*: 0; *Max*: 720 [min]
			Descriptives (according to contact type) (in minutes; plots: in seconds)	
			Friends (frie_dur_obj)	
			M = 161.25, *SD* = 204.61, *range* = 0.02 – 1,440.00	*M* = 115.55, *SD* = 146.87, *range* = 0.02 – 720.00
				

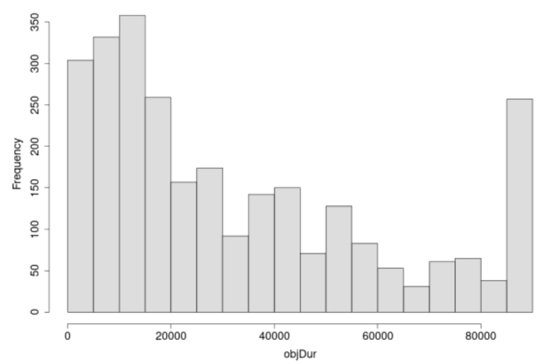
M = 249.02, *SD* = 203.56, *range* = 0.02 – 1,440.00	*M* = 261.91, *SD* = 196.10, *range* = 0.02 – 720.00

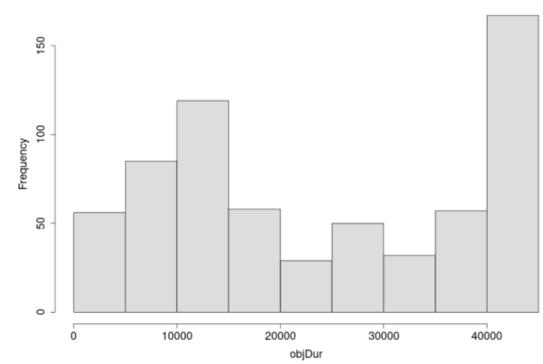


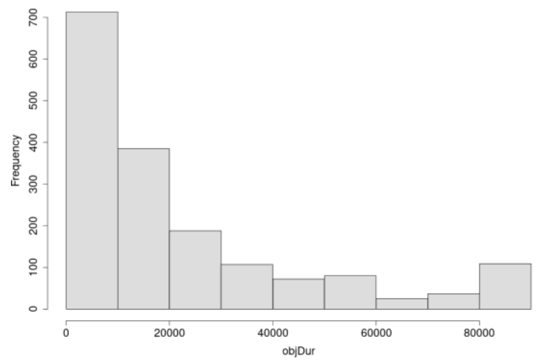
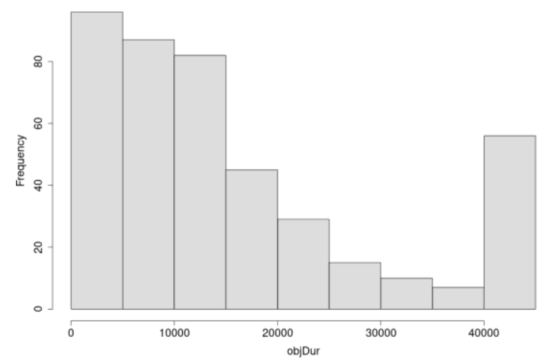
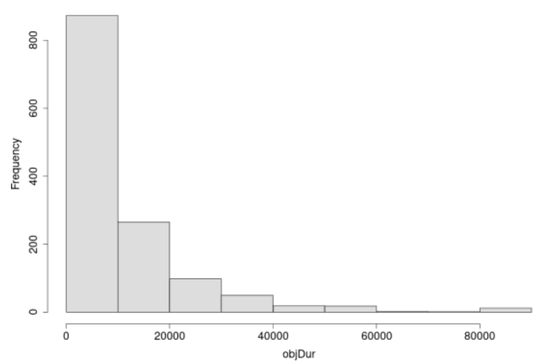
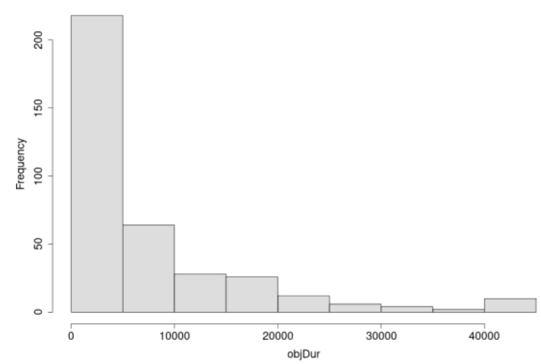


Partner (part_dur_obj)

M = 545.09, *SD* = 450.62, range = 0.02 – 1,440.00	*M* = 399.75, *SD* = 246.58, *range* = 0.02 – 720.00





Children (kids_dur_obj)	
M = 371.44, *SD* = 401.17, *range* = 0.02 – 1,440.00	*M* = 260.28, *SD* = 224.67, *range* = 0.02 – 720.00
	
Family (fami_dur_obj)	
M = 171.78, *SD* = 225.03, *range* = 0.02 – 1,440.00	*M* = 118.05, *SD* = 159.11, *range* = 0.02 – 720.00
	

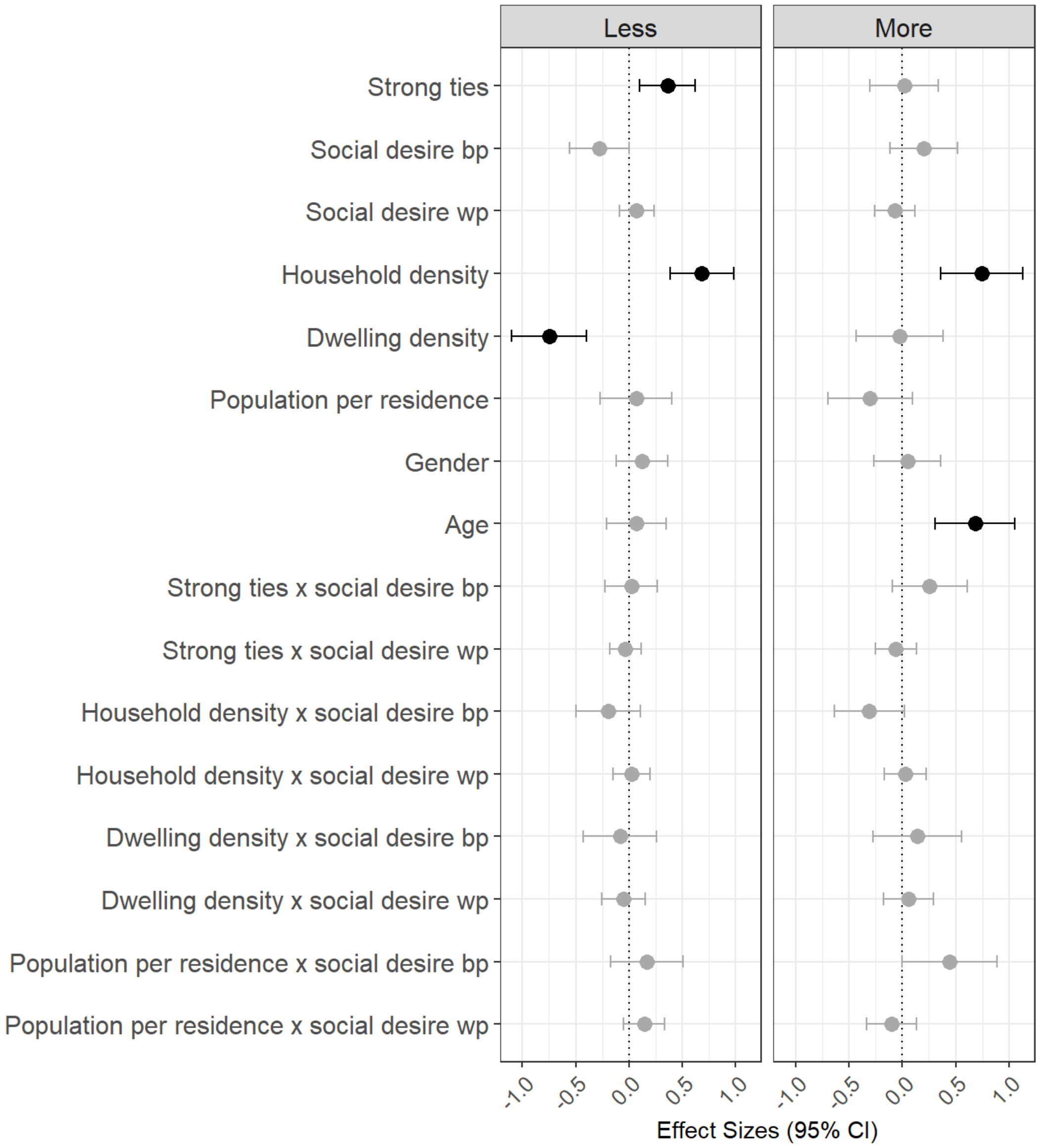
5	64	In the call-triggered experience sampling questionnaire, participants were asked about the type of relationship with the person they just spoke to; for one of the answer categories (bold) the label differed.	***Descriptives*** (Proportion of observations in which the respective category was indicated)	
			Friends: 16.7% Partner: 21.3% Chrildren: 10.4% Other Family: 16.2% **Colleagues:** 12.2% Strangers: 8.9% Other: 14.2%	Friends: 17.9% Partner: 15.1% Chrildren: 14.1% Other Family: 19.2% **Colleagues/fellow students:** 11.1% Strangers: 12.0% Other: 10.7%

* The Item ID column specifies the id of the item by which the variable can be found in the raw dataset on the server.

Appendix G

Figure G1

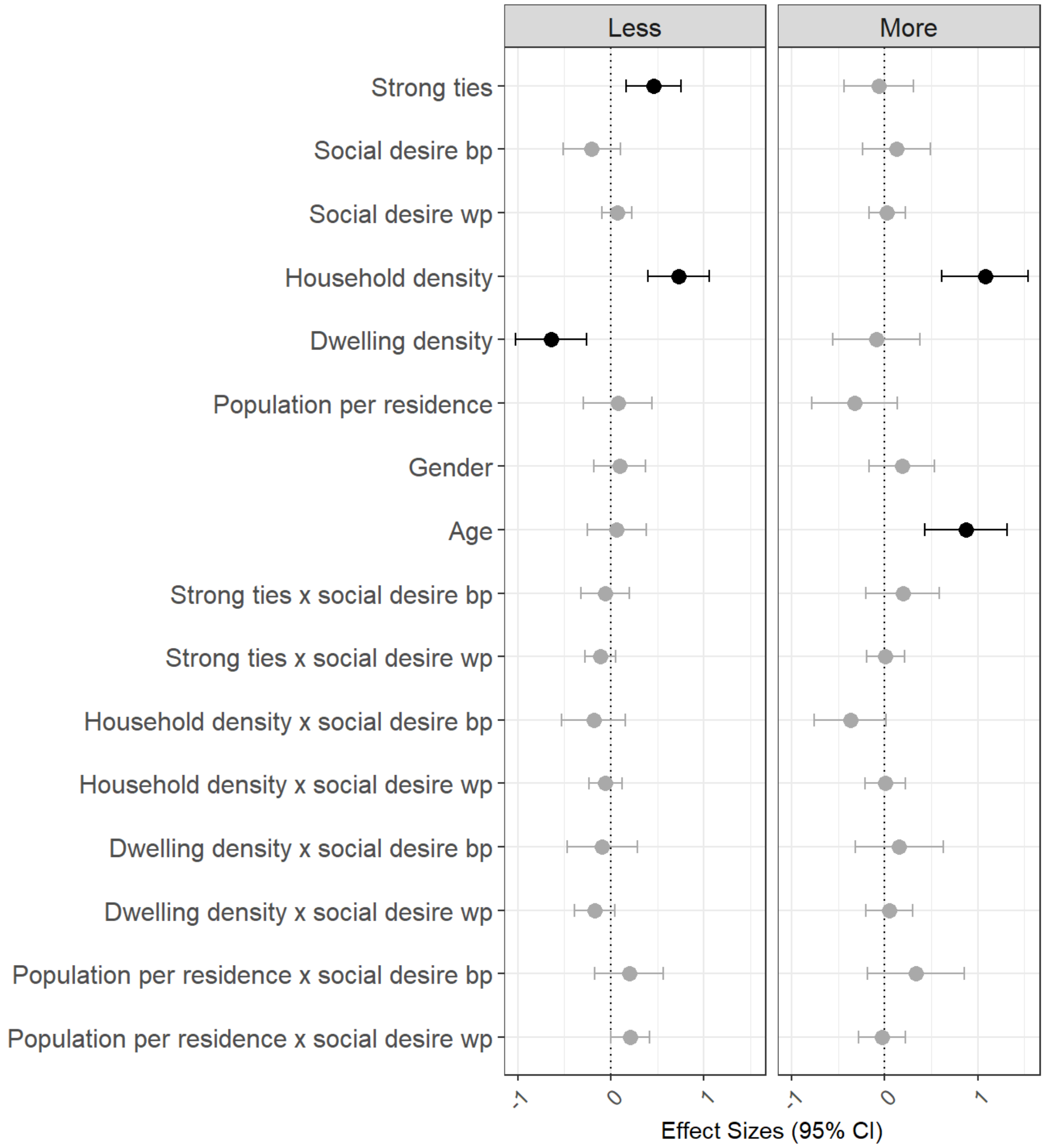
Study 2: Social Contact Two Days Later (Lead 2) Predicted by Social Desires and Social Context on Days with Less or More Social Contact Than Typical



Note. Effects with CIs that included zero are displayed in grey. In the left panel, based on all days during which participants had less contact than typical, social desire refers to the desire to interact. Conversely, in the right panel, based on days during which participants had more contact, higher values on social desire indicate a higher desire to be alone. Positive effect sizes indicate a higher probability of having more social contact than the sample median on the next day. The left panel was based on 1,476 observations from 234 participants, and the right panel was based on 1,402 observations from 244 participants.

Figure G2

Study 2: Social Contact Three Days Later (Lead 3) Predicted by Social Desires and Social Context on Days with Less or More Social Contact Than Typical

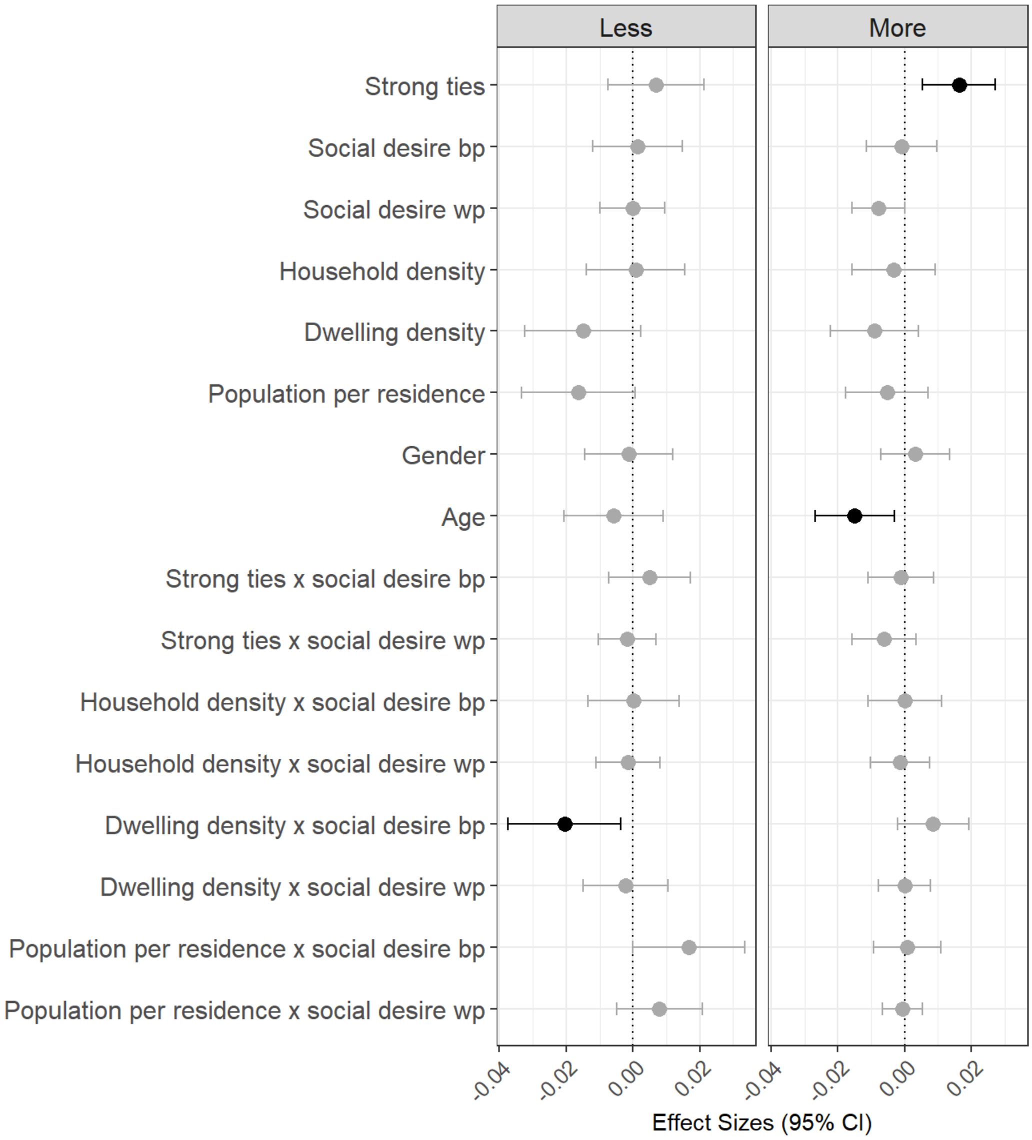


Note. Effects with CIs that included zero are displayed in grey. In the left panel, based on all days during which participants had less contact than typical, social desire refers to the desire to interact. Conversely, in the right panel, based on days during which participants had more contact, higher values on social desire indicate a higher desire to be alone. Positive effect sizes indicate a higher probability of having more social contact than the sample median on the next day. The left panel was based on 1,328 observations from 228 participants, and the right panel was based on 1,271 observations from 243 participants.

Appendix H

Figure H1

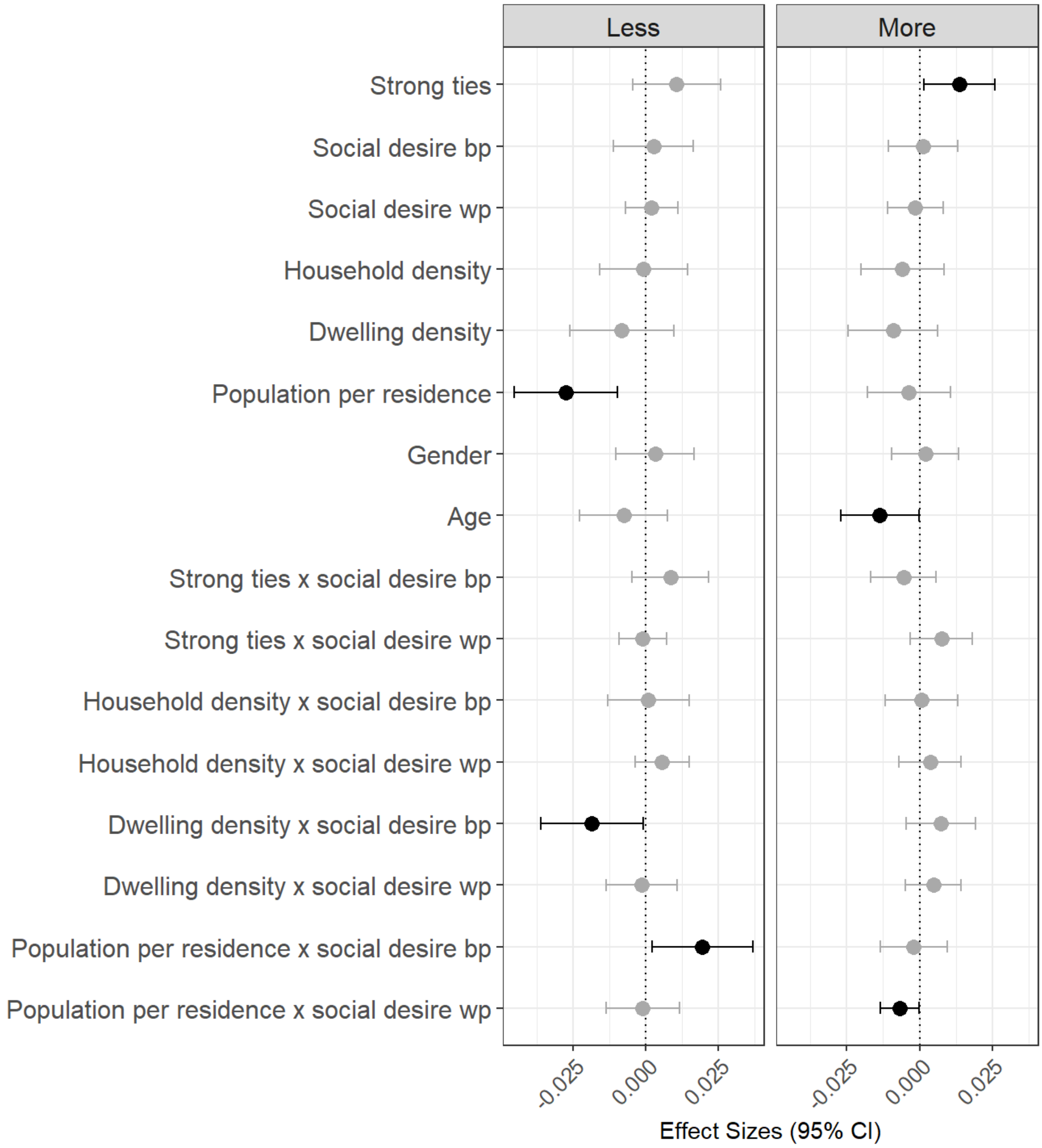
Study 2: Proportion of Conversation at Next Day Predicted by Social Desires and Social Context on Days with Less or More Social Contact Than Typical



Note. Effects with CIs that included zero are displayed in grey. In the left panel, based on all days during which participants were around less conversation than typical, social desire refers to the desire to interact. Conversely, in the right panel, based on days during which participants were around more conversation than typical, higher values on social desire indicate a higher desire to be alone. Positive effect sizes indicate a higher probability of being around more conversation than the sample median on the next day. The left panel was based on 955 observations from 224 participants, and the right panel was based on 910 observations from 230 participants.

Figure H2

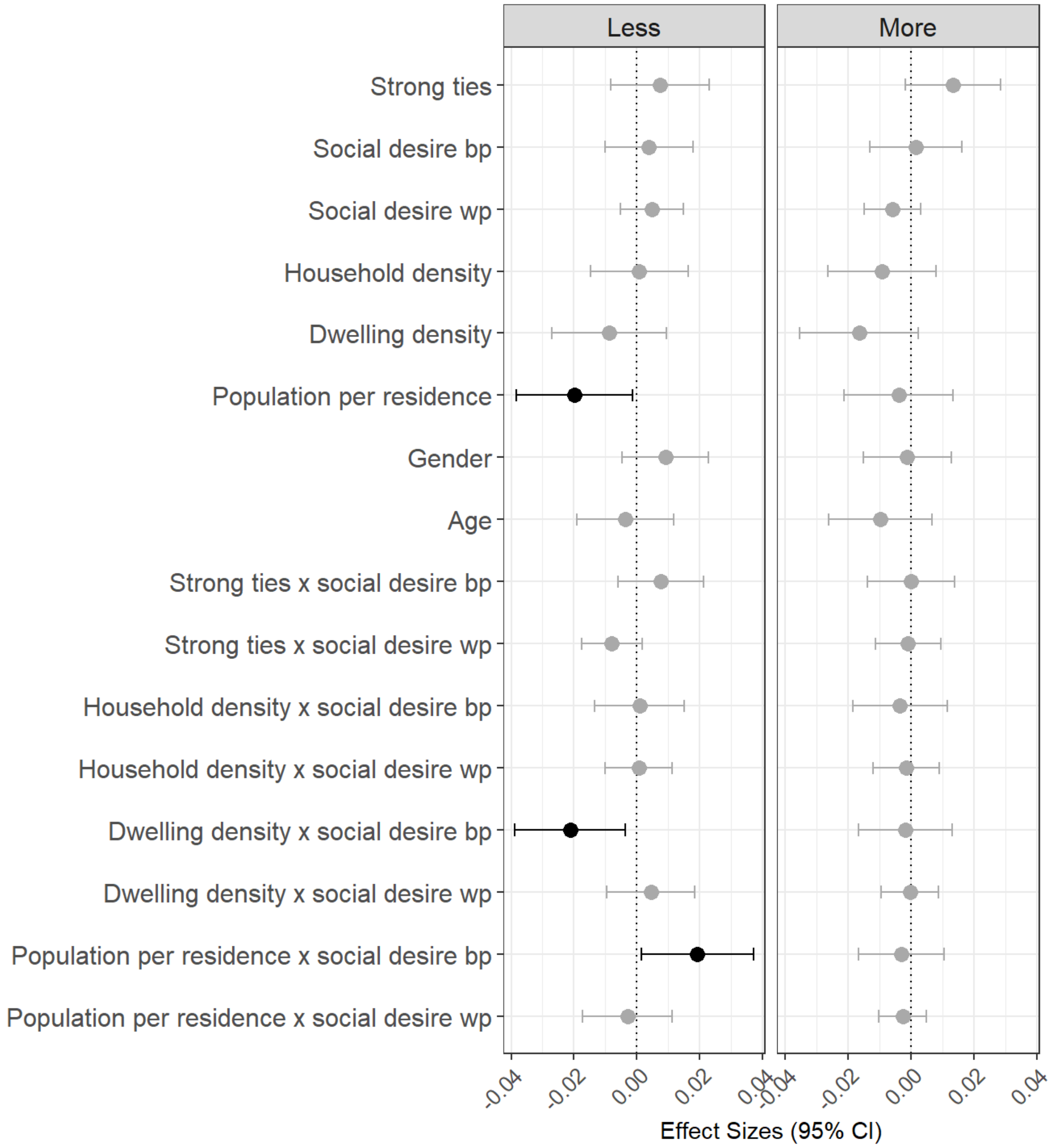
Study 2: Proportion of Conversation Two Days Later (Lead 2) Predicted by Social Desires and Social Context on Days with Less or More Social Contact Than Typical



Note. Effects with CIs that included zero are displayed in grey. In the left panel, based on all days during which participants were around less conversation than typical, social desire refers to the desire to interact. Conversely, in the right panel, based on days during which participants were around more conversation than typical, higher values on social desire indicate a higher desire to be alone. Positive effect sizes indicate a higher probability of being around more conversation than the sample median on the next day. The left panel was based on 822 observations from 209 participants, and the right panel was based on 765 observations from 211 participants.

Figure H3

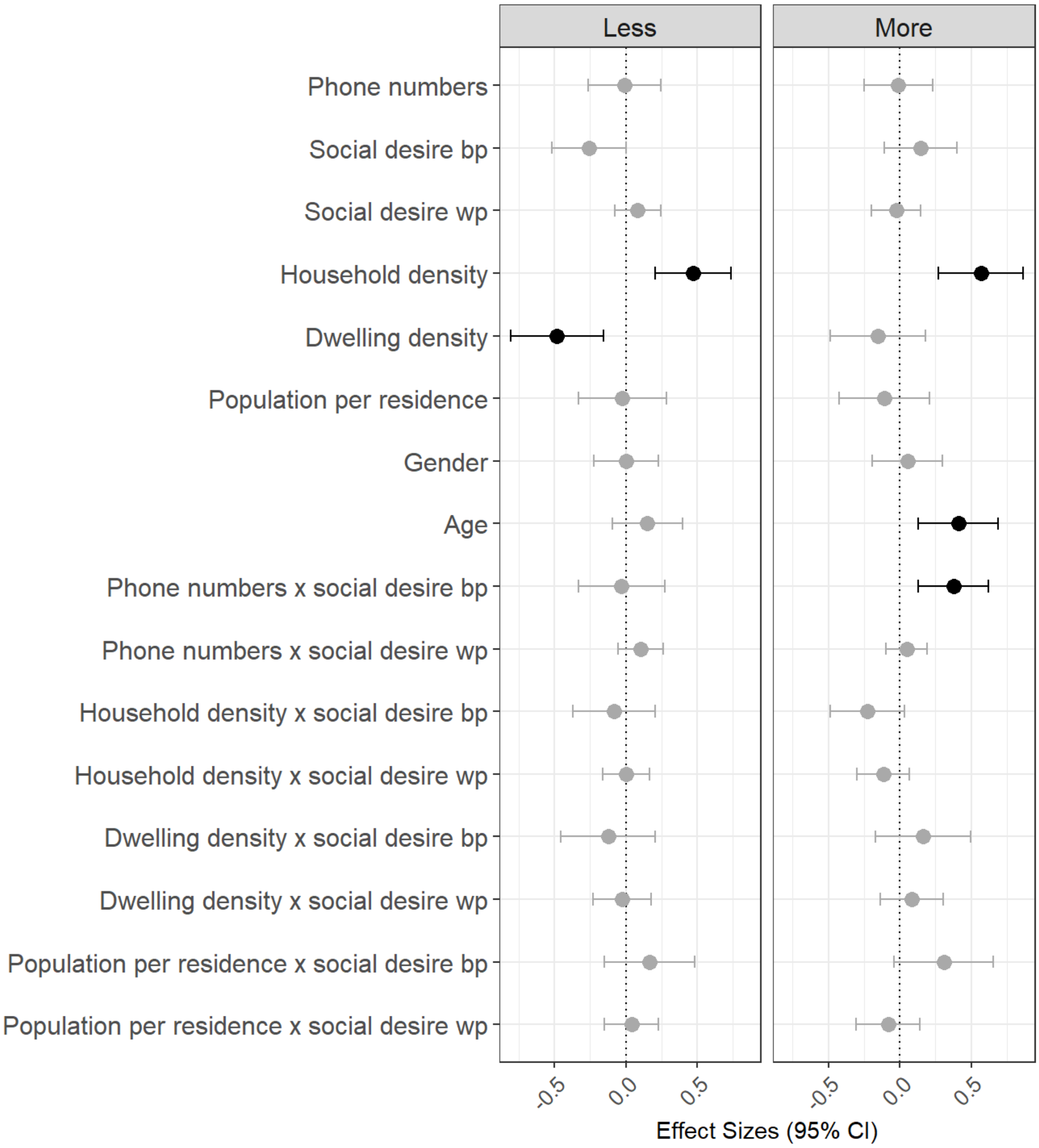
Study 2: Proportion of Conversation Three Days Later (Lead 3) Predicted by Social Desires and Social Context on Days with Less or More Social Contact Than Typical



Note. Effects with CIs that included zero are displayed in grey. In the left panel, based on all days during which participants were around less conversation than typical, social desire refers to the desire to interact. Conversely, in the right panel, based on days during which participants were around more conversation than typical, higher values on social desire indicate a higher desire to be alone. Positive effect sizes indicate a higher probability of being around more conversation than the sample median on the next day. The left panel was based on 705 observations from 193 participants, and the right panel was based on 666 observations from 197 participants.

Figure H4

Study 2: Social Contact at the Next Day Predicted by Phone Numbers and Context Variables on Days With Less or More Social Contact Than Typical



Note. Effects with CIs that included zero are displayed in grey. In the left panel, based on all days during which participants had less contact than typical, social desire refers to the desire to interact. Conversely, in the right panel, based on days during which participants had more contact, higher values on social desire indicate a higher desire to be alone. Positive effect sizes indicate a higher probability of having more social contact than the sample median on the next day. The left panel was based on 1,605 observations from 239 participants, and the right panel was based on 1,498 observations from 245 participants.

Supplemental Material for Chapter 6: Resuming Social Contact After Months of Contact Restrictions: Social Traits Moderate Associations Between Changes in Social Contact and Well-being

Michael D. Krämer, Yannick Roos, David Richter, & Cornelia Wrzus

Full Equations

First, to predict personal and indirect contact frequency (H1a, H1b), we estimated models with a cross-level interaction of $time_{ti}$ (linear effect, zero at the first wave) and each trait:

$$\begin{aligned} contact_{ti} = \quad & \beta_{0i} + \beta_{1i} time_{ti} + e_{ti} \\ & \beta_{0i} = \gamma_{00} + \gamma_{01} trait_i + \upsilon_{0i} \\ & \beta_{1i} = \gamma_{10} + \gamma_{11} trait_i \end{aligned} \tag{A1}$$

$$contact_{ti} = \gamma_{00} + \gamma_{01} trait_i + \gamma_{10} time_{ti} + \gamma_{11} time_{ti} trait_i + {,}_{0i} + e_{ti} \text{ ,} \qquad \text{(Reduced-form)}$$

where at time t for person i $e_{ti} \sim N(0, \sigma_e^2)$ and $\upsilon_{0i} \sim N(0, \tau_{00})$ (for a fixed slope model). We estimated separate models for the two dependent variables, personal and indirect contact, and for each of the four traits. Second, to predict well-being, that is, life satisfaction and depressivity/anxiety (H2a, H2b), we estimated cross-level interactions of the within-person effect of higher-than-baseline contact (either personal or indirect contact), $contactWP_{ti}$, with each social trait:

$$wellbeing_{ti} = \beta_{0i} + \beta_{1i} time_{ti} + \beta_{2i} contactWP_{ti} + e_{ti}$$

$$\beta_{0i} = \gamma_{00} + \gamma_{01} trait_i + \gamma_{02} contactBP_i + \gamma_{03} trait_i contactBP_i + {,}_{0i}$$

$$\beta 1i = \gamma 10 \tag{A1}$$

$$\beta_{2i} = \gamma_{20} + \gamma_{21} trait_i$$

$$wellbeing_{ti} = \gamma_{00} + \gamma_{01} trait_i + \gamma_{02} contactBP_i + \gamma_{03} trait_i contactBP_i$$

$$+ \gamma_{10} time_{ti} + \gamma_{20} contactWP_{ti} + \gamma_{21} contactWP_{ti} trait_i \qquad \text{(Reduced-form)}$$

$$+ {,}_{0i} + e_{ti} \text{ ,}$$

where $e_{ti} \sim N(0, \sigma_e^2)$ and $\upsilon_{0i} \sim N(0, \tau_{00})$ (for a fixed slope model). Again, we estimated separate models for the two dependent variables life satisfaction and depressivity/anxiety, for personal and indirect contact, and for each social trait.

Robustness Check

In order to judge how robust the multilevel models were to violated assumptions regarding multivariate normality and contamination by outliers, we re-estimated all models presented in the main part of the article with robust linear mixed-effects models using the *robustlmm* package (Koller, 2016, 2019). Based on the random effects contamination model and the central contamination model, this method supports hierarchically grouped data structures such as observations nested in participants. There is no universally accepted way to obtain confidence intervals or p-values based on the method implemented in the *robustlmm* package (Koller, 2019) which is why we decided not to report these robust models in the main part of the article. Generally, the results reported in the main part of the article were very similar to these robust estimates (see Tables S7, S8, S9, S10, & S11), especially for models related to hypotheses H1a and H1b. Differences between robust and non-robust models were slightly larger for models testing hypotheses H2a and H2b, where $trait * contactWP$ effects were slightly reduced in magnitude for affiliation motive and social anxiety in the robust models.

Supplemental Tables

Table S1

Means and Standard Deviations of the Included Variables Over Time and their ICCs

	M_1	SD_1	M_2	SD_2	M_3	SD_3	M_4	SD_4	ICC
Personal contact frequency	1.85	0.78	1.9	0.83	2.14	0.78	2.25	0.83	0.62
Indirect contact frequency	2.30	0.69	2.25	0.72	2.15	0.64	2.13	0.64	0.8
Life satisfaction	6.75	2.36	6.46	2.42	6.44	2.37	6.48	2.32	0.74
Depressivity/anxiety	1.67	0.65	1.67	0.62	1.6	0.59	1.65	0.68	0.72
Extraversion	3.05	0.70							
Affiliation motive	3.25	0.96							
Need to be alone	5.23	1.01							
Social anxiety	1.76	0.77							

Note. Presented are the uncentered variables. Personal and indirect contact frequency have a range from 1 to 5 (observed ranges: 1 – 4.5, 1 – 4.25), life satisfaction from 0 to 10, depressivity/anxiety from 1 to 4 (observed range: 1 – 3.6), extraversion from 1 to 5 (observed range: 1.25 – 4.75), affiliation motive from 1 to 6, need to be alone from 1 to 7 (observed range: 2.75 – 7), and social anxiety from 1 to 5 (observed range: 1 – 4.08). M_1 = mean at the first wave. SD_1 = standard deviation at the first wave. ICC = intra-class correlation, that is, proportion of variance that lies at the between-person level.

Table S2

Fixed Effects of Social Contact Frequency Predicted by Time and Social Traits (Alternative Random Slope Configuration to Table 1)

	Personal contact				Indirect contact			
Parameter	$\hat{\gamma}$	95% CI	*t*	*p*	$\hat{\gamma}$	95% CI	*t*	*p*
Extraversion (M1a, M1b)								
Intercept, $\hat{\gamma}_{00}$	1.82	[1.71, 1.92]	33.60	< .001	2.30	[2.21, 2.38]	52.25	< .001
Time, $\hat{\gamma}_{10}$	0.15	[0.11, 0.18]	8.29	< .001	-0.06	[-0.08, -0.04]	-5.70	< .001
Extraversion, $\hat{\gamma}_{01}$	0.05	[-0.11, 0.20]	0.60	.552	0.39	[0.27, 0.52]	6.24	< .001
Time * Extraversion, $\hat{\gamma}_{11}$	0.01	[-0.04, 0.06]	0.50	.616	-0.04	[-0.07, -0.01]	-2.72	.007
Affiliation motive (M2a, M2b)								
Intercept, $\hat{\gamma}_{00}$	1.82	[1.71, 1.92]	33.79	< .001	2.30	[2.21, 2.38]	52.31	< .001
Time, $\hat{\gamma}_{10}$	0.15	[0.11, 0.18]	8.41	< .001	-0.06	[-0.08, -0.04]	-5.63	< .001
Affiliation motive, $\hat{\gamma}_{01}$	0.09	[-0.02, 0.20]	1.65	.100	0.26	[0.17, 0.35]	5.77	< .001
Time * Affiliation motive, $\hat{\gamma}_{11}$	0.04	[0.00, 0.07]	1.97	.051	-0.01	[-0.03, 0.01]	-0.98	.326
Need to be alone (M3a, M3b)								
Intercept, $\hat{\gamma}_{00}$	1.82	[1.71, 1.92]	33.53	< .001	2.30	[2.21, 2.39]	49.25	< .001
Time, $\hat{\gamma}_{10}$	0.15	[0.11, 0.18]	8.45	< .001	-0.06	[-0.08, -0.04]	-5.62	< .001
Need to be alone, $\hat{\gamma}_{01}$	-0.01	[-0.12, 0.09]	-0.26	.796	-0.09	[-0.18, 0.00]	-1.97	.050
Time * Need to be alone, $\hat{\gamma}_{11}$	-0.05	[-0.08, -0.01]	-2.53	.012	0.00	[-0.02, 0.02]	-0.40	.690
Social anxiety (M4a, M4b)								
Intercept, $\hat{\gamma}_{00}$	1.82	[1.71, 1.92]	33.58	< .001	2.30	[2.21, 2.39]	49.43	< .001
Time, $\hat{\gamma}_{10}$	0.14	[0.11, 0.18]	8.31	< .001	-0.06	[-0.08, -0.04]	-5.66	< .001
Social anxiety, $\hat{\gamma}_{01}$	0.01	[-0.13, 0.15]	0.17	.868	-0.16	[-0.28, -0.04]	-2.65	.009
Time * Social anxiety, $\hat{\gamma}_{11}$	-0.04	[-0.08, 0.01]	-1.63	.106	0.02	[-0.01, 0.04]	1.27	.205

Note. Two models were computed for each social trait: as predictors of personal contact frequency (models MXa) and of indirect contact frequency (models MXb). CI = confidence interval. Models MXa feature random slopes of time.

Table S3

Fixed Effects of Well-Being Predicted by Time, Contact Frequencies, and Extraversion (Alternative Random Slope Configuration to Table 2)

	Life satisfaction				Depressivity/anxiety			
Parameter	$\hat{\gamma}$	95% CI	t	p	$\hat{\gamma}$	95% CI	t	p
Personal contact frequency (M1a, M1b)								
Intercept, $\hat{\gamma}_{00}$	6.73	[6.42, 7.04]	42.33	< .001	1.66	[1.58, 1.75]	38.24	< .001
Time, $\hat{\gamma}_{10}$	-0.11	[-0.20, -0.03]	-2.60	.010	0.00	[-0.03, 0.02]	-0.28	.782
Personal contact (BP) , $\hat{\gamma}_{02}$	0.33	[-0.03, 0.70]	1.78	.077	-0.02	[-0.12, 0.09]	-0.32	.747
Personal contact (WP) , $\hat{\gamma}_{20}$	0.22	[0.00, 0.44]	1.96	.052	0.00	[-0.06, 0.06]	-0.01	.990
Extraversion, $\hat{\gamma}_{01}$	1.16	[0.74, 1.58]	5.37	< .001	-0.26	[-0.38, -0.15]	-4.51	< .001
Personal contact (BP) * Extraversion, $\hat{\gamma}_{03}$	-0.09	[-0.62, 0.44]	-0.33	.740	0.01	[-0.14, 0.16]	0.12	.906
Personal contact (WP) * Extraversion, $\hat{\gamma}_{21}$	-0.01	[-0.29, 0.27]	-0.07	.944	-0.02	[-0.10, 0.06]	-0.51	.613
Indirect contact frequency (M2a, M2b)								
Intercept, $\hat{\gamma}_{00}$	6.68	[6.36, 7.00]	41.16	< .001	1.66	[1.57, 1.75]	37.10	< .001
Time, $\hat{\gamma}_{10}$	-0.08	[-0.17, 0.00]	-1.99	.047	0.00	[-0.03, 0.02]	-0.39	.696
Indirect contact (BP) , $\hat{\gamma}_{02}$	0.23	[-0.21, 0.68]	1.03	.306	0.13	[0.00, 0.25]	2.03	.044
Indirect contact (WP) , $\hat{\gamma}_{20}$	-0.11	[-0.49, 0.27]	-0.56	.578	0.01	[-0.09, 0.11]	0.22	.824
Extraversion, $\hat{\gamma}_{01}$	1.16	[0.72, 1.60]	5.20	< .001	-0.32	[-0.44, -0.20]	-5.23	< .001
Indirect contact (BP) * Extraversion, $\hat{\gamma}_{03}$	-0.26	[-0.84, 0.33]	-0.86	.391	-0.03	[-0.19, 0.13]	-0.37	.709
Indirect contact (WP) * Extraversion, $\hat{\gamma}_{21}$	0.19	[-0.30, 0.67]	0.76	.451	-0.09	[-0.21, 0.03]	-1.49	.137

Note. Two models were computed for each personal and indirect contact frequency: predicting life satisfaction (models MXa) and depressivity/anxiety (models MXb). CI = confidence interval; BP = between-person effect; WP = within-person effect. Models M1a, M1b, and M2a feature random slopes of within-person contact.

Table S4

Fixed Effects of Well-Being Predicted by Time, Contact Frequencies, and Affiliation Motive (Alternative Random Slope Configuration to Table 3)

Parameter	Life satisfaction				Depressivity/anxiety			
	$\hat{\gamma}$	95% CI	*t*	*p*	$\hat{\gamma}$	95% CI	*t*	*p*
Personal contact frequency (M1a, M1b)								
Intercept, $\hat{\gamma}_{00}$	6.71	[6.38, 7.05]	39.54	< .001	1.66	[1.57, 1.75]	36.09	< .001
Time, $\hat{\gamma}_{10}$	-0.11	[-0.20, -0.03]	-2.61	.009	0.00	[-0.03, 0.02]	-0.22	.825
Personal contact (BP) , $\hat{\gamma}_{02}$	0.30	[-0.10, 0.69]	1.45	.149	-0.02	[-0.13, 0.09]	-0.38	.703
Personal contact (WP) , $\hat{\gamma}_{20}$	0.17	[-0.05, 0.39]	1.54	.126	0.00	[-0.06, 0.07]	0.14	.891
Extraversion, $\hat{\gamma}_{01}$	0.41	[0.08, 0.74]	2.43	.016	-0.05	[-0.14, 0.04]	-1.08	.280
Personal contact (BP) * Affiliation motive, $\hat{\gamma}_{03}$	0.12	[-0.30, 0.54]	0.56	.575	-0.02	[-0.13, 0.10]	-0.27	.786
Personal contact (WP) * Affiliation motive, $\hat{\gamma}_{21}$	0.21	[-0.02, 0.43]	1.80	.076	-0.03	[-0.09, 0.04]	-0.84	.403
Indirect contact frequency (M2a, M2b)								
Intercept, $\hat{\gamma}_{00}$	6.68	[6.36, 7.01]	40.19	< .001	1.66	[1.57, 1.75]	35.61	< .001
Time, $\hat{\gamma}_{10}$	-0.09	[-0.17, -0.01]	-2.11	.035	0.00	[-0.03, 0.02]	-0.27	.789
Indirect contact (BP) , $\hat{\gamma}_{02}$	0.49	[0.03, 0.95]	2.10	.037	0.03	[-0.10, 0.15]	0.41	.684
Indirect contact (WP) , $\hat{\gamma}_{20}$	-0.17	[-0.55, 0.21]	-0.89	.373	0.01	[-0.09, 0.11]	0.20	.840
Extraversion, $\hat{\gamma}_{01}$	0.41	[0.09, 0.74]	2.49	.014	-0.07	[-0.16, 0.03]	-1.41	.161
Indirect contact (BP) * Affiliation motive, $\hat{\gamma}_{03}$	-0.29	[-0.70, 0.12]	-1.40	.164	0.00	[-0.12, 0.11]	-0.08	.933
Indirect contact (WP) * Affiliation motive, $\hat{\gamma}_{21}$	0.40	[0.03, 0.77]	2.14	.035	-0.07	[-0.17, 0.02]	-1.55	.122

Note. Two models were computed for each personal and indirect contact frequency: predicting life satisfaction (models MXa) and depressivity/anxiety (models MXb). CI = confidence interval; BP = between-person effect; WP = within-person effect. Models M1a, M1b, and M2a feature random slopes of within-person contact.

Table S5

Fixed Effects of Well-Being Predicted by Time, Contact Frequencies, and Need to be Alone (Alternative Random Slope Configuration to Table 4)

	Life satisfaction				Depressivity/anxiety			
Parameter	$\hat{\gamma}$	95% CI	*t*	*p*	$\hat{\gamma}$	95% CI	*t*	*p*
Personal contact frequency (M1a, M1b)								
Intercept, $\hat{\gamma}_{00}$	6.75	[6.42, 7.08]	40.48	< .001	1.65	[1.57, 1.74]	36.81	< .001
Time, $\hat{\gamma}_{10}$	-0.12	[-0.21, -0.04]	-2.79	.006	0.00	[-0.03, 0.02]	-0.10	.917
Personal contact (BP) , $\hat{\gamma}_{02}$	0.41	[0.03, 0.80]	2.10	.037	-0.04	[-0.14, 0.07]	-0.67	.501
Personal contact (WP) , $\hat{\gamma}_{20}$	0.21	[-0.01, 0.43]	1.87	.064	0.00	[-0.06, 0.06]	-0.02	.980
Extraversion, $\hat{\gamma}_{01}$	0.27	[-0.04, 0.58]	1.69	.093	-0.04	[-0.13, 0.04]	-1.04	.300
Personal contact (BP) * Need to be alone, $\hat{\gamma}_{03}$	-0.27	[-0.71, 0.17]	-1.20	.233	0.08	[-0.04, 0.19]	1.25	.214
Personal contact (WP) * Need to be alone, $\hat{\gamma}_{21}$	-0.19	[-0.39, 0.00]	-1.93	.057	0.02	[-0.03, 0.08]	0.87	.385
Indirect contact frequency (M2a, M2b)								
Intercept, $\hat{\gamma}_{00}$	6.61	[6.30, 6.93]	40.99	< .001	1.66	[1.57, 1.75]	36.96	< .001
Time, $\hat{\gamma}_{10}$	-0.09	[-0.17, 0.00]	-2.06	.040	0.00	[-0.03, 0.02]	-0.32	.748
Indirect contact (BP) , $\hat{\gamma}_{02}$	0.71	[0.27, 1.14]	3.19	.002	-0.01	[-0.13, 0.11]	-0.21	.835
Indirect contact (WP) , $\hat{\gamma}_{20}$	-0.07	[-0.45, 0.31]	-0.35	.724	-0.02	[-0.11, 0.08]	-0.35	.727
Extraversion, $\hat{\gamma}_{01}$	0.28	[-0.03, 0.59]	1.76	.079	-0.05	[-0.14, 0.03]	-1.24	.216
Indirect contact (BP) * Need to be alone, $\hat{\gamma}_{03}$	0.08	[-0.34, 0.51]	0.37	.711	-0.02	[-0.13, 0.10]	-0.28	.782
Indirect contact (WP) * Need to be alone, $\hat{\gamma}_{21}$	-0.20	[-0.56, 0.16]	-1.10	.274	-0.01	[-0.10, 0.07]	-0.31	.753

Note. Two models were computed for each personal and indirect contact frequency: predicting life satisfaction (models MXa) and depressivity/anxiety (models MXb). CI = confidence interval; BP = between-person effect; WP = within-person effect. Models M1a, M1b, and M2a feature random slopes of within-person contact.

Table S6

Fixed Effects of Well-Being Predicted by Time, Contact Frequencies, and Social Anxiety (Alternative Random Slope Configuration to Table 5)

	Life satisfaction				Depressivity/anxiety			
Parameter	$\hat{\gamma}$	95% CI	*t*	*p*	$\hat{\gamma}$	95% CI	*t*	*p*
Personal contact frequency (M1a, M1b)								
Intercept, $\hat{\gamma}_{00}$	6.77	[6.46, 7.08]	42.68	< .001	1.65	[1.57, 1.73]	42.61	< .001
Time, $\hat{\gamma}_{10}$	-0.12	[-0.20, -0.03]	-2.63	.009	0.00	[-0.03, 0.02]	-0.22	.823
Personal contact (BP) , $\hat{\gamma}_{02}$	0.48	[0.11, 0.85]	2.55	.012	-0.05	[-0.14, 0.04]	-1.07	.286
Personal contact (WP) , $\hat{\gamma}_{20}$	0.20	[-0.02, 0.43]	1.79	.076	0.01	[-0.06, 0.07]	0.18	.856
Extraversion, $\hat{\gamma}_{01}$	-0.84	[-1.22, -0.46]	-4.28	< .001	0.39	[0.30, 0.48]	8.27	< .001
Personal contact (BP) * Social anxiety, $\hat{\gamma}_{03}$	0.64	[0.10, 1.17]	2.32	.021	-0.11	[-0.24, 0.03]	-1.58	.115
Personal contact (WP) * Social anxiety, $\hat{\gamma}_{21}$	0.07	[-0.23, 0.36]	0.43	.670	0.07	[-0.01, 0.15]	1.64	.104
Indirect contact frequency (M2a, M2b)								
Intercept, $\hat{\gamma}_{00}$	6.65	[6.34, 6.96]	42.38	< .001	1.66	[1.58, 1.73]	42.43	< .001
Time, $\hat{\gamma}_{10}$	-0.09	[-0.17, 0.00]	-2.07	.039	0.00	[-0.03, 0.02]	-0.36	.719
Indirect contact (BP) , $\hat{\gamma}_{02}$	0.50	[0.08, 0.92]	2.33	.021	0.08	[-0.03, 0.18]	1.46	.146
Indirect contact (WP) , $\hat{\gamma}_{20}$	-0.07	[-0.45, 0.31]	-0.37	.713	0.00	[-0.09, 0.09]	0.05	.961
Extraversion, $\hat{\gamma}_{01}$	-0.86	[-1.23, -0.48]	-4.46	< .001	0.43	[0.34, 0.52]	9.24	< .001
Indirect contact (BP) * Social anxiety, $\hat{\gamma}_{03}$	0.27	[-0.28, 0.82]	0.95	.341	0.05	[-0.08, 0.18]	0.73	.464
Indirect contact (WP) * Social anxiety, $\hat{\gamma}_{21}$	0.14	[-0.31, 0.60]	0.62	.536	0.16	[0.05, 0.27]	2.76	.006

Note. Two models were computed for each personal and indirect contact frequency: predicting life satisfaction (models MXa) and depressivity/anxiety (models MXb). CI = confidence interval; BP = between-person effect; WP = within-person effect. Models M1a, M1b, and M2a feature random slopes of within-person contact.

Table S7

Robust Estimates: Fixed Effects of Social Contact Predicted by Time and Social Traits

	Life satisfaction				Indirect contact			
Parameter	$\hat{\gamma}_r$	SE	*t*	Δ	$\hat{\gamma}_r$	SE	*t*	Δ
Extraversion								
Intercept, $\hat{\gamma}_{00}$	1.77	0.06	30.36	0.04	2.18	0.05	45.77	0.12
Time, $\hat{\gamma}_{10}$	0.14	0.01	9.64	0.00	-0.05	0.01	-6.26	0.00
Extraversion, $\hat{\gamma}_{01}$	0.04	0.08	0.46	0.01	0.39	0.07	5.70	0.00
Time * Extraversion, $\hat{\gamma}_{11}$	0.01	0.02	0.62	0.00	-0.04	0.01	-2.94	0.00
Affiliation motive								
Intercept, $\hat{\gamma}_{00}$	1.78	0.06	30.70	0.04	2.16	0.05	47.15	0.13
Time, $\hat{\gamma}_{10}$	0.14	0.01	9.78	0.00	-0.05	0.01	-5.98	0.00
Affiliation motive, $\hat{\gamma}_{01}$	0.08	0.06	1.33	0.01	0.28	0.05	5.83	-0.02
Time * Affiliation motive, $\hat{\gamma}_{11}$	0.04	0.02	2.62	0.00	-0.01	0.01	-0.72	0.00
Need to be alone								
Intercept, $\hat{\gamma}_{00}$	1.77	0.06	30.50	0.04	2.18	0.05	43.92	0.12
Time, $\hat{\gamma}_{10}$	0.14	0.01	9.78	0.00	-0.05	0.01	-5.95	-0.01
Need to be alone, $\hat{\gamma}_{01}$	-0.03	0.06	-0.49	0.01	-0.13	0.05	-2.54	0.03
Time * Need to be alone, $\hat{\gamma}_{11}$	-0.04	0.02	-2.60	0.01	-0.01	0.01	-0.79	0.00
Social anxiety								
Intercept, $\hat{\gamma}_{00}$	1.78	0.06	30.32	0.04	2.19	0.05	42.48	0.11
Time, $\hat{\gamma}_{10}$	0.14	0.01	9.69	0.00	-0.05	0.01	-6.01	0.00
Social anxiety, $\hat{\gamma}_{01}$	0.02	0.08	0.21	0.00	-0.12	0.07	-1.71	-0.05
Time * Social anxiety, $\hat{\gamma}_{11}$	-0.03	0.02	-1.70	0.00	0.01	0.01	1.03	0.00

Note. CI = confidence interval. SE = standard error. Δ = difference between non-robust and robust estimates.

Table S8

Robust Estimates: Fixed Effects of Well-Being Predicted by Time, Contact Frequencies, and Extraversion.

	Life satisfaction				Depressivity/anxiety			
Parameter	$\hat{\gamma}_r$	SE	t	Δ	$\hat{\gamma}_r$	SE	t	Δ
Personal contact frequency								
Intercept, $\hat{\gamma}_{00}$	6.93	0.15	46.20	-0.22	1.60	0.04	40.68	0.06
Time, $\hat{\gamma}_{10}$	-0.10	0.03	-3.44	-0.02	-0.01	0.01	-0.91	0.00
Personal contact (BP) , $\hat{\gamma}_{02}$	0.33	0.19	1.76	0.01	-0.01	0.05	-0.13	-0.01
Personal contact (WP) , $\hat{\gamma}_{20}$	0.12	0.07	1.73	0.07	0.01	0.02	0.28	0.00
Extraversion, $\hat{\gamma}_{01}$	1.22	0.21	5.78	-0.04	-0.26	0.05	-4.86	0.00
Personal contact (BP) * Extraversion, $\hat{\gamma}_{03}$	-0.06	0.27	-0.23	0.01	0.00	0.07	-0.04	0.01
Personal contact (WP) * Extraversion, $\hat{\gamma}_{21}$	-0.04	0.09	-0.50	0.01	-0.02	0.03	-0.68	0.00
Indirect contact frequency								
Intercept, $\hat{\gamma}_{00}$	6.92	0.16	44.01	-0.24	1.56	0.04	38.60	0.10
Time, $\hat{\gamma}_{10}$	-0.08	0.03	-2.91	-0.2	-0.01	0.01	-0.79	0.00
Indirect contact (BP) , $\hat{\gamma}_{02}$	0.27	0.23	1.18	-0.04	0.13	0.06	2.35	0.00
Indirect contact (WP) , $\hat{\gamma}_{20}$	0.02	0.11	0.16	-0.08	0.04	0.04	1.07	-0.02
Extraversion, $\hat{\gamma}_{01}$	1.21	0.22	5.40	-0.04	-0.27	0.06	-4.80	-0.05
Indirect contact (BP) * Extraversion, $\hat{\gamma}_{03}$	-0.40	0.30	-1.35	0.13	-0.08	0.07	-1.15	0.05
Indirect contact (WP) * Extraversion, $\hat{\gamma}_{21}$	0.05	0.14	0.37	0.15	-0.07	0.05	-1.39	-0.01

Note. $\hat{\gamma}_r$ = robust estimate; Δ = difference between non-robust and robust estimate; BP = between-person effect; WP = within-person effect.

Table S9

Robust Estimates: Fixed Effects of Well-Being Predicted by Time, Contact Frequencies, and Affiliation Motive.

	Life satisfaction				Depressivity/anxiety			
Parameter	$\hat{\gamma}_r$	SE	t	Δ	$\hat{\gamma}_r$	SE	t	Δ
Personal contact frequency								
Intercept, $\hat{\gamma}_{00}$	6.97	0.16	43.58	-0.26	1.59	0.04	37.60	0.07
Time, $\hat{\gamma}_{10}$	-0.10	0.03	-3.42	-0.02	-0.01	0.01	-0.83	0.00
Personal contact (BP) , $\hat{\gamma}_{02}$	0.33	0.20	1.62	-0.01	-0.01	0.05	-0.18	-0.01
Personal contact (WP) , $\hat{\gamma}_{20}$	0.08	0.07	1.21	0.06	0.01	0.02	0.29	0.00
Extraversion, $\hat{\gamma}_{01}$	0.48	0.16	2.79	-0.05	-0.04	0.04	-1.04	-0.01
Personal contact (BP) * Affiliation motive, $\hat{\gamma}_{03}$	-0.01	0.21	-0.03	0.12	-0.01	0.06	-0.16	-0.01
Personal contact (WP) * Affiliation motive, $\hat{\gamma}_{21}$	0.12	0.07	1.69	0.10	-0.02	0.02	-0.62	-0.01
Indirect contact frequency								
Intercept, $\hat{\gamma}_{00}$	6.93	0.16	43.29	-0.25	1.53	0.04	36.08	0.13
Time, $\hat{\gamma}_{10}$	-0.08	0.03	-3.06	-0.01	-0.01	0.01	-0.84	0.00
Indirect contact (BP) , $\hat{\gamma}_{02}$	0.52	0.23	2.24	-0.03	0.03	0.06	0.49	0.00
Indirect contact (WP) , $\hat{\gamma}_{20}$	-0.04	0.11	-0.37	-0.10	0.02	0.04	0.60	0.00
Extraversion, $\hat{\gamma}_{01}$	0.48	0.17	2.88	-0.06	-0.03	0.04	-0.77	-0.03
Indirect contact (BP) * Affiliation motive, $\hat{\gamma}_{03}$	-0.36	0.21	-1.72	0.07	-0.03	0.05	-0.565	0.02
Indirect contact (WP) * Affiliation motive, $\hat{\gamma}_{21}$	0.22	0.11	1.98	0.19	-0.05	0.04	-1.23	-0.01

Note. $\hat{\gamma}_r$ = robust estimate; Δ = difference between non-robust and robust estimate; BP = between-person effect; WP = within-person effect.

Table S10

Robust Estimates: Fixed Effects of Well-Being Predicted by Time, Contact Frequencies, and Need to be Alone.

Parameter	Life satisfaction				Depressivity/anxiety			
	$\hat{\gamma}_r$	SE	*t*	Δ	$\hat{\gamma}_r$	SE	*t*	Δ
Personal contact frequency								
Intercept, $\hat{\gamma}_{00}$	7.01	0.16	44.29	-0.26	1.58	0.04	38.69	0.07
Time, $\hat{\gamma}_{10}$	-0.10	0.03	-3.67	-0.02	-0.01	0.01	-0.77	0.00
Personal contact (BP) , $\hat{\gamma}_{02}$	0.41	0.19	2.13	0.00	-0.02	0.05	-0.43	-0.01
Personal contact (WP) , $\hat{\gamma}_{20}$	0.12	0.07	1.72	0.07	0.00	0.02	0.11	0.00
Extraversion, $\hat{\gamma}_{01}$	0.29	0.16	1.88	-0.02	0.06	0.04	-1.55	0.02
Personal contact (BP) * Need to be alone, $\hat{\gamma}_{03}$	-0.18	0.22	-0.84	-0.07	0.04	0.06	0.64	0.04
Personal contact (WP) * Need to be alone, $\hat{\gamma}_{21}$	-0.15	0.06	-2.55	-0.05	0.01	0.02	0.41	0.01
Indirect contact frequency								
Intercept, $\hat{\gamma}_{00}$	6.84	0.16	43.57	-0.23	1.52	0.04	37.65	0.14
Time, $\hat{\gamma}_{10}$	-0.08	0.03	-2.99	-0.01	-0.01	0.01	-0.84	0.00
Indirect contact (BP) , $\hat{\gamma}_{02}$	0.71	0.22	3.20	0.00	0.06	0.06	0.0,7	-0.01
Indirect contact (WP) , $\hat{\gamma}_{20}$	0.03	0.11	0.26	-0.04	0.04	0.04	0.00	0.01
Extraversion, $\hat{\gamma}_{01}$	0.30	0.16	1.86	-0.01	0.04	0.04	-1.69	0.02
Indirect contact (BP) * Need to be alone, $\hat{\gamma}_{03}$	-0.01	0.22	-0.05	0.08	0.05	0.05	-0.28	0.00
Indirect contact (WP) * Need to be alone, $\hat{\gamma}_{21}$	-0.13	0.10	-1.31	-0.04	0.04	0.04	-0.83	0.02

Note. $\hat{\gamma}_r$ = robust estimate; Δ = difference between non-robust and robust estimate; BP = between-person effect; WP = within-person effect.

Table S11

Robust Estimates: Fixed Effects of Well-Being Predicted by Time, Contact Frequencies, and Social Anxiety.

	Life satisfaction				Depressivity/anxiety			
Parameter	$\hat{\gamma}_r$	SE	*t*	Δ	$\hat{\gamma}_r$	SE	*t*	Δ
Personal contact frequency								
Intercept, $\hat{\gamma}_{00}$	6.95	0.15	46.16	-0.19	1.61	0.04	45.19	0.04
Time, $\hat{\gamma}_{10}$	-0.09	0.03	-3.37	-0.02	-0.01	0.01	-0.82	0.00
Personal contact (BP) , $\hat{\gamma}_{02}$	0.60	0.19	3.24	-0.13	-0.07	0.04	-1.62	0.02
Personal contact (WP) , $\hat{\gamma}_{20}$	0.12	0.07	1.79	0.06	0.02	0.02	0.66	0.00
Extraversion, $\hat{\gamma}_{01}$	-0.96	0.19	-4.99	0.12	0.37	0.04	8.41	0.01
Personal contact (BP) * Need to be alone, $\hat{\gamma}_{03}$	0.74	0.27	2.71	-0.11	-0.16	0.06	-2.54	0.05
Personal contact (WP) * Need to be alone, $\hat{\gamma}_{21}$	0.14	0.09	1.57	-0.07	0.05	0.03	1.52	0.03
Indirect contact frequency								
Intercept, $\hat{\gamma}_{00}$	6.86	0.15	45.01	-0.21	1.58	0.04	44.52	0.07
Time, $\hat{\gamma}_{10}$	-0.08	0.03	-2.94	-0.01	-0.01	0.01	-0.60	0.00
Indirect contact (BP) , $\hat{\gamma}_{02}$	0.60	0.22	2.80	-0.10	0.05	0.05	1.08	0.03
Indirect contact (WP) , $\hat{\gamma}_{20}$	0.04	0.11	0.40	-0.05	0.07	0.04	1.80	-0.05
Extraversion, $\hat{\gamma}_{01}$	-0.87	0.19	-4.52	0.01	0.39	0.04	9.06	0.03
Indirect contact (BP) * Need to be alone, $\hat{\gamma}_{03}$	0.47	0.28	1.66	-0.19	0.05	0.06	0.77	0.03
Indirect contact (WP) * Need to be alone, $\hat{\gamma}_{21}$	0.10	0.14	0.75	0.03	0.15	0.05	3.11	-0.02

Note. $\hat{\gamma}_r$ = robust estimate; Δ = difference between non-robust and robust estimate; BP = between-person effect; WP = within-person effect.

Multilevel SEM Analyses Performed in Mplus (Version 8.4)

To account for empirical overlap (i.e., shared variance) among extraversion, affiliation motive, need to be alone, and social anxiety, the four constructs are modeled as the latent factor *social trait*. Throughout the analyses presented in Tables S12 and S13, the latent between-subjects factor (*socTrait*) is measured by the four manifest social trait variables, extraversion (*extra*), affiliation motive (*affil*), need to be alone (*nalone*), and social anxiety (*socanx*; the latter two reverse-scored; all grand-mean centered). The latent factor *social trait* is used to predict individual differences in changes of social contact (related to Hypothesis 1) and changes in well-being associated with changing social contact (related to Hypothesis 2). As in the main analyses pertaining to H2, social contact predictors (either personal or indirect contact) are baseline-centered and split into the within- and between-person components (*pers_wp*, *pers_bp* / *ind_wp*, *ind_bp*). Mplus scripts and data can be found on the OSF in the folder "*MS2: Social Contact, Well-Being, and Social Traits During Contact Restrictions*" → "*Mplus ML-SEM*".

We conduct this investigation into the overlap of the social trait constructs by means of multilevel SEM instead of entering all social traits into the same multilevel regression model for two reasons: First, in a multilevel regression model, effects of each social trait would not be interpretable when controlling for the others. For example, effects of need to be alone, when controlled for extraversion and affiliation motive, are not interpretable—despite the constructs being related. Second, the large number of variables and interaction terms would strain a regular multilevel model to a high degree resulting in imprecise estimates.

Hypothesis 1:

Table S12

Personal or Indirect Contact Frequency Predicted by Time and Social Trait and Their Cross-Level Interaction

	Personal contact				Indirect contact			
Parameter	Est.	S.E.	Est./S.E.	*p*	Est.	S.E.	Est./S.E.	*p*
Intercept	1.82	0.05	33.54	< .001	2.30	0.05	46.40	< .001
Time	0.15	0.02	8.29	< .001	-0.06	0.01	-4.95	< .001
Social trait	0.22	0.14	1.60	.109	0.66	0.12	5.55	< .001
Time * Social trait	0.09	0.05	2.00	.045	-0.04	0.04	-0.89	.375

Note. Est. = estimate; S.E. = standard errors. *Social trait* represents the latent factor (i.e., the shared variance) of the four assessed traits extraversion, affiliation motive, need to be alone, and social anxiety.

Table S12 shows that, similar to the results from the main analyses, personal contact increased over time as contact restrictions were eased, and this increase was more pronounced with higher scores in the latent factor *social trait*. Interestingly, with higher levels of the latent factor *social* *trait*, indirect contact but not personal contact was more pronounced at the first assessment (i.e., when contract restrictions were strictest)—this also mirrors results from the main analyses.

Hypothesis 2:

Table S13

Life Satisfaction or Depressivity/Anxiety Predicted by Time, Social Trait, and Personal or Indirect Contact Frequency

	Life satisfaction				Depressivity/anxiety			
Parameter	Est.	S.E.	Est./S.E.	*p*	Est.	S.E.	Est./S.E.	*p*
Personal contact								
Intercept	6.72	0.17	39.77	< .001	1.66	0.05	36.61	< .001
Time	-0.11	0.04	-2.74	.006	0.00	0.01	-0.27	.791
Personal contact (BP)	0.31	0.21	1.47	.142	-0.01	0.06	-0.22	.827
Personal contact (WP)	0.15	0.10	1.42	.155	0.00	0.03	0.10	.921
Social trait	1.02	0.45	2.25	.024	-0.36	0.10	-3.76	< .001
Personal contact (BP) * Social trait	0.25	0.57	0.45	.656	0.02	0.11	0.14	.890
Personal contact (WP) * Social trait	0.52	0.34	1.53	.126	-0.05	0.06	-0.88	.378
Indirect contact								
Intercept	6.70	0.17	38.64	< .001	1.65	0.05	35.18	< .001
Time	-0.09	0.04	-2.08	.038	-0.01	0.01	-0.56	.577
Indirect contact (BP)	0.45	0.26	1.73	.084	0.15	0.07	2.11	.035
Indirect contact (WP)	-0.17	0.18	-0.90	.369	0.03	0.06	0.49	.624
Social trait	1.10	0.55	2.02	.044	-0.44	0.11	-3.97	< .001
Indirect contact (BP) * Social trait	-0.76	0.54	-1.40	.160	-0.03	0.11	-0.26	.796
Indirect contact (WP) * Social trait	0.90	0.47	1.89	.058	-0.10	0.10	-0.97	.331

Note. Est. = estimate; S.E. = standard errors; BP = between-person effect; WP = within-person effect. *Social trait* represents the latent factor (i.e., the shared variance) of the four assessed traits extraversion, affiliation motive, need to be alone, and social anxiety.

Although we see considerably large coefficients for the cross-level interaction of within-person changes in personal and indirect contact (as compared to the first assessment) with the latent factor *social trait* on life satisfaction, these effects are not significant at $\alpha = .05$ (see Table S13). We also do not find significant effects for the cross-level interaction of within-person changes in personal or indirect contact with the latent factor *social trait* on depressivity/anxiety. This could indicate that the effects for affiliation motive and need to be alone on life satisfaction and the effects for social anxiety on depressivity/anxiety as discussed in the main manuscript are specific for these social traits and do not surface when only considering the shared variance.

Supplemental Figures

Figure S1

Raw Correlation Plots (Wei & Simko, 2017a) Between the Constructs Included in Analyses Based on Data from the First Assessment (Top Plot; N = 190), and From the Last Assessment (Bottom Plot; N = 165).

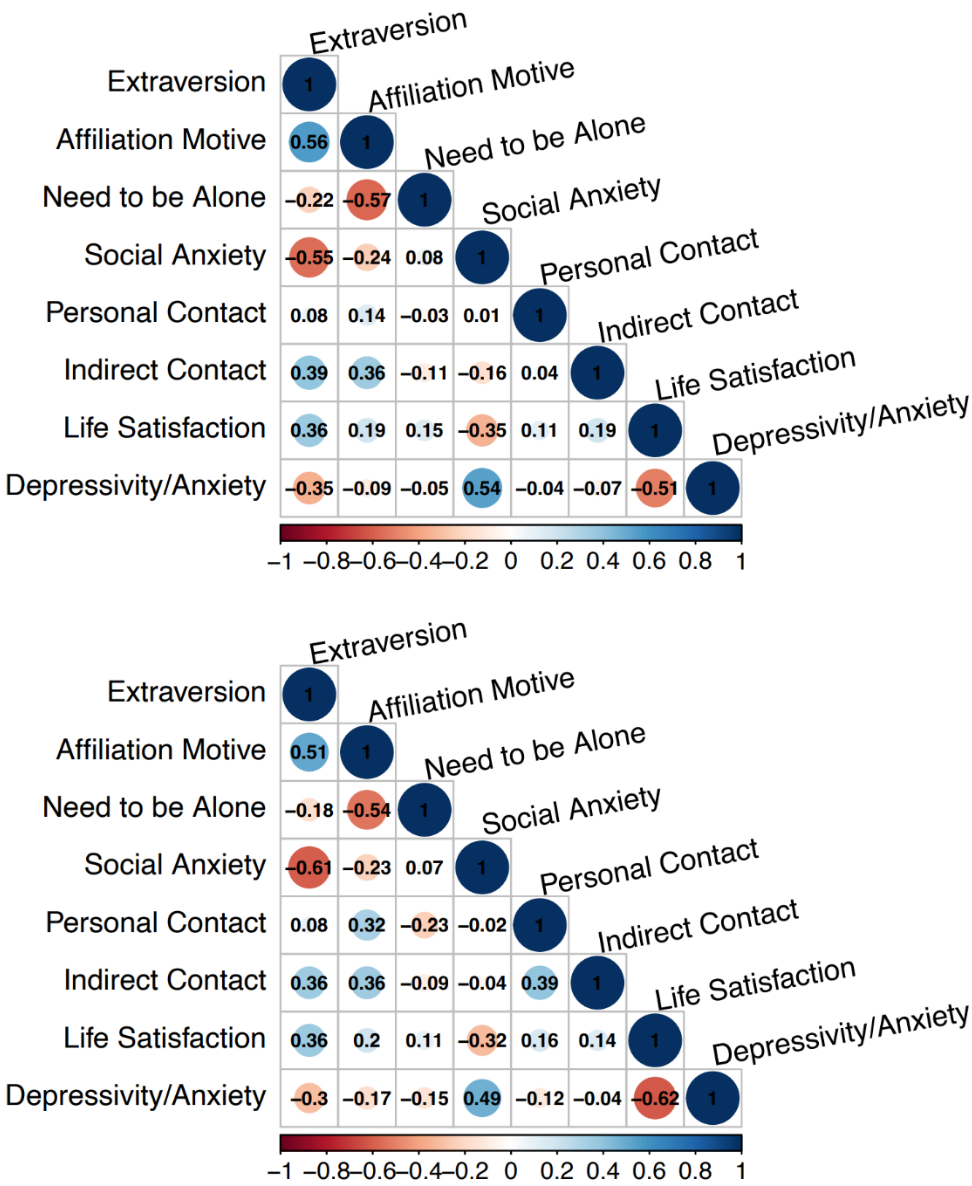
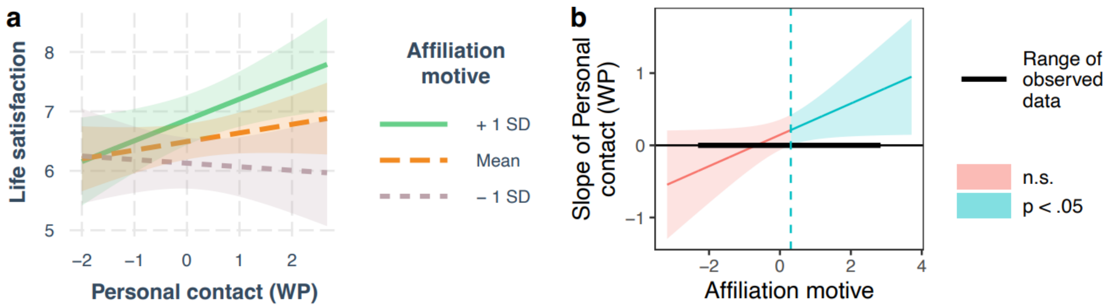


Figure S2

Simple-slopes Plot (a) and Neyman-Johnson Regions-of-significance Plot (b) for the non-significant cross-level interaction effect of affiliation motive and higher-than-baseline personal contact predicting well-being.



Note. Confidence bands represent 95% confidence intervals. The variable presented on the X-axis (b) is grand-mean centered; original scale values can be computed by adding the mean of the respective variable reported in Table S1.

Complete Software and Session Information

We used R (Version 4.0.4; R Core Team, 2020) and the R-packages *car* (Version 3.0.12; Fox & Weisberg, 2019; Fox et al., 2020; Yentes & Wilhelm, 2018), *carData* (Version 3.0.4; Fox et al., 2020), *careless* (Version 1.1.3; Yentes & Wilhelm, 2018), *citr* (Version 0.3.2; Aust, 2019), *corrplot2017* (Wei & Simko, 2017b), *cowplot* (Version 1.1.1; Wilke, 2020), *dplyr* (Version 1.0.7; Wickham, François, et al., 2020), *effects* (Version 4.2.0; Fox & Weisberg, 2018; Fox, 2003; Fox & Hong, 2009), *forcats* (Version 0.5.1; Wickham, 2020a), *Formula* (Version 1.2.4; Zeileis & Croissant, 2010), *ggplot2* (Version 3.3.5; Wickham, 2016), *GPArotation* (Version 2014.11.1; Bernaards & I.Jennrich, 2005), *Hmisc* (Version 4.6.0; Harrell Jr, 2021), *interactions* (Version 1.1.5; Long, 2019), *jtools* (Version 2.1.4; Long, 2020), *lattice* (Version 0.20.41; Sarkar, 2008), *lme4* (Version 1.1.27.1; Bates et al., 2015), *lmerTest* (Version 3.1.3; Kuznetsova et al., 2017), *magick* (Version 2.7.3; Ooms, 2021), *MASS* (Version 7.3.53; Venables & Ripley, 2002), *Matrix* (Version 1.3.2; Bates & Maechler, 2019), *MplusAutomation* (Hallquist & Wiley, 2018), *multcomp* (Version 1.4.18; Hothorn et al., 2008), *mvtnorm* (Version 1.1.1; Genz & Bretz, 2009), *nlme* (Version 3.1.152; Pinheiro et al., 2021), *papaja* (Version 0.1.0.9997; Aust & Barth, 2020), *patchwork* (Version 1.1.1; Pedersen, 2020), *png* (Version 0.1.7; Urbanek, 2013), *psych* (Version 2.1.9; Revelle, 2020), *purrr* (Version 0.3.4; Henry & Wickham, 2020), *readr* (Version 2.1.1; Wickham & Hester, 2020), *robustlmm* (Version 2.5.0; Koller, 2019), *scales* (Version 1.1.1; Wickham & Seidel, 2020), *shiny* (Version 1.7.1; Chang et al., 2020), *simr* (Green & MacLeod, 2016), *stringr* (Version 1.4.0; Wickham, 2019), *survival* (Version 3.2.7; Terry M. Therneau & Patricia M. Grambsch, 2000), *TH.data* (Version 1.0.10; Hothorn, 2019), *tibble* (Version 3.1.6; Müller & Wickham, 2020), *tidyr* (Version 1.1.4; Wickham, 2020b), *tidyverse* (Version 1.3.1; Wickham, Averick, Bryan, Chang, McGowan, François, et al., 2019), and *tinylabels* (Version 0.2.2; Barth, 2020) for data wrangling, analyses, and plots.

The following is the output of R's *sessionInfo()* command, which shows information to aid analytic reproducibility of the analyses.

R version 4.0.4 (2021-02-15) Platform: x86_64-apple-darwin17.0 (64-bit) Running under: macOS Big Sur 10.16

Matrix products: default BLAS:

/Library/Frameworks/R.framework/Versions/4.0/Resources/lib/libRblas.dylib LAPACK:

/Library/Frameworks/R.framework/Versions/4.0/Resources/lib/libRlapack.dylib

locale: [1]

en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8

attached base packages: [1] grid stats graphics grDevices utils datasets methods

[8] base other attached packages: [1] png_0.1-7 magick_2.7.3 corrplot_0.84

[4] careless_1.1.3 car_3.0-12 scales_1.1.1

[7] patchwork_1.1.1 effects_4.2-0 carData_3.0-4

[10] cowplot_1.1.1 jtools_2.1.4 interactions_1.1.5

[13] lmerTest_3.1-3 robustlmm_2.5-0 lme4_1.1-27.1

[16] Matrix_1.3-2 GPArotation_2014.11-1 psych_2.1.9

[19] forcats_0.5.1 stringr_1.4.0 dplyr_1.0.7

[22] purrr_0.3.4 readr_2.1.1 tidyr_1.1.4

[25] tibble_3.1.6 ggplot2_3.3.5 tidyverse_1.3.1

[28] citr_0.3.2 papaja_0.1.0.9997 tinylabels_0.2.2

loaded via a namespace (and not attached): [1] TH.data_1.0-10 minqa_1.2.4 colorspace_2.0-2

[4] ellipsis_0.3.2 estimability_1.3 fs_1.5.2

[7] rstudioapi_0.13 farver_2.1.0 fansi_1.0.2

[10] mvtnorm_1.1-1 lubridate_1.8.0 xml2_1.3.3

[13] codetools_0.2-18 splines_4.0.4 mnormt_2.0.2

[16] robustbase_0.93-6 knitr_1.37 jsonlite_1.7.3

[19] nloptr_1.2.2.2 broom_0.7.11.9000 dbplyr_2.1.1

[22] shiny_1.7.1 compiler_4.0.4 httr_1.4.2

[25] emmeans_1.7.1-1 backports_1.4.1 assertthat_0.2.1

[28] fastmap_1.1.0 survey_4.0 cli_3.1.1

[31] later_1.3.0 htmltools_0.5.2 tools_4.0.4

[34] coda_0.19-4 gtable_0.3.0 glue_1.6.1

[37] Rcpp_1.0.7 cellranger_1.1.0 vctrs_0.3.8

[40] nlme_3.1-152 insight_0.14.5 xfun_0.29

[43] rvest_1.0.2 mime_0.12 miniUI_0.1.1.1

[46] lifecycle_1.0.1 DEoptimR_1.0-8 MASS_7.3-53

[49] zoo_1.8-8 hms_1.1.1 promises_1.2.0.1

[52] parallel_4.0.4 sandwich_3.0-0 yaml_2.2.2

[55] pander_0.6.3 fastGHQuad_1.0 stringi_1.7.6

[58] highr_0.9 boot_1.3-26 rlang_0.4.12

[61] pkgconfig_2.0.3 evaluate_0.14 lattice_0.20-41

[64] labeling_0.4.2 tidyselect_1.1.1 magrittr_2.0.2

[67] bookdown_0.24 R6_2.5.1 generics_0.1.1

[70] multcomp_1.4-18 DBI_1.1.0 pillar_1.6.5

[73] haven_2.4.3 withr_2.4.3 abind_1.4-5

[76] survival_3.2-7 nnet_7.3-15 modelr_0.1.8

[79] crayon_1.4.2 utf8_1.2.2 tmvnsim_1.0-2

[82] tzdb_0.2.0 rmarkdown_2.11 readxl_1.3.1

[85] reprex_2.0.1 digest_0.6.29 xtable_1.8-4

[88] httpuv_1.6.5 numDeriv_2016.8-1.1 munsell_0.5.0

[91] mitools_2.4

List of Publications and Personal Contributions

Chapter 2:

Roos, Y., Krämer, M. D., Richter, D., Schoedel, R., & Wrzus, C. (2023). Does your smartphone "know" your social life? A methodological comparison of day reconstruction, experience sampling, and mobile sensing. *Advances in Methods and Practices in Psychological Science, 6*(3), 1–12. https://doi.org/10.1177/25152459231178738.

My contribution included conceptualization, data curation, formal analysis, investigation, methodology, visualization, and writing the original draft. MDK contributed to conceptualization, data curation, investigation, methodology, and reviewed and writing review and editing. DR contributed to conceptualization, funding acquisition, methodology, project administration, and writing review and editing. RS contributed to investigation, software, and writing review and editing. CW contributed to conceptualization, funding acquisition, methodology, project administration, and writing review and editing.

Chapter 3:

Wrzus, C., Roos, Y., Krämer, M., & Richter, D. (2024). Individual differences in short-term social dynamics: Theoretical perspective and empirical development of the Social Dynamics Scale. *Current Psychology*. Advance online publication. https://doi.org/10.1007/s12144-024-05868-y

CW contributed to conceptualization, funding acquisition, methodology, project administration, resources, supervision, visualization, writing the original draft, and writing review and editing. My contribution included data curation, formal analysis, investigation, methodology, project administration, visualization, writing of the original draft (methods and results section), and writing review and editing. MDK contributed to data curation, investigation, methodology, project administration, and writing review and editing. DR contributed to conceptualization, funding acquisition, methodology, project administration, resources, supervision, and writing review and editing.

Chapter 4:

Wrzus, C., Roos, Y., Krämer, M. D., Schoedel, R., Back, M. D., & Richter, D. (2024). *Affiliation Motive and Social Interactions in People's Daily Life: A Temporal Processes Approach Using Ecological Momentary Assessment and Mobile Sensing*.[Manuscript submitted for publication; currently under rewiew at Journal of Personality and Social Psychology] Department of Psychological Aging Research, Institute of Psychology, Heidelberg University.

CW contributed to conceptualization, funding acquisition, methodology, project administration, resources, supervision, visualization, and writing the original draft.
My contribution included data curation, formal analysis, investigation, methodology, project administration, visualization, and writing review and editing. MDK contributed to data curation, investigation, methodology, project administration, and writing review and editing. RS contributed to investigation, methodology, project administration, resources, software, and writing review and editing. MDB contributed to methodology and writing review and editing. DR contributed to conceptualization, funding acquisition, methodology, project administration, resources, supervision, and writing review and editing.

Chapter 5:

Roos, Y., Krämer, M. D., Richter, D., & Wrzus, C. (2024). Persons in contexts: The role of social networks and social density for the dynamic regulation of face-to-face interactions in daily life. *Journal of Personality and Social Psychology.* Advance online publication. https://doi.org/10.1037/pspp0000512

My contribution includes conceptualization, data curation, formal analysis, investigation, methodology, visualization, writing the original draft, and writing review and editing. MDK contributed to conceptualization, data curation, investigation, methodology, and writing review and editing. DR contributed to conceptualization, funding acquisition, methodology, project administration, and writing review and editing. CW contributed to conceptualization, funding acquisition, methodology, project administration, and writing review and editing.

Chapter 6:

Krämer, M. D., Roos, Y., Richter, D., & Wrzus, C. (2022). Resuming social contact after months of contact restrictions: Social traits moderate associations between changes in social contact and well-being. *Journal of Research in Personality, 98*, 104223. https://doi.org/10.1016/j.jrp.2022.104223

MDK contributed to conceptualization, data curation, formal analysis, methodology, visualization, writing the original draft, and writing review and editing. I contributed to conceptualization, data curation, methodology, and writing review and editing. DR contributed to conceptualization, funding acquisition, supervision, and writing review and editing. CW contributed to conceptualization, funding acquisition, supervision, methodology, and writing review and editing.

Declaration in accordance to § 8 (1) c) and d) of the doctoral degree regulation of the Faculty

FAKULTÄT FÜR VERHALTENS- UND EMPIRISCHE KULTURWISSENSCHAFTEN

UNIVERSITÄT HEIDELBERG ZUKUNFT SEIT 1386

Promotionsausschuss der Fakultät für Verhaltens- und Empirische Kulturwissenschaften der Ruprecht-Karls-Universität Heidelberg / Doctoral Committee of the Faculty of Behavioural and Cultural Studies of Heidelberg University

Erklärung gemäß § 8 (1) c) der Promotionsordnung der Universität Heidelberg für die Fakultät für Verhaltens- und Empirische Kulturwissenschaften / Declaration in accordance to § 8 (1) c) of the doctoral degree regulation of Heidelberg University, Faculty of Behavioural and Cultural Studies

Ich erkläre, dass ich die vorgelegte Dissertation selbstständig angefertigt, nur die angegebenen Hilfsmittel benutzt und die Zitate gekennzeichnet habe. / I declare that I have made the submitted dissertation independently, using only the specified tools and have correctly marked all quotations.

Erklärung gemäß § 8 (1) d) der Promotionsordnung der Universität Heidelberg für die Fakultät für Verhaltens- und Empirische Kulturwissenschaften / Declaration in accordance to § 8 (1) d) of the doctoral degree regulation of Heidelberg University, Faculty of Behavioural and Cultural Studies

Ich erkläre, dass ich die vorgelegte Dissertation in dieser oder einer anderen Form nicht anderweitig als Prüfungsarbeit verwendet oder einer anderen Fakultät als Dissertation vorgelegt habe. / I declare that I did not use the submitted dissertation in this or any other form as an examination paper until now and that I did not submit it in another faculty.

Vorname Nachname / First name Family name	Yannick Roos
Datum / Date	16.07.2024
Unterschrift / Signature	Dem Dekanat der Fakultät für Verhaltens- und Empirische Kulturwissenschaften liegt eine unterschriebene Version dieser Erklärung vom 16.07.2024 vor.