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Everyday social interactions and intra-individual variability in affect: A systematic review and meta-analysis of ecological momentary assessment studies

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Abstract
Intra-individual variability in affect has been associated with aspects of individuals' lives, such as everyday social interactions. Ecological momentary assessment (EMA) has been tailored to assess the dynamics of everyday events and feelings and in recent decades there has been a burgeoning of EMA research on the intra-individual links between social interactions and momentary affect in daily life. This systematic review and meta-analysis was conducted to identify within-person relationships between social interactions with positive affect (PA) and negative affect (NA). Both quantitative and qualitative features of social interaction (i.e., uniqueness of the partner, interpersonal perceptions of an interaction) predict within-person variance in PA and NA. The results of meta-analysis indicated small-sized associations between quantitative features of social interactions with PA and NA, and moderate-sized associations between qualitative features of social interactions with PA and NA, which were only somewhat moderated by methodological factors. We conclude that EMA is a promising method of investigating intra-individual variability in affect unfolding in everyday social environments and offer suggestions for substantiating the within-person perspective to both researchers and clinicians.

Keywords Everyday life · Social interaction · Momentary affect · Intra-individual variability · Psychological traits

Introduction

It is well-established that interpersonal environment shapes affective experiences throughout adult life (Deindl et al. 2016; Yang et al. 2016). A large body of research has documented how features of social context contribute to affective well-being, typically defined as the frequent experience of positive affect and infrequent experience of negative affect (Diener and Larsen 1993). For example, individuals with stronger relationship ties and more frequent social contact often report better affective outcomes over the long-term (Hsieh and Lee 2014; Litwin and Shiovitz-Ezra 2011; Schneider et al. 2013; Wolff et al. 2013).This research has drawn on the between-person approach to examine how individual differences in social relations are related to individual differences in affective well-being, and thus has been useful in identifying people who may be susceptible to poor emotional health. However, as well as between-person differences in the associations between affect and social situations, there is also within-person covariations of momentary affect and social interactions, which reflect the changes of how people negotiate their way through an ever-changing environment across days and weeks (Brose et al. 2015; Wilhelm and Grossman 2010). While most emotions occur in the context of social environments, all of an individual's everyday social interactions are likely to shape the temporal patterns in his or her affective experiences in subtle but consistent ways (Carstensen et al. 2011; Röcke and Brose 2013).

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The development of ecological momentary assessment (EMA; Stone and Shiffman 1994) opened up new opportunities for the within-person study of affective experiences unfolding in everyday social environments (Fraley and Hudson 2013; Wrzus and Mehl 2015). Instead of relying on retrospective reports, EMA is based on individuals' immediate reports of momentary social and affective experiences, typically repeated over several occasions (Beal 2015). These repeated assessments are considered ideally suited to analysis of the within-person coupling of momentary affect in the context of an ongoing social interaction with specific features of the interaction and appraisals (i.e., positive feeling coupled with a contact with a friend) (Shiffman 2000). Past decades have seen a burgeoning of EMA studies on intra-individual variations in affect related to everyday social encounters (Ebner-Priemer and Trull 2009), which has generated a sizeable body of evidence on both within-person covariation of momentary affect and social interactions (Rook et al. 2007). A synthesis of this body of research is timely and valuable for a number of reasons.

First, both interpersonal processes and affective experiences are fundamentally dynamic phenomena. A synthesis focusing on the within-person relations between short-term social and affective dynamics would complement the between-person studies on long-term affective implications of social relationships. In doing so, it would respond directly to initiatives that emphasize the importance of both stable and dynamic components of emotion for understanding overall psychological well-being (Brose et al. 2015; Houben et al. 2015), and provide a more nuanced picture of how people deal with changes in interpersonal contexts and manage their affective well-being (Charles and Gatz 2001; Röcke and Brose 2013; Wilhelm and Schoebi 2007).

Second, it has been widely documented that positive affect (PA) and negative affect (NA) are relatively independent dimensions: they are characterized by different patterns of neural activity (Carver and Scheier 1990; Kim and Hamann 2007), by different appraisal patterns (Diener and Emmons 1984; Smith and Lazarus 1993) and by different personality traits (Gross and John 2003; Larsen and Ketelaar 1991). The two-factor theory of affect posits that PA is influenced more by environmental experiences whereas NA is influenced more by personality traits (Baker et al. 1992; Zheng et al. 2016). Therefore, a synthesis focusing on both PA and NA is needed for understanding within-person variations of affective experiences in relation to everyday social interactions (Ram et al. 2014).

Third, recent advancements in mobile technology have greatly enhanced the feasibility of EMA studies tracking behavioral and affective experiences of day-to-day life (Geiger and MacKerron 2016; MacKerron and Mourato 2013), and fostered interest in the development of mobile technology-based behavioral and mental health research and applications (Portell et al. 2015). Solid knowledge of the contemporary variation in affective and social experiences would provide valuable information for the developers of tailored ecological momentary interventions targeting changes in behavior and mental health outcomes and for clinicians seeking to understand how aspects of interpersonal relations contribute to targeted mood or symptoms (Wolff-Hughes et al. 2018).

Finally, prior reviews of EMA studies mainly focused on describing the methods used and the feasibility of using EMA in various populations (see, for example, aan het Rot et al. 2012; Wenze and Miller 2010) and provide little information about the strength of the overall relationships between within-person variations in affect and features of social environment. The extant EMA studies are methodologically diverse (i.e. different time frames, assessment intensities, sample sizes and both clinical and non-clinical samples) and the extent to which the findings are generalizable across research methods remains unclear. A quantitative synthesis of the findings is required to determine the extent to which methodological factors influence conclusions about the relationships investigated.

The primary goal of the current systematic review and meta-analysis was to identify within-person relationships between specific features of everyday social interactions and momentary positive and negative affect. Since the relevant body of evidence is methodologically diverse, the secondary aim was to investigate how the relationships vary as a function of various methodological characteristics.

Methods

Search strategy and article selection

We searched the online databases PsycInfo, PubMed, and Medline for relevant publications up to July 2017, using the following string of search terms: (diary OR momentary assessment OR experience sampling OR ecological momentary assessment OR ecologic momentary assessment OR event-contingent recording OR micro longitudinal OR ambulatory assessment OR ambulatory monitoring OR momentary measures OR ambulatory measures) AND (affect OR affective OR emotion OR mood) AND (social OR interpersonal). We used filters to limit our search results to articles published in peer reviewed journals in the English language. The reference lists of reviews and selected studies were examined manually to identify additional studies.

Studies were included in the review according to the following eligibility criteria: (1) Reported original empirical findings based on quantitative analysis of EMA data (i.e., qualitative designs, reviews, comments, opinion/position papers, practice or protocol recommendations, letters

and conference abstracts were excluded); (2) Aimed to examine the links between everyday social interactions with different social partners and momentary affect (i.e., instrument validation studies, treatment monitoring studies, studies that solely targeted emotional processes were excluded); (3) Measurements of everyday social interactions and momentary affect (state-level) were obtained using the EMA method, which means these measurements were obtained multiple times each day during the study period (i.e., studies that only obtained global measures of social functioning/relations and trait-level affective well-being were excluded); (4) Restricted the study sample to adults aged 18 and above.

Study eligibility screening

We conducted the study eligibility screening with guidance from the PRISMA 2009 statement (Moher et al. 2009). Titles and abstracts of the initially identified articles were scanned by two independent reviewers for exclusion criteria. Subsequently, full-text articles were obtained for further eligibility assessment. A third reviewer also assessed the articles when there were uncertainties about eligibility. Altogether, 984 titles and abstracts were screened, of which 193 full-text articles were assessed for eligibility. After application of the study inclusion and exclusion criteria, 28 independent studies (from 30 articles) were finally identified as eligible for the qualitative synthesis. Of the 28 independent studies, 20 studies (from 23 articles) were eligible for the following meta analyses. See Fig. 1 for a detailed flow-chart describing the selection process.

Data extraction

All included articles were assessed by two independent raters (doctoral students working in the field of psychosocial functioning of community and clinical population) who extracted data including background information about the study, sampling characteristics (e.g., sample size, sample mean age, inclusion of a clinical group), procedures and design (e.g., assessments per day and per person; duration; contingency; format), measurement of everyday social interactions and affect (and other explanatory variables of interest) and main results concerning the interplay between social interactions and momentary affect. Interrater reliability was assessed by calculating the Kappa coefficient for categorical variables (e.g., study contingency) and Pearson correlation coefficients for continuous variables (e.g., assessments per day). These statistics indicated high interrater agreement, with all correlations being higher than 0.90.

Meta-analyses

The available 20 studies provided 26 independent samples for meta-analyses. Because the independence of PA and NA have been widely documented (Watson et al. 1999) and the quantitative and qualitative variables convey qualitatively different information about patterns of social interactions (Bajaj et al. 2016), we conducted separate meta-analyses for the relation between quantity of interactions and PA ($k = 11$), the relation between quantity of interactions and NA ($k = 9$), the relation between quality of interactions and PA ($k = 10$), and the relation between quality of interactions and NA ($k = 12$). Each sample examined one or more bivariate associations between social interactions with PA and/or NA (e.g., regression coefficient, correlations, difference between-group means). We converted all associations into correlation coefficients to provide a common measure of effect size (see methods proposed by Borenstein et al. 2009; Rosenthal and Rosnow 1991). To avoid including more than one effect size per construct per sample, we averaged the effect sizes for studies that contained multiple measures of the quantity/quality of social interactions (when necessary, we changed the direction of correlation coefficient to ensure that each effect size reflected the relation between higher levels of quantity/quality of social interactions with greater PA or fewer NA). For example, when both positive and negative quality of social interactions were examined in relation to PA using the same sample, we first changed the direction of the correlation coefficient for negative quality and PA, and averaged the individual effect sizes to generate a single one termed the overall quality of social interaction; or in case the quantity of interactions with different partners were separately reported, we also averaged these effect sizes to generate a single one termed the quantity of social interactions. Random effects models were applied to estimate the weighted mean effect size using the comprehensive meta-analysis (CMA) software (Borenstein et al. 2005). The precision of effect sizes was expressed as the 95% confidence intervals (CIs) (a combined effect is considered significant if the CI does not include zero). The Q statistic was used to assess homogeneity across studies, significant values of Q imply heterogeneity. I-squared (I^2) was used to measure the inconsistency between studies. Finally, moderator analyses (univariate) were performed to determine whether the heterogeneity in effect sizes across studies was explained by methodological factors, namely sample size, assessments per day, assessments per person, study duration, total assessments, contingency, data collection tool and the inclusion or otherwise of a clinical group (all coded as binary variables using the study-level median as a cut-off value).

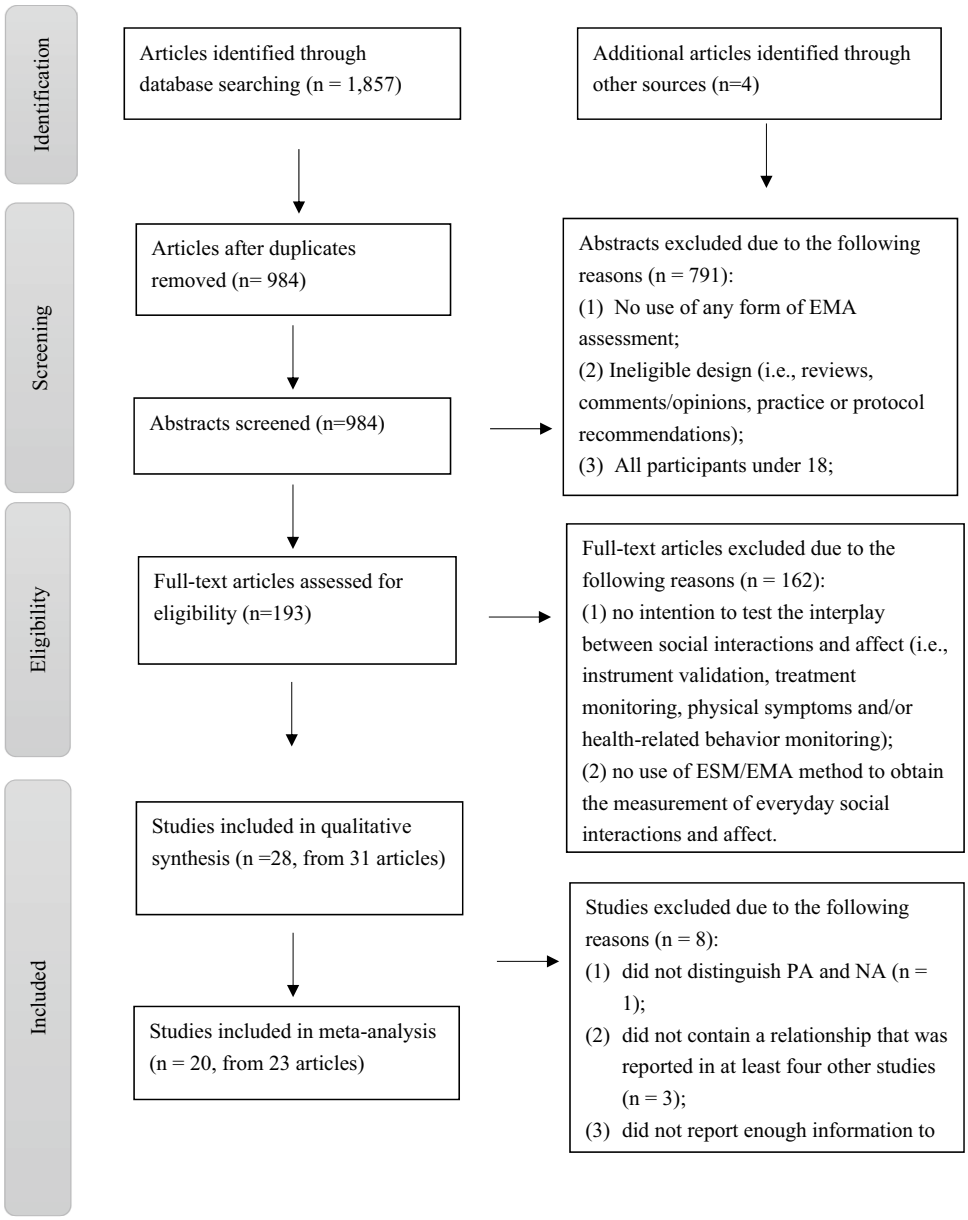

Fig. 1 PRISMA 2009 flow diagram

Results

Sample characteristics

We calculated the mean sample size of 27 reviewed studies (mean 107.4, median 89.0, SD 107.0, range 21–610), while one large-scale study was considered exceptional with a sample of 6759 adults (Gillian M. Sandstrom et al. 2017). The majority of these studies targeted non-clinical populations ($n = 23$), of which eight studies used university student samples, two studies focused on retired older adults, two studies focused on full-time employees, two studies focused on female participants, and the remaining nine were based on community-dwelling adult samples and each of them had a relatively wide range of ages. Four studies focused on clinical populations: a sample of 145 individuals with schizophrenia or schizoaffective disorder; a sample of 80 patients with Borderline Personality Disorder (BPD) and 51 patients with Depressive Disorder (DD); a sample of 38 patients with BPD and 31 healthy controls; and a sample of 21 patients experiencing psychosis with one of their closest relatives. See Table 1 for a summary of sample characteristics of the 27 included studies.

Study procedure design

Across all studies, the average number of days for data collection was 14.3 days (range 3–63, Median 10.0, SD 12.2), and the average number of data entries per day was 7.7 (range 2–25, Median 6.0, SD 5.6). Studies that asked

Table 1 Overview of data collection methods of reviewed ESM/EMA studies (n = 28)

Authors	Sample population	Mean age/range	Data entries/day	Days	Total obs	Contingency	Format
Healthy population (n = 23)							
Alshamsi et al. (2016)	52 employees	M = 36.0; R = 23–53	3	30	2254	Time	Phone + sensor
Bernstein et al. (2017)	115 employees	M = 41.1; R = 19–63	6	3	1729	Signal	PDA
Brandstätter (1983)	24 housewives	NR	6	28	2808	Time	Paper
Burgin et al. (2012)	429 university students	M = 19.8	8	7	18,018	Signal	PDA
Chui et al. (2014)	74 community elders	M = 88.7; R = 84–102	6	7	3071	Signal	Paper + beeper
Côté and Moskowitz (1998)	Sample 1: 89 adults	M = 33.8; R = 20–69	M = 6	20	S1 = 10,769	Event	Paper
	Sample 2: 115 adults	M = 33.0; R = 19–61			S2 = 14,375		
Flory et al. (2000)	100 community adults	M = 36.5; R = 30–45	M = 25	3	6397	Time	Paper + sensor
Hawkley et al. (2007)	134 undergraduates	M = 19.2	9	7	6722	Signal	Paper + beeper
Vittengl and Holt's (1998a)	25 university students	M = 19.2; R = 18–22	3	28	81	Time	Paper
Vittengl and Holt's (1998b)	49 university students	M = 18.7; R = 17–21	Total = 10	M = 13.5	10	Event	Paper
Kashdan et al. (2014)	162 university students	M = 21.7	M = 2.5	14	5510	Event	PDA
Larson et al. (1985, 1986)	Sample1: 61 retirees	R = 55–88	7	7	S1 = 2269	Signal	PDA
	Sample 2: 31 retirees				S2 = 1143		
Lucas et al. (2008)	Sample 1: 133 students	R = 19–21	S1 = 7		S1 = 6240		
	Sample 2: 168 students	R = 18–25	S2 = 8	7	S2 = 6888	Signal	PDA
Pauly et al. (2017)	185 adults	M = 49.0; R = 20–81	5	10	8658	Signal	PDA
Sadikaj et al. (2011)	113 adults	M = 40.9; R = 20–70	M = 6	20	13,560	Event	Paper
Sandstrom and Dunn (2014)	Sample 1: 58 students	M1 = 19.22	M1 = 25.59	6	1484	Event	PDA
	Sample 2: 53 adults	M2 = NR	M2 = 18.10		742		
Sandstrom et al. (2017)	6759 users of an App	R = 18–47	2 (by default)	NA		Signal	Phone + sensor
Timmermans et al. (2010)	63 university students	M = 20.3; R = 18–26	9	14	3276	Signal	PDA
Torquati and Raffaelli (2004)	69 university students	Not reported	6–7	7	2311	Signal	PDA
Vella et al. (2012)	171 healthy adults	M = 40.9	M = 12.0	3	6173	Time	PDA
Vogel et al. (2017)	150 community adults	M = 47.1; R = 18–89	M = 6.92	21*3	64,213	Event	Phone
Wang et al. (2014)	184 university students	M = 19.3; R = 18–54	M = 5.87	7	7568	Event	Paper
Wichers et al. (2015)	610 female participants	M = 27.0; R = 18–46	10	5	20,261	Signal	Paper + beeper
Clinical populations (n = 5)							
Burns et al. (2016)	105 back pain patients and their spouses	M = 46.3; R = 18–70	5	14	7350	Signal	PDA
Granholm et al. (2013)	145 schizophrenia patients	M = 46.5	4	7	2737	Signal	PDA
Hepp et al. (2017)	Sample1: 80 BPD patients; Sample2: 51 DD patients	R = 18–65	6	28	11,760 7497	Signal	PDA

Table 1 (continued)

Authors	Sample population	Mean age/range	Data entries/day	Days	Total obs	Contingency	Format
Sadikaj et al. (2010, 2013) and Russell et al. (2007)	38 female BPD patients and 31 female controls	*BPD* M = 27.8; R = 19–38 *Control* M = 31.5; R = 23–41	*BPD* M = 4.8 *Control*: M = 6.2	20	6722	Event	Paper
Vasconcelos e Sa et al. (2016)	21 psychosis patients and their closest relatives	Patients: M = 26; R = 19–51 Relatives: M = 52; R = 22–79	10	6	903	Signal	PDA

PDA personal digital assistant (e.g., electronic pager; a palm device; tally counter), *OBS* observations, *BPD* borderline personality disorder, *DD* depressive disorder, *NR* not reported, *NA* not applicable

for more frequent data entries were typically designed with shorter duration to reduce burden. Vogel et al. (2017) used a measurement-burst design by separating the data collection into three 21-day periods (spaced at about 4.5-month intervals), of which participants made data entries 6–7 times per day. This provided a rich dataset that contained information from different time levels (e.g., between measurements, between days, between periods). Note that these numbers represent the designs of studies, not results. As for the data collection schedule, the time-contingent approach was used in five studies that asked participants to enter the diary data at pre-determined time points of the day (ranged from 3 times to every 30 min per day). The signal-contingent schedule was used by 15 studies, which asked participants to make data entries at random time points during the day, with a fixed number of data entries per day (range 2–10 times). While some studies assigned the same time window for data entry across all the participants (e.g., a 12-h time window such as 8:00–20:00), a number of studies allowed the use of individualized time windows. Eight studies used an event-contingent sampling schedule, which asked participants to report on their social interaction and affect shortly after the actual occurrence. Unlike time- or signal-contingent sampling studies, these event-contingent studies allowed participants to have different numbers of daily data entries during each day of assessment (the average number of data entries per day ranged from 2.5 to 10.9). Unlike most studies, Vittengl and Holt (1998b) asked participants to return their reports when they completed a total number of 10 event-contingent data entries, where the time period from first to last entry ranged from 3 to 41 days ($M = 13.45$ days) across participants. In terms of data collection tools, the number of studies using personal digital assistants (PDAs) was highest (n = 13), followed by studies using paper ($n = 12$), and studies using smartphones (n = 3). Two of three phone-based studies combined the use of phone and wearable sensors, and four of twelve paper-based studies coupled paper-diary with an electronic signaling device (e.g., beeper, wristwatch).

Operationalization of everyday social interactions and momentary affect

A clear operational definition of social interaction exhibits at least one of the following two properties: (1) a situation involving the subject and at least one other person (inclusive of situations where persons were physically involved or interacted with others electronically such as phone calls and social media); (2) a situation in which the behavior of the subject directly influenced, and was directly influenced by the behavior of the other(s) (Duck et al. 1991). Over half of the studies included in this review used definitions that exhibited both properties, the most common approach to data collection was to ask participants to report on face-to-face interactions with others that lasted a minimum duration (e.g., 5 or 10 min). Only two studies considered both face-to-face interactions and digital interactions (Alshamsi et al. 2016; Pauly et al. 2017). The other eight studies only collected immediate reports on the presence of other persons. See Online Appendix A for an overview of the operationalization of key measures and the main findings of all studies.

For over three decades affect research has been gradually converging on a two-factor model as the basic structure of affect: positive affect (PA) and negative affect (NA) (for historical reviews, see Posner et al. 2005). In line with this conceptual development most of the studies in this review ($n = 26$) treated PA and NA as independent and potentially influenced differently by the features of social interactions. Twenty-one studies obtained parallel reports of PA and NA over time and situations and another five studies focused on either PA or NA as the primary variable of interest. Most of these studies were based on unipolar scales containing selected items from the literature and the Positive and Negative Affect Schedule (PANAS; Watson et al. 1988). Only seven studies reported both high and low arousal affective

states. Two studies distinguished high-arousal PA (happy, alert, excited) from low-arousal PA (calm, quiet), as well as high-arousal NA (nervous, irritated) from low-arousal NA (sad, sleepy). Five studies explicitly stated that they captured valence and arousal as separate dimensions of core affect, using bipolar scales with a number of opposing affective states (e.g., pleasant–unpleasant, energetic–sleepiness).

Within-person associations between social interactions and momentary affect

Quantitative features of social interactions

Several studies examined within-person differences between momentary affect when subjects were alone and with other people. Overall the results indicated that the presence of others was associated with greater PA across samples, including samples of university students (Lucas et al. 2008; Torquati and Raffaelli 2004), retired people (Chui et al. 2014), and two lifespan samples of community adults (Pauly et al. 2017; Sandstrom et al. 2017). This within-person association between being with others and feeling happy was also evident at the between-person level, in that people who spent more time with others experienced greater PA (Brandstätter 1983; Larson et al. 1986). However, findings regarding the within-person association between being with others and NA were somewhat mixed: some studies reported that people experienced less NA when they were in a social situation than when they were alone (Pauly et al. 2017; Sandstrom et al. 2017), whereas others reported that the presence of others did not affect NA (Bernstein et al. 2017; Chui et al. 2014). In particular, Pauly et al. (2017) observed a positive association between being alone and low-arousal PA (calm and relaxed), indicating the potential affective benefit of solitude.

Many studies also examined the relationship between the uniqueness of the people we interact with and affect during those interactions. With regard to relationship types, being with one's friends has consistently been found to be associated with affective benefits in diverse populations, including university students (Lucas et al. 2008), a sample of the oldest-old (Chui et al. 2014), and community adults (Vogel et al. 2017). On the other hand, being with one's romantic partner is not always a positive experience and may even be associated with negative affect for individuals with certain characteristics. For instance, Chui et al. (2014) found that the presence of one's spouse was associated with neither PA nor NA in the very old, but the presence of one's spouse predicted greater NA in older women and in older people with a high number of chronic illnesses.

Several studies distinguished between close and peripheral social partners. People experienced greater PA when they reported more interactions with close social partners (Sandstrom and Dunn 2014; Vogel et al. 2017). This is consistent with Vittengl and Holt's (1998b) finding that people who spent more time with familiar partners reported greater affective well-being. However, Sandstrom and Dunn (2014) indicated that additional weak tie interactions also benefitted day-to-day affective well-being, and such effects were stronger on days when people had fewer interactions than usual with people to whom they had strong ties. This highlights the contribution that peripheral ties make to affective well-being, especially in the absence of interactions with close social partners. In addition, Alshamsi et al. (2016) reported a weak relationship between diversity of interaction partners and affect and concluded that partner diversity was insufficient to explain the dynamics of daily affect states.

Qualitative features of social interactions

Interpersonal theory defines two important dimensions of psychological input, agentic perception (e.g., dominant versus submissive, assured versus unassured) and communal perception (e.g., friendly versus cold, agreeable versus quarrelsome), that can be used to describe the dynamics of affect in daily life (Hopwood et al. 2013; Roche et al. 2013). Four studies have used interpersonal theory to provide a framework for examination of associations between interpersonal perceptions and momentary affect. Two studies examined individuals' perceptions of their own behaviors during interactions. Côté and Moskowitz (1998) observed that people reported a more positive affective state when they perceived their behaviors as more agentic or more communal than usual. Timmermans et al. (2010) found a strong correspondence between a flux (intra-individual variability) measure of affect and flux measures of interpersonal perceptions, indicating that people whose moment-to-moment affect shows greater variability in valence and arousal also display more variable perceptions of interpersonal behavior. The authors suggested that as both directions of influence (variability in affect causes variability in behavior and vice versa) were plausible further investigations were warranted.

With regard to partner's behavior, a higher level of communion has been associated with positive valence in a sample of university students (Wang et al. 2014), as well as in a lifespan sample of community adults aged between 20 and 70 (Sadikaj et al. 2011). The latter study demonstrated that affective state is influenced by the communal behavior of interaction partners; lower communal behavior triggered increased NA, whereas greater communal behavior increased PA. These effects have been observed in various types of relationship (romantic partnership, friendship, co-worker relationship, acquaintance), with the most pronounced effects occurring in interactions with a romantic partner. In addition, interaction partner's agency has been shown to be strongly positively associated with arousal

(Wang et al. 2014), especially in the context of high partner communion. The increase in arousal has been attributed to a subject's elevated efforts to navigate interpersonal bids for dominance, which may be challenged under circumstances where the partner's behavior was perceived as dominant.

Some studies focused on one or multiple conversational parameters to represent the perceived positivity and negativity of a given interaction. For example, the pleasantness of an ongoing interaction has been examined as a potential predictor of concurrent affective state. Several studies consistently reported that interactions that were perceived as more pleasant than usual were associated with positive valence (Bernstein et al. 2017; Kashdan et al. 2014), whereas exposure to unpleasant social interactions was often coupled with negative valence (Flory et al. 2000). These findings are consistent with previously established associations at the between-person level, between affect and the type of social encounter (Vittengl and Holt's 1998a). In addition to the pleasantness of interaction, Burns et al. (2016) examined the influence on negative affect of perceived support, hostility and criticism from spouses during interactions in a sample of 51 individuals with chronic lower back pain. Higher NA arousal was reported by individuals when they perceived more criticism and hostility and less support from their spouses, indicating the importance of the interpersonal environment of a marriage to the affective well-being of patients coping with chronic pain.

Two studies used multiple interaction parameters to represent the positivity and negativity of an interaction. Vella et al. (2012) asked participants to provide immediate responses to items capturing both negative interaction variables, e.g. "someone was in conflict with you" and positive interaction variables, e.g. "whether the interaction is agreeable". Only negative interaction variables predicted elevated hostile mood, suggesting that negative interactions had a more enduring impact on NA than positive interactions. However, this finding was not supported by another study, which documented that both positive features of interactions (i.e., comfortable, involved) and negative features (i.e., conflicted, disconnected) contributed to affective outcomes. Time-lagged effects have also been observed, namely that positive interaction features predict more PA and less NA in subsequent assessments whereas negative interaction features predict more NA and less PA. In addition, although most studies interpreted their findings in terms of the impact of social interactions on individuals' affective state, the reverse possibility has also been examined in several studies. Two studies found that prior PA was predicted greater positivity in subsequent social interactions. Hawkley et al. (2007) suggested that the reciprocal influence they observed may last longer than 90 min, supporting the assertion that affective states have relatively persistent effects on interaction quality. The evidence was less clear yet concerning affective states leading to subsequent negative interaction, since neither PA nor NA have been found to be predictive for the negativity of subsequent (Hawkley et al. 2007; Vella et al. 2012).

Associations between social interaction quality and momentary affect in clinical populations

Five studies in this review examined the within-person associations between the perceived characteristics of social interactions and subjects' affective state in clinical populations. Two studies focused on emotional vulnerability to negative interpersonal perceptions in patients with BPD. Thirty-eight patients with BPD were compared with 31 healthy controls (Russell et al. 2007, 2010, 2013) and the BPD patients reported a greater increase in NA than controls in response to perceptions of less communal behavior by an interaction partner and a smaller increase in PA in response to behavior perceived as more communal than usual. Moreover, negative affective states persisted longer in BPD patients than controls, which may indicate that people with BPD experience affective spillover from one event to another. Further evidence that BPD is associated with emotional vulnerability to interpersonal events was provided by a study which compared 80 patients with BPD and 51 patients with DD (Hepp et al. 2017). The complementarity between lower communion (rejecting and disagreement) and NA was more pronounced amongst BPD patients than DD patients. Taken together these findings suggest that BPD may have multiple effects on affective responsivity, including causing affect to spill over from one interpersonal event to another and influence perceptions of others' behaviors in subsequent interactions.

Three studies examined perceptions of the valence of social interactions. Using a sample of 145 patients with schizophrenia or schizoaffective disorder, Granholm et al. (2013) found that patients experienced more PA and less NA when they perceived social interactions as more positive, replicating the results of studies of non-clinical populations. The other two studies focused on social interactions within specific relationships: one examined features of social interactions between patients experiencing psychosis and their closest relatives (Vasconcelos e Sa et al. 2016) and the other examined features of social interactions between patients experiencing chronic pain and their spouses (Burns et al. 2016). Both studies collected reports of social interactions from both parties, the patients and their partners. The first one found that contact time with relatives was not related to patient affect, but patients experienced greater NA when they perceived their relatives' behavior as more controlling. Burns et al. (2016) reported that patients experienced greater NA arousal when they perceived high levels of criticism and hostility and a low level of support from their spouse.

This within-person association was more pronounced in male patients than in female patients, suggesting that male patients with chronic pain were more sensitive to perceived negative interactions with their spouse.

Results of meta-analyses

Strength of the within-person relations

Combining results from 11 independent samples in which quantitative social interaction variables were examined for PA yielded an estimated mean effect size of 0.233 (95% CI 0.216 to 0.250). The results of z-tests ($z = 6.191$, $p = .000$) suggested an overall significant association between quantity of social interactions and affective well-being. There was significant variation between independent samples ($Q = 286.515$, $p = .000$) and the I^2 statistic ($I^2 = 96.510$) suggested that approximately 96.5% of the between-study variance was due to heterogeneity. Similarly, the results from 9 independent samples in which quantitative social interaction variables were examined for NA indicated an estimated mean effect size of −0.175 (95% CI −0.227 to −0.123). The results of z-tests ($z = -6.465$, $p = .000$) suggested an overall significant association between quantity of social interactions and affective well-being. There was significant variation between independent samples ($Q = 25.935$, $p = .000$) and the I^2 statistic ($I^2 = 69.154$) suggested that approximately 69.2% of the between-study variance was due to heterogeneity.

Combining results from 10 independent samples in which the quality of social interactions was examined for PA yielded an estimated mean effect size of 0.509 (95% CI 0.470 to 0.547) for total affective well-being, a moderate effect size. The results of z-tests ($z = 4.082$, $p = .000$) suggested an overall significant association between quality of social interactions and affective well-being. There was significant variation between independent samples ($Q = 242.175$, $p = .000$) was found and the I^2 value (96.284) suggested that approximately 96.3% of between-study variance was due to heterogeneity. As for 12 independent samples in which social interaction quality was examined for NA, the results indicated an estimated mean effect size of −0.407 (95% CI −0.447 to −0.365) for total affective well-being, a moderate effect size. The results of z-tests ($z = -4.402$, $p = .000$) suggested an overall significant association between quality of social interactions and affective well-being. There was significant variation between independent samples ($Q = 174.468$, $p = .000$) was found and the I^2 value (93.695) suggested that approximately 93.7% of between-study variance was due to heterogeneity (see Online Appendix B for the computed effect sizes for each sample and the forest plots of relationships between social interactions with PA and NA).

Methodological factors as moderators of the within-person relations

Univariate moderator analysis was undertaken to assess whether methodological factors affected the strength of

Table 2 Moderator analyses for the relation between affective well-being and quantity of social interactions and quality of social interactions

Moderator	Coding	Quantity of SIs				Quality of SIs			
		k	Effect size	Between-groups Q	*p* value	k	Effect size	Between-groups Q	*p* value
Sample size	≤ 97 subjects	6	0.324			7	0.444		
	> 97 subjects	8	0.455	1.804	0.179	7	0.426	0.572	0.449
Assessment intensity	≤ 6 per day	4	0.454			10	0.553		
	> 6 per day	10	0.427	0.576	0.448	4	0.315	0.895	0.344
Study duration	≤ 9 days	10	0.446			3	0.352		
	> 9 days	4	0.452	0.939	0.333	11	0.505	0.011	0.915
Assessments per person	≤ 42	11	0.458			4	0.345		
	> 42	3	0.277	0.112	0.738	10	0.520	0.306	0.580
Data collection tool	Paper	3	0.253			7	0.455		
	PDA	8	0.440			6	0.412		
	Phone	3	0.404	3.275	0.194	1	0.320	1.526	0.466
Contingency	Time	3	0.200			2	0.434		
	Signal	10	0.461			6	0.312		
	Event	1	0.110	18.290	0.000	6	0.611	2.058	0.357
Clinical population	No	14	–	–	–	9	0.450		
	Yes	0	–	–	–	5	0.365	1.903	0.168

observed within-person relations between social interactions and momentary affect. As shown in Table 2, only one methodological factor, contingency of EMA, contributed significantly to the strength of within-person relations between quantity of social interactions and momentary affect (signal-contingency > event-contingency > time-contingency; $Qb = 18.290$, $p = .000$). As for the within-person relations between quality of social interactions and momentary affect, none of the variables listed in Table 2 contributed significantly to between-group variance in effect sizes.

Discussion

Summary of findings

This review has drawn together evidence from extant EMA studies of the within-person relationships between daily social interactions and momentary affective states of adults. The main findings are that within-person variances in affective state during the course of an interaction are predicted by various features of the interaction (i.e., the uniqueness of the interacting partner; interpersonal perceptions of an interaction). The meta-analyses indicated small-sized associations between quantitative features of social interactions with PA and NA, and moderate-sized associations between qualitative features of social interactions with PA and NA; these associations were only moderated by methodological factors to a limited extent.

Implications of the literature review

The within-person approach is the key to why EMA is valuable in research linking people's internal states to their social environment on the basis of within-interaction changes in affect. In the most general sense, being with other people has a beneficial impact on affect in daily life, extending the well-established between-person level positive association between social connectedness and global well-being (Cohen 2004; Deindl et al. 2016; Kawachi and Berkman 2001). Being with others may not necessarily ease loneliness, whilst solitude may provide affective benefits, by promoting low-arousal positive affect. Moreover, the uniqueness of social partners (i.e., relationship type, familiarity) appears to contribute to within-person variations in affect. To date research has tended to focus on the long-term structural properties of social ties that contribute to overall satisfaction and well-being (Thoits 2011; Uchino 2006; Wethington et al. 2016) and the findings presented here provide new insight into short-term process properties of social relations that are related to intra-individual differences in affective experiences (Deindl et al. 2016; Litwin and Shiovitz-Ezra 2006).

As well as the structural aspects of social ties, people's perceptions of their social environment have been related to concurrent fluctuations in affective state. There is agreement that people's perceptions of interpersonal behaviors (e.g., the extent to which an interaction partner's behaviors are perceived as friendly and communal) predict within-person variances in affective state. Individuals reported more PA during interactions in which they perceived their interaction partner's behavior to be more communal, supporting the prediction of interpersonal theory that the perception of communion may indicate social acceptance of the perceiver and thus lead to PA experiences (Fournier et al. 2011; Hopwood et al. 2013; Kiesler et al. 1997). Individuals also reported higher physiological arousal during interactions when their own behavior was more agentic. This extends the between-person level evidence that dominance in interactions is positively associated with arousal (Galinsky et al. 2003; Tsai 2007).

Limitations of included studies

The conceptualization of social interaction quality

Most studies relied on the subjects' appraisals of a given interaction for data on the quality of interactions and typically used higher order concepts representing multiple interaction parameters. For example, the positivity of social interaction was represented by the extent to which an individual perceived an interaction as warm, comfortable etc. and negativity was represented by the extent to which an individual perceived an interaction as conflicted, disagreeable etc.; but as these measures may overlap with self-reports of affective valence it is difficult to interpret effects of interaction quality on affective experience. A further problem is that these assessments may exert competing influences on individuals' subsequent affective states, given that EMA studies collect time series data in daily life settings. With this aspect, it might be more appropriate to focus on theory-driven concepts to capture the quality of interaction. For example, interpersonal theory emphasizes that agency and communion are important psychological inputs that can be used to describe the emotional dynamics of daily life. Continued research might benefit from using measurements of interpersonal perceptions to investigate the dynamics of the relationship between social situation and affect.

The reliability of EMA measurement of affective states

With respect to assessment of affective states, all EMA studies are hampered by the lack of standardized item sets with known psychometric properties (Haynes and Yoshioka 2007). The most common approach to measurement in the reviewed studies was to select a number of items from

PANAS (Thompson 2007; Watson et al. 1988), a trait measure originally developed to assess between-person differences in the average valence of affect. However only half of the studies provided information about the reliability of the scales, and most of these estimated reliability (e.g., Cronbach's alpha) based on overall means. This method is similar to estimating the reliability of a trait level measure and does not describe the consistency of within-subject responses (Nezlek 2017). Within the field of EMA there have been efforts to develop indicators of within-person reliability (for review see Wilhelm and Schoebi 2007). These methods share the key goal of decomposing the total variance into trait, state, and error components (Cranford et al. 2006; Jahng et al. 2008), and have often been used within a multilevel modeling framework that can estimate the observation-level reliability of scales (Geldhof et al. 2014). One study (Chui et al. 2014) included in this review describes the use of a generalizability theory framework to estimate the reliability of selected items intended to measure PA and NA and reports that the measurements had moderate to excellent within-person reliability. Future EMA studies should go beyond estimation of mean Cronbach's alpha across observations, and make cautious decisions about appropriate methods for estimating reliability according to their underlying assumptions and what is known about their accuracy (Jahng et al. 2008).

Approaches to analysis of within-person relations

Multilevel modeling (MLM) (Raudenbush and Bryk 2002) is currently widely regarded as the best practice method of analyzing hierarchically structured EMA data (observations are nested within days, which in turn are nested within persons). MLM not only enables examination of within-person variability in associations between lower-level variables (e.g., affect and social interactions at the beep-level), but also allows within- and between-person associations to be separated, because regression parameters at lower levels (e.g., beep level) can be modeled as dependent variables in regression equations at higher levels (e.g., person-level). Although most studies in this review used MLM, many researchers were not familiar with the best techniques for statistical analysis of EMA data (aan het Rot et al. 2012; Ebner-Priemer and Trull 2009). An important issue is that many researchers treated intensive longitudinal data (ILD)—in which observations are often subject-dependent in the same way as traditional longitudinal data—where observations are typically well-scheduled. Analyses of traditional longitudinal data commonly assumed homogenous residual covariance structure in MLM; however applying the same assumption to ILD is problematic as individually heterogeneous covariance structures often exist, for example, recent EMA studies showed substantial between-person heterogeneity in the variance and autocorrelations of emotional states over time (Ebner-Priemer et al. 2015; Rocke et al. 2009). Notably, this issue cannot be addressed by the use of unstructured error covariance structure when the number of assessments per individual is large (e.g., above 50), instead researchers need to consider using MLM with specific transformation methods to model ILD (for details, see Jahng and Wood 2017). Another issue that was largely ignored was the need to split the time-varying and time-invariant components of predictor variables assessed at lower levels (Bolger and Laurenceau 2013). For example, researchers need to consider splitting occasion-level measures of interaction quality into trait-level interaction quality (e.g., the arithmetic mean across repeated assessments) and occasion-specific interaction quality (e.g., the occasion-level deviations from person-specific means).

Opportunities for the future

Testing the temporal and lead-lag relationships

Most EMA studies in this review reported correlations between social interactions and within-person variation in affective states (e.g., people feel happier when they have positive interaction with others), but few provided strong evidence of temporal and lead-lag associations. To overcome this limitation the use of multivariate time-series designs and denser measurement schedules should be considered as this would provide more frequent within-person observations of behavior and affective states with a variety of contextual factors (Houtveen and de Geus 2009). With better statistical control of a range of confounding effects, these observations (nested within persons) could be modeled to investigate the complex relationships between two or more variables of interest, thus allowing researchers to make stronger inferences about directional relationships (Bussmann et al. 2009; Jahng et al. 2008; Schwartz and Stone 2007). In brief, future researchers should familiarize themselves with best practice statistical techniques for analysis of EMA data, which would enable them to derive maximum benefit from intensive, repeated measurement of multiple variables.

Using EMA to assess psychological traits

Many EMA studies paid attention to the role of psychological traits in explaining the dynamics of the within-person process involving behavior and affect. In examination of traits as possible moderating factors the more robust approach may be to use EMA-derived traits (the aggregation of momentary experiences) rather than retrospective assessments of traits, because the former should provide a more accurate reflection of tendencies of individuals, thus providing a potentially more robust method of assessing traits than traditional scales (Beal 2015; Charles et al. 2013). Compared

with traditional methods of assessing traits that are used for predicting main effects of a given variable or process (i.e., extraversion and positive affectivity), EMA-based assessments of traits seem to be well suited to interacting with interpersonal and affective events in predicting immediate reactions to these events (Shockley et al. 2012). Only two of the studies in this review (Sadikaj et al. 2011; Timmermans et al. 2010) showed an interest in such EMA-based trait assessments (e.g., affect spin as an EMA-derived trait measure of variability in affective state). Future research might profit from examining the predictive utility of these EMA-derived trait indicators, especially in relation to moderation of affective reactions.

Linking micro-level processes to long-term outcomes

To date EMA studies have been designed to support the within-person perspective by investigating the dynamics of behaviors and psychosocial process. To achieve greater recognition of the promise of EMA for capturing immediate and naturalistic contexts, it is important to connect this extreme micro-level analysis to higher-level analysis (Beal 2015; Trull and Ebner-Priemer 2009). For instance, there have been a number of good studies that successfully linked micro-level processes to long-term health outcomes (Bajaj et al. 2016; Charles et al. 2013; Kamarck et al. 2002, 2005). These studies typically involved a multiple time-scale design, such as a measurement-burst design that combined the use of longitudinal and intensive longitudinal assessment. This approach provides opportunities for linking short-term change processes (a micro time scale) to a long-term (a macro time-scale) change process, which should help to benefit a wider range of clinical psychology research areas (Ram et al. 2014).

Conclusion

We have systematically reviewed all EMA studies on the dynamic interactions between everyday social interactions and momentary affective states published to date. The qualitative results show that a variety of quantitative (e.g., partner uniqueness) and qualitative features (e.g., interpersonal perceptions) of daily social interactions contribute to within-person variance in momentary PA and NA. The meta-analyses indicated small-sized associations between quantitative features of social interactions with PA and NA, and moderate-sized associations between qualitative features of social interactions with PA and NA. Methodological factors only moderated the observed relationships to a limited extent. The studies conducted to date contribute to understanding of the dynamics of external, interpersonal events and internal affective states and provide insights for researchers and clinicians interested in the dynamic interplay between everyday social functioning and affective experiences. Many opportunities remain for future studies, of which perhaps the most exciting is to find ways to make the within-person process insights obtained from EMA studies relevant to a wider audience of researchers and practitioners across a range of clinical areas so that they can be used to benefit specific clinical populations.

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Compliance with ethical standards

Conflict of interest All authors declare that they have no conflicts of interest.

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