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Discovering different profiles in the dynamics of depression based on real–time monitoring of mood: a first exploration

Claire R. van Genugten [a,b,*], Josien Schuurmans [a,b], Wouter van Ballegooijen [a,b,c], Adriaan W. Hoogendoorn [a,b], Jan H. Smit [a,b], Heleen Riper [a,b,c,d]

[a] Department of Research and Innovation, GGZ inGeest, Specialized Mental Health Care, Amsterdam, the Netherlands
[b] Department of Psychiatry, Amsterdam Public Health Research Institute, Amsterdam UMC, Vrije Universiteit, Amsterdam, the Netherlands
[c] Department of Clinical, Neuro and Developmental Psychology, Clinical Psychology Section, Vrije Universiteit Amsterdam and Amsterdam Public Health Research Institute, Amsterdam, the Netherlands
[d] Institute of Telepsychiatry, University of Southern Denmark, Odense, Denmark

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ABSTRACT

Background: Although depression is typically characterized by a persistent depressed mood, mood dynamics do seem to vary across a depressed population. Heterogeneity of mood variability (magnitude of changes) and emotional inertia (speed at which mood shifts) is seen in clinical practice. However, studies investigating the heterogeneity of these mood dynamics are still scarce. The aim of the present study is to explore different distinctive profiles in real-time monitored mood dynamics among depressed persons.
Methods: After completing baseline measures, mildly-to-moderately depressed persons ($n = 37$) were prompted to rate their current mood (1–10 scale) on their smartphones, 3 times a day for 7 consecutive days. Latent profile analyses were applied to identify profiles based on average mood, variability of mood and emotional inertia as reported by the participants.
Results: Two profiles were identified in this sample. The overwhelming majority of the sample belonged to profile 1 ($n = 31$). Persons in profile 1 were characterized by a mood just above the cutoff for positive mood (M = 6.27), with smaller mood shifts (lower variability [SD = 1.05]) than those in profile 2 ($n = 6$), who displayed an overall negative mood (M = 4.72) and larger mood shifts (higher variability [SD = 1.95]) but at similar speed (emotional inertia) (AC = 0.19, AC = 0.26, respectively).
Conclusions: The present study provides preliminary indications for patterns of average mood and mood variability, but not emotional inertia, among mildly-to-moderately depressed persons.

1. Introduction

Increasingly complex conceptualizations of depression have been proposed over the years. While the diagnostic manual of mental disorders (DSM-5) might suggest otherwise (American Psychiatric Association, 2013) clinicians and researchers have highlighted that clinical manifestations of depression are heterogeneous (Cuthbert, 2014). Various cross-sectional studies identified multiple homogeneous profiles that differed in terms of symptom presence, symptom severity and the interplay between various depressive symptoms (e.g., (Goldberg, 2011; Lux and Kendler, 2010; ten Have et al., 2016)). In clinical settings, recognition of these subclassifications is relevant to determining the severity of a particular patient's disease and planning specific treatments accordingly.

Parallel to this there is a surge in research that stresses the importance of ecological context and studies linking mood dynamics to depression (Houben et al., 2015; MyinGermeys et al., 2018; Schoevers et al., 2020). Traditionally, mood assessments have been conducted

Abbreviations: AC, autocorrelation; AIC, Akaike information criterion; BIC, Bayesian information criterion; BLRT, bootstrapped likelihood ratio test; CES-D, Center for Epidemiological Studies Depression Scale; DSM-5, Diagnostic manual of mental disorders, 5th edition; EMA, ecological momentary assessment; IQR, interquartile range; LMRA-LRT, Lo-Mendell-Rubin adjusted likelihood ratio test; LPA, latent profile analysis; M, mean; Mdn, median; PHQ-9, Patient Health Questionnaire; SD, Standard deviation; VAS, Visual analogue scale.

* Corresponding author at: Department of Research and Innovation, GGZ inGeest, Specialized Mental Health Care. Oldenaller 1, 1081HJ Amsterdam, the Netherlands.
E-mail address: c.genugten@ggzingeest.nl (C.R. van Genugten).

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using retrospective standardized assessments. This type of assessment is not suited to capture the fine-grained dynamics of mood, since people are asked to recall and summarize a certain period of time ("How did you feel last week?"). Mood dynamics can be measured by applying ecological momentary assessment (EMA) methods, previously conducted via paper-and-pencil diaries, but nowadays technologies such as smartphones provide a powerful tool (Colombo et al., 2019; Girolamo et al., 2020; MyinGermeys et al., 2018; van Genugten et al., 2020). With EMA, persons provide real-time information on their mental well-being and related features within their ecological habitat instead of retrospectively at the clinic (Shiffman et al., 2008; Stone et al., 2007; Stone and Shiffman, 1994). Since phenomena are measured frequently and close to their occurrence, EMA response patterns are expected to be more ecologically valid by showing us a detailed picture of mood dynamics over time (Mofsen et al., 2019; Solhan et al., 2009; Wenze et al., 2012).

In EMA studies, various ways have been proposed to operationalize the dynamics of mood. The most common operationalizations are focused on "instability", "variability", and "emotional inertia" (Houben et al., 2015; Jahng et al., 2008; Vansteelandt and Verbeke, 2016). It is argued that instability is a combination of variability and emotional inertia (Jahng et al., 2008; Vansteelandt and Verbeke, 2016). Variability represents the magnitude of mood changes over an entire period of time – with higher variability meaning larger mood shifts and lower variability smaller mood shifts (Jahng et al., 2008; Vansteelandt and Verbeke, 2016). Emotional inertia denotes the extent to which mood is carried over from one moment to the next and the speed at which mood shifts (Kuppens et al., 2010a), but not the magnitude. Higher emotional inertia equals slower mood shifts and lower emotional inertia equals faster mood shifts (Jahng et al., 2008; Vansteelandt and Verbeke, 2016). In order to capture mood dynamics accurately, both variability and emotional inertia should be taken into account (Houben et al., 2015; Jahng et al., 2008; Vansteelandt and Verbeke, 2016).

As mentioned above, some studies have shown that depression is heterogeneous and others have linked mood dynamics to depression, highlighting the importance of real–time mood monitoring. In clinical practice it is seen that mood dynamics (variability of mood and emotional inertia) do seem to vary across depressed persons. However, studies on the heterogeneity of these mood dynamics are still scarce, while recognition of potential patterns of mood dynamics can provide us with valuable information, including, for example, into persons' emotional regulation (e.g., Lamers et al., 2018; van Winkel et al., 2015).

To the best of our knowledge, the present study is the first to explore different profiles of real-time monitored mood dynamics among mild to moderate depressed persons. Data from a subsample of the MoodMonitor study ($n = 37$) is used to this end. The main objective of the MoodMonitor study was to examine assessment reactivity of EMA to symptoms in individuals with mild to moderate depression (van Ballegooijen et al., 2016b). This study uses data from the first week of the study, during which participants were prompted to rate their current mood 3 times a day. Dynamics of mood are operationalized by a combination of average mood, variability of mood and emotional inertia, as measured with smartphone-based EMA.

2. Methods

2.1. Recruitment

Data were obtained from a subsample of the MoodMonitor study (van Ballegooijen et al., 2016b). Participants of the MoodMonitor study were recruited through advertisements at the campus of Vrije Universiteit (Amsterdam, the Netherlands), social media platforms (Facebook, Twitter), and Dutch websites for mental health issues. The advertisements contained a link to the study's website, and those who were interested in participating could click on the link to be directed to the online screening questionnaire. Candidates were screened on whether they (1) were at least 18 years of age, (2) reported mild to moderate depression symptoms (Patient Health Questionnaire [PHQ-9] score between 5 and 15) (Kroenke et al., 2001), and (3) owned an Android smartphone. After which they could read the study information again and agree to partake by entering their email address (electronic informed consent). If applicable, those interested received an email containing a link to the baseline questionnaire and an instruction to download the EMA app MoodMonitor to their smartphone. This app is developed by the E-COMPARED consortium (Kleiboer et al., 2016). After the study, individuals that actively participated earned a gift voucher (up to €32.50).

The MoodMonitor randomized controlled trial had a duration of 12 weeks and included 3 arms: a group that completed evaluations of mood EMAs ("How is your mood right now?"), a group that completed energy levels EMAs ("How energetic do you feel right now?"), and a control group that completed no EMA but only the baseline characteristics and standardized Center for Epidemiological Studies Depression Scale (CES-D) (Bouma et al., 1995; Radloff, 1977) questionnaire. During the course of the trial, participants were invited to complete 1 assessment a day, with the exception of weeks 1 and 12, when in order to measure mood fluctuations they were asked to complete 3 assessments a day. Data of week 12 were not analyzed, as we were interested in mood dynamics in depression and the participants might no longer be depressed 12 weeks after the start of the monitoring period. For purposes of this study, only EMAs of mood that were completed in the first 7 days of the trial were taken into consideration. Of the 54 initially selected mood participants, 17 were excluded for analyses as they did not actively participate in the EMA questions. Active participation was considered as having completed at least 50% EMA questions on at least 4 out of the 7 days. According to previous research, mood dynamics show a certain self-similarity across different time intervals (Guestello and Liebovitch, 2009; Kuppens et al., 2010b).

A detailed description of the MoodMonitor study design can be found elsewhere (van Ballegooijen et al., 2016b). The Medical Ethical Committee of VU University Medical Center Amsterdam judged participant risk and burden to be minimal and confirmed that the MoodMonitor study is not subject to the Medical Research Involving Human Subjects Act (WMO) (file no. 15.333). The trial is registered in the Netherlands Trials Register (no. NTR5803) (12 April 2016).

2.2. Measures

2.2.1. Demographic characteristics

Demographic characteristics (age, gender, educational status) were gathered using standard questions. Participants were also asked to report on possible lifetime psychiatric disorders and on whether they currently received any professional help for mental health problems.

2.2.2. Clinical characteristics

Severity of depressive symptoms was assessed at baseline by administering the CES-D (Bouma et al., 1995; Radloff, 1977) online. The CES-D is a retrospective self-report questionnaire that measures depressive symptoms in the week preceding the moment of administration. This 20-item list detects not only the more severe depressive symptoms, mild symptoms are also covered. Items are scored on from 0 (rarely or none of the time [less than 1 day] to 3 (most or all of the time [5–7 days]). The sum score ranges from 0 to 60, with higher sum scores representing more symptoms and more severe depressive symptoms. The standard cut-off score suggests that depression in the general population is >16 (Bouma et al., 1995; Radloff, 1977). When administered online, the CES-D shows good internal consistency (van Ballegooijen et al., 2016a).

2.2.3. Smartphone–based Ecological Momentary Assessment

EMA of one of the core depression symptoms (i.e. mood) was conducted for the momentary assessments, where participants were asked

to rate their mood at that moment on a visual analogue scale (VAS) that ranged from 1 (worst) to 10 (best), with 1 precision digit after the decimal point. Participants received a notification on their smartphones 3 times a day at random time points between 10 AM and 10 PM. They were instructed to answer the EMA question promptly, but the notification remained visible until the next question. Additionally, participants were free to complete the EMA question at any time other than the scheduled prompts, and could do so by opening the app. After answering the EMA question, the rating was automatically time-stamped and participants could see on their smartphone a graph that showed the values of their ratings over time.

2.3. Profile indicators: average mood, variability, and emotional inertia

"Average mood" refers to the mean (M) scores of all EMA questions that were rated across the 7 days. No official cutoff value is available to specify whether mood is negative or positive, but in general a score below 6 (range 1–10) is considered negative (Groot, 2010). "Variability" refers to the amount by which mood shifts and is mathematically defined as the standard deviation (SD) of the M in time-series data (Ruwaard et al., 2018). A larger SD equals higher variability and a smaller SD equals lower variability. While variability refers to the extremity of the mood shifts, "emotional inertia" refers to the extent to which mood is carried over from one moment (t–1) to the subsequent assessment (t). With time-series data, this is mathematically defined as the autocorrelation (AC) (Ruwaard et al., 2018). Theoretically, AC ranges from −1 to 1. A positive correlation indicates that a higher or lower score at t–1 directly corresponds with a high or low score at t (Chatterjee and Simonoff, 2013). A larger positive autocorrelation equals higher emotional inertia (Houben et al., 2015; Vansteelandt and Verbeke, 2016). A negative autocorrelation indicates that if the score at t–1 was above the M, the score at t is more likely to be below the M, and vice versa (Chatterjee and Simonoff, 2013). A larger negative correlation equals lower emotional inertia (Houben et al., 2015; Vansteelandt and Verbeke, 2016). So far, there are no official cutoff values to specify variability or emotional inertia to be considered high, moderate or low.

2.4. Statistical analysis

First, descriptive statistics were calculated for the baseline characteristics for the full analytic sample. In order to check for possible selection bias, comparative analyses on baseline demographic (age, gender, educational level), lifetime psychiatric diagnosis (yes/no) or current help (yes/no) between the participants of the study ($n = 37$) and the participants who did not actively participate in the EMA questions ($n = 54–37 = 17$) were performed. Hereafter, we applied latent profile analyses (LPA). LPA can be used to classify a group of individuals into multiple homogeneous profiles based upon a set of continuous variables (Masyn, 2013). In short, LPA tests the fit of a 1-profile model and then increases the number of profiles, until adding more profiles does not result in a gain in information (Masyn, 2013). To compare model fit (i.e. to evaluate the optimal number of profiles) different solutions were used: the Bayesian information criterion (BIC) (Schwarz, 1978), Akaike information criterion (AIC) (Akaike, 1974), bootstrapped likelihood ratio test (BLRT), Lo-Mendell-Rubin adjusted likelihood ratio test (LMRA-LRT) (Lo et al., 2001) and entropy values (Celeux and Soromenho, 1996). BIC and AIC are used to compare different model solutions. Lower values of the BIC and AIC are indicative for better model fit (Schwarz, 1978; Sclove, 1987; van de Schoot et al., 2012). Both the BLRT and LMRA-LRT test whether the model with K profiles significantly fits the data better than a model with $K–1$ profiles. A significant p-value (<0.05) supports the more complex model (Lo et al., 2001; Nylund et al., 2007). The entropy values are those for correctly classifying individuals to different latent profiles based on the model. Entropy values range from 0 to 1 (with a value of 1 indicating perfect classification). As of yet, there is no official cutoff value for entropy statistics, but ≥ 0.80 is often considered as having adequate model classification (Celeux and Soromenho, 1996). Due to our small sample size, we limited our LPAs to a maximum of 4 profile models. We used the 3 indicators listed above to quantify mood experienced by each person: (1) average mood (M), (2) variability of mood (SD) and (3) emotional inertia (AC). After conducting the LPA, participants were assigned to their most likely profile. This was done post-hoc by allocating each participant to the profile with maximal posterior probabilities. The posterior probability is the probability of a participant being classified in a given profile (Masyn, 2013). Hereafter, the conceptual meaning of the different profiles was described by comparing the standardized mean scores on the indicators. Lastly, descriptive statistics of the demographic and clinical characteristics within each of the profiles of the best-fitting model were calculated, and possible inter-profile differences were examined. Continuous variables were checked on normality of distribution with Kolmogorov-Smirnov tests. Mean and standard deviation were reported for normally distributed continuous variables, and median and interquartile range (IQR) for non-normally distributed data. In order to deal with the unequal sample sizes of the profiles, we performed Fisher's exact and Mann-Whitney tests as appropriate to examine inter–profile differences. The TidyLPA R package (Rosenberg et al., 2018) was used for the latent profile analyses and the emaph R package (Ruwaard, 2018; Ruwaard et al., 2018) to generate data for the visuals of Fig. 1.

3. Results

3.1. Characteristics of the study sample

In the overall sample ($n = 37$), 86% (32/37) of the participants were female, the median age was 32.0 years (IQR = 24.0–46.0) and education was distributed as elementary (41% [15/37]), secondary (16% [6/37]) or higher (43% [16/37]) education. Participants reported depressive symptoms at baseline, with a score well above the cutoff of 16 (M = 26.9 [SD = 8.7]). Moreover, 49% (18) of the sample reported having a lifetime psychiatric diagnosis and 43% (16/37) received professional help during the study period.

The comparative analyses found no selection bias. That is, the MoodMonitor participants who did not meet the inclusion criteria (i.e. failed to actively participate in the EMA questions [$n = 54–37 = 17$]) did not statistically significantly differ from the participants who were included in the study ($n = 37$) in terms of demographic characteristics (age, gender, educational level), lifetime psychiatric diagnosis (yes/no) or current help (yes/no).

3.2. Latent profile analyses: choosing the best–fitting model

Table 1 provides the fit indices of the models with the different number of profiles estimated. Both the BIC and the AIC values are lowest for the 2-profile model compared to the other models. A discrepancy is found when looking at the BLRT and the LMRA-LRT p-value. The BLRT supports the 2-profile model, while the LMRA-LRT supports the 4-profile model. Classification accuracy of each model was subsequently examined using the entropy values. The model with 1 profile obviously has perfect classification since all participants are classified into 1 profile. With an entropy value of 0.951, the 2-profile model scores above the cutoff value of 0.80 for entropy statistics. The 3- and 4-profile models both score just below this cutoff. In conclusion, except for the LMRA-LRT test, the fit indices prefer the 2-profile model over the other models. This is why, on balance, based on the fit indices we considered the 2-profile model most suitable for the present sample.

3.3. Conceptual meaning of the best-fitting model

The persons in profile 1 (prevalence 84%, $n = 31$) are characterized by an overall positive mood (rolling mean; M = 6.27), with an average M just above the cutoff value of 6. Still, mood scores reported in the 7 days

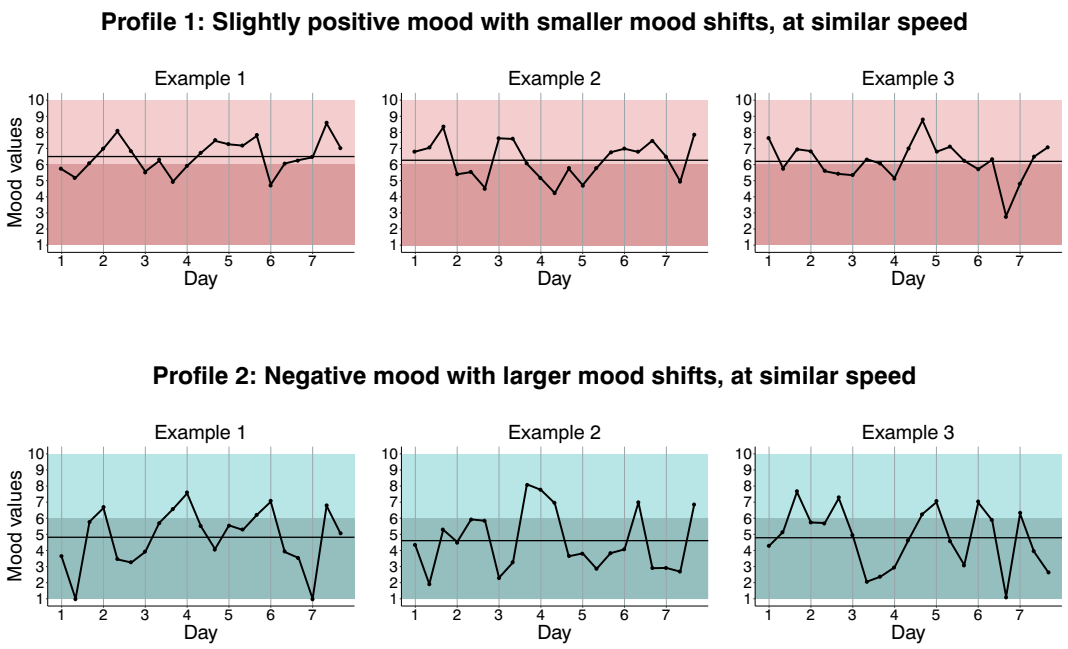

Fig. 1. Generated EMA response patterns for the two profiles of the best-fitting model.
Notes: Data for these figures were generated using the standardized mean scores of the indicators of the profiles: three completed EMA assessments a day, at random timepoints between 10 AM and 10 PM. The horizontal black line represents the average mood across the seven days. Backgrounds of the figures were given multiple colors, with darker areas representing negative mood (<6) and lighter areas positive mood (>6).

Table 1
Fit indices of the latent profile analysis.

Profiles	Log likelihood	BIC	AIC	BLRT	LMRA-LRT	Entropy values
				p	*p*	
1	−70.560	162.786	153.121	–	–	1.000
2	**−59.876**	**155.860**	**139.751**	**0.010**	**<0.001**	**0.951**
3	−57.718	165.988	143.435	0.584	<0.001	0.772
4	−55.384	175.764	146.768	0.624	<0.001	0.761

Notes: Best-fitting model is bolded. BIC = Bayesian information criterion; AIC = Akaike information criterion; BLRT = Bootstrapped likelihood ratio test; LMRA-LRT = Lo-Mendell-Rubin adjusted likelihood ratio test.

Table 2
Standardized mean scores on the indicators for the best-fitting model.

	Prevalence	Average mood	Variability	Emotional inertia
	n (%)	*M*	*SD*	*AC*
Profile 1	32 (84%)	6.27	1.05	0.19
Profile 2	6 (16%)	4.72	1.95	0.26

Notes: M = rmean, SD = standard deviation, AC = autocorrelation of the EMA questions across the 7 days.

fluctuate around the cutoff value; with an SD of 1.05, 68% of the EMA questions are scored at 6.27–1.05 = 5.22 and 6.27 + 1.05 = 7.32, so negative scores were also reported on the EMA questions. For emotional inertia (AC), a score of 0.19, a positive correlation, indicates slower mood shifts. The persons in profile 2 (prevalence 16%, $n = 6$) are characterized by an overall negative mood (M = 4.72), with an M well below the cutoff value of 6. They show higher mood variability (SD = 1.95) than profile 1 persons, meaning larger mood shifts. When looking at the average emotional inertia, a similar result is found as for profile 1 (AC = 0.26). Summing up, inter-profile differences are found for average mood and variability but not for emotional inertia, with profile 1 persons characterized by an overall positive mood with smaller mood shifts (variability) than profile 2 persons, who display an overall negative mood with larger mood shifts (variability) but at similar speed (emotional inertia). Fig. 1 provides multiple examples of generated EMA response patterns for both profiles, illustrating the differences in average mood, variability of mood, and emotional inertia (Table 2).

3.4. Demographic and clinical characteristics of the study sample

Table 3 shows the demographic and clinical characteristics of the sample. At baseline, significantly more symptoms and more severe depression symptoms were reported by the persons in profile 2 (M = 33.8, SD = 8.5) than by those in profile 1 (M = 25.6, SD = 8.2). Statistical tests found no differences between the 2 profiles in terms of demographic characteristics (age, gender, educational level), number of completed EMA assessments, lifetime psychiatric diagnosis (yes/no) or current professional help (yes/no).

4. Discussion

The results of this explorative study found a first indication for 2 homogeneous profiles of mood dynamics among mild to moderate depressed persons. These 2 profiles differed in average mood and amount of variability of mood, but not in emotional inertia. The profiles were labeled as “slightly positive mood with smaller moods shifts, at similar speed” and “negative mood with larger mood shifts, at similar speed”.

In this sample, the persons with more depression and more severe depression at baseline experienced more negative but also more variable moods than those with less severe depression at baseline, while emotional inertia was similar across the 2 profiles. These inter-profile differences are generally in line with a meta-analysis by (Houben et al., 2015), who showed that variability of mood was higher when depression was worse (Houben et al., 2015). And yet contrary to variability, emotional inertia did not increase with depression. Hence the fact that we did find inter-profile differences in terms of average mood and variability of mood but not emotional inertia across the profiles with different levels of depression concords with the meta-analysis (Houben

Table 3
Descriptive statistics of demographic and clinical characteristics of the best-fitting model.

	Total	Profile 1[a]	Profile 2[a]	Test statistics	*p*-value
n	**37**	**31**	**6**		
Age, median (IQR)	32.0 (24.0–46.0)	32.0 (23.0–46.0)	31.5 (24.3–40.3)	U = 105.56	0.612
Female[b], *n* (%)	32 (86%)	28 (90%)	4 (67%)	OR = 4.4 (0.3–53.7)	0.177
Educational level, *n* (%)					
Elementary	15 (41%)	14 (45%)	1 (17%)	U = 74	0.396
Secondary	6 (16%)	4 (13%)	2 (33%)		
Higher	16 (43%)	13 (42%)	3 (50%)		
Completed EMA assessments, mean (SD)	17.9 (4.0)	17.5 (3.5)	19.5 (6.4)	U = 83	0.694
CES-D at baseline, mean (SD)	26.9 (8.7)	25.6 (8.2)	33.8 (8.5)	U = 44	**0.045**
Lifetime diagnosis[c], *n* (%)					
Yes	18 (49%)	14 (45%)	4 (67%)	OR = 0.4 (0.0–3.4)	0.405
None	19 (51%)	17 (55%)	2 (33%)		
Current professional help[d], *n* (%)					
Yes	16 (43%)	12 (39%)	4 (67%)	OR = 3.3 (0.0–2.7)	0.370
None	21 (57%)	19 (61%)	2 (33%)		

Notes: Fisher's exact tests and Mann-Whitney tests were used as appropriate, so test statistics are OR [odds ratio] (95%) or U, respectively. Bold *p*-values represent statistically significant tests.

[a] Profile 1: "slightly positive mood with smaller mood shifts, at similar speed", Profile 2: "negative mood with larger mood shifts, at similar speed".

[b] Females were used as reference group.

[c] No lifetime diagnosis was used as reference group.

[d] No current help was used as reference group.

et al., 2015).

The study findings should be considered in the context of several limitations. First and utmost, due to the size of our sample, the study is considered underpowered (Tein et al., 2013). An underpowered study has the risk of concluding that there is no difference, when in fact, there is a difference (Tein et al., 2013). Despite the small sample size, we still chose to proceed with the study and 2 profiles of mood dynamics were revealed. As far as we are concerned, the study taps into an important topic, but little was known about it. That is why we proceeded the study, with the intention to replicate the study in a larger sample. Second, the study lacked validated cutoff scores for the indicators of mood dynamics, and we were only able to describe the inter-profile differences on the indicators. Third, our study had a short duration sampling scheme, with only a limited number of assessments per participant. Fourth, our sample comprised an overwhelming majority of females and consisted of mild-to-moderately depressed persons who were recruited from the general population. As a result of these restrictions, we should be very cautious when generalizing our results to other settings.

The study nonetheless has valuable implications for future research aimed at an improved understanding of the complex conceptualizations of depression. The importance of using innovative methods such as smartphone-based EMA and mood dynamics in depression has been confirmed over the years (Heininga et al., 2019; Houben et al., 2015; MyinGermeys et al., 2018), and it is argued that studying variation among depressed persons is relevant to fully understanding depressive disorders (Cuthbert, 2014). Future research is warranted. Replication and validation of the study findings across different and larger samples is needed to further increase the confidence of the profiles and patterns identified.

Even though we should be very cautious seen the limitations of our study sample and design, for clinical purposes our study has implications too. In our sample the most affected persons show the largest discrepancy between retrospectively monitored mood and mood experienced throughout the day, that is more variable mood. Since patients report depressed mood most of the day when asked to report retrospectively on their mental well-being, one might not expect to identify large mood fluctuations when measured real-time. The results could be explained by a body of research on cognitive distortions in depressed persons, with findings showing a stronger negative mood recall and impaired ability to recall positive mood when depression is worse (Gotlib and Joorman, 2010; LeMoult and Gotlib, 2019). Previous studies have underlined the potential of EMA methods as an add-on tool for depression treatment (e.g., (Bos et al., 2019; Burns et al., 2011; Hartmann et al., 2015; Kramer et al., 2014)) and our study results could possibly indicate that especially individuals with more symptoms and more severe depressive symptoms should intensively monitor their mood in a real-life context. However, if the aim is to study who benefits the most from mood monitoring, studies with larger samples are needed and more severely depressed patients should be included, recruited in clinical settings.

5. Conclusion

To conclude, this study identified 2 profiles of average mood and mood variability among mild to moderate depressed persons, which were measured during a 7-day monitoring period using smartphone-based EMA. Although we should be very cautious when generalizing the results, the findings do provide us with initial insights into the heterogeneity of average mood, mood variability, but not emotional inertia, in the realm of daily lives of depressed persons.

Authors' contributions

All authors have contributed substantially to the work reported. All authors critically revised the paper. Conceptualization, CRvG, JS, JHS; methodology, CRvG, JS, AH, JHS; formal analysis, CRvG, AH; Investigation, WvB; writing – original draft preparation, CRvG; writing – review and editing, JS, AH, WvB, JHS, HR; Visualization, CRvG; Supervision: JS, JHS, HR; Funding acquisition, WvB, HR. All authors have read and agreed to the published version of the manuscript.

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Declaration of competing interest

None.

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