

Examining the Reliability and Validity of Ecological Momentary Assessment Response Time Based Measures of Emotional Clarity

Raymond Hernandez, Claire Hoogendoorn, Jeffrey S. Gonzalez, Elizabeth A. Pyatak, Gladys Crespo-Ramos, Stefan Schneider

Submitted to: JMIR Mental Health on: March 13, 2024

Disclaimer: © **The authors. All rights reserved.** This is a privileged document currently under peer-review/community review. Authors have provided JMIR Publications with an exclusive license to publish this preprint on it's website for review purposes only. While the final peer-reviewed paper may be licensed under a CC BY license on publication, at this stage authors and publisher expressively prohibit redistribution of this draft paper other than for review purposes.

Table of Contents

Original Manuscript	5
Supplementary Files	44
Multimedia Appendixes	
Multimedia Appendix 1	

Examining the Reliability and Validity of Ecological Momentary Assessment Response Time Based Measures of Emotional Clarity

Raymond Hernandez¹; Claire Hoogendoorn^{2, 3}; Jeffrey S. Gonzalez^{2, 3}; Elizabeth A. Pyatak⁴; Gladys Crespo-Ramos³; Stefan Schneider^{1, 5}

Corresponding Author:

Raymond Hernandez Center for Economic and Social Research University of Southern California 635 Downey Way, VPD Los Angeles US

Abstract

Background: Emotion regulation is an important aspect of both hedonic and eudemonic well-being. One component of emotion regulation is emotional clarity, a person's ability to lucidly identify the emotion they are experiencing. Emotional clarity has often been assessed with self-report measures, but efforts have also been made to measure it passively, which has advantages such as avoiding potential inaccuracy in responses stemming from social desirability bias and/or poor insight of emotional clarity. Response times to emotion items administered with Ecological Momentary Assessments (EMA) may be an indirect indicator of emotional clarity. Another proposed indicator is the "drift rate" parameter, which can be estimated from the combination of responses and response times to EMA emotion items based on a mental process model for choosing a response (drift diffusion model). An assumption underlying the drift rate parameter is that, aside from how fast a person responds to emotion items, the measurement of emotional clarity also requires consideration of how careful participants were in providing responses.

Objective: This paper examined the reliability and validity of response times and drift rate parameters from EMA emotion items as indicators of individual differences in emotional clarity.

Methods: Validity was examined by testing response times and drift rate parameters (from EMA emotion items) for expected associations with six validated scales of relevance to emotional clarity: life satisfaction, neuroticism, depression, anxiety, diabetes distress, and emotion regulation. Because of prior literature suggesting the emotional clarity could be valence specific, EMA items for negative and positive affect items were examined separately.

Results: Reliability of the proposed indicators of emotional clarity was acceptable with a small number of EMA prompts (i.e., 4 to 7). Consistent with expectations, the average drift rate of negative affect items across multiple EMAs had expected associations with other measures, such as correlations of r=-0.26 (P<.001) with depression symptoms, r=-0.26 (P=.001) with anxiety symptoms, r=-0.16 (P=.013) with emotion regulation difficulties, and r=0.63 (P<.001) with response times to the negative affect items. People with higher NA drift rate responded faster to the NA emotion items, had greater subjective well-being (e.g., less depression symptoms), and less difficulties with overall emotion regulation, which are all aligned with expectation for an emotional clarity measure. Contrary to expectations, the validities of average response times to negative affect items, drift rate of positive affect items, and response times to positive affect items were not strongly supported by our results.

Conclusions: Study finding supported the validity of NA drift rate as an indicator of emotional clarity, but not other response time based clarity measures. Further research is needed to examine the validities of passive emotional clarity indicators.

(JMIR Preprints 13/03/2024:58352)

¹Center for Economic and Social Research University of Southern California Los Angeles US

²Ferkauf Graduate School of Psychology Yeshiva University Bronx US

³Fleischer Institute for Diabetes and Metabolism Division of Endocrinology, Department of Medicine Albert Einstein College of Medicine Bronx US

⁴Chan Division of Occupational Science and Occupational Therapy University of Southern California Los Angeles US

⁵Department of Psychology University of Southern California Los Angeles US

DOI: https://doi.org/10.2196/preprints.58352

Preprint Settings

- 1) Would you like to publish your submitted manuscript as preprint?
- ✓ Please make my preprint PDF available to anyone at any time (recommended).
 - Please make my preprint PDF available only to logged-in users; I understand that my title and abstract will remain visible to all users. Only make the preprint title and abstract visible.
 - No, I do not wish to publish my submitted manuscript as a preprint.
- 2) If accepted for publication in a JMIR journal, would you like the PDF to be visible to the public?
- ✓ Yes, please make my accepted manuscript PDF available to anyone at any time (Recommended).
 - Yes, but please make my accepted manuscript PDF available only to logged-in users; I understand that the title and abstract will remain v Yes, but only make the title and abstract visible (see Important note, above). I understand that if I later pay to participate in <a href="http://example.com/above/library/

Original Manuscript

Examining the Reliability and Validity of Ecological Momentary Assessment Response Time Based Measures of Emotional Clarity

·

Raymond Hernandez^{1*}, Claire Hoogendoorn^{2,3}, Jeffrey S. Gonzalez^{2,3}, Elizabeth A. Pyatak⁴, Gladys

Crespo-Ramos³, Stefan Schneider^{1,5}

¹Center for Economic & Social Research, University of Southern California, Los Angeles, CA, US

²Ferkauf Graduate School of Psychology, Yeshiva University, Bronx, NY, US

³Fleischer Institute for Diabetes and Metabolism, Division of Endocrinology, Department of

Medicine, Albert Einstein College of Medicine, Bronx, NY, US

⁴Chan Division of Occupational Science and Occupational Therapy, University of Southern

California

⁵Department of Psychology, University of Southern California, Los Angeles, CA, US

Corresponding Author:

Raymond Hernandez, PhD

University of Southern California

Dornsife Center for Self-Report Science

635 Downey Way

Los Angeles, CA, 90089-3332

United States

Email: hern939@usc.ede

Abstract

Background: Emotional clarity has often been assessed with self-report measures, but efforts have also been made to measure it passively, which has advantages such as avoiding potential inaccuracy in responses stemming from social desirability bias and/or poor insight of emotional clarity. Response times to emotion items administered with Ecological Momentary Assessments (EMA) may be an indirect indicator of emotional clarity. Another proposed indicator is the "drift rate" parameter, which assumes that, aside from how fast a person responds to emotion items, the measurement of emotional clarity also requires consideration of how careful participants were in providing responses.

Objective: This paper examined the reliability and validity of response times and drift rate parameters from EMA emotion items as indicators of individual differences in emotional clarity. **Methods:** Secondary data analysis was conducted on data from 196 adults with type 1 diabetes who completed a two-week EMA study involving the completion of 5-6 surveys daily. If lower response times and higher drift rates (from EMA emotion items) were indicators of emotional clarity, we hypothesized that greater levels (i.e., higher clarity) should be associated with greater life satisfaction, and lower neuroticism, depression, anxiety, diabetes distress, and fewer difficulties with emotion regulation. Because of prior literature suggesting the emotional clarity could be valence specific, EMA items for negative and positive affect items were examined separately.

Results: Reliability of the proposed indicators of emotional clarity was acceptable with a small number of EMA prompts (i.e., 4 to 7 prompts total, or 1 to 2 days of EMA surveys). Consistent with expectations, the average drift rate of negative affect items across multiple EMAs had

expected associations with other measures, such as correlations of r=-0.27 (P<.001) with depression symptoms, r=-0.27 (P=.001) with anxiety symptoms, r=-0.16 (P=.014) with emotion regulation difficulties, and r=0.63 (P<.001) with response times to the negative affect items. People with higher NA drift rate responded faster to the NA emotion items, had greater subjective well-being (e.g., less depression symptoms), and less difficulties with overall emotion regulation, which are all aligned with expectation for an emotional clarity measure. Contrary to expectations, the validities of average response times to negative affect items, drift rate of positive affect items, and response times to positive affect items were not strongly supported by our results.

Conclusions: Study findings provided initial support for the validity of NA drift rate as an indicator of emotional clarity, but not other response time-based clarity measures. Evidence was preliminary because the sample size was not sufficient to detect small but potentially meaningful correlations, as the sample size of the diabetes EMA study was chosen for other more primary research questions. Further research on passive emotional clarity measures is needed.

Keywords: drift-diffusion model; ecological momentary assessment; emotional clarity; emotion regulation; response times; positive affect; negative affect

Introduction

Emotion regulation is highly relevant to subjective well-being from both hedonic and eudaimonic perspectives. According to the hedonic perspective, well-being is the experience of happiness, or the occurrence of positive affect and absence of negative affect [1]. In the eudaimonic perspective, well-being arises when individuals live with a sense of growth, meaningfulness, and/or purpose [2]. People often engage in emotion regulation to obtain hedonic benefits (e.g., feel more positive affect and reduce negative affect) [3], but eudaimonic motivations have been found to be important as well [4] (e.g., down-regulation of negative emotions to achieve a sense of growth in one's ability to handle daily stressors).

One important aspect of emotion regulation is emotional clarity, a person's ability to lucidly identify the type of emotion they are experiencing [5]. Emotional clarity is highly relevant to James Gross's Model of Emotion Regulation [6]. Gross' model consists of emotion regulation strategies that are either "antecedent-focused" or "response-focused", which refers to whether the strategy is used before or after an emotional response fully develops. In Gross's updated emotion regulation model, understanding and identifying one's emotions accurately (i.e., emotional clarity) are precursors to both these types of emotion regulation strategies [7]. Thus, individuals with low emotional clarity are less likely to use emotion regulation strategies (as they are failing to identify the need for them), which can negatively impact well-being. Lower emotional clarity has often been associated with reduced mental health [8–10], though there are exceptions. For instance, prior research has suggested that higher emotional clarity may be adaptive primarily for individuals that do not have very frequent and strong experiences of negative emotions, but maladaptive for those that frequently have strong feelings of negative

Passive Emotional Clarity Measures

4

affect [11].

Both direct and indirect measures of emotional clarity have been developed [12,13]. Direct assessments involve the metacognitive task of reflecting on one's emotional clarity level, while indirect assessments measure performance of a task relevant to emotional clarity (i.e., answering emotion items) and do not require self-insight [12]. Emotional clarity is commonly directly assessed with cross-sectional self-report measures such as the clarity subscales of the Trait Meta-Mood Scale [14] and the Difficulties in Emotion regulation Scale [15], but indirect measures have been argued to have potential advantages over self-report assessments [12,13]. For instance, they could help avoid possible issues with subjective reports, including poor insight of emotional clarity and possibility of social desirability bias (i.e., participants not wanting to report uncertainty about their feelings) [12,16]. For the potential utility to be realized however, further investigations of the validity of indirect measures of emotional clarity are needed.

Assessing emotional clarity with item response times

Response times (RTs) to emotion questions in ecological momentary assessments (EMAs) have been argued to be indirect measures of emotional clarity at the momentary (within-person) level [12]. Theoretically, the greater an individual's momentary affective clarity, the less time should be needed to provide a rating of momentary affect [12], whereas longer RTs to affect items should be indicative of lower emotional clarity. Evidence supporting this theory has been found, such as shorter RTs to affect items being associated with better momentary emotion regulation and mood [12]. However, emotional clarity may be confounded with emotional intensity [9] and evidence suggests the validity of RTs as a measure of affective clarity is enhanced by controlling for emotional intensity at the within (and not between) person level [17].

There was not strong evidence that the study long aggregate of emotion item RTs (between-person level) could act as indicators of trait emotional clarity [12,17]. These aggregates were found to not have significant relationships with global measures of emotional clarity, and inconsistent relationships with global emotion regulation measures [12,17]. Suggested reasons for the lack of a relationship between global measures of emotional clarity and the aggregate of emotion item RTs include a modality difference (i.e., self-report versus indirect behavior-based assessment), low conceptual correspondence (i.e., different forms of emotional clarity are being assessed), and difference in assessment timing (i.e., one time versus repeated EMA measurement) [12,17]. The relationships between the study long aggregate of emotion item RTs and subjective well-being variables of relevance to emotional clarity (e.g., depression and anxiety) [8,18] were not examined, which could have served as useful additional convergent validity tests. Finally, the possibility that processing speed had a confounding effect on correlations between study long aggregates of emotion item RTs and other variables was not investigated. In prior research, RTs to emotion EMA items have been found to have moderate correlations with processing speed measures [19], suggesting that individual differences in emotion item RTs may at least in part be attributable to processing speed.

Assessing emotional clarity with the drift rate parameter

Another indirect measure of emotional clarity was recently proposed, drift rate, which is computed using the drift diffusion model [20]. This model, which is often used in cognitive psychology, was explicitly developed to disentangle different components of RTs [21]. The drift diffusion model proposes that decisions (e.g., choosing responses on EMA items) are made by the accumulation of information until a threshold of sufficient information (as determined by the individual) is reached [21]. Decisions can be fast if the speed of information accumulation (i.e.,

drift rate) is fast, if the threshold for a decision (i.e., boundary separation, or response caution) is low, or both. The D-diffusion IRT model is an item response theory (IRT) version of the drift diffusion model that was specifically designed for the analysis of self-report ratings such as emotion ratings [22]. In the context of answering mood questions, the D-diffusion IRT model additionally considers that response times may also be fast if extremes of the emotion are experienced (i.e., very high or low levels), making the provision of ratings more straightforward [20]. When the D-diffusion model is applied to EMA responses and their RTs, it can take into account all the aforementioned influences on response times and output drift rate. In the EMA context drift rate can be interpreted as speed of access to information relevant to the question being asked [20,21], which here is information regarding emotions. A more detailed description of how the drift rate parameter was computed can be found in the methods section, under "Emotional clarity measure 2: Drift rate from drift-diffusion model.

A person would be considered to have high emotional clarity when responding both fast and carefully to emotion items, which differs from how emotional clarity assessed via RTs considers only speed. As the absolute difference between a person's negative affect level and level of negative affect captured by an item increases, the D-diffusion model assumes that an individual would be expected to have faster response times as a result of the so-called "distance-difficulty" principle, a well-established phenomenon in the RT literature [23] whereby items are easier the more they contrast with a person's state. For instance, an individual very low on negative affect would be expected to quickly respond to an item asking about being scared (an item often associated with high negative affect) [24], whereas the same individual would be expected to require a longer RT for an item asking about irritability (which has been associated with low negative affect) [24]. According to the D-diffusion model, response caution is low

when a person responds similarly quickly (or slowly) to all items regardless of their content (an indication that the person did not answer carefully). Assuming a particular observed item RT, when response caution is lower (i.e., less information is gathered), drift rate (i.e., rate of information accumulation, or information divided by time) would also be lower. Conversely, for a person with a higher response caution, the estimated drift rate (and emotional clarity) would be greater for the same RT.

Our initial evidence suggested that the drift rate parameter derived from EMA negative affect items may be an indicator of emotional clarity of low versus high negative affect, including expected relationships (i.e., negative associations) at the between-person level with neuroticism and depression [20], but we did not account for factors aside from emotional clarity that could impact drift rate. For instance, drift rate could be impacted by individual differences in general speed of responding on questionnaires (e.g., due to reading speed, motor behavior, and familiarity with computer usage). Studies on emotional clarity measured by survey item RTs had accounted for individual differences in this baseline speed of responding by adjusting for it [12], but this was not done in our prior study [20]. Cognitive processing speed was hypothesized to also potentially impact drift rate, but was also not adjusted for as the measure was not available in the prior study [20].

1.3 The present study

There has been substantial prior research and interest in examining emotional clarity as a trait [12,14,15], but further research on indirect (instead of direct) measurement of individual differences in emotional clarity via EMA data is needed. Compared to traditional cross-sectional self-report measures, indirect measurement of individual differences in emotional clarity potentially has the advantage of less susceptibility to self-report biases stemming from causes

such as social desirability and poor insight [12,16]. Furthermore, if emotion is being assessed via EMA, *indirect assessment of emotional clarity via emotion items affords the possibility of capturing individual differences in emotional clarity without burdening participants with additional items*. Use of EMA methodology is ubiquitous in a broad range of fields [25–27], and use of EMA emotion items is commonplace [28]. Indirect assessment of trait emotional clarity would therefore make investigation of emotional clarity possible for a large number of EMA datasets without additional emotional clarity items.

The focus of this paper was to examine the reliability and validity of two RT based indirect indicators of individual differences in emotional clarity in adults with type 1 diabetes (T1D). One indicator was the average of repeated measures of RTs to emotion items, and the other was the average of repeated measures of drift rate (i.e., the speed of accessing information about one's current affect) derived from emotion items. In validity testing, in contrast to prior work [20], individual differences in baseline speed of responding and processing speed were controlled for. We examined data from an EMA study of adults with T1D [29]. EMA surveys (which included emotion items) were completed 5-6 times a day (depending on the participants' sleep schedule) for two weeks, and the RTs for the completion of each item were recorded. Note that the RT based metrics can vary within people, and their study long averages can vary across people. Multilevel modeling was used to account for both these potential sources of variance.

Emotional clarity may be of particular relevance for adults with T1D. Compared to the general population, adults with T1D may be exposed to stressors more frequently, specifically emotional distress related to daily care of diabetes. A prior study estimated that performing all recommended diabetes self-management activities would require more than two hours daily [30]. Given such burden and associated diabetes distress (emotional distress specific to the daily care

of diabetes), individuals with diabetes are more likely to experience lower subjective well-being compared to healthy populations such as more symptoms of depression [31]. Diabetes distress has been found to be negatively associated with emotion regulation ability [32]. Thus, emotional clarity, a possible precursor to emotion regulation [10], may be integral for adults with T1D to cope with the burden of the condition. Poor coping with diabetes can lead to neglect of diabetes self-management behaviors, which can amplify the health consequences of diabetes. Greater diabetes distress has been associated with lower adherence to insulin regimens [33,34], while greater depressive symptoms has been associated with lower adherence to diet, exercise, and glucose testing recommendations [35].

Reliability

Reliability of the proposed measures for emotional clarity was investigated by examining the test-retest stability of the measures across EMA measurement occasions.

Validity

Validity of the RT-based indicators of emotional clarity was tested by examining their associations with well validated measures of relevance to emotional clarity. In forming our hypotheses (summarized in Table 1), we made a distinction between clarity of positive affect (PA) and clarity of negative affect (NA) because of prior research suggesting that the latter had associations with mental health while the former did not [9]. Thus, we speculated that awareness of NA is a more direct precursor to application of coping strategies and successful coping, relative to awareness of PA.

Table 1. Hypothesized associations of the negative and positive affect clarity indicators with subjective well-being and emotion regulation.

	Emotional Clarity Indicator									
	NA	Drift	PA	Drift	NA RT ^a	PA RT ^a				
	Rate		Rate							
Subjective well-being										
Satisfaction with Life	Pos.		Null		Pos.	Null				
Neuroticism	Neg.		Null		Neg.	Null				
Depression	Neg.		Null		Neg.	Null				
Anxiety	Neg.		Null		Neg.	Null				
Diabetes distress	Neg.		Null		Neg.	Null				
Emotion regulation and its										
six components										
Emotion regulation	Neg.		Null		Neg.	Null				
Difficulties (overall)										
1.Limited Strategies	Neg.		Null		Neg.	Null				
2.Non-acceptance	Neg.		Null		Neg.	Null				
3.Impulse control difficulties	Neg.		Null		Neg.	Null				
4.Difficulties with goal	Neg.		Null		Neg.	Null				
directedness										
5.Lack of Awareness	Neg.		Neg.		Neg.	Neg.				
6.Lack of emotional	Neg.		Neg.		Neg.	Neg.				
clarity						-				

Neg.-negative; NA-negative affect; PA-positive affect; Pos.-positive; RT-response time;

Hypothesized associations with subjective well-being

Past literature has found that increased emotional clarity and emotion regulation ability, as assessed by questionnaires or response times to emotion items, was associated with greater subjective well-being, including greater life satisfaction [36], lower neuroticism [9], lower depression [18], fewer anxiety symptoms [8], and less diabetes distress [32]. However, following the results by Thompson et al. (2015), we hypothesized that these relationships should only hold for indicators of NA clarity, not PA clarity.

Hypothesized associations with emotion regulation

We considered the valence of emotions in the generation of our hypotheses regarding associations between passively collected indicators of emotional clarity and emotion regulation,

^aMultiplied by -1 so that higher values indicate greater emotional clarity

given previous work showing that clarity of positive emotions had different associations with other measures (e.g., neuroticism, depression) compared to clarity of negative emotions [9]. The Difficulties in Emotion regulation Scale (DERS) [15] has six subscales representative of emotion regulation components (listed in Table 1), as well as an overall score. Four of the six DERS subscales specifically assess problems with regulating NA (i.e., limited access to emotion regulation strategies when upset, nonacceptance of negative emotional responses, impulse control difficulties when upset, and difficulties with goal-directed behaviors when upset); we hypothesized that greater difficulties indicated on each of these component scales would be associated with lower NA clarity on the proposed RT based measures [10], whereas we did not expect them to be associated with PA clarity using the RT based measures (Table 1). That is, we expected NA clarity to precede and hence be more relevant to NA regulation than PA clarity, consistent with prior findings of associations between neuroticism and NA clarity, but not PA clarity [9]. The remaining two components of emotion regulation (lack of emotional awareness, and lack of emotional clarity) are not specific to the regulation of NA [15]; thus, we hypothesized that they would be associated with the clarity of both NA and PA using the RT based measures. Note that one of these two components assesses self-reported emotional clarity; we expected that this component would have associations of greater magnitude with RT based measures of NA/PA clarity compared to other emotion regulation subscales. Finally, we hypothesized an association between the DERS total score and indicators of NA clarity, but not indicators of PA clarity, because four of the six DERS subscales were relevant to emotion regulation when experiencing NA.

Adjustment by individual differences in RT and processing speed

We examined whether adjusting the RT based emotional clarity indicators by individual

differences in RT and participant processing speed would affect the results of the convergent/divergent validity tests. Both RTs to survey items and drift rate were expected to not be purely indicators of emotional clarity, but likely also impacted by processing speed [19,20,37] and differences in baseline speed of responding [12]. Thus, we examined the robustness of the results of validity testing when statistically adjusting for both these variables.

Methods

The analyzed data was from an EMA study focused on investigating the relationships between momentary blood glucose, emotional state, and functioning in adults with T1D [29]. Participants were recruited from three clinical sites through healthcare provider referrals, mailings, flyers, and emails. Inclusion criteria included having a diagnosis of T1D, being able to speak and read English or Spanish, and ability and willingness to carry out study procedures (e.g., completion of EMAs and cognitive tests on smartphones). Informed consent was provided before study participation. Study procedures included completion of baseline surveys, training in use of study devices, two weeks of 5-6 EMAs and ambulatory cognitive tests daily, and followup surveys. EMA surveys began at participants' selected wake up time each day, and were administered at three hour intervals after that until sleep time. If a participant reported that she would likely be sleeping by the time of the sixth survey (i.e., 15 hours after the first survey), then she was given the option to complete 5 surveys daily instead of 6. To encourage EMA compliance, three brief check-in emails/calls were scheduled with study staff. Additionally, if EMA survey completion was low, then study staff would contact the participant to guery if any support was required. The study procedures are described in greater depth in a protocol paper [29]. All study procedures were approved by the University of Southern California's Institutional Review Board (Proposal #HS-18-01014).

Measures

RT Based Measures of Emotional Clarity

Clarity of PA was assessed with RTs from EMA items about how happy/content/enthusiastic/excited participants felt right now, while clarity of NA was assessed with RTs from EMA items asking how tense/upset/sad/disappointed participants felt. These emotion adjectives were taken from the "Stress and Working Memory" study [38], and were chosen because they mapped neatly onto the circumplex model of affect [39]. That is, there were two items in each of the circumplex dimensions (i.e., unpleasant-activated, unpleasant-deactivated, pleasant-activated, and pleasant-deactivated) thereby ensuring that a range of emotion types were represented. The responses were all given on slider scales from 0 (not at all) to 100 (extremely). These emotion items were administered at every EMA prompt using the Mobile EMA application (mEMA: ilumivu.com) application. Items were presented one at a time on study provided smartphones. For each item, RTs were recorded in milliseconds. RTs that were deemed too fast (i.e., less than 0.2 seconds) or too slow (i.e., greater than 30 seconds) were set to missing for analyses (1.3% of observations) because such outliers could be indicative of careless responding or distractions during survey completion [20,40].

Emotional clarity measure 1: median RTs

NA and PA clarity were computed as the median RT of the four NA items and the median RT of the four PA items at each EMA prompt [12,17] (RTs were multiplied by negative one such that higher values indicate greater clarity). In this paper, median NA RT will be referred to as NA RT, and median PA RT as PA RT.

Following prior research, the median RTs were adjusted for baseline speed of responding, to partial out individual differences in RT stemming from factors such as reading and

screen tapping speed [12,17]. We assessed participants' baseline speed by taking the median RT across all EMA occasions on a multiple-choice question asking what they were doing immediately prior to the survey.

Emotional clarity measure 2: Drift rate from drift-diffusion model

Drift rate for both the NA and PA items were calculated for each EMA following procedures described in detail in a prior study [20] with software code available at https://osf.io/r82hn/. In brief, we estimated the drift rates for each person and EMA measurement occasion using item-response theory (IRT) based variant of the drift diffusion model that was specifically developed for use with self-report (e.g., EMA) items. Because the IRT model requires binary variables, responses to the PA and NA items were converted into dichotomous variables such that responses below the midpoint of the scale were coded as 0, while responses at or above the scale midpoint were coded as 1. Previous analyses have shown that drift rate measures derived from continuous items that were dichotomized demonstrate convergent validity with items that were already presented to respondents in a binary response format [20]. Next, we examined if the dichotomized PA and NA item sets were unidimensional, a condition necessary for calculation of drift rate; we conducted a confirmatory factor analysis in Mplus version 8.8 [41] using the WLSMV estimator, employing cluster-robust standard errors to account for the nesting of multiple EMA measurement occasions within individuals. We examined if fit indices were within the traditional ranges for acceptable model fit, including root mean square error of approximation (RMSEA) of at least <0.08, comparative fit index (CFI) and Tucker–Lewis Index (TLI) of at least >0.90, and standardized root mean square residual (SRMR) < 0.08 [42]. Within and between-person reliability (McDonald's omega) coefficients were also computed for the dichotomized and non-dichotomized NA and PA items [51].

A drift diffusion model was then applied to the RTs and dichotomized response values for PA and NA items using the diffIRT package in R [22], where drift rate and RTs were modeled as latent factors. Factor score estimates for the drift rate parameter were then calculated for each EMA occasion, separately for NA and PA. To examine the fit of the drift diffusion model on the PA and NA item sets, we examined the level of consistency between observed and diffusion model predicted RT distributions with histograms and density plots.

The drift rate parameters used in our primary analyses are a processed version of the drift rate parameters from the diffusion IRT models referred to as "absolute drift rate", computed as the mean absolute difference between the drift rate parameter factor scores and the item difficulty levels. The drift rate parameter is an estimation of a person's tendency to report high NA (or PA) in a moment, after taking into account both a person's responses and item RTs. However, emotional clarity should be indicated by speed in carefully accessing one's mood regardless of its valence (e.g., high or low NA). Thus, following the distance-difficulty hypothesis informed formula for speed of information accumulation in the D-diffusion model [22], we found the absolute value of the difference between the drift rate parameter and average item difficulty, and operationalized this absolute drift rate as emotional clarity. These absolute drift rates were then log transformed to normalize their distributions. When used in analyses, drift rates were also adjusted by baseline speed.

Other measures

The measures used for convergent/divergent validity testing were completed prior to ("baseline") or after ("follow-up") the EMA study period. Life satisfaction was assessed with the Satisfaction with Life Scale (SWLS) [43], neuroticism with the Ten Item Personality Inventory (TIPI) [44], depression with the Patient Health Questionnaire (PHQ) [45], anxiety with the

Generalized Anxiety Disorder Scale (GAD) [46], diabetes distress with the Problem Areas in Diabetes Scale short form (PAID-5) [47], and emotion regulation with the Difficulties in Emotion Regulation Scale short form (DERS-SF) [15]. The TIPI, PHQ, GAD, and DERS were administered at baseline while the SWLS and PAID were completed at follow-up [29].

Processing speed was assessed with the Symbol Search task [48], an ambulatory cognitive test administered as part of every EMA prompt [29]. The Symbol Search task captured perceptual speed, which is one component of processing speed [48,49]. Participants were presented with two cards at the top and two at the bottom of the phone screen, each with two symbols. As quickly as they could, they were asked to choose the card at the bottom of the screen that matched one of the cards on top. The task consisted of 20 trials, and processing speed was measured as the median RT in accurate trials, only for sessions with at least 70% matching accuracy [48]. Symbol Search RTs were calculated such that higher values indicate faster processing speed.

Statistical Analyses

Reliability

Reliability was assessed for each of the emotional clarity indicators: NA drift rate, PA drift rate, NA RT, and PA RT. It was calculated using the formula Between-Person Reliability= Var(BP)/(Var(BP) + Var(WP)/n) [50], where Var(BP) is the between-person variance in the average of scores across measurement occasions (i.e., EMA prompts), Var(WP) is the variance of scores across measurement occasions within a person, and n is the number of measurement occasions. Var(BP) and Var(WP) were calculated with multilevel models, with EMA prompts nested in individuals, where the measure of interest (e.g., NA drift rate) was specified at both Level 1 and Level 2. To examine how many measurement occasions would be needed to obtain

acceptable reliability (≥ 0.7) for each emotional clarity indicator, we estimated how reliability changed as a function of the number of measurement occasions, moving from two EMA prompts to a maximum of 70 prompts. M*plus* version 8.10 [41] was used for reliability analyses via the package MplusAutomation [52] in the statistical software R [53].

Validity

Validity testing was performed for average NA drift rate, PA drift rate, NA RT, and PA RT. To account for the nested data structure, with multiple EMA prompts nested in individuals, we estimated correlation coefficients between the emotional clarity indicators and other measures using multilevel structural equation models (MSEM). Multilevel variables with both within- and between-person variance (NA drift rate, PA drift rate, NA RT, PA RT, processing speed) were specified at both Level 1 (within-person) and Level 2 (between-person), with latent means estimated at Level 2 of the MSEM. As all cross-sectional measures only contained betweenperson variance, they were entered into the MSEM at Level 2 and allowed to correlate with the NA drift rate, PA drift rate, NA RT, and PA RT variables. To adjust for individual differences in baseline speed, NA drift, PA drift, NA RT, and PA RT were regressed on baseline speed at Level 2 of the MSEM. Additionally, covariances were specified between baseline speed and all other level 2 variables. Prior research indicated that response times to tasks were affected by time of day [19,54]. Thus, at level 1 all the RT based metrics were adjusted for (i.e., regressed on) time of day coded as a categorical variable where a participants' first survey per day was categorized as taking place in the morning, final scheduled survey of the day as evening, and all surveys in between as midday. The reference group was "midday", meaning that at level 2 the latent means for the RT based metrics were for midday surveys.

Various sensitivity tests were also conducted. Separate multilevel regression models

explored whether adjustment for emotional intensity impacted the relationships between RT and each cross-sectional measure, such that NA RT and PA RT were additionally regressed on linear and quadratic terms of overall NA and PA ratings (i.e., average rating across NA or PA items within an EMA survey), respectively. In supplemental analyses in which all the proposed emotional clarity indicators were controlled for processing speed, they were all regressed on processing speed at level two. Finally, we tested if the association between NA/PA drift and other measures would differ if the drift metrics were computed from mood items that were dichotomized at each person's mean NA/PA response rather than the scale midpoint. For all analyses, data from all participants was included regardless of completion rates, because MSEM models estimate latent averages of variables at level 1 that account for potential unreliability stemming from sparse participant data [55]. All validity analyses were conducted in Mplus version 8.10 [41] using maximum likelihood with robust standard errors. Code for both the reliability and validity analyses is provided at https://osf.io/gc7ez/.

Results

Characteristics of the study sample, 196 adults with T1D, are shown in Table 2. The median EMA completion rate over the 2-week study period was 92%, with ranges from 17% to 100% completion. Descriptives for the EMA variables are shown in Table 3. Distributions for RTs to individual NA and PA items are shown in Figures S1 and S2 respectively in Appendix 1. Tables S1 and S2 in Appendix 1 show the between-person correlations between (unadjusted) study measures.

Table 2. Participant characteristics.

Characteristic	Mean (SD) or n (%)
Age (years, range 18-75)	39.6 (14.3)
Gender	
Male	88 (44.9%)

Female	108 (55.1%)
Ethnicity	
White	56 (28.6%)
Latino	80 (40.8%)
African American	29 (14.6%)
Multi-ethnic	14 (7.1%)
Asian	7 (3.6%)
Other	6 (3.1%)
Not reported	4 (2.0%)
Employment Status	
Full-time	69 (35.2%)
Part-time	23 (11.7%)
Full-time homemaker	9 (4.6%)
Student	18 (9.2%)
Unemployed	27 (13.8%)
Retired	15 (7.7%)
Disabled	23 (11.7%)
Other	8 (4.1%)
Not reported	4 (2.0%)
Annual household income	
< \$25,000	47 (24.0%)
\$25,000-\$49,999	43 (21.9%)
\$50,000-\$74,999	15 (7.7%)
≥\$75,000	40 (20.4%)
Not provided	51 (26.0%)
Mental health ^a	
SWLS score (range 5 to 35)	22.0 (7.5)
TIPI neuroticism (range 1 to 7)	3.2 (1.3)
PHQ score (range 0 to 24)	5.4 (4.3)
PHQ>=9, moderate or	30 (15.3%)
higher depression	
GAD score (range 0 to 21)	4.6 (3.8)
GAD>=9, moderate or	19 (9.7%)
higher anxiety	
PAID (range 0 to 20)	8.0 (5.5)
DERS (range 1 to 5)	1.9 (0.6)
DERS- Difficulties in emotion regulation sca	ale: GAD- Generalized Anxie

DERS- Difficulties in emotion regulation scale; GAD- Generalized Anxiety Disorder Assessment; PAID- Problem areas in diabetes scale assessing diabetes distress; PHQ- Patient health questionnaire; SWLS- Satisfaction with life scale; TIPI- Ten item personality inventory

^aNote that possible score ranges for the surveys were listed. Only for GAD was the observed score range (0 to 19) different from the possible range.

Table 3. Summary statistics for EMA variables.

						variances
NA drift rate	-0.05 (0.84)	-2.43 to 2.31	0.19	0.54	0.27	0.27
PA drift rate	-0.53 (0.83)	-1.68 to 2.05	0.19	0.51	0.28	0.18
NA RT	2.22 (1.70)	0.31 to	0.70	1.95	0.26	1.00
		24.20				
PA RT	2.39 (1.83)	0.22 to	0.84	2.02	0.29	0.89
		28.24				
Sum of 4 NA	19.69	0 to 100	247.10	243.15	0.50	1.60
items	(20.26)					
Sum of 4 PA	49.78	0 to 100	338.85	327.01	0.51	1.40
items	(23.87)					
Sum of dichot.	0.71 (1.21)	0 to 4	0.75	1.95	0.28	3.27
NA items						
Sum of dichot.	2.43 (1.50)	0 to 4	1.05	1.88	0.36	1.64
PA items						

dichot.- dichotomized; ICC-intraclass correlation coefficient; NA-negative affect; PA-positive affect; RT-response time;

A unidimensional model was found to fit both the (dichotomized) four NA and four PA items acceptably, justifying the calculation of drift rates for both types of items. For NA, $\chi 2=10.64$, p=.005; CFI = .998; TLI = .994; RMSEA = .018; SRMR = .018, while for PA, $\chi 2=53.33$, p<.001; CFI = .989; TLI = .966; RMSEA = .044; SRMR = .031. All these values were within commonly suggested ranges for acceptable model fit [42]. The within-person omega estimate for the four dichotomized NA items was 0.710, while the between-person omega estimate was 0.938. For the four dichotomized PA items, the within-person omega estimate was 0.674 and the between-person omega estimate was 0.939. The within-person omega estimate for the four non-dichotomized NA items was 0.793, while the between-person omega estimate was 0.955. For the four non-dichotomized PA items, the within-person omega estimate was 0.773 and the between-person omega estimate was 0.937. For all PA and NA items, the observed RT distributions (histograms) were consistent with drift diffusion model predicted RT distributions as per density plots of these RTs (Figures S1 and S2 in Appendix 1), indicating good fit overall for the drift diffusion IRT model [22].

Reliability

Figure S3 in Appendix 1 shows the between-person reliabilities as a function of number of EMA prompts completed, for each proposed emotional clarity indicator. For all indicators, reliability increased with more prompts, but each of the proposed emotional clarity indicators demonstrated acceptable reliability (i.e., .70 or greater) with a relatively small number of EMA occasions. NA RT required 5 EMA prompts for acceptable reliability, and PA RT required 4 prompts. Both average NA and PA drift rate showed .70 reliability when 7 EMA prompts were completed.

Validity

Relationships between NA RT and other measures were not consistent with our hypotheses. No significant associations were found with subjective well-being or emotion regulation measures (Table 4). PA RT was not significantly associated with any variable except, unexpectedly, for diabetes distress (r=0.17, P=.009). After adjustment for processing speed, the associations between both NA RT and PA RT and diabetes distress were unexpectedly significant in a positive direction (r=0.14, P=.030 and r=0.20, P=.002, respectively). Adjustment for emotional intensity changed effects very minimally at the between-person level, consistent with findings of a prior study [17], so results from that model were not reported here. Both NA RT and PA RT had significant associations with processing speed (r=0.24, P<.001 and r=0.21, P=.001, respectively).

Table 4. Between-person correlations between emotional clarity indices and other measures. All correlations were adjusted for baseline speed of responding and time of day, but only columns with "adjusted" additionally had processing speed as a control variable.

	NA	Drift	NA	Drift	PA	Drift	PA	Drift	NA RT ^c	NA	RT,	PA RT ^c	PA	R
	Rate		Rate,	,	Rate		Rate,	,		adjust	$ed^{\scriptscriptstyle \mathrm{b,c}}$		adjuste	$\mathrm{d}^{\mathrm{b,c}}$
			adjus	sted ^b			adjus	sted ^b						
Subjective we	ll-being													
Satisfaction with Life	.1 (P	=.174)	.1 (P	=.18)	1 (P=.0	92)	1 (P=.0	093)	03 (<i>P</i> =.673)	04 (P=.57	7)	04 (<i>P</i> =.513)	05 (P	=.445

								'
Neuroticism	18	18	08	08	06	06	01	01 (P=.854
	$(P=.011)^{a}$	$(P=.01)^{a}$	(P=.294)	(P=.288)	(P=.509)	(P=.437)	(P=.906)	!
Depression	27	27	.03	.03	0 (P=.982)	0 (P=.985)	.06	.06 (P=.454)
	$(P \le .001)^a$	$(P \le .001)^a$	(P=.725)	(P=.725)			(P=.472)	!
Anxiety	27	 27	09	09	09	09	03	03 (P=.74)
	$(P \le .001)^a$	$(P \le .001)^a$	(P=.212)	(P=.209)	(P=.338)	(P=.284)	(P=.766)	!
Diabetes	17	16	.17	.17	.09 (P=.14)	.14	.17	.2 (P=.002) ^a
distress	$(P=.005)^{a}$	$(P=.008)^{a}$	$(P=.009)^{a}$	$(P=.008)^{a}$	•	$(P=.03)^{a}$	$(P=.009)^{a}$	
Emotion regula	ation							
DERS (total)	15	16	.03	.03	.03	.01	.05	.03 (P=.576)
,	$(P=.026)^{a}$	$(P=.014)^{a}$	(P=.767)	(P=.779)	(P=.639)	(P=.917)	(P=.393)	1
1.Limited	15	15	.03	.03	04	04	03	03 (P=.673
Strategies	$(P=.048)^{a}$	$(P=.042)^{a}$	(P=.759)	(P=.755)	(P=.589)	(P=.592)	(P=.66)	
2.Non-	1	11	.04	.03	01	03	0 (P=.934)	01 (P=.85)
acceptance	(P=.176)	(P=.134)	(P=.642)	(P=.658)	(P=.866)	(P=.606)	0 (=)	··- (- ·/
3.Impulse	.02	.03 (P=.65)	` '	.13	.02	.04	.02	.05 (P=.327)
control	(P=.764)	.00 (2 .02)	(P=.184)	(P=.184)	(P=.788)	(P=.392)	(P=.671)	100 (1 101)
difficulties	(1 ., 5 .)		(1 .10.)	(1 .10 .)	(1 1,00)	(1 .552)	(1 .0, 1)	
4.Difficulties	07	08	11	11	.11	.09	.08	.06 (P=.362)
with goal	(P=.323)	(P=.261)	(P=.198)	(P=.183)	(P=.082)	(P=.132)	(P=.252)	100 (1 100-)
directedness	(1 .020)	(1 .201)	(1 .155)	(1 .100)	(1 .002)	(1 .102)	(1 .252)	
5.Lack of	18	18	09	09	07	1	01	03 (P=.642
Awareness	$(P=.009)^{a}$	$(P=.005)^{a}$	(P=.201)	(P=.18)	(P=.346)	(P=.194)	(P=.843)	.05 (1 .5.2
6.Lack of	11	12	.04	.04	0 (P=.945)	03	.03	0 (P=.949)
emotional	(P=.127)	(P=.094)	(P=.586)	(P=.594)	0 (15-5)	(P=.64)	(P=.732)	0 (1 –.545)
clarity	(112/)	(105-)	(1500)	(I =.55 -1)		(1 –.04)	(1752)	
Processing	.09		.02		.25		.21	
Speed (control	(P=.176)	_	.02 (P=.777)		$(P < .001)^a$	_	$(P=.001)^{a}$	_
variable)	(F170)		$(\mathbf{r}///)$		(I \.001)		(I001)	
variable)								

DERS- Difficulties in Emotion Regulation Scale; NA-negative affect; PA-positive affect; RT-response time; ^ap<.05

The associations between NA drift rate and other measures were consistent with our hypotheses overall. Unexpectedly, NA drift rate was not related to lack of emotional clarity (though the relationship was approaching significance) or three of the other DERS subscales (Table 4). It was also not associated with life satisfaction. However, Greater NA drift rate was significantly associated with lower neuroticism (r=-0.18, P=.011), depression (r=-0.27, P<.001), anxiety (r=-0.27, P<.001), diabetes distress (r=-0.17, P=.005), lower overall difficulties with emotion regulation (total DERS score, r=-0.15, P=.024), less limited emotion regulation strategies (r=-0.15, P=.026), and lower lack of emotion awareness (r=-0.18, P=.009). Adjustment by processing speed resulted in minimal changes. When NA and PA drift rates were computed

^bAdjusted for processing speed

^cMultiplied by -1 so that higher values indicate greater emotional clarity

from mood items that were dichotomized at each person's mean NA and PA ratings (rather than at the scale midpoint), the results showed mostly non-significant correlations with other measures (see supplementary Table S3).

Consistent with expectations, PA drift rate was not significantly associated with most subjective well-being or NA-specific emotion regulation measures. Unexpectedly, PA drift rate was not significantly associated with emotional clarity or emotional awareness before or after adjustment for processing speed. Also contrary to expectations, greater PA drift rate was associated with greater diabetes distress (r=0.17, P=.009). Neither NA drift rate or PA drift rate had significant associations with processing speed. Without adjustment for baseline speed, a few of the associations differed, such as the relationship between NA drift rate and life satisfaction (r=0.16, P=.022) (Table 5).

Table 5. Between-person correlations between emotional clarity indices and other measures. Correlations were adjusted for time of day but not baseline speed of responding, and only

columns with "adjusted" had processing speed as a control variable.

	NA Drift Rate	NA Drift Rate, adjusted ^b	PA Drift Rate	PA Drift Rate, adjusted ^b	NA RT ^c	NA RT, adjusted ^{b,c}	PA RT ^c	PA RT, adjusted ^{b,c}
Subjective well-	being							
Satisfaction	.16	.14	0 (P=.96)	03	.1 (P=.15)	.06	.09	.05
with Life	$(P=.022)^{a}$	(P=.05)		(P=.671)		(P=.398)	(P=.15)	(P=.422)
Neuroticism	14	16	05	06	01	04	.02	0 (P=.938)
	$(P=.037)^{a}$	$(P=.019)^{a}$	(P=.475)	(P=.376)	(P=.866)	(P=.625)	(P=.74)	
Depression	27	28	01	0 (P=.995)	05	04	01	0 (P=.949)
	$(P < .001)^{a}$	$(P < .001)^{a}$	(P=.917)		(P=.432)	(P=.57)	(P=.846)	
Anxiety	25	26	08	09	07	08	03	03
	$(P \le .001)^a$	$(P < .001)^{a}$	(P=.237)	(P=.211)	(P=.336)	(P=.236)	(P=.686)	(P=.643)
Diabetes	25	2	.04	.1	08	.03	04	.07
distress	$(P < .001)^a$	$(P=.003)^{a}$	(P=.528)	(P=.169)	(P=.229)	(P=.667)	(P=.59)	(P=.325)
Emotion regula	tion							
DERS (total)	15	17	0 (P=.97)	01	01	04	0 (P=.949)	02
	$(P=.045)^{a}$	$(P=.009)^{a}$		(P=.916)	(P=.91)	(P=.513)		(P=.702)
1.Limited	12	13	.03	.04	02	02	01	01
Strategies	(P=.115)	(P=.073)	(P=.701)	(P=.666)	(P=.812)	(P=.782)	(P=.896)	(P=.897)
2.Non-	06	09	.06	.04	.04	01	.05	0 (P=.947)
acceptance	(P=.409)	(P=.184)	(P=.421)	(P=.606)	(P=.584)	(P=.832)	(P=.444)	
3.Impulse	0 (P=.992)	.03	.09	.12	02	.04	02	.04
control		(P=.666)	(P=.364)	(P=.214)	(P=.79)	(P=.482)	(P=.821)	(P=.472)
difficulties		0.0	_	4.5		0.4	0.4	0.4
4.Difficulties	07	09	1	12	.07	.04	.04	.01

Passive Emotional Clarity Measures

24

with goal directedness	(P=.352)	(P=.205)	(P=.234)	(P=.144)	(P=.273)	(P=.457)	(P=.468)	(P=.789)
5.Lack of	19	21	12	13	1	14	06	09
Awareness	$(P=.01)^{a}$	$(P=.002)^{a}$	(P=.125)	(P=.07)	(P=.129)	$(P=.024)^{a}$	(P=.319)	(P=.12)
6.Lack of	14	16	01	02	07	1	05	07
emotional clarity	(P=.072)	$(P=.037)^{a}$	(P=.919)	(P=.812)	(P=.381)	(P=.169)	(P=.543)	(P=.317)
	20		25				40	
Processing	.28	-	.25	-	.5	-	.48	-
Speed (control	$(P < .001)^a$		$(P=.005)^{a}$		$(P < .001)^a$		$(P < .001)^a$	

DERS- Difficulties in Emotion Regulation Scale; NA-negative affect; PA-positive affect; RT-response time;

Discussion

Primary findings

The most notable finding from this study was that average NA drift rate, one proposed indicator of typical emotional clarity, had expected associations overall with validated measures of subjective wellbeing and emotion regulation, both before and after adjustment for processing speed and emotional intensity. In contrast, NA RT, another proposed indicator of typical emotional clarity, did not have the anticipated associations with the validated measures. Relative to NA drift rate, NA RT may be confounded by a greater number of factors aside from emotional clarity.

Nevertheless, there is not sufficient evidence to conclude that average NA drift rate is a valid indicator of NA clarity, while average NA RT is not, due to sample size constraints. In post hoc power analyses, with our sample size of 196 participants there was 80% power to detect a between-person correlation of 0.20. Thus, the study may have been underpowered to detect small correlations that might still be meaningful. Furthermore, the sample size was not chosen a priori to be sufficiently powered to detect between-person relationships after adjustment for multiplicity of testing [56] because the sample size was conditioned on research questions that were more primary for the diabetes EMA study.

^bAdjusted for processing speed

^cMultiplied by -1 so that higher values indicate greater emotional clarity

While we cannot conclude that NA drift rate is a valid indicator of NA clarity, our results suggest that researchers in future studies should continue to investigate NA drift rate as an implicit measure of emotional clarity. We applied stringent validity tests by adjusting for both individual differences in baseline speed of responding and processing speed, and found significant associations between NA drift rate and four of five subjective well-being ratings. Correlations with five of the six emotion regulation subscales were in the expected directions and approaching significance. Finally, note that NA drift rate had a 0.63 (P<.001) correlation with NA RT. People with higher NA drift rate responded faster to the NA emotion items, had greater subjective well-being (e.g., less depression symptoms), and less difficulties with overall emotion regulation, which are all aligned with expectation for an emotional clarity measure. Collectively,

study results suggest that NA drift rate deserves further attention in future research.

Some of the magnitudes of correlations between NA drift rate and other study measures were comparable to sizes of correlations between formal (self-report) assessments of emotional clarity and other measures found in prior studies. One study found that in a group with generalized anxiety disorder a self-report assessment of emotional clarity had correlations of -0.29 and -0.33 with depression and anxiety respectively [57], which are similar to the correlations found here. In the same study, the association between emotional clarity and depression/anxiety was not significant in the healthy control group [57], suggesting that the mental health status of the sample may affect the magnitude of the observed relationships. Other correlations found between emotional clarity and depression were -0.24 in a clinical sample [58] and -0.29 in elementary school age children [59]. Correlations between self-reported emotional clarity and neuroticism have ranged between -0.31 in a sample of adolescents [60] and -0.37 in college students [61], and correlations between emotional clarity and life satisfaction have

ranged between 0.31 in adolescents [62] and 0.35 in undergraduate students [36], which are larger than the correlations observed here.

When NA drift was computed from mood items that were dichotomized at each person's mean response rather than the scale midpoint, no significant associations were observed with other study measures. The distance-difficulty hypothesis underlying the D-diffusion model that was used to generate the NA drift parameter assumes that people respond faster to items that contrast more with their current state [23]. According to this hypothesis, an individual very low on negative affect (regardless of their average level of negative affect) was expected to quickly report not being scared (an item often associated with high negative affect). Dichotomizing mood at each person's own midpoint created a variable representing whether or not their mood was higher or lower relative to their personal average, and not higher or lower in absolute terms (which could be approximated by dichotomizing at the scale midpoint). Perhaps the former was less relevant to the distance-difficulty hypothesis compared to the latter since it captured relative mood and not actual mood, leading to the creation of NA drift parameters with no associations with other study measures.

The reliabilities for average NA drift rate, PA drift rate, NA RT, and PA RT were all acceptable with a small number of EMA prompts (i.e., 4 to 7 EMAs, or 1 to 2 days of EMA surveys). Thus, reliable measurement of these proposed emotional clarity indicators would likely be feasible in most EMA studies where affect items are administered, and RTs are recorded.

Secondary findings

We found preliminary evidence supporting the argument that emotional clarity deficits are valence specific [9]. NA drift rate and PA drift rate had differential associations with self-report measures. Furthermore, they were moderately correlated with each other (r= .38; see

supplementary table S1). Had NA and PA drift rate been redundant with one another, a high correlation would have been expected.

Greater PA drift rate and PA RT were unexpectedly found to be associated with higher diabetes distress, and not associated with the awareness or clarity subscales of the DERS. It is unclear why people with greater diabetes distress would have greater clarity of positive emotions. Perhaps, when overwhelmed with burden from diabetes, people had greater appreciation of positive emotional states, and hence greater clarity of positive affect. One possible reason why PA drift rate and PA RT were not significantly associated with self-reported emotional clarity may have been because, given that other items in the DERS-SF asked questions relevant to the NA context, participants may have been primed to answer the emotional clarity questions with reference to feeling NA. More assessments of the validity of PA drift rate and PA RT are needed.

Future directions

More conclusive evidence of the validity of RT based measures of emotional clarity may come from studies where NA clarity can be manipulated, and the proposed emotional clarity indicators can be compared for sensitivity to these changes. For instance, people that undergo a mindfulness intervention may be expected to have higher NA clarity in the period following the intervention, and this effect should be reflected in changes in drift rates and/or RTs to NA EMA items.

EMA mood item RT based measures of emotional clarity have great potential utility.

They can serve as indices of emotional clarity that do not require burdening participants with additional emotional clarity items. Furthermore, they can help avoid possible issues with subjective reports, including poor insight of emotional clarity and possibility of social

desirability bias [12]. Though the validity of the RT based emotional clarity measures at the within-person level was not investigated here, such validity would allow for investigation of changes in emotional clarity within and across days and the situational factors that contribute to them. For the potential utility of EMA mood item RT based measures of emotional clarity to be realized, further investigations of the validity of EMA RT based measures of emotional clarity (i.e., at both the between and within-person levels) are needed.

Limitations

We had decided not to adjust for multiple comparisons, but to also acknowledge that any results would require replication by future studies. It has been argued that the need for adjustment for multiple comparisons should be evaluated on a case-by-case basis, and not utilized for all analyses [63]. For instance, adjustment for multiple comparisons comes with the benefit of lowering type I error, but also the disadvantage of increasing the chance of type II error. Thus, one factor to consider when deciding whether to adjust for multiple comparisons is the relative cost of type I and type II errors for a particular research question [64]. In confirmatory studies with results that have implications for changes in clinical practice or use of a treatment, the cost of type I error may be higher relative to type II error and hence p-value adjustment for multiple comparisons would be sensible [63]. When performing post-hoc analyses on existing data as part of theory building and testing (and without direct treatment implications), the relative cost of type II error may be higher and hence there may be a stronger argument for not using multiple comparisons adjustment [63]. That is, type II error could cause researchers to not detect potentially important findings [65]. If adjustment is not used, there would need to be acknowledgement that, to account for the possibility of type I error, further research is needed to examine if results can be replicated [63].

Nevertheless, we still tested the effect of false discovery rate (FDR) adjustment on the p-values of correlations for the different groups of hypotheses that were tested (e.g., association between NA drift rate and subjective well-being measures). Adjustments for multiple comparisons are often applied separately for distinct families of hypotheses [66]. Tables S4 and S5 in the appendix show the FDR adjusted p-values associated with Tables 4 and 5 respectively. The biggest differences to note were that several of the associations between NA drift rate and emotional regulation measures were no longer significant.

Use of the drift diffusion model had the advantage of reducing the impact of individual differences in response caution (and potential careless responding) from emotion item RTs, but the disadvantage of assuming a two-choice task (e.g., high versus low NA) underlying people's emotion ratings. Since the drift diffusion model required making the continuous PA and NA items dichotomous for data analysis, granular differences in emotional clarity may be missed with the drift rate parameter.

We were unable to examine within-person validity of RT based clarity measures because measures key to such testing (e.g., self-reported emotional clarity and mood regulation success) [12] were not administered in EMA data collection. Future studies are needed to examine the within-person validity of the drift rate parameter as a within-person indicator of emotional clarity.

The context in which RTs for emotion items were calculated were similar but not identical to prior work. For instance, here median RTs for EMA were calculated based on RTs to 4 items. In prior studies, the median RTs for 5 to 8 items were computed [12,17]. In the original paper examining the validity of RTs to emotion items as indicators of emotional clarity, bipolar mood items were used (e.g., an items with options from 'very unhappy' to 'very happy') [12],

whereas our study analyzed unipolar mood items. Results of this study may have been impacted to an extent by differences in EMA administration, such as variations in the type of emotion items used.

Additional evidence is needed that study results generalize beyond adults with T1D.

Other populations with increased likelihood of experiencing lower subjective well-being (e.g., individuals with various chronic conditions) [67] may be appropriate targets for future emotional clarity studies.

Conclusion

A measure of NA drift rate derived from RTs to momentary NA items had expected associations with validated measures of relevance to emotional clarity, providing initial evidence supporting its validity as an indicator of individual differences in the clarity of negative emotions. The validities of NA RT, PA RT, and PA drift rate were not strongly supported by our results. More studies are needed to investigate the validities of NA/PA drift rate and NA/PA RT with larger sample sizes. Development of passive measures of emotional clarity would help create minimally burdensome measures of emotional clarity that are less vulnerable to possible issues from subjective self-reports such as poor clarity insight and social desirability bias. Such measures may be useful in investigations relevant to the role of emotional clarity in people's experience of well-being.

31

Funding/Acknowledgements

This work was supported by the National Institutes of Health, National Institute of Diabetes and Digestive and Kidney Diseases, under grant number NIH/NIDDK 1R01DK121298-01, and the National Institutes of Health, National Institute of Aging, under grant number NIH/NIA R01 AG068190. The Southern California CTSI supported the use of REDCap in this study (NIH/NCATS UL1TR001855 and UL1TR000130). Additional support was provided by the New York Regional Center for Diabetes Translation Research (NIH/NIDDK P30 DK111022). The Symbol Search cognitive test was developed in a project supported by the National Institute on Aging at the NIH (NIH/NIA #1U2CAG060408-01; Principal Investigator: Martin Sliwinski).

Disclosure of Interest

The authors have no conflicts of interest to report.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author, R.H., upon reasonable request. Code for the primary analyses is provided at https://osf.io/r82hn/. Software code for computing the drift rate parameter is provided at https://osf.io/r82hn/.

Abbreviations

EMA: ecological momentary assessment

NA: negative affect PA: positive affect RT: response time

References

- 1. Kahneman D, Diener E, Schwarz N. Well-Being: Foundations of Hedonic Psychology. Russell Sage Foundation; 1999. ISBN:978-1-61044-325-8
- 2. Stone AA, Mackie C. Subjective well-being: measuring happiness, suffering, and other dimensions of experience. Subjective Well-Being: Measuring Happiness, Suffering, and Other Dimensions of Experience [Internet]. National Academies Press (US); 2013. Available from: https://www.ncbi.nlm.nih.gov/books/NBK179225/ [accessed Jan 15, 2023]
- 3. Tamir M, Chiu CY, Gross J. Business or Pleasure? Utilitarian Versus Hedonic Considerations in Emotion Regulation. Emotion (Washington, DC) 2007 Sep 1;7:546–54. doi: 10.1037/1528-3542.7.3.546
- 4. Ortner CNM, Corno D, Fung TY, Rapinda K. The roles of hedonic and eudaimonic motives in emotion regulation. Personality and Individual Differences 2018 Jan 1;120:209–212. doi: 10.1016/j.paid.2017.09.006
- 5. Coffey E, Berenbaum H, Kerns J. The dimensions of emotional intelligence, alexithymia, and mood awareness: Associations with personality and performance on an emotional stroop task. Cognition and Emotion 2003 Jan;17(4):671–679. doi: 10.1080/02699930302304
- 6. Gross JJ. The Emerging Field of Emotion Regulation: An Integrative Review. Review of General Psychology SAGE Publications Inc; 1998 Sep 1;2(3):271–299. doi: 10.1037/1089-2680.2.3.271
- 7. Gross JJ. Emotion Regulation: Current Status and Future Prospects. Psychological Inquiry 2015 Jan 2;26(1):1–26. doi: 10.1080/1047840X.2014.940781
- 8. Sendzik L, Ö. Schäfer J, C. Samson A, Naumann E, Tuschen-Caffier B. Emotional Awareness in Depressive and Anxiety Symptoms in Youth: A Meta-Analytic Review. J Youth Adolescence 2017 Apr 1;46(4):687–700. doi: 10.1007/s10964-017-0629-0
- 9. Thompson RJ, Kuppens P, Mata J, Jaeggi SM, Buschkuehl M, Jonides J, Gotlib IH. Emotional clarity as a function of neuroticism and major depressive disorder. Emotion 2015 Oct;15(5):615–624. doi: 10.1037/emo0000067
- 10. Vine V, Aldao A. Impaired Emotional Clarity and Psychopathology: A Transdiagnostic Deficit with Symptom-Specific Pathways through Emotion Regulation. Journal of Social and Clinical Psychology 2014 Apr 1;33:319. doi: 10.1521/jscp.2014.33.4.319
- 11. Park J, Naragon-Gainey K. Is More Emotional Clarity Always Better? An Examination of Curvilinear and Moderated Associations Between Emotional Clarity and Internalizing Symptoms. Cogn Emot 2020 Mar;34(2):273–287. PMID:31122138

- 12. Lischetzke T, Angelova R, Eid M. Validating an indirect measure of clarity of feelings: Evidence from laboratory and naturalistic settings. Psychological Assessment 2011;23(2):447–455. doi: 10.1037/a0022211
- 13. Eckland NS, Thompson RJ. State Emotional Clarity Is an Indicator of Fluid Emotional Intelligence Ability. Journal of Intelligence Multidisciplinary Digital Publishing Institute; 2023 Oct;11(10):196. doi: 10.3390/jintelligence11100196
- 14. Salovey P, Mayer JD, Goldman SL, Turvey C, Palfai TP. Emotional Attention, clarity, and repair: exploring emotional intelligence using the trait meta-mood scale. American Psychological Association; 1995;
- 15. Kaufman EA, Xia M, Fosco G, Yaptangco M, Skidmore CR, Crowell SE. The Difficulties in Emotion Regulation Scale Short Form (DERS-SF): Validation and Replication in Adolescent and Adult Samples. J Psychopathol Behav Assess 2016 Sep;38(3):443–455. doi: 10.1007/s10862-015-9529-3
- 16. Lucas RE, Baird BM. Global Self-Assessment. American Psychological Association; 2006; Available from: https://psycnet.apa.org/record/2005-16426-003 [accessed Dec 19, 2023]
- 17. Arndt C, Lischetzke T, Crayen C, Eid M. The assessment of emotional clarity via response times to emotion items: shedding light on the response process and its relation to emotion regulation strategies. Cognition and Emotion 2018 Apr 3;32(3):530–548. doi: 10.1080/02699931.2017.1322039
- 18. Blöte AW, Westenberg PM. The temporal association between emotional clarity and depression symptoms in adolescents. Journal of Adolescence 2019 Feb 1;71:110–118. doi: 10.1016/j.adolescence.2019.01.005
- 19. Hernandez R, Hoogendoorn C, Gonzalez JS, Jin H, Pyatak EA, Spruijt-Metz D, Junghaenel DU, Lee P-J, Schneider S. Reliability and Validity of Noncognitive Ecological Momentary Assessment Survey Response Times as an Indicator of Cognitive Processing Speed in People's Natural Environment: Intensive Longitudinal Study. JMIR mHealth and uHealth 2023 May 30;11(1):e45203. PMID:37252787
- 20. Schneider S, Hernandez R, Junghaenel DU, Orriens B, Lee P-J, Stone AA. Response times in Ecological Momentary Assessment (EMA): shedding light on the response process with a drift diffusion model. Curr Psychol 2023 May 27; doi: 10.1007/s12144-023-04773-0
- 21. Ratcliff R, McKoon G. The Diffusion Decision Model: Theory and Data for Two-Choice Decision Tasks. Neural Comput 2008 Apr;20(4):873–922. PMID:18085991
- 22. Molenaar D, Tuerlinckx F, Maas HLJ van der. Fitting Diffusion Item Response Theory Models for Responses and Response Times Using the *R* Package **diffIRT**. J Stat Soft 2015;66(4). doi: 10.18637/jss.v066.i04
- 23. Ferrando PJ. Person-item distance and response time: An empirical study in personality measurement. Psicológica Universitat de València; 2006;27(1):137–148.

JMIR Preprints

Passive Emotional Clarity Measures

- 24. Medvedev ON, Roemer A, Krägeloh CU, Sandham MH, Siegert RJ. Enhancing the precision of the Positive and Negative Affect Schedule (PANAS) using Rasch analysis. Curr Psychol 2023 Jan;42(2):1554–1563. doi: 10.1007/s12144-021-01556-3
- 25. Fonseca LM, Strong RW, Singh S, Bulger JD, Cleveland M, Grinspoon E, Janess K, Jung L, Miller K, Passell E, Ressler K, Sliwinski MJ, Verdejo A, Weinstock RS, Germine L, Chaytor NS. Glycemic Variability and Fluctuations in Cognitive Status in Adults With Type 1 Diabetes (GluCog): Observational Study Using Ecological Momentary Assessment of Cognition. JMIR Diabetes 2023 Jan 5;8(1):e39750. PMID:36602848
- 26. Kwasnicka D, Kale D, Schneider V, Keller J, Yeboah-Asiamah Asare B, Powell D, Naughton F, Ten Hoor GA, Verboon P, Perski O. Systematic review of ecological momentary assessment (EMA) studies of five public health-related behaviours: review protocol. BMJ Open 2021 Jul;11(7):e046435. doi: 10.1136/bmjopen-2020-046435
- 27. Wrzus C, Neubauer AB. Ecological Momentary Assessment: A Meta-Analysis on Designs, Samples, and Compliance Across Research Fields. Assessment SAGE Publications Inc; 2023 Apr 1;30(3):825–846. doi: 10.1177/10731911211067538
- 28. Scott SB, Sliwinski MJ, Zawadzki M, Stawski RS, Kim J, Marcusson-Clavertz D, Lanza ST, Conroy DE, Buxton O, Almeida DM, Smyth JM. A Coordinated Analysis of Variance in Affect in Daily Life. Assessment 2018 Sep 9;107319111879946. doi: 10.1177/1073191118799460
- 29. Pyatak EA, Hernandez R, Pham L, Mehdiyeva K, Schneider S, Peters A, Ruelas V, Crandall J, Lee P-J, Jin H, Hoogendoorn CJ, Crespo-Ramos G, Mendez-Rodriguez H, Harmel M, Walker M, Serafin-Dokhan S, Gonzalez JS, Spruijt-Metz D. Function and Emotion in Everyday Life with Type 1 Diabetes (FEEL-T1D): A fully remote intensive longitudinal study of blood glucose, function, and emotional well-being in adults with type 1 diabetes. JMIR Res Protoc 2021 Aug 1; PMID:34463626
- 30. Russell LB, Suh D-C, Safford MA. Time requirements for diabetes self-management: too much for many. J Fam Pract 2005;54(1):52–56.
- 31. Gendelman N, Snell-Bergeon JK, McFann K, Kinney G, Paul Wadwa R, Bishop F, Rewers M, Maahs DM. Prevalence and Correlates of Depression in Individuals With and Without Type 1 Diabetes. Diabetes Care 2009 Jan 26;32(4):575–579. doi: 10.2337/dc08-1835
- 32. Coccaro EF, Lazarus S, Joseph J, Wyne K, Drossos T, Phillipson L, Groot M de. Emotional Regulation and Diabetes Distress in Adults With Type 1 and Type 2 Diabetes. Diabetes Care American Diabetes Association; 2021 Jan 1;44(1):20–25. PMID:33444157
- 33. Kumar N, Unnikrishnan B, Thapar R, Mithra P, Kulkarni V, Holla R, Bhagawan D, Kumar A, Aithal S. Distress and Its Effect on Adherence to Antidiabetic Medications Among Type 2 Diabetes Patients in Coastal South India. Journal of Natural Science, Biology, and Medicine Wolters Kluwer -- Medknow Publications; 2017 Dec;8(2):216. PMID:28781491
- 34. Halepian L, Saleh MB, Hallit S, Khabbaz LR. Adherence to Insulin, Emotional Distress,

- and Trust in Physician Among Patients with Diabetes: A Cross-Sectional Study. Diabetes Ther 2018 Apr;9(2):713–726. doi: 10.1007/s13300-018-0389-1
- 35. Aikens JE. Prospective Associations Between Emotional Distress and Poor Outcomes in Type 2 Diabetes. Diabetes Care 2012 Dec 1;35(12):2472–2478. doi: 10.2337/dc12-0181
- 36. Extremera N, Fernández-Berrocal P. Perceived emotional intelligence and life satisfaction: Predictive and incremental validity using the Trait Meta-Mood Scale. Personality and Individual Differences Elsevier; 2005;39(5):937–948.
- 37. Roque N, Sliwinski M, Ram N. Questionnaire-Based Everyday Reaction Time: Reliable, Valid, and Unobtrusive Measure of Cognition. Innovation in Aging Oxford University Press; 2020;4(Suppl 1):599. doi: 10.1093/geroni/igaa057.2015
- 38. Scott SB, Ram N, Smyth JM, Almeida DM, Sliwinski MJ. Age differences in negative emotional responses to daily stressors depend on time since event. Developmental Psychology 2017 Jan;53(1):177–190. doi: 10.1037/dev0000257
- 39. Posner J, Russell JA, Peterson BS. The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology. Dev Psychopathol 2005;17(3):715–734. PMID:16262989
- 40. Jaso BA, Kraus NI, Heller AS. Identification of careless responding in ecological momentary assessment research: From posthoc analyses to real-time data monitoring. Psychological Methods 2021 Sep 16; doi: 10.1037/met0000312
- 41. Muthén LK, Muthén BO. Mplus user's guide. Los Angeles. CA: Muthén & Muthén 1998;2017.
- 42. Hu L, Bentler PM. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural equation modeling: a multidisciplinary journal 1999;6(1):1–55.
- 43. Diener E, Emmons RA, Larsen RJ, Griffin S. The Satisfaction With Life Scale. Journal of Personality Assessment 1985 Feb;49(1):71–75. doi: 10.1207/s15327752jpa4901_13
- 44. Gosling SD, Rentfrow PJ, Swann WB. A very brief measure of the Big-Five personality domains. Journal of Research in Personality 2003 Dec;37(6):504–528. doi: 10.1016/S0092-6566(03)00046-1
- 45. Kroenke K, Strine TW, Spitzer RL, Williams JBW, Berry JT, Mokdad AH. The PHQ-8 as a measure of current depression in the general population. Journal of Affective Disorders 2009 Apr;114(1–3):163–173. doi: 10.1016/j.jad.2008.06.026
- 46. Spitzer RL, Kroenke K, Williams JBW, Löwe B. A Brief Measure for Assessing Generalized Anxiety Disorder: The GAD-7. Arch Intern Med 2006 May 22;166(10):1092. doi: 10.1001/archinte.166.10.1092

- 47. McGuire BE, Morrison TG, Hermanns N, Skovlund S, Eldrup E, Gagliardino J, Kokoszka A, Matthews D, Pibernik-Okanović M, Rodríguez-Saldaña J, de Wit M, Snoek FJ. Shortform measures of diabetes-related emotional distress: the Problem Areas in Diabetes Scale (PAID)-5 and PAID-1. Diabetologia 2010 Jan;53(1):66–69. doi: 10.1007/s00125-009-1559-5
- 48. Sliwinski MJ, Mogle JA, Hyun J, Munoz E, Smyth JM, Lipton RB. Reliability and Validity of Ambulatory Cognitive Assessments. Assessment 2018 Jan 1;25(1):14–30. PMID:27084835
- 49. Salthouse TA. Aging and measures of processing speed. Biological Psychology 2000 Oct;54(1–3):35–54. doi: 10.1016/S0301-0511(00)00052-1
- 50. Raykov T, Marcoulides GA. On multilevel model reliability estimation from the perspective of structural equation modeling. Structural Equation Modeling Taylor & Francis; 2006;13(1):130–141. doi: 10.1207/s15328007sem1301_7
- 51. Geldhof G, Preacher KJ, Zyphur MJ. Reliability estimation in a multilevel confirmatory factor analysis framework. Psychological methods 2014;19(1):72–91. doi: 10.1037/a0032138
- 52. Hallquist MN, Wiley JF. MplusAutomation: An R Package for Facilitating Large-Scale Latent Variable Analyses in Mplus. Structural Equation Modeling: A Multidisciplinary Journal 2018 Jul 4;25(4):621–638. doi: 10.1080/10705511.2017.1402334
- 53. R Core Team. R: A language and environment for statistical computing. R Foundation for Statistical Computing. 2020. Available from: https://www.r-project.org/ [accessed Jan 14, 2021]
- 54. Hawks ZW, Strong R, Jung L, Beck ED, Passell EJ, Grinspoon E, Singh S, Frumkin MR, Sliwinski M, Germine LT. Accurate Prediction of Momentary Cognition From Intensive Longitudinal Data. Biological Psychiatry: Cognitive Neuroscience and Neuroimaging 2023 Aug 1;8(8):841–851. doi: 10.1016/j.bpsc.2022.12.002
- 55. Asparouhov T, Muthén B. Latent Variable Centering of Predictors and Mediators in Multilevel and Time-Series Models. Structural Equation Modeling: A Multidisciplinary Journal 2019 Jan 2;26(1):119–142. doi: 10.1080/10705511.2018.1511375
- 56. Leon AC. Multiplicity-Adjusted Sample Size Requirements: A Strategy to Maintain Statistical Power With. J Clin Psychiatry 2004 Nov 15;65(11):1511–1514. doi: 10.4088/JCP.v65n1111
- 57. Lizeretti NP, Extremera N. Emotional Intelligence and Clinical Symptoms in Outpatients with Generalized Anxiety Disorder (GAD). Psychiatr Q 2011 Sep;82(3):253–260. doi: 10.1007/s11126-011-9167-1
- 58. Vine V, Marroquín B. Affect Intensity Moderates the Association of Emotional Clarity with Emotion Regulation and Depressive Symptoms in Unselected and Treatment-Seeking

- Samples. Cognit Ther Res 2018 Feb;42(1):1–15. PMID:29657347
- 59. Flynn M, Rudolph KD. A Prospective Examination of Emotional Clarity, Stress Responses, and Depressive Symptoms During Early Adolescence. The Journal of Early Adolescence SAGE Publications Inc; 2014 Oct 1;34(7):923–939. doi: 10.1177/0272431613513959
- 60. Oropesa Ruiz NF, Mercader Rubio I, Gutiérrez Ángel N, Pérez García MA. Neuroticism and Emotional Intelligence in Adolescence: A Mediation Model Moderate by Negative Affect and Self-Esteem. Behavioral Sciences Multidisciplinary Digital Publishing Institute; 2022 Jul;12(7):241. doi: 10.3390/bs12070241
- 61. Abeyta AA, Routledge C, Juhl J, Robinson MD. Finding meaning through emotional understanding: emotional clarity predicts meaning in life and adjustment to existential threat. Motiv Emot 2015 Dec;39(6):973–983. doi: 10.1007/s11031-015-9500-3
- 62. Ramos-Díaz E, Rodríguez-Fernández A, Axpe I, Ferrara M. Perceived Emotional Intelligence and Life Satisfaction Among Adolescent Students: The Mediating Role of Resilience. Journal of Happiness Studies 2019 Dec 1;20. doi: 10.1007/s10902-018-0058-0
- 63. Althouse AD. Adjust for Multiple Comparisons? It's Not That Simple. The Annals of Thoracic Surgery Elsevier; 2016 May 1;101(5):1644–1645. doi: 10.1016/j.athoracsur.2015.11.024
- 64. Rothman KJ. Six Persistent Research Misconceptions. J GEN INTERN MED 2014 Jul 1;29(7):1060–1064. doi: 10.1007/s11606-013-2755-z
- 65. Rothman KJ. No Adjustments Are Needed for Multiple Comparisons: Epidemiology 1990 Jan;1(1):43–46. doi: 10.1097/00001648-199001000-00010
- 66. Veazie PJ. When to Combine Hypotheses and Adjust for Multiple Tests. Health Serv Res 2006 Jun;41(3 Pt 1):804–818. PMID:16704513
- 67. Lotfaliany M, Bowe SJ, Kowal P, Orellana L, Berk M, Mohebbi M. Depression and chronic diseases: Co-occurrence and communality of risk factors. Journal of Affective Disorders 2018 Dec 1;241:461–468. doi: 10.1016/j.jad.2018.08.011

Supplementary Files

Multimedia Appendixes

This word document contains supplementary figures and supplementary tables that were referenced in the manuscript. URL: http://asset.jmir.pub/assets/fc8eff62bbf8e6c395863e724b2da614.docx