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Exploring Within-Person Variability in Qualitative Negative and Positive Emotional Granularity by Means of Latent Markov Factor Analysis

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ABSTRACT
Emotional granularity (EG) is an individual's ability to describe their emotional experiences in a nuanced and specific way. In this paper, we propose that researchers adopt latent Markov factor analysis (LMFA) to investigate within-person variability in qualitative EG (i.e., variability in distinct granularity patterns between specific emotions across time). LMFA clusters measurement occasions into latent states according to state-specific measurement models. We argue that state-specific measurement models of repeatedly assessed emotion items can provide information about qualitative EG at a given point in time. Applying LMFA to the area of EG for negative and positive emotions separately by using data from an experience sampling study with 11,662 measurement occasions across 139 participants, we found three latent EG states for the negative emotions and three for the positive emotions. Momentary stress significantly predicted transitions between the EG states for both the negative and positive emotions. We further identified two and three latent classes of individuals who differed in state trajectories for negative and positive emotions, respectively. Neuroticism and dispositional mood regulation predicted latent class membership for negative (but not for positive) emotions. We conclude that LMFA may enrich EG research by enabling more fine-grained insights into variability in qualitative EG patterns.

KEYWORDS
Emotion; emotional granularity; emotion differentiation; latent Markov factor analysis; qualitative differences

Introduction

Emotions are an integral part of human life. One important construct in research on how individuals experience and process different emotions is *emotional granularity* (EG) or emotion differentiation. EG is defined as the "specificity of one's emotional experiences and representations or an individual's ability to make fine-grained, nuanced distinctions between similar emotional states" (Smidt & Suvak, 2015, p. 48). Individuals with high EG tend to use discrete emotion labels in a specific, context-dependent manner, whereas individuals with low EG tend to use them interchangeably across different contexts.

Traditionally, EG researchers have distinguished between granularity of negative emotions (negative EG) and granularity of positive emotions (positive EG), as negative EG and positive EG have been found to be unrelated to each other (Demiralp et al., 2012; Willroth et al., 2020). In particular, low negative EG has been identified as a relevant risk factor for behavioral and emotional dysregulation in both clinical and nonclinical contexts (Seah & Coifman, 2022). These findings are consistent with the notion that the use of discrete negative emotions may provide individuals with accurate information about the causes of and the factors that help them maintain their negative emotional states. Thus, if individuals do not have much fine-grained knowledge about their own negative emotional experiences due to low EG, they may be less able to skillfully regulate their negative emotions (Kashdan et al., 2015).

EG is typically assessed indirectly through studies using the experience sampling method (ESM; Thompson et al., 2021). In these studies, participants are repeatedly prompted to rate the momentary or short-term retrospective intensity levels of a predetermined set of

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emotions (e.g., "sad," "angry," "scared"). To obtain an index of EG for each participant, researchers usually calculate the intraclass correlation coefficient (ICC), where a high ICC indicates high covariation and thus low differentiation between different emotion ratings across measurement occasions.

Traditionally, EG has therefore been approached as a person-level variable, under the assumption that it is a stable trait. In recent years, however, researchers have increasingly investigated EG as a time-varying phenomenon, either by calculating multiple ICCs over separate, shorter time periods (e.g., day-specific ICCs; Erbas et al., 2018) or by introducing momentary indices of EG that indicate individuals' EG levels at a given point in time (Erbas et al., 2022; Lane & Trull, 2022). These studies highlight the dynamic nature of EG: Negative EG has been shown to be lower on days with higher stress (Erbas et al., 2018). In addition, lower momentary EG has been found to be associated with higher momentary rumination and lower momentary positive affect (Erbas et al., 2022) and to predict higher momentary impulsivity in individuals with borderline personality disorder (Tomko et al., 2015). Taken together, these studies demonstrate that within-person variability in EG is meaningful and important to investigate further.

Previous research on EG has typically examined EG as a purely quantitative phenomenon by aggregating information about the granularity between *all* similarly-valenced emotions into a single index. Such a single-index approach aims to model global quantitative differences in EG between individuals or across measurement occasions within individuals, that is, differences in the levels at which individuals differentiate between all similarly-valenced emotions over time or at a particular point in time. However, a few recent studies (e.g., Erbas et al., 2019; Hoemann et al., 2020) have taken a more qualitative perspective on EG. These studies have aimed to investigate specific patterns of EG beyond a single global EG index, for example by examining which specific emotions individuals are more or less able to differentiate (e.g., are individuals better able to discriminate between anger and sadness than between fear and sadness?). In a first attempt to qualitatively disentangle EG, Erbas et al. (2019) distinguished between two types of EG, namely, the ability to make distinctions between emotions from different categories (e.g., anger and sadness) and the ability to make fine-grained distinctions between emotions that can be subsumed under the same category (e.g., anxiety-related emotions, e.g., worry, fear, and nervousness). In a study designed to examine the link between within-category EG and depression, lower granularity between sadness-related emotions (but not between anxiety-related, anger-related, or guilt-related emotions) was associated with depressive symptoms beyond mean emotion intensity (Willroth et al., 2020). This line of research suggests that individuals do not differentiate equally between emotions and that the relationships between EG and well-being may depend on which specific emotions individuals are able to differentiate.

To date, we are aware of only one study that has accounted for within-person variability in qualitative EG: Hoemann et al. (2020) estimated person-specific emotion networks in which nodes represented emotion ratings obtained from two ESM studies and edges represented within-person correlations between emotion ratings across 3 consecutive days. They found substantial variability in the structure of person-specific emotion networks across days, suggesting that patterns qualitative EG vary over time.

However, one limitation of Hoemann et al.'s (2020) network-analytic approach was that the predefined time period of 3 days for which they estimated time-varying emotion networks was rather large. Therefore, such an approach does not allow researchers to examine changes in qualitative EG that occur within a much shorter time period (i.e., within a few hours or even from moment to moment) or to determine how such changes might be related to short-term changes in specific contexts (e.g., momentary stress or situational characteristics). To overcome this issue, a statistical method is needed that can identify qualitative EG patterns at the level of measurement occasions. In the present research, we aimed to address this gap by proposing the recently introduced *latent Markov factor analysis* (LMFA; Vogelsmeier, Vermunt, van Roekel, & De Roover, 2019) as a statistical framework that can be used to uncover qualitatively distinct EG states and examine how individuals transition between these EG states across time. LMFA clusters measurement occasions into latent states according to state-specific measurement models of emotion ratings. As we will illustrate in the following subsection, measurement models that characterize the states can provide an informative way to describe qualitatively distinct EG patterns at the momentary level.

Latent Markov factor analysis as a statistical framework for studying time-varying qualitative EG

LMFA was originally introduced as a tool that can be applied to identify violations of measurement invariance across time in intensive longitudinal studies

(Vogelsmeier, Vermunt, van Roekel, & De Roover, 2019). In LMFA, measurement occasions that adhere to strict factorial invariance (i.e., they are characterized by the same measurement model) are assigned to the same latent state.

LMFA is a combination of two building blocks: latent Markov modeling (Bartolucci et al., 2012) and exploratory factor analysis (Gorsuch, 1983). Latent Markov modeling (also called latent transition or hidden Markov modeling) is an extension of latent class or latent profile analysis to longitudinal data in that it allows researchers to estimate a participant's probability of being assigned to a particular latent class at the first measurement occasion (initial state probabilities) and the changes in latent class membership (i.e., transition probabilities) across adjacent measurement occasions. The categories of the latent variable in latent Markov modeling are commonly referred to as latent states (or dynamic latent classes). Note that individuals do not have to go through each of the identified latent states.

Based on the second building block (i.e., exploratory factor analysis), the latent states in LMFA are characterized by state-specific measurement models of individuals' responses (in our case, continuous emotion items). Model constraints (e.g., on factor loadings) can be defined if desired. To define the measurement models, let y_{ijt} denote the observed scores on continuous emotion items, where $i = 1, \ldots, I$ refers to individuals, $j = 1, \ldots, J$ refers to emotion items, and $t = 1, \ldots, T$ refers to measurement occasions. The multivariate responses for subject i at measurement occasion t are collected in the $J \times 1$ vector $\mathbf{y}_{it} = (y_{i1t}, y_{i2t}, \ldots, y_{iJt})$'. The state-specific measurement models are given by

$$\boldsymbol{y}_{it} = \mathbf{v}_k + \boldsymbol{\Lambda}_k \cdot \mathbf{f}_{it} + \mathbf{e}_{it}. \quad (1)$$

The state-specific factor loadings are captured by the $J \times F_k$ factor loading matrix $\boldsymbol{\Lambda}_k$ (where F_k is the number of factors in state k). The factor scores specific to individual i at time point t are in the $F_k \times 1$ vector $\mathbf{f}_{itk} \sim MVN(\mathbf{0}; \boldsymbol{\Psi}_k)$, where $\boldsymbol{\Psi}_k$ denotes the state-specific interfactor covariance matrix in which the diagonal elements (i.e., factor variances) are 1. The state-specific intercepts are captured by the $J \times 1$ vector $\mathbf{v}_k$, while $\mathbf{e}_{itk} \sim MVN(\mathbf{0}; \mathbf{D}_k)$ is the individual- and occasion-specific $J \times 1$ vector of residuals, with the off-diagonal elements of $\mathbf{D}_k$ (i.e., residual covariances) being zero. Since factor scores are centered on zero, the state-specific intercepts in $\mathbf{v}_k$ represent the state-specific item means. The factor solutions can later be rotated to approximate a simple structure.

When LMFA is applied to repeated emotion ratings over time, the combination of factor loadings, interfactor correlations, and intercepts in state-specific measurement models can provide useful information about momentary EG patterns (see Figure 1 for a simplified illustration of state-specific measurement models for describing qualitative EG). In terms of factor loadings, emotions that have high loadings on the same factor can be considered less differentiated from each other than emotions that do not have high loadings on the same factor. The resulting factors represent higher order emotion categories that summarize different emotion instances that individuals perceive to be similar (Hoemann & Feldman Barrett, 2019). The higher the emotions load on one factor, the more individuals categorize different emotional instances together and the less specific this higher-order emotion category is (e.g., a "pure" anger factor vs. a more general negative affect factor with high loadings from different negative emotions). If states differ in the emotions that have high loadings on the same factor, there is likely to be temporal variation in terms of which particular emotions individuals perceive as similar. Such variation may be the result of temporal variability in the emotion concepts that individuals use to categorize and make sense of their emotional experiences (Hoemann & Feldman Barrett, 2019). State-specific interfactor correlations in turn indicate the extent to which these emotion categories overlap or are independent of one another (Hoemann et al., 2017). Moreover, state-specific intercepts serve two important functions: First, because an intercept represents the estimated mean of an emotion item, the set of state-specific intercepts can provide contextual information about the mean intensity levels of emotions at which specific factor patterns emerge. For example, a general negative affect factor may emerge in states with high mean intensities of all emotions, whereas more specific factors (such as a "pure" anger factor) may emerge only at moderate mean intensities of anger-related emotions. Second, there may be states in which individuals report only some of the emotions to some extent, while other specific emotions are not reported at all (i.e., the rated intensities of these emotions are zero in these states). Such constellations can also be interpreted in terms of EG as here individuals report some emotions in complete isolation from other similarly-valenced emotions. This is indicated by intercept values of zero for non-reported emotions. Thus, in combination, the state-specific factor structure and intercepts provide valuable information about differences in qualitative EG across latent states.

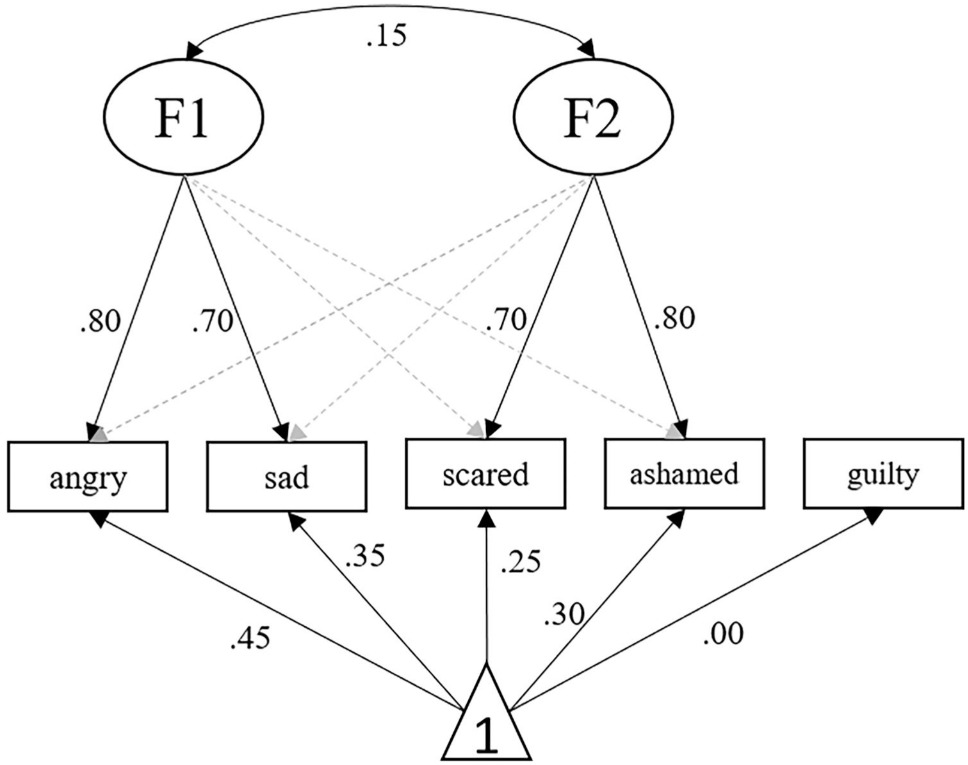

Figure 1. Hypothetical simplified state-specific measurement model for negative emotions. Here, individuals mentally represent "angry" and "sad" under one emotion category, which is represented by Factor 1 (F1). Due to high standardized loadings on F1, the items "angry" and "sad" can be considered to be weakly differentiated. The same logic applies to the items "scared" and "ashamed", both of which have high loadings on Factor 2 (F2). Given the low correlation between F1 and F2, individuals differentiate between the categories "anger/sadness" versus "fear/shame." For a continuous (slider) response format that ranges from 0 to 1, intercept values could theoretically range from 0.00 to 1.00. Hence, an intercept value of zero for "guilty" would indicate that individuals do not experience any guilt in this state. Grey, dashed arrows indicate low standardized cross-loadings. Item residuals are not depicted.

The latent Markov modeling part of LMFA provides a way to model temporal dependence between the latent EG states (for a mathematical description, see Supplementary Material). More specifically, we can obtain information about the relative stability with which individuals are in a given EG state and about specific trajectories with which EG patterns change over time through the probabilities of transitioning between latent states. These are defined as the probability that an individual is in a given latent state k at a particular measurement occasion t given his or her membership in a latent state l at the previous measurement occasion $t-1$. In discrete-time LMFA, intervals between measurement occasions, δ_{ti}, are assumed to be equal. In contrast, in continuous-time (CT-)LMFA (Vogelsmeier, Vermunt, Böing-Messing, & De Roover, 2019), non-invariant time intervals between measurement occasions are allowed. Because non-invariant time intervals are more realistic in ESM studies (e.g., when individuals do not provide data on some measurement occasions or when the sampling scheme involves non-invariant time intervals due to random sampling within a time frame), we focus on continuous-time latent Markov modeling in this paper. In CT-LMFA, transition probabilities are a function of the time interval between measurement occasions, δ_{ti}, and transition intensities. Transition intensities (or rates) q_{lk} are defined as the probability of transitioning from l to k (for $l \neq k$) per very small unit of time (i.e., when the time δ spent in l approximates zero). From these transition intensities, transition probabilities can be calculated for any time interval of interest (Vogelsmeier, Vermunt, Böing-Messing, & De Roover, 2019). If desired, covariates (i.e., explanatory variables) can be added as predictors of transition intensities. By including a specific contextual variable (e.g., momentary stress) as a time-varying predictor of transition intensities, EG researchers can identify the contexts in which individuals are more or less likely to transition between different EG states. Furthermore, population heterogeneity (i.e., between-person differences) in the transition patterns of EG states can be estimated by extending the LMFA model to a *mixture* LMFA. By using mixture LMFA, researchers can identify latent classes of individuals who differ in the variability versus stability of qualitative EG states over time (Vogelsmeier et al., 2020).

The use of (mixture) LMFA to study individual differences in the factor structure of emotions seems similar to previous P-technique factor analytic approaches to repeated emotion ratings (e.g., Foster & Beltz, 2022; Larsen & Cutler, 1996). In these approaches, factor analyses on repeated emotion ratings are conducted for each individual separately. In subsequent analyses, researchers can analyze between-person differences in the individuals' factor structures, for instance, by inspecting differences in the number of factors extracted in each individual's factor structure (Foster & Beltz, 2022). However, P-technique factor analytic approaches assume a stable measurement model over time for each individual and do not account for potential changes in the measurement model within individuals. Instead of assuming a stable measurement model for each individual, LMFA parsimoniously uncovers the most salient measurement model differences between measurement occasions by means of a latent state variable. Between-person heterogeneity can then be explored in a mixture LMFA model by adding a latent class variable that clusters individuals according to common trajectory patterns across states over time (e.g., a class of individuals who mostly stay in a specific measurement model state vs. a class of individuals who frequently transition between different measurement model states). Thus, in contrast to previous approaches based on P-technique factor analysis, mixture LMFA allows researchers to study both between-person and within-person variability in measurement models of emotion ratings simultaneously.

The present study

Using data from an ESM study in which participants repeatedly rated their emotional experiences on 15 negative and 12 positive emotion items, we aimed to test the applicability of LMFA for examining within-person variability in qualitative EG. To examine whether situation- and person-specific characteristics are related to trajectories between qualitative EG states, we entered time-varying and time-constant variables that have already been established in the literature as correlates of quantitative measures of EG as external covariates into the latent Markov parts of our models. By computing (mixture) LMFAs for negative and positive emotions separately, we aimed to address the following research questions:

Research Question 1: Can qualitatively distinct EG states based on state-specific measurement models of emotion ratings be identified?

Research Question 2: Is momentary stress related to the probability of transitioning between EG states? We chose momentary stress as a time-varying predictor of transition intensities because higher stress was associated with a decrease in time-varying granularity of negative emotions in previous research (Erbas et al., 2018).

Research Question 3: Do individuals differ in the transitions between EG states? To address this research question, we extended our LMFA models to mixture LMFA models by including an additional latent class variable that clusters individuals according to their transition intensities.

Research Question 4: Do neuroticism and dispositional mood regulation (negative mood repair and positive mood maintenance) predict latent class membership of individuals who differ in transitions between EG states? We selected these trait measures based on previous studies that found higher neuroticism (Erbas et al., 2014) and lower affect regulation (Feldman Barrett et al., 2001) to be associated with lower negative EG.

We chose to compute LMFA models for negative and positive emotions separately to be consistent with the definition of EG (i.e., the extent to which individuals differentiate between similarly-valenced emotional states; e.g., Smidt & Suvak, 2015) and the tradition of separating between negative and positive EG in the literature.[1]

Given the novelty of our approach in the area of EG, we did not preregister our analyses. Data and syntax files are available at https://osf.io/w4tye/.

Method

Study design and procedure

The study consisted of an initial online survey and a 14-day ESM phase with eight short surveys per day. Data were collected between June and September 2021.

Participants were recruited through university mailing lists and social media platforms (Facebook, Instagram). After registering for the study, participants completed an initial 30-min online survey on SoSci Survey (Leiner,

[1]Previous P-technique factor analytic approaches have used positive and negative emotion items simultaneously for individual specific factor analyses (e.g., Larsen & Cutler, 1996) in order to assess each individual's affective complexity. Affective complexity is an umbrella term that includes both EG and emotional dialecticism (i.e., the extent to which positive and negative emotional states are experienced simultaneously) as subcomponents (Lindquist & Feldman Barrett, 2008). In order to focus exclusively on EG, which by definition is divided into negative and positive EG, and not to confuse it with emotional dialecticism, separate models for negative and positive emotions are needed.

2019), where they completed questionnaires on demographics and, among others, baseline self-report measures of neuroticism and dispositional mood regulation. At the end of the survey, participants could choose a 14-day period for the upcoming ESM phase. They could also choose between two time schedules (8:00 am to 8:10 pm or 10:00 am to 10:10 pm) that best fit their waking hours when they wanted to participate in the ESM phase.

The ESM phase was administered via the Android app movisensXS, version 1.4.8 (movisens GmbH, Karlsruhe, Germany), which participants were instructed to install on their smartphones. Each short survey took approximately 5 min to complete and included, among others, momentary intensity ratings of different emotions. For each participant, the ESM phase started on a Monday and ended on a Sunday 13 days after the start.

Eight 30-min intervals were selected to distribute the eight surveys over the course of the day. In each of these intervals, a prompt to take part in a survey was randomly sent to the participants' smartphones. A prompt was active on the smartphones for 15 min. The ESM questionnaire expired if participants did not complete it within this interval. Prompt intervals were programmed to be 70 min apart, such that the expected mean interval between two questionnaires on any given day was 100 min.

After the study, participants were reimbursed up to 70 EUR, depending to some extent on their compliance during the ESM phase. In addition, they received an individual emotion profile from the data they provided in the ESM phase if they so wished. The study procedure was approved by the institutional ethics committee of the psychology department at the University of Koblenz-Landau (approval number LEK-344).

Participants

Participants were eligible if they were at least 18 years old and had access to a smartphone with Android version 4.4 or higher, as movisensXS is only available for Android. A total of 273 individuals registered for the study, of which 215 completed the initial online survey. In the end, 163 individuals took part in the ESM phase, providing 12,499 observations. The 46 participants who dropped out after the initial online survey (M_{age} = 41.46 years, $SD = 15.49$) were significantly older than those who participated in the ESM phase (M_{age} = 30.87 years, $SD = 9.21$), $t(54.28) = 4.42$, $p < .001$, $d = 0.83$, but did not differ significantly from the remaining participants with respect to gender, $p = .718$ (Fisher's exact test). For our analyses, we only included data from participants who completed at least 30% of the surveys that were not affected by technical errors or that we did not classify as careless responding (see the next section for details). Data from 24 participants who did not meet this criterion were excluded from the analyses. The excluded participants did not differ significantly from the remaining participants with respect to age, $t(161) = 1.18$, $p = .240$, $d = .26$, and gender, $p = .200$ (Fisher's exact test). Our final sample thus consisted of 139 participants (81% female, 17% male, 2% nonbinary; M_{age} = 30.52 years, $SD = 9.03$).

Data cleaning and compliance

Out of a maximum of 18,256 possible ESM surveys, 163 participants completed 12,499 surveys, corresponding to an overall compliance rate of 68%. For two participants, due to technical problems the time windows for the prompts were not as intended (e.g., prompts occurred outside the 12-hr interval). We excluded 148 occasions that were affected by these problems. We screened for surveys with careless responding by inspecting response times (Meade & Craig, 2012). A cutoff value for extremely fast response times was established in an ESM pilot study in which research assistants were instructed to complete the ESM surveys as quickly as possible without resorting to careless responding. The fastest response time for a measurement occasion (i.e., including responses to all items) in the pilot study was 50 s. Thus, 264 ESM surveys that were completed within less than 50 s were excluded from the analyses. Subsequently, we excluded data from 24 participants who did not provide at least 30% (i.e., 34) valid surveys (i.e., non-missing surveys without technical problems or careless responding). Our final sample thus consisted of 11,662 measurement occasions nested in 139 participants. The compliance rate in the final sample was 75%.

Measures

Within-person (momentary) measures

Emotion intensity ratings. The emotion items we used as observed variables for the state-specific measurement models were adapted from the modified Differential Emotions Scale (Fredrickson, 2013). In this scale, each of the 20 items contains three rather synonymous emotion terms that tap into one broader emotion category (e.g., for sadness: "sad," "downhearted," "unhappy"). For our study, we selected nine of the items (measuring anger, sadness, fear, shame, and guilt as negative emotion categories and joy, interest, love, and pride as positive emotion categories) and used the three emotion terms in each category as separate items, such that participants rated their emotional experiences on a total of 27 items. We decided to use multiple, rather synonymous items for each emotion category in order to allow distinct emotion-specific factors (such as an anger factor measured by three anger items) to be identified. In order to make the items sound closer to everyday German, we deviated in some cases from the literal translations of the items from English into German. A complete list of the 27 emotion items we used in our study, along with their English translations and the original items from Fredrickson (2013), can be found in Tables S1 and S2 in the Supplementary Material. The items were presented in a randomized order on each measurement occasion. Participants were instructed to indicate the intensity with which they had experienced each emotion within the past hour on a slider scale ranging from 0 (*not at all*) to 100 (*very much*). In order to facilitate convergence for our main analyses, we scaled the slider values so that they ranged from 0 to 1.00 in steps of 0.01.

Momentary stress. . Following the approach of Erbas et al. (2018), we asked participants to indicate how stressed they felt within the past hour on a single item using a slider ranging from 0 (*not at all*) to 1.00 (*very much*).[2]

Between-person (trait) measures

Neuroticism. We assessed neuroticism using the 12-item Negative Emotionality scale from the German version of the Big Five Inventory 2 (BFI-2; Danner et al., 2016; Soto & John, 2017). Participants indicated their agreement with the statements (e.g., "I am someone who tends to feel depressed, blue") on a Likert scale ranging from 1 (*strongly diasgree*) to 5 (*strongly agree*). We calculated a mean score across all the items, with higher scores indicating greater neuroticism. Omega total (McNeish, 2018) was 0.90.

Dispositional mood regulation. Dispositional mood regulation was assessed with an 11-item scale (Lischetzke & Eid, 2006) that consisted of two subscales, namely, Negative Mood Repair (six items; e.g., "It is easy for me to improve my bad mood") and Positive Mood Maintenance (five items; e.g., "It is easy for me to maintain my good mood for a long time"). Each item was answered on a 4-point frequency scale ranging from 1 (*almost never*) to 4 (*always*). Omega totals were 0.86 and 0.82 for Negative Mood Repair and Positive Mood Maintenance, respectively.

Data-analytic strategy

Data preparation and ancillary analyses were conducted in R (R Core Team, 2021), whereas the main analyses were conducted using the syntax module of Latent GOLD version 6.0 (Vermunt & Magidson, 2021).[3] We conducted all our analyses separately for negative and positive emotions. In line with previous ESM studies using slider scales (e.g., Koval et al., 2015; Lischetzke et al., 2021), we recoded all ratings $\leq$ 0.05 to 0 as it may have been difficult for participants to indicate a value of exactly 0 on the smartphone touchscreen.

Given the complexity of our modeling approach (i.e., the inclusion of covariates and extension to mixture LMFA), we chose the three-step approach to LMFA (3S-LMFA; Vogelsmeier et al., 2023). Compared with one-step full information maximum likelihood (FIML) estimation, the approach we chose is less computationally demanding and more flexible in that it decomposes the model estimation into three successive steps and separates the estimation of the measurement part (i.e., state-specific measurement models via mixture factor analysis) from the estimation of the structural part (i.e., relating the latent states to each other via a latent Markov chain and to covariates) of LMFA (for a more detailed description of the 3S-LMFA approach, see Vogelsmeier et al., 2023). In the following, we describe the three steps we applied in our analyses.

Step 1

In Step 1, we computed mixture factor analyses across measurement occasions. Thus, in this step, we estimated the state-specific measurement models for

[2]It can be argued that feeling stressed as operationalized here represents another negative emotion, calling into question our decision to treat the stress item as an external covariate and not to add it to the other negative emotion items for the measurement models. However, additional analyses by Erbas et al. (2018) tested whether a single-item measure of stress and the other negative emotion items acted interchangeably in predicting EG. The authors repeatedly excluded one negative emotion item from the calculation of the EG index and predicted EG by the remaining single emotion item (note that the stress item was treated the same way as the other negative emotion items). Only stress, but not the other negative emotion items, prospectively predicted EG. This suggests that feeling stressed as operationalized in our study represents a unique affective state beyond distinct emotions such as anger or sadness, which justifies treating momentary stress as an external predictor variable of EG.

[3]Tutorials on how to use Latent GOLD can be found on the software website: https://www.statisticalinnovations.com.

Research Question 1. The models in this step did not yet include a latent Markov model, as the structural part (containing the Markov models) was not included until Step 3. To make a decision about the number of latent states K and the number of factors F_k in each state, we estimated a series of models that differed in the number of states and the number of factors per state and compared them using log-likelihood-based selection criteria. We considered state-specific measurement models with up to five factors per state for negative emotions and up to four factors per state for positive emotions to reflect the structure of our item set (which included five negative and four positive emotion categories). In nearly 12% of the measurement occasions, participants did not report any negative emotions at all—that is, all negative emotion ratings on these occasions were zero. Hence, for the negative emotion models in Step 1, we decided to add a "no negative emotions" state in which all intercepts, factor loadings, and residual variances were fixed at zero. This ensured that all occasions in which all negative emotion intensities were rated as zero were assigned to this state by design and that the remaining EG states were composed of measurement occasions in which at least a subset of negative emotions was experienced and differentiated in a specific way.[4]

Regarding the number of latent EG states, we considered up to three EG states that should reflect different EG patterns for both the negative and positive emotion models. For the negative emotion models, we specified models with two to four latent measurement model states. In total, we compared 55 different models for negative emotions, such that the two-state model [1 0] (i.e., one EG state with one factor and the no negative emotions state) was the most parsimonious, and the four-state model [5 5 5 0] (i.e., three EG states with five factors each and the no negative emotions state) was the most complex. For positive emotions, we specified models with one to three latent measurement model states. In total, we compared 34 different models, such that the one-state model [1] (i.e., one EG state with one factor) was the most parsimonious and the three-state model [4 4 4] (i.e., three EG states with four factors each) was the most complex. To obtain global maximum likelihood solutions rather than solutions due to local maxima, we estimated each model five times with 2,500 sets of random starting values each. We considered model solutions to be global if the absolute differences between the log-likelihood values across the five replications were less than 0.01 (Vogelsmeier et al., 2023). Models with absolute differences $\geq$ 0.01 across replications and models that did not converge were discarded from the model selection procedure. We used several methods to select the optimal models: First, we compared the values of the Bayesian Information Criterion (BIC; Schwarz, 1978). Second, we plotted the values of the BIC against the number of parameters to graphically check for substantial gains in relative fit with increasing complexity (Masyn, 2013). Finally, we applied the CHull method (Wilderjans et al., 2013) via the R package *multichull* (Vervloet et al., 2017). The CHull method is an automated multi-step procedure that weighs the model fit (i.e., log-likelihood) against complexity (i.e., number of model parameters) and identifies the optimal model by evaluating the elbow in the scree plot with models at the upper bound of the convex hull. In the two selected models (one for negative and one for positive emotions), we z-standardized the factor loadings using the state-specific item standard deviations and oblimin-rotated the factors in multifactor states using the R package *GPArotation* (Bernaards & Jennrich, 2005) in order to approach a simple structure.

Step 2

In Step 2, we allocated each measurement occasion to one of the K latent states on the basis of the estimated posterior state probabilities of the models that were selected in Step 1. To this end, we extracted the posterior state probabilities for each measurement occasion using the syntax option in Latent GOLD. In line with recommendations for three-step approaches in latent Markov modeling (Di Mari et al., 2016), we selected modal assignment in which each measurement occasion was assigned to the latent state with the highest posterior state probability. Along with the estimated classification error matrix, the state classifications formed the basis of the analyses in Step 3.

Step 3

In Step 3, we estimated transitions between the latent EG states (i.e., we specified the latent Markov models) and added person-mean-centered momentary stress as a predictor of the transition intensities (Research Question 2). Moreover, in another set of analyses, we extended our LMFA models to mixture LMFA models by adding a latent class variable to the models to account for between-person heterogeneity in EG state

[4]For positive emotions, the proportion of occasions with emotion ratings of zero for all positive emotion items was only 0.6%. Thus, the inclusion of a residual state was not necessary for the positive emotion models.

transitions (Research Question 3).[5] We specified four mixture latent Markov models that differed in the number of classes (i.e., one to four classes) for negative and positive emotions separately. We determined the number of latent classes by examining and comparing the BIC values of the models, plotting the BIC values of the models against the number of parameters, and applying the CHull method. The effects of momentary stress or the latent class variable on transition intensities were log-linearly modeled for $l \neq k$ (Vogelsmeier et al., 2023). Adding the classification error matrix to the syntax files for Step 3 ensured that classification error was controlled for when separating the estimation of the structural portion from the estimation of the measurement portion (Di Mari et al., 2016; Vogelsmeier et al., 2023).

After selecting the mixture models, we used modal assignment to assign each participant to one of the extracted latent classes. To address Research Question 4, we entered the between-person covariates as predictors of the latent classes in regression multinomial logistic models for each covariate separately while accounting for classification errors in the latent class assignments. For all hypothesis tests, we used Wald tests to assess the statistical significance of the (log-linear or multinomial logistic) regression parameters at $\alpha = 0.05$.

Sample size considerations

With 11,662 observations from 134 participants, we clearly exceeded the recommended sample size of 2,000 to 4,000 observations for accurate recovery of up to four states in the simulation study by Vogelsmeier, Vermunt, van Roekel, and De Roover (2019). In Crayen et al. (2017)'s simulation study, person-level sample sizes similar to the sample size in our study were shown to yield reasonable accuracy in estimating mixture continuous-time latent Markov models. Therefore, we considered our final sample to be large enough to apply mixture LMFA to our dataset.

[5]Note that theoretically, latent classes could also differ with respect to initial state probabilities (in addition to transition intensities). In the models reported here, we allowed the latent classes to differ only in transition intensities (and not in initial state probabilities). The results of alternative mixture models in which the latent classes were also allowed to differ in initial state probabilities were comparable to the mixture models we report (i.e., the rank order of the initial state and transition probabilities for the states remained the same). Furthermore, we also intended to test mixture models in which the effect of momentary stress on state transitions varied across latent classes for both the negative and positive emotions. However, these models either did not converge or had estimation problems due to a large number of unidentified regression parameters.

Results

In the following, we report the results of our analyses for negative emotions in more detail. For the sake of manuscript length, we report the results for positive emotions in a summarized fashion, but refer to the Supplementary Material for a more detailed description of these results.

Negative emotions

Research question 1: Identifying latent emotional granularity states

Of the 55 estimated Step 1 models for negative emotions, 13 models were not stable across the five replications (i.e., there were local instead of global maxima in the maximum likelihood estimations). Of the remaining 42 models, two also failed to converge. Finally, 40 models remained for the model selection procedure. The model with the lowest BIC value was the four-state model [5 4 2 0] (i.e., five factors in the first state, four factors in the second state, two factors in the third state, and a fourth state with negative emotion ratings of zero). However, plotting the BIC values against the number of model parameters revealed that the BIC values of all remaining four-state models were very similar in magnitude (see Figure S1 in the Supplementary Material). The least complex model (i.e., with the lowest number of parameters) among the four-state models was model [3 1 1 0].

The CHull method identified three models on the upper bound of the convex hull: models [1 0], [1 1 0], and [3 1 1 0] (see Figure S2 in the Supplementary Material). However, identifying the "elbow model" with only three models on the upper bound of the convex hull would not make sense because the model between the two models with the lowest and highest loglikelihood would always be automatically favored, while there would be no more neighboring models for the lower and upper models to compare.

We selected model [3 1 1 0] (i.e., three factors in the first state, one factor each in the second and third states, and a fourth state with negative emotion ratings of zero) as our final Step 1 model after combining the results of the CHull method and the BIC-by-complexity plot. The intercepts, factor loadings, and interfactor correlations of the state-specific measurement models are shown in Table 1 and Figure 2. The latent states were very well separated (entropy $R^2 = 0.9995$), and the overall classification accuracy was very high (overall classification error $= 0.0002$) for this model.

Table 1. State-specific measurement models for negative emotions.

	State 1 High negative intensity, low granularity					State 2 Low differentiation between anger and sadness			State 3 High differentiation between anger and sadness		
Item	Intercept	F1 loading	F2 loading	F3 loading	Residual variance	Intercept	F1 loading	Residual variance	Intercept	F1 loading	Residual variance
angry	0.271	0.015	0.020	0.783	0.023	0.114	0.560	0.025	0.082	0.705	0.015
irritated	0.306	0.012	−0.019	0.847	0.020	0.135	0.541	0.031	0.105	0.824	0.012
annoyed	0.344	0.021	0.000	0.853	0.019	0.210	0.534	0.046	0.158	0.791	0.020
sad	0.318	0.910	−0.009	−0.042	0.018	0.163	0.734	0.022	0.097	0.166	0.032
downhearted	0.346	0.843	−0.014	0.040	0.021	0.193	0.774	0.022	0.133	0.270	0.041
unhappy	0.360	0.837	−0.031	0.044	0.020	0.232	0.778	0.022	0.195	0.209	0.057
terrified	0.190	0.383	0.175	0.075	0.031	0.000	–	–	0.000	–	–
scared	0.232	0.532	0.161	0.011	0.037	0.086	0.299	0.024	0.000	–	–
worried	0.375	0.602	0.132	0.070	0.036	0.244	0.575	0.041	0.126	0.283	0.035
ashamed	0.181	−0.014	0.835	−0.021	0.016	0.048	0.212	0.015	0.000	–	–
humiliated	0.179	0.006	0.446	0.294	0.027	0.000	–	–	0.000	–	–
disgraced	0.147	−0.135	0.749	0.069	0.018	0.000	–	–	0.000	–	–
guilty	0.207	0.118	0.794	−0.064	0.014	0.082	0.332	0.023	0.000	–	–
repentant	0.246	0.045	0.737	0.056	0.024	0.151	0.398	0.042	0.000	–	–
bad conscience	0.236	0.044	0.796	−0.019	0.020	0.165	0.306	0.045	0.000	–	–
		Factor correlations									
F1			.62	.65							
F2				.44							

Note. Factor loadings were *z* standardized by using state-specific item standard deviations. No measurement model for State 4 (the "no negative emotions" state) depicted as all item values were zero in this state.

State S1_neg (see top left part of Figure 2) was the only negative EG state in which all of the negative emotions were reported at some point, as indicated by intercept values of > 0 for all negative emotions. Furthermore, the intercepts (i.e., mean intensity levels) of the negative emotion items were highest in this state.[6] The factor structure revealed three factors on which the emotion items loaded: anger, sadness/fear, and shame/guilt. However, the correlations between the factors were relatively high, suggesting that the extent to which these factors reflected clearly separable higher order emotion categories under which individuals structured their negative emotional experiences was limited. Given the high mean emotion intensities and the high interfactor correlations, and because all negative emotions were reported over the measurement occasions of this state, we labeled this state "high negative intensity, low granularity" state.

In State S2_neg (see upper right part of Figure 2), the emotions "terrified", "humiliated", and "disgraced" were not experienced at all, whereas the other 12 emotions were experienced to some extent. The sadness- and anger-related emotion items as well as "worried" had high loadings on the single factor, suggesting that in this state, participants represented these emotions in a common category and did not differentiate very well between feelings of anger and sadness. The other emotions reported in this state (e.g., the guilt-related emotions) had lower loadings on this factor. We labeled this state "low differentiation between anger and sadness" state.

In State S3_neg (see lower left part of Figure 2), participants reported even fewer emotions than in the "low differentiation between anger and sadness" state (e.g., no reports of the shame- and guilt-related emotion items). The single factor in this state mainly represented anger, given that the anger-related items had high loadings on this factor, whereas the factor loadings of the sadness-related items and "worried" were comparatively low. Thus, participants differentiated more between anger and sadness in this state, as opposed to the "low differentiation between anger and sadness" state. Moreover, because participants did not report any other emotions besides "worried," they apparently experienced instances of sadness and anger as distinct from other negative emotions. To emphasize the contrast between this state and the "low differentiation between anger and sadness" state, we labeled this state "high differentiation between anger and sadness" state.[7]

Research question 2: Momentary stress as a predictor of transitions between EG states

Momentary stress had an overall significant effect on transition intensities between negative EG states,

[6]Given the large sample size for measurement occasions in our study, which would result in significant results even for very small effects, we refrained from comparing the differences in item intercepts between states on the basis of significant test results, but compared them graphically.

[7]We did not further interpret the "no negative emotions" state (State S4_neg; see the lower right part of Figure 2) in terms of EG because the only purpose of this state was to filter out measurement occasions in which participants did not experience any negative emotions at all.

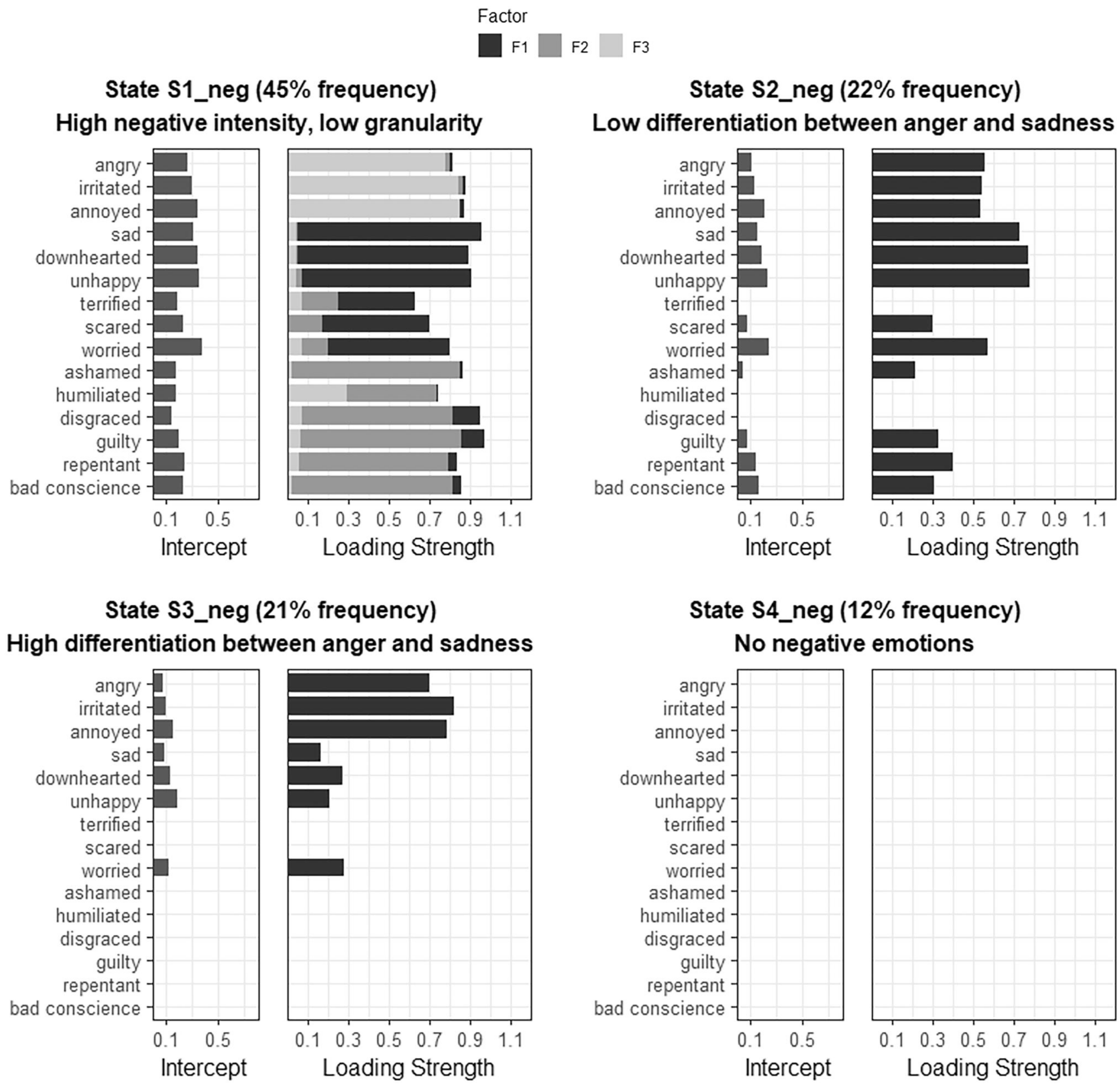

Figure 2. State-specific measurement models for negative emotions. The strengths of the loadings are absolute values of the standardized factor loadings. For interfactor correlations, see Table 1.

$\chi^2(12) = 511.08$, $p < .001$ (for log-linear regression estimates, see Table S9 in the Supplementary Material). Because transition probabilities for a given time interval are easier to interpret than transition intensities, we calculated transition probabilities for an interval of 4 hr as a function of lower ($M - 1$ SD) and higher ($M + 1$ SD) levels of person-mean-centered momentary stress (i.e., at 0.21 units below and above the individuals' mean momentary stress levels). We selected a transition interval of 4 hr because this interval was close to the mean interval between measurement occasions (within-day and between-day intervals combined) in our data ($M = 3.82$, $SD = 4.75$). These transition probabilities are shown in Table 2. Higher momentary stress was associated with a higher probability of transitioning from the "high differentiation between anger and sadness" state to the "high negative intensity, low granularity" and "low differentiation between anger and sadness" states and a lower probability of transitioning from the "high negative intensity, low granularity" and "low differentiation between anger and sadness" states to the "high differentiation between anger and sadness" state.

Table 2. Stress-specific transition probabilities of latent negative EG states for an interval of 4 hr.

		Low stress				High stress			
		State (negative EG)				State (negative EG)			
State − 1	Initial state probabilities	S1	S2	S3	S4	S1	S2	S3	S4
S1 High negative intensity, low granularity	.623	.583	.184	.138	.096	.719	.177	.089	.015
S2 Low differentiation between anger and sadness	.259	.289	.242	.283	.186	.467	.309	.188	.036
S3 High differentiation between anger and sadness	.095	.164	.224	.333	.279	.357	.279	.290	.073
S4 No negative emotions	.023	.142	.217	.305	.336	.268	.236	.347	.150

Note. The transition probabilities indicate the probability of transitioning from the previous latent state (State − 1, rows) to the current latent state (State, columns). For each previous latent state, the latent state that individuals were most likely to transition to is shaded in grey. Probabilities might not add up to 1 due to rounding errors. Stress was person-mean-centered. Low stress corresponds to a score of –0.21 (1 *SD* below the person mean), and high stress corresponds to +0.21 (1 *SD* above the person mean).

Research question 3 and 4: Identifying and predicting latent classes of individuals who differ in state transitions

Of the four mixture LMFA models for negative emotions, the four-class model had the lowest BIC value. When the BIC values were plotted against the number of model parameters, there was a sharp decrease in the BIC from the one-class model to the two-class model and a moderate decrease from the two-class model to the three-class model (see Figure S3 in the Supplementary Material). The two-class mixture LMFA model was favored by the CHull method (see Figure S4 in the Supplementary Material). Since the two-class mixture LMFA model provided the best fit vs. complexity tradeoff in both the BIC-by-complexity plot and the CHull method, we selected this model as our final mixture LMFA model.[8]

The two latent classes were very well separated (entropy R^2 = 0.9959), and the overall classification accuracy was very high (overall classification error = 0.002) for this model. Class-specific transition probabilities for a 4-hr interval are presented in Table 3; estimates of log-linear regression coefficients for the class-specific transition intensities are presented in Table S11 in the Supplementary Material. Class C1_neg was characterized by lower probabilities of remaining in a particular state than Class C2_neg—that is, Class C1_neg showed greater variability in EG states over time than Class C2_neg. Class C2_neg showed a very high overall probability of transitioning to or remaining in the "high negative intensity, low granularity" state, a low to moderately high probability of transitioning to or remaining in the "low differentiation between anger and sadness" state, and low probabilities of transitioning to or remaining in the "high differentiation between anger and sadness" and "no negative emotions" states. Thus, we were able to identify one class that showed greater variability in the granularity patterns with which they experienced negative emotions and one class that was characterized by a propensity to experience multiple, poorly differentiated negative emotions at relatively high intensity levels. We named these classes "variability in negative granularity" and "high negative intensity, low granularity" class, respectively.

Each between-person covariate significantly predicted class membership; neuroticism: $\chi^2(1)$ = 8.14, $p = .004$; negative mood repair: $\chi^2(1)$ = 7.32, $p = .007$; positive mood maintenance: $\chi^2(1)$ = 10.81, $p = .001$ (for multinomial regression estimates, see Table 4).[9] The predicted probabilities of belonging to either class as a function of the time-constant covariates are illustrated in Figure 3. Individuals with low neuroticism scores had a very high probability of being in the "variability in negative granularity" class, but this probability decreased as neuroticism increased (while the probability of being in the "high negative intensity, low granularity" class increased). In contrast, individuals with low scores on negative mood repair or positive mood maintenance had high probabilities of being in the "high negative intensity, low granularity" class, and

[8]In the mixture LMFA models for both negative and positive emotions, a few log-linear regression parameters of the class effects on transition intensities had boundary estimates for which Latent GOLD reported standard errors of 10,000. The estimates of these parameters varied minimally across replications but were all strongly negative. The log-likelihood of the models was stable across replications. Furthermore, the transition intensities resulting from the different regression parameters all approximated zero (indicating transition probabilities of zero for a very short transition interval), and the resulting transition probabilities for a 4-hr interval were identical across replications. We suspected that the proximity of the transition intensities to their lower bound of zero may have been the reason why Latent GOLD could not reliably estimate a stable value for the corresponding regression parameter. However, since the unstable estimates did not affect the values of the transition probabilities for the time interval of interest (i.e., 4 hr), we decided to report and interpret the results of our mixture LMFA model.

[9]To test the robustness of these results, we also simultaneously entered all three covariates into the model as predictors of latent class membership. Only positive mood maintenance significantly predicted latent class membership beyond the other two predictors, $\chi^2(1)$ = 4.97, p = .026, with higher dispositional positive mood maintenance decreasing the probability of belonging to the "high negative intensity, low granularity" class.

Table 3. Class-specific transition probabilities of latent negative EG states for an interval of 4 hr in mixture LMFA.

State − 1	Initial state probabilities	Class C1 Variability in negative granularity (size: 59%) State (negative EG) S1	S2	S3	S4	Class C2 High negative intensity, low granularity (size: 41%) State (negative EG) S1	S2	S3	S4
S1 High negative intensity, low granularity	.623	.246	.322	.288	.144	.875	.099	.022	.004
S2 Low differentiation between anger and sadness	.259	.210	.335	.305	.150	.788	.159	.042	.011
S3 High differentiation between anger and sadness	.095	.175	.267	.364	.194	.738	.189	.054	.019
S4 No negative emotions	.023	.140	.231	.340	.289	.631	.212	.082	.075
	Overall state membership probabilities	.199	.291	.323	.186	.857	.111	.026	.006

Note. The transition probabilities indicate the probability of transitioning from the previous latent state (State − 1, rows) to the current latent state (State, columns). For each previous latent state, the latent state that individuals were most likely to transition to is shaded in grey. Probabilities might not add up to 1 due to rounding errors.

Table 4. Multinomial logistic regression parameters of latent classes regarding transitions between negative EG states predicted by time-constant covariates.

Predictor	Class C2_neg (vs. Class C1_neg) Intercept	Coef.	*SE*	Wald test χ^2	*df*	*p*
Neuroticism	−2.559	0.687*	0.241	8.14	1	.004
Negative mood repair	1.721	−0.810*	0.299	7.32	1	.007
Positive mood maintenance	2.190	−0.961*	0.292	10.81	1	.001

Note. C1_neg represents the "variability in negative granularity" class" and C2_neg the "high negative intensity, low granularity" class.
*$p < .01$.

these probabilities decreased as scores on either of these variables increased.[10]

Positive emotions

We selected a [4 2 2] (i.e., four factors in the first state and two factors each in the second and third states) model as our final Step 1 model for positive emotions. State S1_pos was characterized by high mean intensities of all positive emotions and a highly differentiated four-factor structure. We labeled this state "high positive intensity, high granularity" state. In State S2_pos, mean intensities of the positive emotions were quite low and love-related emotions were not reported at all. The two moderately correlated factors of this state were one factor comprising joy- and (with lower loadings) interest-related items and one factor comprising confidence-related items. We labeled this state "high differentiation between love, joy, and confidence" state. State S3_pos was characterized by high mean intensities of all positive emotions, similar to the "high positive intensity, high granularity" state. However, the two factors, on either of which all positive emotions loaded, were very highly correlated with each other. We labeled this state "high positive intensity, low granularity" state to emphasize its contrast to the "high positive intensity, high granularity" state.

Regarding the effects of momentary stress on transitions, higher momentary stress was associated with higher probabilities of transitioning between the "high positive intensity, high granularity" and "high positive intensity, low granularity" states within a transition interval of 4 hr. However, transitions to and from the "high differentiation between love, joy, and confidence" state were rather unaffected by momentary stress.

We selected a three-class mixture LMFA model to explore between-person differences in transitions between positive EG states. Class C1_pos was characterized by high probabilities of transitioning between the "high positive intensity, high granularity" and "high positive intensity, low granularity" states. We labeled this class "high positive intensity, variability in granularity" class. Class C2_pos, which we labeled "complex positive granularity" class, represented a mixture of two subclasses in which one subclass transitioned between the "high positive intensity, high granularity" and "high differentiation between love, joy, and confidence" states, while the other subclass always remained in the "high positive intensity, low granularity" state. Class C3_pos mainly showed a high probability of remaining in the "high positive intensity, high granularity" state. We named this class "high positive intensity, high granularity" class. None of the time-constant covariates significantly predicted class membership.

Discussion

Only a few studies have investigated more qualitative aspects of EG (e.g., by examining which emotions are

[10]In the Supplementary Material, we further report additional analyses in which we tested the predictive effect of latent EG states on time-varying self-rated emotion regulation success.

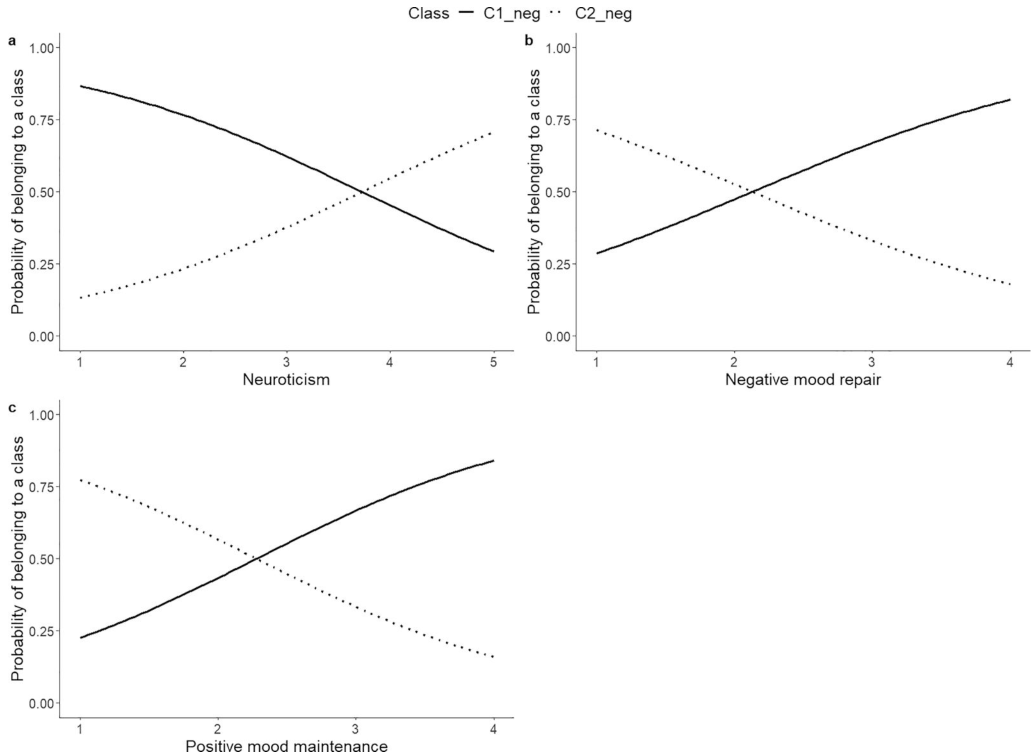

Figure 3. Predicting latent class membership from **a** neuroticism, **b** negative mood repair, and **c** positive mood maintenance for negative emotions. Class C1_neg represents the "variability in negative granularity" class, Class C2_neg the "high negative intensity, low granularity" class.

more or less differentiated from each other rather than examining how individuals differentiate more globally between all the emotions of interest). However, these studies have mostly been limited to stable between-person differences, whereas research on the extent to which such qualitatively distinct EG patterns are stable or variable over time is still lacking. To address this gap, we proposed (mixture) latent Markov factor analysis (LMFA; Vogelsmeier, Vermunt, van Roekel, & De Roover, 2019)—which represents a combination of latent Markov modeling and exploratory factor analysis—as a novel statistical framework for modeling within-person variability in qualitative EG states and individual differences therein. Applying LMFA to individuals' repeated emotion ratings over time allowed us to identify distinct latent EG states that differ with respect to state-specific measurement models of the emotion ratings and to estimate the trajectories between these latent states over time.

For both negative and positive emotions, we identified three distinct latent EG states that differed in the underlying measurement models of emotion intensity ratings. For negative emotions, we identified one state characterized by high mean intensities and low overall granularity ("high negative intensity, low granularity" state) and two states that differed, inter alia, in granularity between anger- and sadness-related emotions ("low differentiation between anger and sadness" vs. "high differentiation between anger and sadness" states). In addition, we specified a so-called no negative emotions state. This state was represented by 12% of all measurement occasions at which all the negative emotion items received a score of zero. For positive emotions, we identified two high mean intensity states that differed in overall granularity ("high positive intensity, high granularity" vs. "high positive intensity, low granularity" states) and a third state that was characterized by a high granularity between love-, joy-, and confidence-related emotions ("high differentiation between love, joy, and confidence" state).

In order to compare the distinct negative and positive EG states, we were able to use a large amount of information from the different parameters of the state-specific measurement models: On the one hand, by examining between-state differences in the factor loading patterns, we were able to distinguish between states in which different emotion items shared high loadings on one common factor and states in which the magnitude of common factor loadings differed substantially among these items. For example, in the "low differentiation between anger and sadness" state, the anger- and sadness-related items both had high loadings on one factor, whereas in the "high differentiation between anger and sadness" state, the sadness-related items had only weak loadings on this factor. Consistent with theoretical accounts suggesting that how individuals conceptualize their emotional experiences varies over time (Hoemann & Feldman Barrett, 2019), this finding suggests that individuals' concepts of anger and sadness may overlap or even dissolve into one broader emotion category under certain circumstances (Hoemann et al., 2017). Therefore, between-state differences in the factor structure reflected temporal variation in how individuals organize their emotional experiences.

On the other hand, between-state differences in emotion item intercepts (which indicate the state-specific mean emotion intensities) provided us with important additional information about EG patterns (i.e., beyond the information provided by the factor structure). First, we found between-state differences in whether some emotions were not reported at all on all state-specific occasions versus whether they were reported at least to some extent on some occasions (i.e., between-state differences in whether intercepts for some emotion items were zero or not). For example, the "high differentiation between love, joy, and confidence" state differed from the other two positive EG states in that participants did not report any love-related emotions in this state (i.e., the state-specific intercepts of love-related emotions were zero). Whereas, in the other two positive EG states, participants reported experiencing love to some extent alongside other positive emotions (although the degree to which they experienced love in synchrony with other positive emotions varied, as indicated by the between-state differences in the factor structure), in the "high differentiation between love, joy, and confidence" state, participants were highly specific in not experiencing any instances of love alongside other positive emotions. Thus, this state may be indicative of a high degree of differentiation between love and other positive emotions. Previous operationalizations of time-varying qualitative EG (i.e., network models of EG; Hoemann et al., 2020) are based only on covariances between similarly-valenced emotions and would therefore ignore instances in which, for example, positive emotions are experienced in complete isolation from love-related emotions. The advantage of LMFA is that time-varying qualitative EG patterns can be described not only by the degree to which emotions covary (indicated by the factor structure) *when* they are experienced to some extent in a state, but also by taking into account whether emotions are actually experienced or not (indicated by [non-]zero intercepts). We would argue that an LMFA approach to EG not only allows for a more fine-grained picture of the particular time-specific EG pattern than would pure covariance-based EG operationalizations, but that it also more naturally reflects the experience of emotions as discrete events rather than a continuous process (Haslbeck et al., 2023).

The latent Markov modeling part of LMFA allowed us to investigate the variability versus stability of EG states across states and potential predictors of transitions between EG states. First, in order to investigate whether transitions between different EG states were dependent on contextual influences, we added momentary stress as a time-varying predictor of transition intensities. For negative emotions, we found higher probabilities of transitioning from a more granular state (i.e., the "high differentiation between anger and sadness" state) to less granular states (i.e., the "low differentiation between anger and sadness" and "high negative intensity, low granularity" states) within a 5-hr interval at higher than usual stress levels compared to lower stress levels. These results are in line with previous research in which daily negative EG was lower on days with higher stress (Erbas et al., 2018). However, our findings may provide further insight into how stress may affect transitions between specific EG patterns. For example, as indicated by higher transition probabilities from the "high differentiation between anger and sadness" to the "low differentiation between anger and sadness" state and lower transition probabilities vice versa at higher levels of momentary stress, individuals may be less able to differentiate anger from sadness when they are under higher stress. Differentiating anger from sadness may be easier under lower stress because individuals may have more cognitive resources available to access their negative emotion concept knowledge, which helps them distinctively assign different pieces of emotional information to specific emotion categories (Lindquist & Feldman Barrett, 2008). For positive emotions, we found that higher momentary stress was associated with a higher probability of transitioning between the "high positive intensity, high granularity" and the "high positive intensity, low granularity" state as well as a lower probability of remaining in these states. As the results suggest, the relationship between momentary stress and trajectories between EG states may be different for negative and positive emotions: Whereas for negative emotions, higher momentary stress is associated with a specific direction of EG state trajectories (i.e., toward less granular negative EG states), for positive emotions, higher momentary stress is associated with an increase in the overall variability between more and less granular positive EG states (but not with a specific direction between more and less granular positive EG states). Because we did not differentiate between specific, external stressors that led to feeling stressed in our ESM prompts, future research assessing specific stressors (e.g., time pressure, pain) in their ESM surveys may provide insight into the effects of stress on EG state trajectories by examining whether EG state trajectories can be predicted by different stressor types.

Second, by extending LMFA to mixture LMFA, we examined between-person heterogeneity in EG state trajectories by using a latent class variable at the between-person level. Moreover, we predicted latent class membership from global trait measures of psychological adjustment: For negative emotions, we obtained a class of individuals (the “variability in negative granularity” class) that was characterized by a rather variable trajectory pattern across the different negative EG states and a class of individuals (the “high negative intensity, low granularity” class) who remained predominantly in a state of multiple high-intensity negative emotions (i.e., the “high negative intensity, low granularity” state). Participants were more likely to belong to the “high negative intensity, low granularity” class if they had higher scores on neuroticism and lower scores on dispositional negative mood repair and positive mood maintenance. This finding suggests that individuals with higher neuroticism or lower mood regulation abilities seemed to remain stuck in a state of high undifferentiated negative emotions and seemed less able to experience certain negative emotions in isolation from each other (e.g., guilt in isolation from anger). For positive emotions, two of the three classes we obtained (the “high positive intensity, variability in granularity” and “high positive intensity, high granularity” classes) tended to experience multiple positive emotions at higher intensities most of the time. However, individuals from the “high positive intensity, variability in granularity” class were more variable in the extent to which they differentiated between intense positive emotions (as indicated by high probabilities of transitioning between the “high intensity, high granularity” and “high intensity, low granularity” classes), whereas individuals from the “high positive intensity, high granularity” class tended to stay in the “high intensity, high granularity” state. In contrast to the classes for negative EG state trajectories, the classes for positive EG state trajectories were not significantly predicted by global trait measures. These findings are similar to those from previous research in which lower negative trait EG, but not positive trait EG, was significantly associated with poorer psychological adjustment in nonclinical populations (O’Toole et al., 2020) and with maladaptive personality traits, such as higher neuroticism or lower self-esteem (Erbas et al., 2014). However, our between-person-level analyses were more specific in that we did not examine associations of between-person differences in global cross-sectional EG levels. Rather, we examined between-person differences in the stability versus variability of specific EG patterns and how these between-person differences were related to personality variables. Thus, examining transitions between state-specific measurement models of emotions (and potential predictors thereof) via LMFA may allow researchers to obtain fine-grained insights into within-person variability in qualitative EG patterns.

Directions for future research and limitations

One aspect of study design that affects state-specific measurement models is the type and number of emotion items that researchers choose to include in the ESM surveys. More specifically, the degree to which some emotion items load on a factor may depend on the presence of other emotion items. In turn, factor interpretations may change depending on whether fewer or more emotion items are subjected to state-specific measurement models. Such researcher degrees of freedom in emotion item selection (see also Brose et al., 2020; Cloos et al., 2023) may limit the comparability of measurement models across studies that apply LMFA to investigate EG but use different emotion items. However, the concern about a lack of comparability due to different emotion item sets in EG research is not specific to LMFA and has already been raised for previous ESM-based operationalizations of EG (Thompson et al., 2021). We recommend that researchers intending to apply LMFA to the field of EG base their selection of emotion items on the range of the emotions for which they are interested in finding specific EG patterns. If researchers are interested in finding different EG patterns across a wide range of similarly-valenced emotions, they should select emotion items that are able to capture that range. However, if they are interested in examining the granularity between specific emotions (e.g., examining the granularity between sadness and anger in patients with borderline personality disorder), they can limit the range of items to that specific subset, but should be careful to include a sufficient number of items so that multiple factors can be identified.

Relatedly, in order to be able to examine between-state differences in the granularity between specific emotions (e.g., anger vs. fear) based on differences in the factor structure, we recommend that researchers follow our approach of using multiple indicators for each discrete emotion category (e.g., "angry" and "irritated" as indicators for anger). This should allow for a highly nuanced factor structure in which specific factors representing "pure" discrete emotions (e.g., a specific anger factor) can be identified. The use of only a single item for each discrete emotion category, which is common in EG research, does not allow for the emergence of an emotion-specific factor structure, and this potentially obscures between-state differences in granularity, especially between emotions that are considered to be more similar (e.g., sadness and fear vs. sadness and anger). However, researchers should be aware that increasing the number of items in ESM surveys may increase participant burden and reduce data quality (Eisele et al., 2022; Hasselhorn et al., 2021). Future research applying LMFA to the EG domain is needed to gain more knowledge about how the number of items and the structure of the item set affect the identification of state-specific measurement models.

The use of LMFA to find different patterns of EG and their variability versus stability may be particularly useful in a clinical context, that is, in a sample drawn from specific clinical populations. There is already preliminary evidence that granularity between specific emotions is related to clinical symptoms (e.g., sadness-related EG in relation to depressive symptoms; Willroth et al., 2020). However, further research on how specific contexts may influence changes in distinct patterns of EG in individuals known to process emotional experiences maladaptively may be useful. Insights gained from such studies using LMFA could then be used to improve interventions aimed at increasing EG (e.g., Vedernikova et al., 2021) by incorporating critical situations into the intervention exercises. Furthermore, the increasing technical advances in smartphone apps used for so-called just-in-time adaptive interventions (Nahum-Shani et al., 2018) could allow researchers and practitioners to implement LMFA to detect critical EG states, so that specific EG intervention exercises could be performed "right at the critical moment". In summary, we argue that clinical research and practice could particularly profit from the benefits of LMFA for EG research.

Our study was based on a convenience sample of mainly younger adults, a very large proportion of whom were women. Previous research on gender differences in EG is rather scarce, although there is empirical evidence that women have, on average, higher negative EG than men (Mankus et al., 2016). We cannot rule out the possibility that the identification of latent EG states and latent classes of individuals differing in EG state trajectories was strongly influenced by the overrepresentation of women in our sample and that the pattern of results would have looked different with a more gender-balanced sample. In future research, it may be interesting to examine how men and women differ in specific qualitative EG patterns (e.g., whether women are better able to differentiate sadness and fear than men, whereas men may be better able to differentiate anger and sadness). This could be investigated with mixture LMFA by testing whether gender predicts membership in classes that differ in the stability in vs. fluctuations between particular EG states.

Conclusion

Latent Markov factor analysis and its extensions provide a comprehensive statistical framework for investigating the within-person dynamics of qualitatively distinct emotional granularity states. Such an application can help researchers gain finer-grained insights into how individuals differentiate between certain discrete emotions at a given point in time, how these patterns vary over time, and how individuals differ in this variability.

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Data availability statement

Data, analysis scripts, and model outputs for this research can be accessed via https://osf.io/w4tye/.

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