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A State Space Model of Daily Dynamics with Moderation Effects from Qualitative Text Data

Samuel D. Aragones, Emorie D. Beck, and Emilio Ferrer

Department of Psychology, University of California, Davis, USA

ABSTRACT

The last two decades have seen a dramatic increase in using intensive longitudinal data to capture psychological processes. Intensive longitudinal data allow researchers to study intra-individual change and variability. Multiple modeling approaches have been developed to examine these dynamics in a process as it unfolds over time. What is often not considered in these models are factors that can influence the dynamics of the given process. In this article, we describe a state space model to examine the dynamics of daily affect and combine it with covariates that moderate the parameters describing such dynamics. In our approach, the moderators represent sentiment values from open responses to a daily questionnaire. Unlike standard Likert-type measures, open text allows individuals to express their thoughts and feelings without numerical or wording restrictions. We apply natural language processing to quantify positive and negative sentiment associated with such written responses reported daily. The implemented model utilizes a functional relationship between the variability in dynamic parameters and a time-varying covariate. The target of the moderator covariates are the autoregressive and cross-lag parameters in a vector autoregressive model. We find that such moderation effects from the covariates are small, yet robust. However, when the covariates are specified as predictors of the process instead of the dynamic parameters, their effects are strong. Our analyses show that, overall, qualitative measures are valuable to help understand dynamic processes.

KEYWORDS

Natural language processing; state space models; idiographic analysis; time series

Introduction

Many important questions in psychological science utilize quantitative scales to study how psychological processes unfold over time. In intensive longitudinal research, for example, these quantitative scales have been useful in improving our understanding of processes such as affect (Curran et al., 2015; Ferrer & Nesselroade, 2003). However, standard Likert-scale variables have some limitations. One major assumption of such scales, which is typically overlooked, is that they require individuals to interpret and quantify their experiences within the constraints of the scale. This assumption may not hold across individuals. For example, endorsing "two" on a pain scale could represent different experiences of pain for different individuals. For a typical person, a "two" may represent pain from some minor injury while a "two" for someone with chronic pain may be representative of a day with lower pain than average. It is reasonable to believe that other types of data without these constraints, such as open-ended responses, may provide richer or different insights into individuals' experiences (Allport, 1942).

In contrast to standard scales, open-ended responses allow individuals to convey their own experiences of the world in more detail. Often, these responses are the ideas most salient in an individual's thoughts. In such responses, individuals are not forced to think within the boundaries of a scale but rather report their experience from their own perspective. Open-ended responses thus can give more qualitative information as well as provide context for other scale-based measures, aiding in their interpretation. In the past, these types of data were difficult to implement in statistical analyses due to the need of human coding and the subjective decisions required to quantify them prior to analyses. However, with developments in data collection and methodologies such as natural language processing (NLP), there has been a rise in the use of text-based data. In psychology, analyses utilizing NLP have shown the value of using text to

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make predictions and enrich theory (Boyd & Pennebaker, 2015; Jacobucci et al., 2021; Martínez-Huertas et al., 2021; Pennebaker, 1997). One area of potential development is the integration of such open-ended responses with traditional scales. In this article, we illustrate one approach for integrating traditional scale-based data with text from open-ended questions. In particular, we use text as a moderator of parameters in time series models of scale data. In our analysis, we model the dynamics of daily measures of affect and use text describing daily major events as moderators of the system dynamics.

Integrating text data with scale measures highlights the value that open-ended responses bring to capture individual experiences (Boyd & Pennebaker, 2017; Nissen & Beck, 2024, 2025; Yarkoni, 2010). These experiences could have important implications for modeling approaches trying to characterize intraindividual processes (Cattell et al., 1947; Nesselroade et al., 2007). Some models assume that a process is ergodic, or that group-level traits are representative of intraindividual change over time, such as the traditional SEM (Jöreskog, 1971). When the goal is to understand a given process at the population level, these traditional methods based on between-individual differences are indeed valuable. However, when the goal is to understand the unique manifestation of a given phenomenon at the individual level, modeling approaches that focus on intraindividual variability and change should be considered (Molenaar, 2004). In characterizing intraindividual variability, one important goal is interpreting individuals' subjective experiences. In this regard, scale measures provide response criteria that are limited. One way to account for some inter-individual differences in how people interpret scale measures is by person-mean centering participant responses. However, while properly scaling to the individual response is important, an additional layer to consider is the context of the response. Such context could help explain, at least in part, intraindividual variability and change in the target process. One way to account for contextual influences is *via* covariates. In the present research, we utilize a covariate representing text to account for intraindividual variability in the affective process. In psychological research, assuming that individuals are homogeneous in their change pattern is often an unreasonable assumption that could lead to spurious inferences (Castro-Schilo & Ferrer, 2013; Molenaar, 2004; Steele et al., 2014). One way to study individual differences in these change patterns is to fit idiographic models.

In this study, we examine the dynamics of daily affect and use a covariate representing text from open-ended responses to account for variation over time in the parameters representing such dynamics. We observe between-person differences across models fit at the individual level. Thus, our proposed approach integrates scale measures with open-ended responses in the context of a dynamic model in an idiographic application of the model.

Affective dynamics

Emotion is a complex psychological phenomenon with multiple components; the exact definition of which has been debated over the years (Coppin & Sander, 2021; Fehr & Russell, 1984; Irons, 1897; Izard, 2010; James, 1884; Russell, 2012). An integral aspect of measuring emotion is affect. Affect is often defined as the consciously accessible state reflecting a blend of valence, (pleasure-displeasure) and arousal, (sleepy-activated) that is the underpinning for the experience of emotion (e.g.Russell, 1980; 2003; Watson & Tellegen, 1985; Wundt, 1912). Abundant research demonstrates that affect fluctuates across time (e.g.Dejonckheere et al., 2019; Ong et al., 2025; Wilson et al., 2017). Thus, the study of affective dynamics aims to understand how, when, and why affect fluctuates within and across people and time (e.g. Kuppens, 2015; Hamaker et al., 2015).

Work on affective dynamics has primarily unfolded to address three broad questions. First, what are the endogenous (e.g.sleep, Ong et al., 2013; menstrual cycles; Stern et al., 2025) and exogenous (e.g. social interactions, Liu et al., 2019a) forces that lead to fluctuations in affect? Such work has demonstrated that affect fluctuates in response to social factors (e.g.partner affect; Bolger et al., 2000; Butler & Randall, 2013), situational factors (e.g. stressful events; Sin et al., 2015), and even the time of day (e.g. Larsen, 1985). Second, how do people differ in their affective dynamics? Work on individual differences in affective dynamics has identified a broad array of relevant dynamics, including within-person variability, inertia, and reactivity, among others (Ong et al., 2025; Ong & Ram, 2017). Finally, what are the short- (e.g. daily physical activity; Liao et al., 2015) and long-term (e.g. Dejonckheere et a., 2019) consequences of individual differences in affective dynamics as indicators for well-being in mental and physical health, general well-being, and life satisfaction? In the domain of relationships, such work has demonstrated that individual differences in dyadic affective dynamics are associated

with relationship maintenance and dissolution (e.g. Sbarra & Ferrer, 2006). In the present study, we focus on the first two points. Primarily, we explore how text data, which captures aspects of the endogenous and exogenous forces, relates to affect dynamics. Second, we study how people at the individual level differ in their expression of emotion and the degree to which text data and partner's affect lead to such dynamics.

While much attention has been paid to the modeling of affect as an often simple dynamic system, much less attention has been paid to how affect is measured in everyday life, which has led to at least three gaps in our understanding of affective dynamics. First, many studies of affect utilize measures, like the positive and negative affective schedule (PANAS; Watson et al., 1988). The PANAS consists of items that are meant to represent the range of emotional states across the valence and arousal dimensions of affect. While the PANAS has aimed to capture the dimensions as described in the circumplex model, this scale has been widely critiqued for having poor factor structure, imbalanced arousal (relative to valence; e.g. Nealis et al., 2016), and more. A second potential gap arises when considering studies that utilize the affective grid or direct measures of valence and arousal (e.g.Kuppens et al., 2013; Russell et al., 1989). These scales allow participants to directly rate their experiences, but these have been critiqued because they miss the way in which affective experiences are constructed *via* language (e.g. Hoemann et al., 2025). Third, participants frequently interpret even the same affective indicators differently, which can lead to both systematic and unsystematic bias in measurement across time (e.g. Siepe et al., 2025).

As a result, there have been increasing calls to measure affective experience using natural language. Natural language has several advantages relative to traditional, scale-based measures. First, natural language approaches to affect are better aligned with both constructivist and appraisal theories of emotions (e.g.Barrett, 2013; Ellsworth, 2024; Moors et al., 2013). In each theory, affective and emotional experience is thought to be best understood *via* complex meaning-making or appraisal processes that unfold within a person across time. From their perspective, there is little reason to believe that any two people experience affect identically. Rather, such experiences are shaped by biological, psychological, cognitive, and behavioral histories within the individual life. Second, natural language approaches allow people to express their experiences using their own language, which improves inclusivity in our science. Standard questionnaires often include items that are differentially interpreted as a function of language, culture, and age (e.g. Fetvadjiev & van de Vijver, 2015). These questionnaires can miss culture, language, and time-specific expressions and understanding of affect. Such issues are exacerbated in dyadic research because of both shared and non-shared ways of experiencing the self, the partner, the relationship, and the world, leaving much to be desired when using traditional, scale-based questionnaires alone.

Fully understanding the utility of natural language within affective dynamics requires linking natural language approaches to existing scale-based data. A number of novel approaches, reviewed in the next sections, have created new opportunities for testing the utility of natural language data in understanding the affective dynamics of both individuals and dyads.

Analytic approaches

Natural language processing (NLP)

Natural Language Processing (NLP) is a broad field that describes the computational methods used in analyzing or quantifying human language (Khurana et al., 2023; Tanana et al., 2021). There are variations in the steps taken in NLP analysis depending on the aims of the study and the particulars of the text. However, most NLP analyses require some form of preprocessing to facilitate the use of text in the algorithms used to quantify the resulting data (Chai, 2023; Kalra & Aggarwal, 2018). Some common preprocessing steps include translating responses to the same case (e.g. uppercase or lowercase), rectifying spelling errors, or removing punctuation. Another common step is the removal of "stop words,," or words that do not greatly influence meaning within the sentence (i.e. "the,," "and,," etc.).

Following these initial steps, NLP methods can be classified into different categories that are applied to standard text-based analyses. NLP can be used in aims different from those in our study. For example, some approaches identify the unique topics that are most commonly mentioned in the data, while others are used in the translation of text across different languages. We refer the reader to Kennedy et al. (2021) for a more exhaustive review on current NLP approaches for psychological data. In our study, we use NLP to transform text into quantitative data for use in the statistical modeling of daily reports of affect. Most notably, as the goal of our study is to contextualize daily affect data with text, we use sentiment analysis.

Sentiment analysis focuses on the emotions that are captured in human language and typically aims to identify the valence of a response, (e.g. positive, negative, or neutral) with some methods also identifying the intensity of the emotion (Tanana et al., 2021). Approaches to assigning sentiment range from utilizing a dictionary and grammatical rules, (i.e. lexicon-based methods) to machine-learning methods, such as neural networks, to "learn" the relationships found among the unique corpus present in the text (Mohammad, 2016). Another distinction can be made between methods that assign categorical classifications such as positive, negative, or neutral, (Devlin et al., 2019; Liu et al., 2019b) to those that assign a specific intensity to the emotion present in the text (Mohammad, 2021; Qi & Shabrina, 2023). For the latter, the intensities are represented as real-valued numbers between −1 and +1 (Hutto & Gilbert, 2014; Loria, 2018). There are advantages to each with machine-learning methods outperforming lexicon-based methods in the classification context (Qi & Shabrina, 2023).

For our study, we utilized Vader, a lexicon-based method that can be compared to the Linguistic Inquiry and Word Count (LIWC), which was developed in the context of affective processes (Hutto & Gilbert, 2014; Pennebaker, 1993; Pennebaker et al., 2001). In its introduction, the lexicon and grammatical rules utilized in Vader were validated against human-coded responses of social media text as well as other lexicon-based methods and machine-based methods in the form of support-vector machines. We primarily use Vader as it generates a score of emotional intensity rather than a classification, and it has performed well among similar methods for emotional scoring (Hutto & Gilbert, 2014; Srivastava et al., 2022). This score is used as our primary covariate of sentiment for our analyses.

Structural Equation modeling and state space modeling

Structural Equation Modeling (SEM) is one of the most common methodologies used in psychological research for both cross-sectional and longitudinal data. SEM can be used to examine questions related to both between-person differences and within-person changes (McArdle, 2009). In recent years, however, there have been extensions of SEM approaches for examining within-person effects (Beltz et al., 2016; Rush & Hofer, 2014). Although implementations of SEM to time series data have existed for over two decades (Ferrer & Nesselroade, 2003), recent developments, such as so-called dynamic structural equation modeling (DSEM; Asparouhov et al., 2018), allow modeling time series data within a SEM framework with the possibility of integrating multiple individuals and random effects. All these benefits notwithstanding, there are still difficulties in characterizing within-person heterogeneity given limitations of the SEM for systems with time-varying covariates and non-stationarity (Asparouhov & Muthén, 2024; Curran & Bauer, 2011).

An alternative approach known as state-space modeling (SSM) has been considered for examining longitudinal psychological data in a wide range of contexts, including: fluctuations of emotion in a dyadic setting, homeostatic self-regulation of emotion and its relationship with outcomes of addiction, and stress as a function of physiological and cognitive load (McKee et al., 2020; Song & Ferrer, 2009; Tavakoli et al., 2022). SSM, like SEM, is a flexible framework for modeling relations among latent and observed variables across time. The method originates from control theory to estimate the position and dynamics of spacecraft using first-order differential equations (Kalman, 1960; Friedland & Director, 1985). Since its introduction, SSM has been used for analysis of intensive longitudinal data in econometrics, medicine, ecology, and psychology (Durbin & Koopman, 2001; Shumway & Stoffer, 2006).

Generally, a state-space model describes the characteristics (i.e. the dynamics and observed measures) of a system or phenomenon and its potential evolution over time. In such a model, latent variables are referred to as "states.," Typically, SSMs assume that there is an underlying latent or hidden Markov process (i.e. the "state process") such that future and past states are conditionally independent on the present state (Shumway & Stoffer, 2006). Additionally, the observed measures are independent, given the states of the system, such that the occasions of observed measures are linked only through the states.

Here we provide a brief description of the model implemented in our analyses. For more detailed information, we refer readers to available literature (Chow et al., 2010; Hunter, 2018).

$$\begin{aligned} y_i &= \tau + \Lambda\eta_i + \mathrm{K}x_i + \epsilon_{\mathrm{i}} \\ \eta_i &= \alpha + \mathrm{B}\eta_{i-1} + \Gamma x_i + \zeta_{\mathrm{i}} \end{aligned} \tag{1}$$

The measurement model, expressed in the first part of the equation, describes the observed measures of the system through linear relationships. In this equation, y represents observations, τ denotes the intercept, Λ is the matrix of factor loadings, K relates to the effects of the covariates, and ϵ contains the

residuals for the manifest variables, which are normally distributed with variance of Θ; $\epsilon_i \sim N(0, \Theta)$.

The second part of Equation (1) refers to the structural model, which describes the latent variable relationships. The baseline model we implement in this study is a vector autoregressive (VAR) model, described in Equation (1), where η is a q x 1 vector of states (e.g. "latent variables"), α represents a q x 1 vector of intercepts, B is a q x q matrix of autoregressions and cross-lagged effects, and ζ are the residuals of the latent variables, which are assumed to be normally distributed with $\zeta_i = N(0, \psi)$. The subscript, i, reflects independent rows of the data matrix. For the purposes of this study, i represents time, t. The term, Γx_i, refers to a covariate (i.e. exogenous predictor), x_i, and its effect on the state. Of note is the term, η_{i-1}, which relates the previous row to the estimation of the current state. While the equations in the SEM and SSM representations of the VAR model are effectively equivalent, there are differences in the estimation procedures. The use of the SSM in this study focuses on a discrete-time state function as described in Equation (1). However, a continuous state function can also be used. In our analyses, we first implement the SSM without covariates in the model. Then, we include a covariate representing the sentiment data and examine its moderating effect of the dynamic parameters of the system, followed by a specification in which the covariate is a predictor of the latent states.

Methods

Empirical data

The data used for the analysis come from the Dynamics of Dyadic Interactions Project (DDIP; Ferrer & Widaman, 2008; Ferrer et al., 2012). Participants in this study were individuals involved in a romantic relationship. They ranged in age from 17 to 74 years old (females: $M = 24.11$, $SD = 9.95$; males: $M = 24.83$, $SD = 10.17$) and the time they had been in their relationship ranged from 0.8 to 54.25 years ($M = 3.03$; $SD = 5.61$). As part of the study, participants completed a daily questionnaire about affect related to their relationship (RSA; Ferrer et al., 2012). The scale included 18 items with a Likert-scale response denoting positive and negative affect. In addition, participants responded daily to an open-ended question asking, "Describe any important event that occurred today in your relationship or your life.," Out of the total 23,308 days represented in the dataset (all individuals across all days), 10,736 days contained comments. Participants reported daily measures for up to 90 consecutive days.

We model the latent process for positive and negative relationship-specific affect at the individual level. We then use the individual's comments, quantified through NLP by their degree of positive and negative sentiment, as moderators of the regression parameters.

Quantifying sentiment values using natural language processing

We performed standard NLP preprocessing on the data to standardize capitalization. To quantify the degree of positive and negative sentiment associated with the written responses, we implemented Vader, a part of the Natural Language Toolkit (NLTK) Python library for NLP analysis that quantifies sentiment in text (Hutto & Gilbert, 2014). The Vader algorithm utilizes a lexicon which associates certain words with positive, negative, or neutral sentiment. A rule-based component, which considers certain grammatical rules and syntactic contexts, is additionally applied and results in a compound sentiment value for the given phrase. Due to the method's consideration of grammatical rules, we did not remove any words or punctuation. Vader quantifies the positivity and negativity associated with a given text on a −1 to 1 scale. For example, the phrase, "I like cats" may result in a score of 0.8 because it is considered a highly positive message. In addition to the compound score, Vader provides separate information on positive and negative sentiments. We extracted sentiment scores from each written response by participants across days and used these scores as a moderator in a state space model to determine the degree to which daily experiences of individuals as taken from text data affect autoregressive, and cross-lag parameters in the model.

State space model with moderator variables

In our analyses, we used an SSM with a moderator variable (Adolf et al., 2017; Bringmann et al., 2024). This approach consists of a time series model that includes time-varying parameters describing the dynamics of a latent process. The variability in such parameters is then modeled through a moderator that is also time-varying. This model estimates the change in the dynamic parameters (e.g. autoregressive, and cross-lagged effects) in a vector autoregressive (VAR) model that is associated with a covariate. The model used in our study is an extension from the model described in Equation (1). First, the time-related

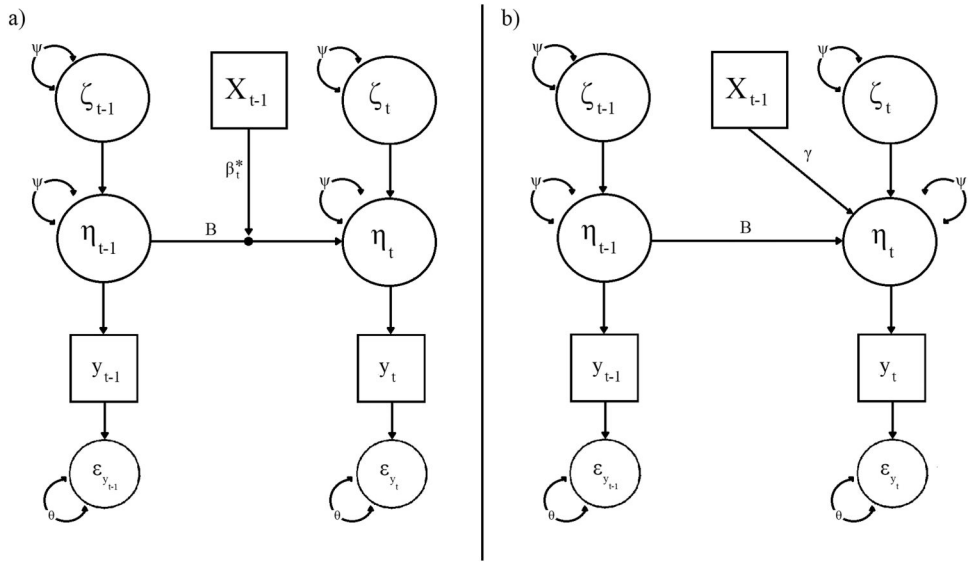


Figure 1. State space model of moderator (panel a) and direct predictor (panel b).

variation of the parameters, B, and ψ (notice the subscript t), are explained as a function of the moderator X (Equation (2)). X is a moderator that is assumed to vary over time but is fixed in the model parameters to allow for the variability to be reflected in two deterministic functions linked to parameters of the model. That is, the change in the parameters over time is entirely explained as a function of the moderator's values (see Equation (3)). In the original approach, the changes in the intercept vector, α, that are explained by the moderator are also estimated. However, we held this parameter constant over time as we were mainly interested in changes in the autoregressive and cross-lagged effects. Figure 1 is a path diagram representing the moderation model (panel a) alongside a model in which the moderator is instead introduced as an exogenous covariate predicting the latent state (b). Panel a shows that the moderation effect acts on the regression parameters that relate the previous state, η_{t-1}, to the current state η_t. This effect varies as a function of the moderator's values across time and is described by the parameter β_t^*. Panel b shows the direct relationship between the values of the covariate and state rather than the changes in parameters. This direct relationship, γ, is represented in panel b and is not assumed to vary across time.

$$\begin{aligned} \eta_t &= \alpha_t + \beta_t^* \eta_{t-1} + \zeta_t; \zeta_t \sim N(0, \psi_t^*) \\ \beta_t^* &= f(X_{t-1}) \end{aligned} \tag{2}$$

$$\psi_t^* = g(X_{t-1}) \tag{3}$$

Our implementation of the SSM included two state variables, positive and negative affect, which represent the average scores of the corresponding items in the RSA scale. This bivariate implementation of the model is depicted in Equation (4). Equation (4) describes the β_t^* parameters as the estimated effects of the moderator on the baseline regression parameters. Here, the matrix of baseline parameters, $\beta^{(0)}$, function as the intercepts, where the parameters in $\beta^{(X)}$ function as the slopes, in relation to the values of the moderator, X_{t-1}. Positive values in β_t^* indicate that we would expect an increase in the relations, while a negative value would mean an expected decrease. We fitted the model for each individual separately to obtain unique parameter estimates for each person. We then performed bootstrap analysis to calculate confidence intervals of the estimates. To not constrain the parameter space of the estimates and to avoid local minima in the fit function, we provided different starting values in 200 restarts[1] of the estimation procedure. In addition, we allowed for up to 50 iterations within each estimation process, utilizing the previous best estimated set of parameters through the *mxTryHard* function in *OpenMx* (Hunter, 2018).

$$\begin{aligned} \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}_t^* &= \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}^{(0)} + X_{t-1} \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}^{(X)} \\ \begin{bmatrix} \psi_{11} & \psi_{12} \\ \psi_{21} & \psi_{22} \end{bmatrix}_t^* &= \begin{bmatrix} \psi_{11} & \psi_{12} \\ \psi_{21} & \psi_{22} \end{bmatrix}^{(0)} + X_{t-1} \begin{bmatrix} \psi_{11} & \psi_{12} \\ \psi_{21} & \psi_{22} \end{bmatrix}^{(X)} \end{aligned} \tag{4}$$

[1]We repeated these analyses with additional conditions of 500- and 1000-iterations and included a variation of the model that allows for a residual term in Equation 4. A subset of these results are included in the Supplementary Materials, with minor differences across the results included in the manuscript and those present in the Supplement.

Estimation of parameters

A common estimation method used within SSM that can capture the time-varying nature of dynamic parameters is the Kalman filter (KF; Kalman, 1960; Chow et al., 2010). The KF is a set of algorithms used to estimate current states, future states, and the parameters underlying such states. In the KF, parameters are updated iteratively in two steps: prediction and update. The prediction is a one-step prediction of the state's mean along with the covariance matrix (Equation (5)). One-step prediction uses time points prior to the predicted state, up to $t-1$ to make an initial prediction. Here, η, α, B, and ψ reflect the parameters of the state space model while P is the associated covariance matrix.

$$\begin{aligned} \eta_{t|t-1} &= \alpha + \mathrm{B}\eta_{t-1|t-1} \\ \mathrm{P}_{t|t-1} &= \mathrm{B}\mathrm{P}_{t-1|t-1}\mathrm{B}' + \psi \end{aligned} \tag{5}$$

Then, the update step (Equation (6)) utilizes the current time point, t, to make an updated prediction.

$$\begin{aligned} \eta_{t|t} &= \eta_{t|t-1} + \mathrm{K}_{\mathrm{t|t}}[y_t - (\Lambda\eta_{t|t-1} + \tau)] \\ \mathrm{P}_{t|t} &= [I - K_{t|t}\Lambda]P_{t|t-1} \\ K_{t|t} &= P_{t|t-1}\Lambda'\left[\Lambda P_{t|t-1}\Lambda' + \Theta\right].^{-1} \end{aligned} \tag{6}$$

This set of equations introduces an additional parameter known as the Kalman gain, $\mathrm{K}_{t|t}$, which is separate from the prior definition of K in Equation (2), which was the direct effect of an exogenous predictor. The Kalman gain is representative of the difference between predicted and actual measurements, $y_t - (\Lambda\eta_{t|t-1} + \tau)$. This allows for an optimal weighting of new information when making predictions about η or P. An additional smoothing step can also be incorporated. Smoothing in the KF is a form of backward prediction which uses future measurements when predicting a state. In the moderated SSM used in our study, the dynamic parameters can vary over time, and this can be captured by the iterative procedure of the KF. However, the moderator, X, is conditioned upon and variations of the dynamic parameters are explained as a function of X.

Results

Quantifying text data into sentiments

In the first step of our analyses, we quantified the text from the daily questionnaire into sentiments *via* NLP. For these analyses, we included individuals who responded to the open question for at least 80% of the days ($M_{complete} = 96.38\%$; $sd_{complete} = 4.83\%$). This criterion resulted in 83 individuals ($females = 46$; $males = 37$). Across all the selected individuals, there were a total of 5,061 comments (females $M_{comments} = 60.11$; males $M_{comments} = 62.05$). Next, we applied Vader to the comments for each individual separately in order to quantify the sentiment associated with each response. Figure 2 depicts the application of the NLP for three statements, (negative, positive, and neutral) and the resulting sentiment values. On the first row, labeled "Statement,," we observe an example of statements from consecutive days that were written in response to the open-ended prompt. On the second row, "Sentiment value,," we observe the value assigned by Vader regarding the magnitude and valence of the emotion expressed in each daily response. If the value is positive, the sentiment detected by Vader can be interpreted as positive. This process is repeated for all individuals and their daily responses resulting in the covariate of sentiment. The distribution of sentiments was identified across the 83 individuals (females $M = 0.068$, $SD = 0.40$; males $M = 0.05$, $SD = 0.38$).[2]

Sentiment data as moderator of individual affect dynamics

Once the text was quantified as sentiment values, the next set of analyses consisted of fitting SSMs to the daily affect data. The first of these models was a baseline specification without the moderator covariates. Figure 3 depicts the estimates and confidence intervals associated with the parameters from such a baseline model. In this figure, each pair of dots represents a parameter estimate and its confidence interval for a given individual. The lighter point represents the lower bound of the confidence interval and the darker point represents the upper bound. To mimic the location of the coefficients in matrix representation, panel a represents the autoregressive coefficient for positive affect; panel b represents the cross-lagged effect from positive affect to negative affect; panel c represents the cross-lagged effect from negative affect to positive affect; and panel d represents the autoregressive coefficient for negative affect. Again, the estimates are the average of the bootstrap consisting of 200 replications with 50 iterations within each replication. This figure shows that, across individuals, the dynamic

[2]We also implemented the method TextBlob to quantify positive and negative sentiments from the text data. TextBlob works similarly to Vader by utilizing a lexicon and a rule-based component which considers the context of the sentence. However, the particulars of the lexicon and rules differ slightly, potentially resulting in different sentiment values. Overall, the distribution of sentiments resulting from both algorithms was similar with regard to the large number of neutral statements detected. However, Vader detected slightly more extreme values than TextBlob overall.

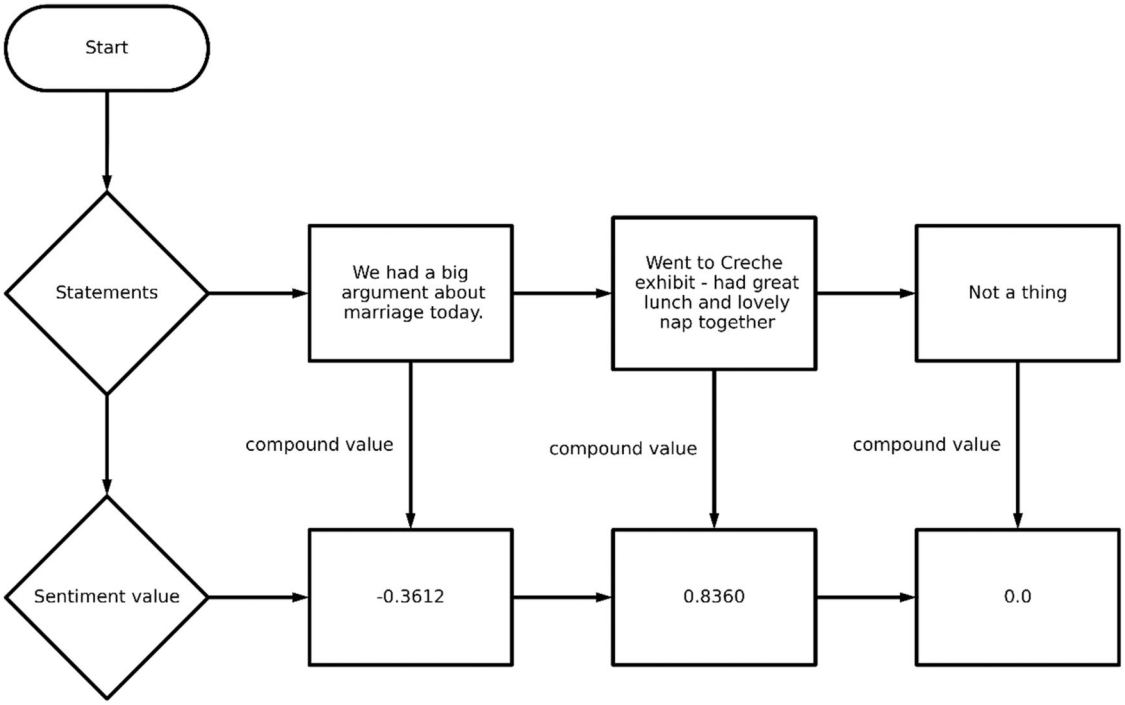


Figure 2. Example statements and their ensuing sentiment values from Vader.

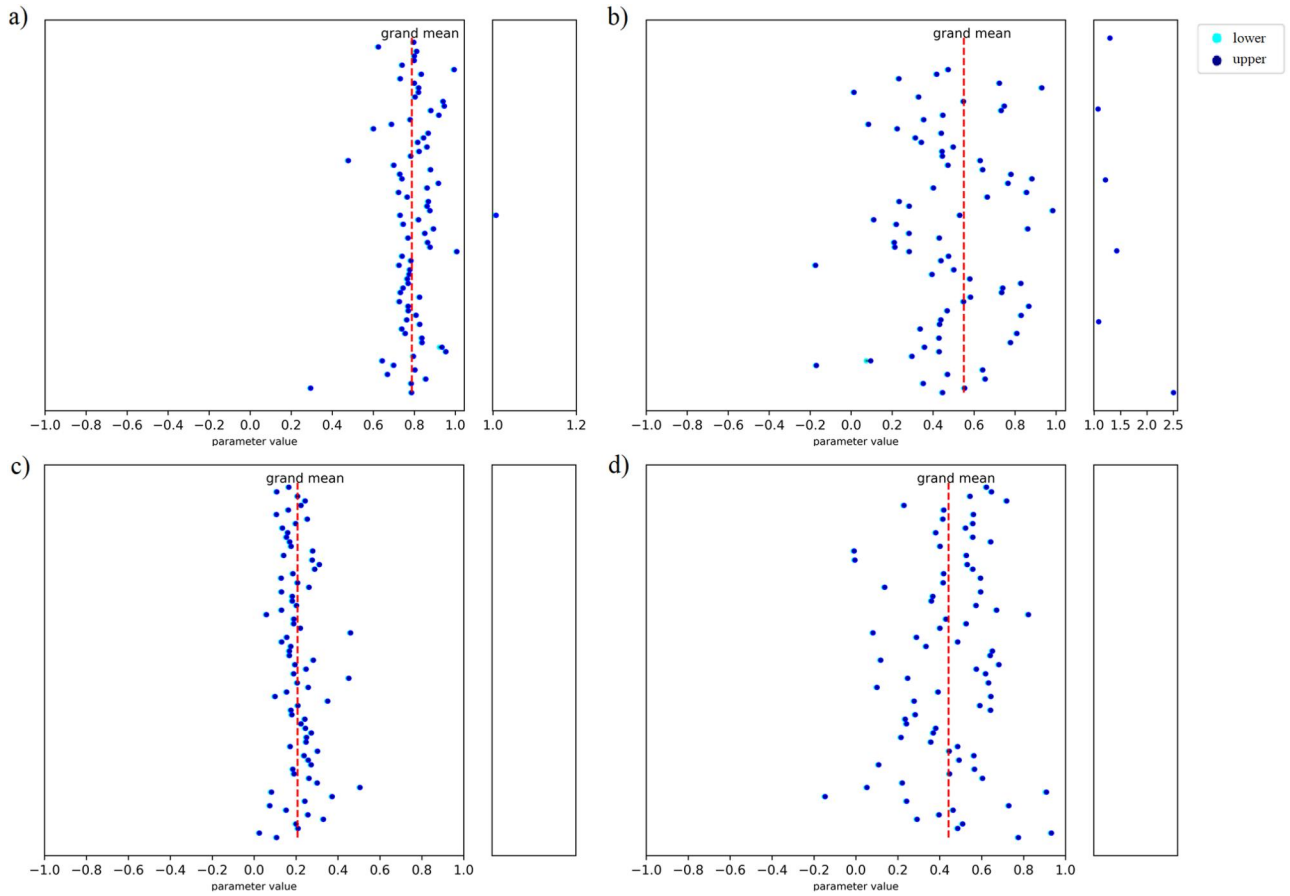


Figure 3. Individual β parameter estimates from a baseline VAR model of positive and negative affect (PA & NA) without moderating effects. Panel a refers to the autoregressive effect of the individual's PA. Panel b refers to the cross-lagged effect of NA on PA. Panel c refers to the cross-lagged effect of PA on NA. Panel d refers to the autoregressive effect of the individual's NA.

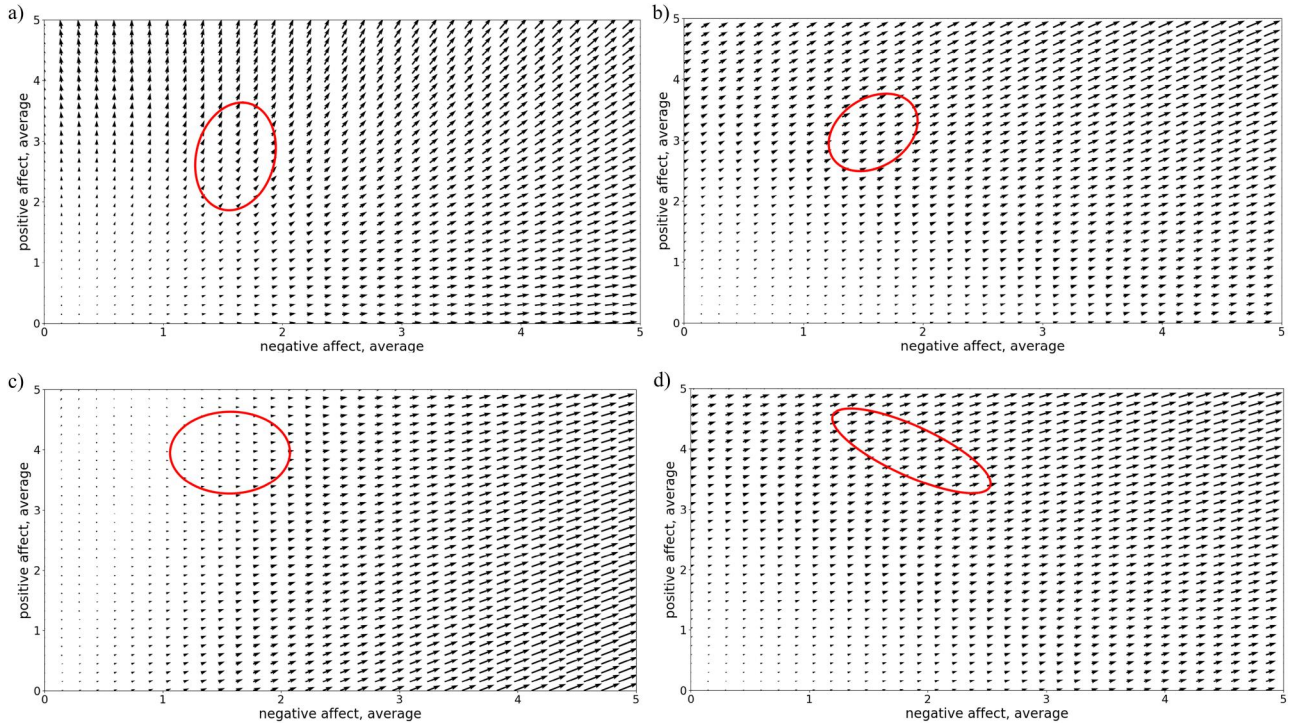


Figure 4. Vector fields of state space parameters and ellipses of observed data for four individuals.

parameters of the baseline SSM specification have very small confidence intervals, suggesting that their estimation is very precise. Furthermore, we observe variation in the parameters across individuals, indicating that fitting the SSM at the individual level is valuable for capturing heterogeneity in the dynamics of affect across individuals. Figure 4 represents vector fields based on the parameters from this baseline model together with an ellipse denoting the location of the data, across four separate individuals. In these plots, the x- and y-axis represent negative and positive affect, respectively. The arrows indicate the expected daily change along both positive and negative affect given a set of values in both measures of affect on any given day. This figure illustrates important differences across the four individuals. Not only are their affective states located in different areas of the plot, but the dynamics and expected change is distinct across the four individuals. For example, for individual in panel a, the expected changes are mostly increments in positive affect. For individual in panel c, in contrast, the changes are very small and along negative affect. Individuals in panels b and d show expected changes in negative affect with slight changes in positive affect.

The second model in our analyses was a SSM specification in which the sentiments from the text data were included as a moderator covariate on the dynamics (see Figure 1, panel a). Figure 5 depicts these moderating effects on the autoregressive (positive affect, panel a; negative affect, panel d) and cross-lagged (panels b and c) coefficients represented in Figure 3. As in Figure 3, each pair of differently colored dots represents the confidence intervals for an individual. Across individuals, the moderator effects are small and similar, but the confidence intervals of these effects are larger than those found in the baseline model. While the overall effects are small, they are different from zero, indicating that the sentiment values provide a reliable moderating effect on the affect dynamics, beyond the individual variation observed in the baseline model. The overall effects are positive for both the autoregressive and cross-lag components. This can be interpreted as, higher sentiment values (the moderator) on any given day are associated with stronger effects of the original parameters, either an autoregressive or a cross-lag, the following day.

To further investigate the robustness of the results obtained in the previous analysis, we fitted an additional SSM in which the sentiments were specified as a direct predictor of the positive and negative latent state variables, instead of as a moderator of the coefficients. One rationale for this model was to examine if the small moderator effects found in the previous analyses was due to a lack of predictive value of the sentiments. Additionally, these analyses would help determine if the sentiment values were reliable predictors of the positive and negative affect states. Figure 6

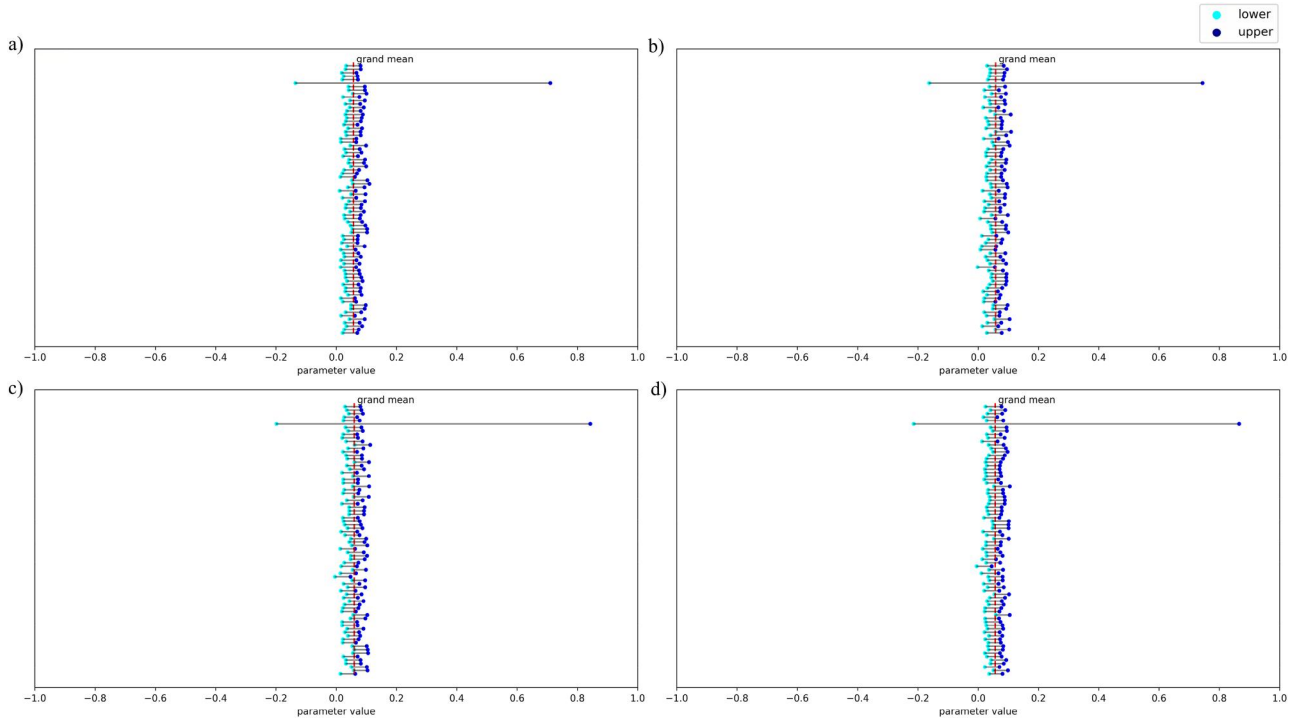


Figure 5. Individual moderating effects of sentiment values on the β parameters. Panel a refers to the moderation of the autoregressive effect of the individual's PA. Panel b refers to the moderation of the cross-lag between NA and PA. Panel c refers to the moderation of the cross-lag between PA and NA. Panel d refers to the moderation of the autoregressive effect of the individual's NA.

shows the resulting coefficients of this model for positive and negative affect (panels a and b, respectively). This figure shows that the effects of this covariate are larger than those when the sentiment values were used as moderators of the dynamic parameters. The small effects in Figure 4 are likely a result of the scale of the dynamic coefficients, in particular their small variation over time.

Partner's affect as a moderator of individual affect dynamics

In the next step, we repeated the previous analyses but used the partner's affect as a moderator of the dynamic parameters. For partner's affect, we constructed a ratio of positive affect in relation to overall affect [*positive*/(*positive* + *negative*)], to represent both aspects of affect (Schwartz, 1997). Research using this approach has shown that ratios of about 0.70 to 0.80 indicate normal and optimal functioning in individuals (Schwartz et al., 2002) and couples (Gottman, 1994). We chose the partner's rather rather than an individual's own affect because the latter measures were part of the time series. Our thought was that measures that are theoretically known to be predictors of one's affect would give insight into the magnitude of effects observed when sentiments were used as a predictor.

The results of this new model are displayed in Figure 7. Figure 7 shows the moderating effects of the partner's affect on the SSM dynamic parameters, for the autoregressive (positive affect, panel a; negative affect, panel d) and cross-lagged (panels b and c) coefficients. The resulting effects were also small, in line with those found when using sentiment values as a moderator. The interpretation of the moderation effect is similar: higher levels of the affect ratio on any given day are related to larger values in the autoregressive or cross-lag parameters the following day. Similarly, lower levels of this ratio are associated with weaker autoregressive or cross-lag parameters.

In the last model, we specified partner affect as a covariate predicting the positive and negative state variables. Figure 8 shows the resulting estimated effects. Again, as was the case with the sentiments, we observe that the direct effects are much larger than the moderating effects on the dynamic parameters. This could again indicate that the scale of the moderated parameter results in the magnitude of effects observed. When partner affect is used as a covariate, larger effects are observed, along with a larger amount of variability among individuals.

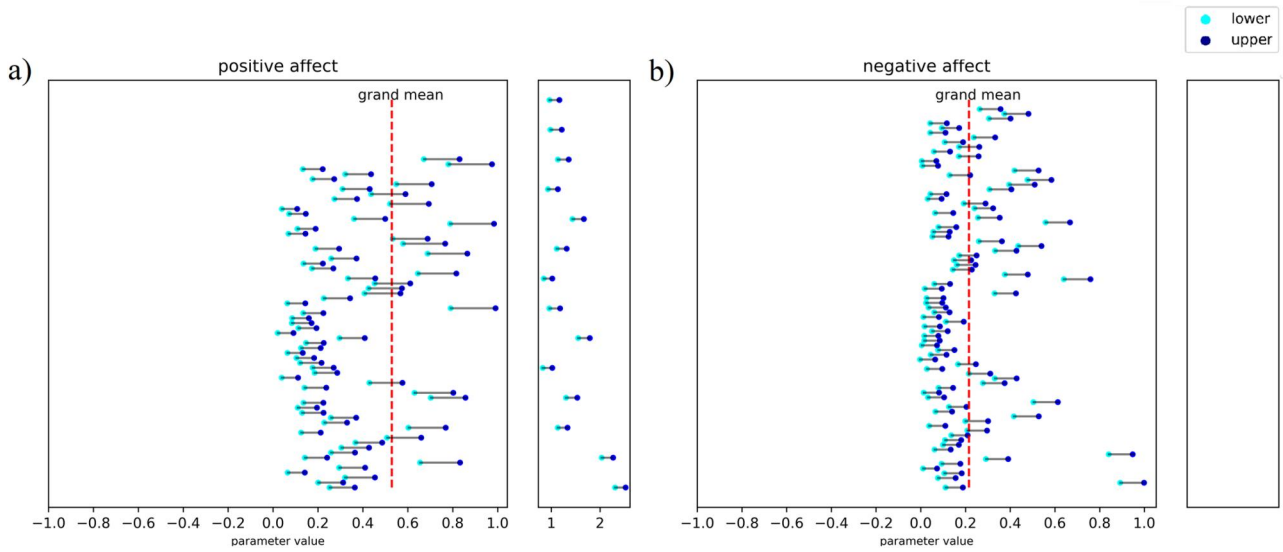


Figure 6. Individual effects of sentiment values predicting positive and negative affect states.

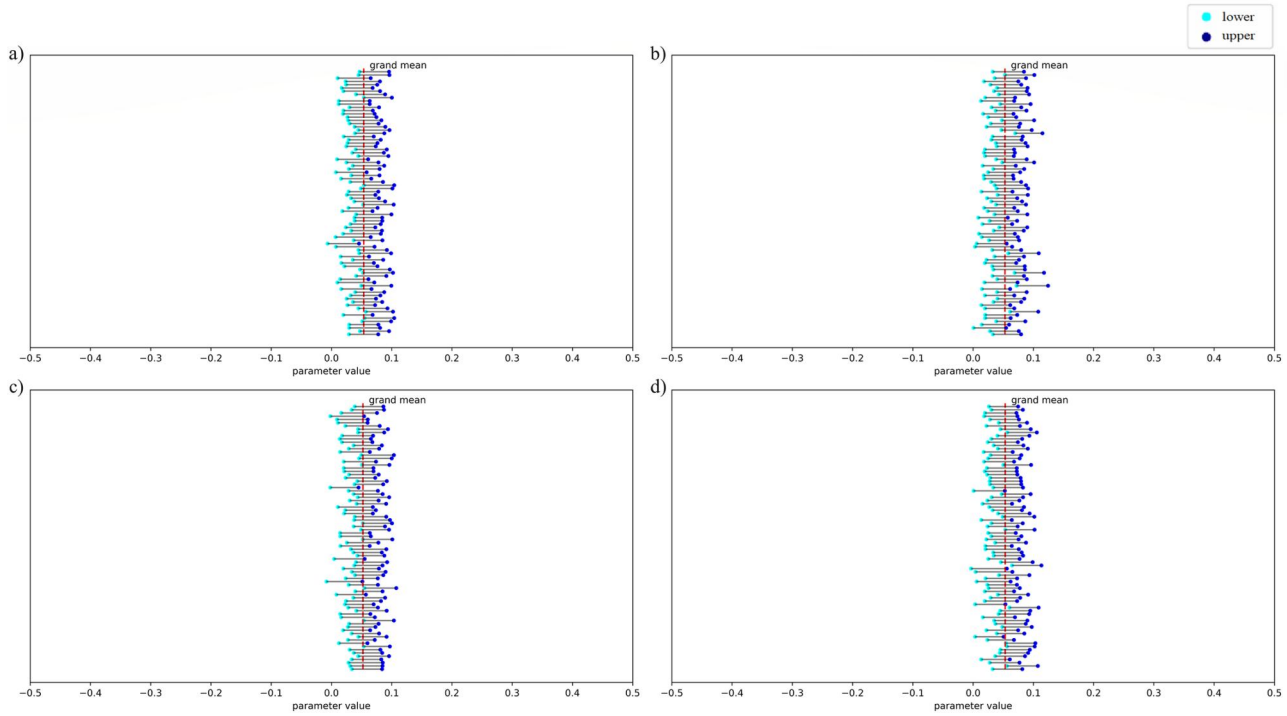


Figure 7. Individual moderating effects of partner affect ratio on the β parameters. Panel a refers to the moderation of the autoregressive effect of the individual's PA. Panel b refers to the moderation of the cross-lag between NA and PA. Panel c refers to the moderation of the cross-lag between PA and NA. Panel d refers to the moderation of the autoregressive effect of the individual's NA.

Discussion

Summary of findings

In this study we implemented a SSM that used text data as a moderator of time-varying dynamic parameters of individual affect. Our goal was to illustrate this approach in an empirical study. We used NLP to quantify positive and negative sentiments associated with responses to an open-ended question. This open-ended question was part of the same daily questionnaire that included a scale of affect specific to one's relationship. We used the sentiment values produced by NLP as moderators of the time-varying effects of the dynamic parameters in the SSM, including autoregressive and cross-regressive effects for both positive and negative affect. We then compared these

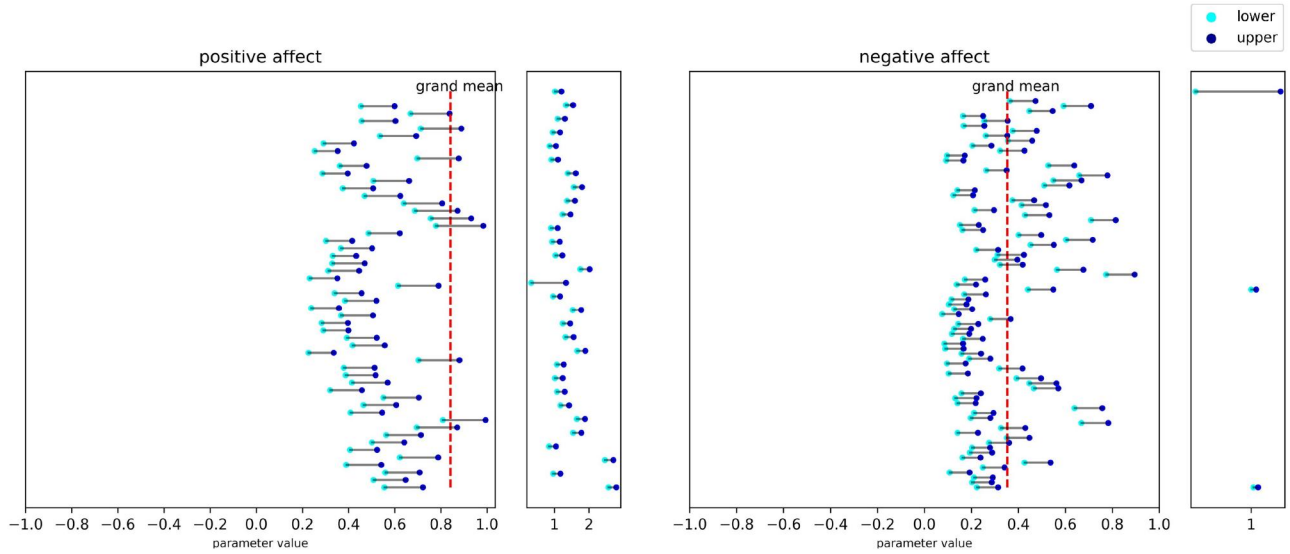


Figure 8. Individual effects of partner affect ratio predicting positive and negative affect states.

moderator effects with those from a model that included the partner's affect instead of the sentiment values. In both cases, the moderation effects were small but consistent across individuals. The small moderating effects could be the result of the smaller scale of the time-varying dynamic coefficients. In addition, the moderation effects from sentiment and partner's affect ratio were positive which yielded similar interpretations. Higher levels of each variable were related to stronger autoregressive and cross-lag effects the following day, and lower levels were related to weaker autoregressive and cross-lag effects. These effects suggest that higher intensities of emotion influence future states of emotion, whether they are the emotions captured in an individual's text responses or those of an individual's partner. We then implemented a model using the same variables as direct predictors of the positive and negative affect states as follow-up analyses in determining the predictive value of the text responses and the partner's affect. These effects showed that these variables were significant predictors of the individual's affective states.

Methodological implications

As expected from prior research (Castro-Schilo & Ferrer, 2013; Kuppens et al., 2010; Suls et al., 1998), the results of the initial SSM without moderating effects confirm strong autoregressive effects for both positive and negative affect (i.e. specific to one's relationship in our data). We observed that the variation across time of these autoregressive effects were moderated in a similar manner across individuals. This was true when using sentiment values from text data or partner's affect as the moderator variable. In both cases, the magnitude of the moderation effects was small, yet different from zero. The effect size could be the result of the scale of the parameters that are moderated, as the time-varying effects in the parameters were small (see Johal & Ferrer, 2024). In our model, the moderator variable, which was also time-varying, was related to the variation across time of the SSM dynamic parameters. If these parameters, such as the autoregressive or cross-lagged regression, do not vary across time, then the moderating effects will reflect that. To further investigate the relationship between the moderators and affect, we used both the sentiment values and the partner's affect as direct predictors of the affective state of an individual at a subsequent time. These analyses revealed larger effects than the moderator model and these parameters were also significant. One interpretation of the small effects in the moderator model could be due to the small scale of the time-varying dynamic parameters.

Our findings indicate that both the sentiment values and the partner's affect are related to affect dynamics. That is, expressing a more positive comment would translate into a higher sentiment value, which, in turn, would act as a moderator of the dynamics. For example, expressing a positive comment due to some important event on any given day would carry a stronger autoregressive effect to the next day, and thereby a higher affect inertia. Studies on affect inertia have shown that the fluctuations of affect we can observe are important when considering outcomes such as psychological well-being. In some cases, emotions that are more resistant to change, or more affective inertia (i.e. higher autoregressive

effects), are related with negative outcomes such as lower well-being (Kuppens et al., 2010; Koval et al., 2016). Additionally, our separate analyses using the moderators as predictors for future affective states show that sentiment values and partner's affect are potential indicators for one's own affect.

As we found similar patterns across the covariates of sentiment values and partner's affect in considering their relationship with affect dynamics, it may be of importance to consider these measures in future analysis of affect in individuals. In addition to using standard scales, we also recommend the use of text data. The former scales have desirable psychometric properties and can be easily implemented in any statistical model. The latter data have the added value of representing unique aspects of the individual without the standard verbal or numerical constraints of a scale. Furthermore, we advocate the use of SSM fitted to the individual. In this case, each model is estimated using the individual's context rather than simply assuming that the individual estimates are normally distributed about a population parameter.

Limitations and future directions

While text data are presumed to be closer to the human experience, there are limits resulting from the handling and cleaning of such data through the natural language processing "pipeline.," Approaching text-based data in a standardized procedure such as NLP can reduce the variability we initially sought to capture and differentiate individuals from their scale-based interpretations. There are multiple NLP methods to quantify sentiment outside of Vader, our choice in these analyses, which could yield different results. In addition, the current analysis quantifies only the positive and negative elements of the text, which may not adequately capture other dimensions of affect, such as arousal. This is a limitation not as widely discussed in the current landscape of sentiment analysis within NLP, which primarily focuses on the valence dimension of affect. Arousal in these methods is used to indicate some magnitude of a particular valence rather than a separate dimension which captures the level of energy associated with an affective state. One way to address such a limitation could be to incorporate neural networks to quantify the extent to which a statement expresses a particular valence and the amount of arousal (Mendes & Martins, 2023). Another possible method to incorporate the broader complexity of affect would be to utilize the LIWC, which allows for quantification of psychologically relevant categorizations of affect such as "anger," or "happiness," represented in text (Tausczik & Pennebaker, 2010).

In the context of the present study, it is important to note that, despite these limitations, the text data maintained information regarding different emotional contexts that individuals found themselves in, as well as vastly different information depending on the individual (e.g. different language use, day, context, emotion). This information, in turn, was shown to be valuable for predicting affective states and capturing heterogeneity in affective dynamics.

In our analyses, the two covariates, sentiment values and partner's affect, had similar effects. This was true when they were used as moderators of time-varying dynamic parameters (both small effects) or direct predictors of state variables (larger effects). Despite these similarities, it would be important to examine whether each has a unique contribution to the understanding of affect dynamics. Future studies could include both variables directly in the same model to partial out any unique effect.

Fitting a structural equation or state space model that includes dynamic components has requirements regarding the amount of data necessary to properly estimate its parameters. To deal with this issue, we applied multiple starts for each individual model and allowed models to converge on more optimal solutions. To account for local optima, we additionally constructed our confidence intervals and estimated standard errors from these. Our results showed that, in general, the results are robust, with some individual exceptions. However, it remains to be explored what is the minimum number of time points necessary to estimate moderation effects from a SSM model such as ours. By estimating our SSM using linear equations and a discrete-time framework, there may be nonlinear relationships in the data that were not described adequately. Given the limited scale of the measures along with the amount of data, we prioritized the use of discrete-time and linear equations. Considering more complex nonlinear dynamics is nonetheless important especially when considering the true complexity of affective processes (Douc et al., 2014; Guastello & Gregson, 2011; Shelhamer, 2007; Strogatz, 2018).

One additional aspect to consider when using data from open responses is that missing data is more difficult to account for than in traditional scale-based measures. For this reason, we chose to include only individuals who completed the written response portion almost daily.

In observational studies, differences in observed outcomes could be a function, at least in part, of an individual's context. The current study focused on one aspect of psychological context arising from information given by individuals on a daily basis in the form of positive or negative sentiments detected in a written response. There certainly are aspects that could be captured by text responses or additional covariates not particular to positive or negative dimensions. For example, instead of sentiments, which are valence-based measures, one could include additional dimensions of emotion such as arousal or activation. Additionally, contextual factors could come in the form of important topics that are commonly mentioned in the written responses, such as relationship issues, family concerns, etc. Identifying these aspects of context and introducing them in analyses can further our understanding of psychological phenomena, particularly intraindividual variability. One potential approach could be to use such topics within change point detection methods to identify shifts in the dynamics (Albers & Bringmann, 2020; Beck & Jackson, 2022). In the context of close relationships, for example, this could include detecting a decrease in affect following an argument or an upward trend following an engagement.

The issues described pertaining to Likert-based scales, such as the difference in interpretation across individuals, extend to other quantitative self-report scales such as visual analogue scales (VAS; Ahearn, 1997). In a VAS, a scale item is presented alongside a slider that contains adjectives describing two extremes of a response to the item. Unlike Likert-based scales, a VAS does not need to provide a visual indicator of the numerical values between these two extremes. Recent studies have shown that these scales, when compared to Likert-based scales for collection of ecological momentary assessment data, are potentially preferred due to their high correlation with baseline questionnaires, nonzero responses, and the lower presence of floor effects (Haslbeck et al., 2025). However, while VAS are much more open in potential response values, the extremes of the scale which are provided by the researcher still limit the individual response. In our study, we do not consider VAS directly and it may be of value to further provide comparison across Likert-based, visual-based, and text-based data.

Another important question to examine further is the extent to which modeling at the individual level when using text-based data is the right choice. Certainly, this may depend on the question one wishes to answer with respect to the text analysis. But it may be important to consider that an individual's context is unique and, therefore, written responses to open-ended questions should convey individual reflections, which in turn are likely to have a distinct relation to the individual's psychological process of interest. With respect to the text data used in this study, the prompt was broad. However, individuals would often mention their partner in their responses. Applying other NLP methods in the context of exploring the relationship could reveal insights into differences across individuals regarding relationship satisfaction or stability.

Conclusion

We extended a state-space model that included a covariate based on text as a moderator of the dynamics of daily affect. This proposed approach illustrates the idea of using moderators for dynamic parameters together with the value of combining standard scale-based measures with qualitative text data.

Article information

Conflict of Interest Disclosures : Each author signed a form for disclosure of potential conflicts of interest. No authors reported any financial or other conflicts of interest in relation to the work described.

Ethical Principles: The authors affirm having followed professional ethical guidelines in preparing this work. These guidelines include obtaining informed consent from human participants, maintaining ethical treatment and respect for the rights of human or animal participants, and ensuring the privacy of participants and their data, such as ensuring that individual participants cannot be identified in reported results or from publicly available original or archival data.

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