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Individual Differences and Stability of Dynamics among Self-Concept Clarity, Impatience, and Negative Affect

Self-concept clarity (SCC) is associated with behavioral and emotion regulation, although the nature of this link is unclear. SCC may serve as a self-regulatory resource, or it may be a product of well-regulated behaviors and emotions. In two studies using experience sampling among undergraduates (*n* = 46 and *n* = 36), we investigate whether models representing relationships among SCC, impatience, and negative affect (NA) states conform to these theories, are similar across individuals, and are stable across a one-month period. Results reveal substantial variation between persons in these dynamic relationships, suggesting that multiple SCC-relevant regulatory processes exist. These patterns were not stable from one month to the next, but changes in them related to changes in stress, suggesting higher-order regulation of these dynamics.

Keywords: self-concept clarity, experience sampling, dynamic factor analysis

Introduction

Self-concept clarity (SCC; Campbell et al., 1996), defined as the clarity, consistency, and stability of an individual's self-concept, seems to play an important role in normal personality functioning, particularly in the domains of self-regulation and emotion regulation. Research has shown, for example, that SCC correlates positively with conscientiousness (Campbell et al., 1996; Fite et al., 2017) and negatively with impulsivity (Campbell et al., 1996; Ellison & Levy, 2012; Matto & Realo, 2001). SCC also negatively predicts compulsive internet use (Israelashvili, Kim, and Bukobza, 2012; Quinones & Kakabadse, 2015) and relates negatively to maladaptive coping behaviors such as procrastination (Petrie, 2014), denial, behavioral disengagement, and emotional disengagement (Smith, Wethington, & Zhan, 1996). In addition, SCC relates negatively to emotion dysregulation variables, including negative affect (Bond, Ruaro, & Wingrove, 2006; Campbell et al., 1996; Lear & Pepper 2016; Lee-Flynn, Pomaki, DeLongis, Biesanz, & Puterman, 2011; Nezlek & Plesko, 2001; Scala et al., 2018), depression (Bobrowski, DeMarree, Lodi-Smith, & Naragon-Gainmey, 2018; Campbell et al., 1996; Chang, 2001; Lee-Flynn et al, 2011), and feelings of tenseness, boredom, and dejection in the context of goal pursuit (Kernis, Paradise, Whitaker, Wheatman, & Goldman, 2000). Thus, SCC seems to have broad connections to adaptive self-regulation, especially in the domains of effortful self-control and emotion regulation.

However, the majority of prior research linking SCC with behavioral and emotion regulation is cross-sectional, focusing on trait SCC and how it relates to individual differences in these other variables. Despite its original conceptualization as an individual-differences variable, self-concept clarity has been shown to vary in a state-like way across time within individuals, and this variation has important consequences (Ayduk, Gyurak, & Luerssen, 2009; Nezlek &

Plesko, 2001; Scala et al., 2018; Schwartz et al., 2011). For example, Ayduk and colleagues (2009) showed that daily depression scores and relationship conflict relate to daily levels of SCC, and Nezlek and Plesko (2001) found similar relations among daily SCC, daily negative affect, and daily stressful events. At an even more fine-grained timescale, Scala and colleagues (2018) found that the link between state negative affect and subsequent self-injury urges in an outpatient clinical sample was only present when state SCC was low. Thus, self-concept clarity exhibits short-term intraindividual variability, which in turn relates to intraindividual variability in important emotional and behavioral outcomes, suggesting that SCC has a dynamic (instead of solely dispositional) relation to self-regulatory processes.

At least two compelling general theories regarding the short-term, dynamic relationships between self-concept clarity and self-regulatory variables can be derived from the literature. One possibility, consistent with the original theory of SCC (Campbell et al., 1996), is that self-concept clarity functions as a resource, enabling the adaptive regulation of behaviors and affects by allowing the individual to draw upon values, goals, and self-regulatory capacities effectively, especially when faced with adverse events (Light, 2017). This theory is supported by evidence that SCC mediates the link between stressful life events and subjective well-being (Ritchie, Sedikides, Wildschut, Arndt, & Gidron, 2011), that state SCC levels moderate the link between state negative affect and urges to self-injure (Scala et al., 2018), and that increases in self-certainty predict increases in positive affect (Baumgardner, 1990). Likewise, SCC increases produce greater relationship satisfaction (Lewandowski, Nardone, & Raines, 2010) while decreases in SCC predict internalizing symptoms (van Dijk et al., 2014). At the state level, according to this theory, increases in state SCC would precede euthymia and well-regulated behaviors, reflecting the individual's current level of SCC "resources."

A second possibility, derived from the observation that self-concept is in part constructed from dynamic self-perceptual processes (Bem, 1967; Hertel, 2017; McConnell, Rydell, & Leibold, 2002; Sedikides & Skowronski, 1995), is that SCC is the outcome of one's own self-concept-congruent emotional and behavioral experiences. That is, individuals experience a clearly defined self-concept (i.e., high state SCC) when their recent behaviors and internal experiences match this self-concept. Several experimental studies provide support for this notion. For example, forgiving an undeserving other decreases self-concept clarity (Luchies, Finkel, McNulty, & Kumashiro, 2010), whereas engaging in a self-confirmation exercise after a threat to the self-concept raises SCC (Slotter & Gardner, 2014). Even engaging in self-reflection changes SCC, but in different directions, depending on whether the individual's SCC level was high or low in the first place (Csank & Conway, 2004). Thus, the notion that SCC changes in the short term as a result of self-relevant experiences has support as well. At the state level, this theory would predict that changes in emotional states and behaviors would precede, not follow, changes in state SCC.

However, these two theories are also not mutually exclusive. It is possible, for example, that SCC state is influenced by the regularity of an individual's emotions and behaviors, while at the same time serving as a resource for further emotion and behavior regulation, as in a positive feedback loop. Recently, Wong and Vallacher (2017) investigated this general question using daily diary data and cross-lagged multilevel structural equation modeling. They found, on average, a reciprocal relationship between SCC and grit, such that SCC predicted grit two days later, and grit predicted SCC across the same interval. This suggests that a positive feedback loop does indeed describe the average connection between these two variables. However, there was a fairly high degree of random variance around these parameters, reflecting differences among individuals in the lagged SCC-grit relationship.

This highlights the possibility that self-concept clarity might function differently in different individuals (and thus that these two hypotheses are both correct, but for different people). For example, one person's SCC state may depend on the regularity of emotions and experiences congruent with their self-concept, while another's SCC state may function as a resource that helps the person regulate their emotions and behaviors. This situation might cause the appearance of a feedback loop in group-level analyses (including multilevel modeling), even if this reciprocal process does not exist within any individual. Uncovering processes that hold within the individual requires a person-specific analytic method, which allows for qualitative (not only quantitative) variation among individuals (Hamaker & Wichers, 2017).

In the current series of studies, we use a high-frequency experience sampling method (ESM) paradigm and dynamic factor analysis (DFA), a form of within-person modeling, to conduct a preliminary examination of the extent of heterogeneity in dynamic models of SCC and self- and emotion regulation, using the variables of SCC and impatience (Study 1) and SCC, impatience, and negative affect (Study 2). We use an undergraduate sample, which affords an opportunity to study a population who are negotiating new social roles and having new experiences and for whom the dynamics of SCC may thus be particularly important (Lodi-Smith & Crocetti, 2017). We investigate the extent to which dynamic factor models conform to the above theories of the dynamics between state SCC and these correlates and the extent to which they differ between individuals. In addition, in Study 2 we utilize a "measurement burst" design to investigate whether these models are stable across a one-month period within individuals.

Study 1

The aims of Study 1 were to establish survey items that are suitable for measuring state self-concept clarity and a putatively related self-regulation variable (impulsivity) in a high-intensity ESM format and to investigate the heterogeneity of within-subject process models for these constructs across individuals. As above, impulsivity and similar constructs (such as conscientiousness) have a robust relation with SCC in cross-sectional analyses (Campbell et al., 1996; Fite et al., 2017; Matto & Realo, 2001), but to date the connection of state impulsivity with state SCC has not been examined.

Method

Participants and procedure

Participants were 46 undergraduate students at a small university in the Southwestern U.S., who were recruited by email, on a random basis, from an introductory psychology class. They were offered course credit for their participation in a study involving "repeated surveys on a smartphone." Participants attended a 10-minute laboratory visit to complete a baseline demographics questionnaire, receive instructions for completing mobile surveys, and pick a schedule for mobile survey completion. For the ESM portion of the study, participants were asked to complete a survey on 64 occasions using the web browser of their smartphone and Qualtrics online survey software. They selected one of three schedule types, according to their preference: a survey every 15 minutes for two days (one eight-hour series per day); a survey every 15 minutes for four days (one four-hour series per day); or a survey every 30 minutes for four days (one eight-hour series per day). A timer application provided auditory prompts for survey completion. Participants could select when to start a series of surveys, but they were asked to complete survey series on days when they would be able to do so without interruption (e.g., from classes, sporting events, or travel) but which were otherwise representative of their everyday life (in order to maximize the relevance of collected data).

Seventy-five individuals (M_{age} = 19.3, age range = 18-23 years) enrolled in the study. Of these, 51 (68%) were women and 24 were men. Fifty-four (72%) reported their race as White, 16 (21%) as Asian/Pacific Islander, one (1.3%) as Black, and nine (12%) as more than one race (participants could also select multiple categories). Eighteen (24%) identified their ethnicity as Hispanic/Latino. Sixty-three individuals of the 75 began returning mobile surveys. Fifteen of these participants did not return enough surveys for their results to be usable (e.g., they completed only one day of surveys instead of the required two). Of the remaining 48 participants, two participants returned excessively stereotyped data (e.g., all zeroes). The remaining 46 individuals constituted the study sample and provided, in aggregate, 2,935 surveys. None of the measured demographic variables (age, gender, race, or ethnicity) related to attrition between enrollment and completion of surveys (p's > 0.3). Among the participants who began returning surveys, the mean number of surveys returned was 57.6 out of 64 (90%), and the median number of surveys returned was 64. Forty-three of these individuals (93%) elected to return surveys every 15 minutes, and the remaining three participants chose to space their surveys 30 minutes apart.

Measurement items

Each mobile survey consisted of six items, each of which was rated on a visual analog scale using a sliding response bar and the phone's touchscreen. Impulsivity was measured using the Momentary Impulsivity Scale (MIS; Tomko et al., 2014), a four-item questionnaire designed as a measure of impulsivity in ESM studies. Self-concept clarity was measured using two items adapted from a prior study of self-concept clarity using ESM ("Since the last prompt, I felt like I had a clear sense of who I am and what I want in life"; and "Since the last prompt, I felt that I am not really the person that I appear to be"; Ayduk, Gyurak, & Luerssen, 2009). Responses were coded using a 0-100 scale with anchors at 0 ("Very slightly or not at all" for the MIS items, and "Not at all" for the SCC items) and 100 ("Extremely" for all items).

Power

Statistical power in DFA increases with the number of occasions, not the number of individuals (because each analysis pertains to only one person). There are no clear guidelines for the number of occasions recommended (Ram, Brose, & Molenaar, 2013), in part because this number may differ depending on whether the desired result is model convergence, detection of model misfit, or accurate estimation of individual model parameters. We therefore chose a target of 64 occasions to approximate recent empirical studies of psychological data using dynamic factor models of similar size (e.g., Fisher, 2015) while attempting to minimize participant burden.

Data preparation and analytic strategy

Examination of the data suggested that responses to three of the MIS items ("Since the last prompt, I said things without thinking," "Since the last prompt, I spent more money than I meant to," and "Since the last prompt, I made a spur of the moment decision") did not show sufficient variability to be used in analyses for most participants. That is, the values for these items across participants were zero-inflated and extremely skewed, presumably reflecting the low rate of these behaviors within any given 15- or 30-minute period among undergraduates. Although there is no consensus threshold for how much intraindividual variability DFA requires (Ram, Brose, & Molenaar, 2013), we disregarded these items as unrepresentative of momentary impulsivity in our sample. However, the remaining MIS item ("Since the last prompt, I have felt impatient"), did vary adequately and normally for each participant.

In addition, the two self-concept clarity items showed a very weak average intra-individual correlation (*r* = -.09). The second of these ("Since the last prompt, I felt that I am not really the person that I appear to be") had inadequate variability for roughly one-sixth of the sample, and informal feedback from participants suggested that the meaning of this item was not always clear. For these reasons, we chose to focus analyses on the positively worded SCC item ("Since the last prompt, I felt like I had a clear sense of who I am and what I want in life.").

The analyses considered here require data with equal intervals between measurement occasions (Molenaar & Rovine, 2011). However, participants did not always respond to prompts exactly as they occurred, violating this assumption. Thus, we used cubic spline interpolation (Forsythe, Malcolm, & Moler, 1977) with the "spline" function in R software to re-sample evenly-spaced data points for the current analyses. This approach fits curves to the observed time series (separately for each variable, day, and individual) and then re-samples from the curves to create time series with equal intervals between observations. In a previous paper using experience sampling, cubic spline interpolation was shown to produce model parameters that closely corresponded to those describing the original data (Fisher, Reeves, Lawyer, Medaglia, & Rubel, 2017).

Model fitting was conducted with LISREL, version 8.12 (Jöreskog & Sörbom, 1993). An autoregressive (AR) model with a lag of 1 occasion, in which each variable was regressed on itself at the prior occasion and allowed to correlate with the other variable at the same occasion, was used as the baseline model for each participant. If this model did not show good fit to the data, modification indices guided the sequential addition of cross-lagged regression parameters between one variable at time $t-1$ and another variable at time t until satisfactory fit was achieved. Fit decisions were based on cutoffs (Hu & Bentler, 1999) on the Standardized Root

Mean Square Residual (SRMR; value ≤ 0.1), the Root Mean Square Error of Approximation (RMSEA; value ≤ 0.08), the Non-Normed Fit Index (NNFI; value ≥ 0.95), and the Comparative Fit Index (CFI; value ≥ 0.95).

Results and Discussion

In the ESM surveys, SCC showed a mean value of 46.6, whereas impatience values had a mean of 29.1. SCC showed a stronger degree of interindividual (between-subject) variability than impatience ($SD_{\text{SCC}} = 27.2$, $SD_{\text{impatience}} = 18.9$), consistent with the notion that SCC varies in a more trait-like way than impatience does. On the other hand, both SCC and impatience showed a considerable degree of intraindividual (within-subject) variability ($SD_{\text{SCC}} = 14.8$, $SD_{\text{impatience}} = 19.8$) as well, suggesting a component of state-like variability for each item.

In dynamic factor analyses, a multivariate AR model, in which levels of SCC and impatience at one time point predicted themselves at the next time point, provided good fit for 26 of the 46 individuals in the sample. For the remaining 20, this model did not show sufficient fit. For nine individuals, modification indices suggested regressing SCC at time t onto impatience at time $t - 1$, after which the model showed good to excellent fit. For an additional two participants, this model only showed approximate fit. In contrast, for six different participants, modification indices suggested instead that the opposite-direction cross-lagged parameter be added (with impatience at t regressed onto SCC at time $t - 1$). For these individuals, this addition resulted in good fit. Finally, for the remaining five individuals, the autoregressive model did not show good fit, and modification indices did not suggest that cross-lagged regression parameters would improve fit. Parameters for final models can be found in Table 1.

Thus, results suggested that SCC predicted impatience 15 minutes later, but only in some participants; in other participants, impatience predicted SCC 15 minutes later, but not vice versa.

Finally, there were many participants for whom SCC and impatience had no significant lagged relationship. There was also considerable heterogeneity in the contemporaneous connections between SCC and impatience. Although the mean within-person correlation was small (r = .05), there were several individuals with strong, statistically significant correlations. Some of these correlations were positive, and some were negative. In short, results revealed substantial heterogeneity across individuals in the form, direction, and sign of the dynamic relationships between SCC and impatience. This general result provides preliminary support for the notion that different theories of how SCC relates to self-regulation may be true, but in different individuals; in some people, SCC may function as a resource, enabling adaptive self-regulation, whereas in others, SCC may be the product of well-regulated emotional experience.

However, because the data collected in Study 1 covered only a short amount of time (usually two consecutive days), we were unable to tell whether these models represent patterns that are characteristic of individuals or, on the other hand, temporary configurations of the dynamics between SCC and impatience that change over time. This question was the focus of Study 2.

Study 2

The purposes of Study 2 were 1) to replicate and extend the results of Study 1 and 2) to investigate the stability within individuals of dynamic process-models describing impatience and self-concept clarity states. To do the latter, we employed a “measurement burst” design (Nesselroade, 1991), in which participants completed two discrete rounds of smartphone surveys. These bursts were separated by one month. We aimed to determine how many participants’ models would change from one month to the next, to characterize the general extent of model change across this interval, and to investigate the correlates of changes in these models. We had no *a priori* expectation for the stability of dynamic factor models, as (to our knowledge) the current paper is the first study to examine this question using the current variables and timeframe.

In order to allow for a greater breadth of models, which would facilitate the detection of heterogeneity across individuals and change across time, we added a third variable to our ESM protocol: state negative affect. Negative affect (NA) has important longitudinal relations with self-concept clarity in daily diary studies (Ayduk et al., 2009; Nezlek & Plesko, 2001) and also has a close connection with impatience and related states such as “searching boredom” (Goetz et al., 2014; Koff & Lucas, 2011; McLeish & Oxoby, 2007).

Method

Participants were 36 undergraduate students at the same university as in Study 1, and recruitment method was identical to that of Study 1. Participants attended an initial lab session to complete a baseline demographics questionnaire, receive instructions for completing mobile surveys, and pick dates for mobile survey completion. In addition, participants completed a stressors survey, consisting of a checklist of stressors that were a current concern for them (roommate issues, financial troubles, academic stress, stress related to extra-curricular activities, sense of belonging at the university, stress related to their social life, and problems with motivation/procrastination). They were also asked to rate their current level of stress related to these domains and their overall level of stress on a sliding scale from 0 (“Extremely low”) to 100 (“Extremely high”). As in Study 1, participants were asked to complete 64 mobile surveys during the first ESM burst. Because of the popularity of the 15-minute interval in Study 1, this schedule was adopted for every participant in Study 2 (surveys every 15 minutes for sixteen hours, split into two blocks). After about one month, these participants were contacted by email and asked to return to the laboratory, where they completed a second, updated survey of current stressors and chose new dates for a second burst of 64 ESM surveys.

Fifty-seven individuals (M_{age} = 18.9, age range = 18-24 years) enrolled in the study. Of these, 34 were women and 22 men; one participant declined to select a gender. Five participants (9%) reported their race as Black, seven (12%) as Asian/Pacific Islander, 40 (70%) as White, and five (9%) as more than one race (as in Study 1, participants could select more than one category). Of the 57 participants who enrolled, 52 began returning surveys for the first measurement burst. Five participants did not return enough data during the first burst to be usable in analyses. Of the remaining 47 participants, three were not invited to participate in the second burst: one because she was discovered to have participated in Study 1 the previous semester, and two because they completed burst-1 surveys on days that were too far apart (27 days in both cases). The remaining 44 participants were invited to complete a second burst, and 39 participants responded to the invitation and began returning burst-2 surveys. Of these, one participant completed the required number of burst-2 surveys, but within only a few minutes rather than on the required 8-hour schedule. Two additional participants returned extremely stereotyped data for burst 2 (one returned mostly values of "2" on the 0-100 scale, and the other returned mostly values of "0" except for self-concept clarity, which was mostly "100"). The remaining 36 participants' burst-1 and burst-2 data, comprising 4,544 surveys in total, were submitted to analyses. As in Study 1, no demographic variable predicted attrition from enrollment to completion of burst-2 surveys, although men dropped out marginally more often than women, $\chi^2(1) = 2.95$, $p = .09$, $\phi = .23$ (all other p-values > .25). Compliance with Study 2 was similar to Study 1. The 52 participants who returned at least one survey for burst 1 returned a median of 63 surveys of the requested 64 (M =

61.27, *SD* = 8.54). The 39 of these who began returning burst-2 surveys also returned a median of 63 surveys (*M* = 63.13, *SD* = 4.80).

ESM surveys consisted of the single SCC and impulsivity items used in Study 1, with a change in the prompt in order to reduce any ambiguity about the timing of the states being measured and to capture the immediate state of these variables for the participant ("Right now, I feel like I have a clear sense…"; "Right now, I feel impatient"). In addition, four negative affect (NA) items were chosen to exemplify both high arousal (stressed, worried) and low arousal (sad, lonely) facets of NA (Feldman, 1995) and to capture the typical momentary experience of negative affectivity among university students. As with the SCC and impatience items, NA items were delivered with the prompt, "Right now, I feel…" Items were rated on a 0-100 scale, ranging from "not at all" to "extremely."

As in Study 1, cubic spline interpolation was used to re-sample the multivariate time series data so that intervals between successive data points were equal. As a second preliminary step, each individual's 4-variate NA time series was submitted to p-technique factor analysis in order to create optimal person-specific NA factors for use in the analysis of dynamic patterns among NA, SCC, and impatience. Nesselroade, Gerstorf, Hardy, and Ram (2007) refer to this step as the "idiographic filter," as it helps to separate idiosyncrasies in the measurement of constructs from differences in the processes that mediate among constructs (Molenaar & Nesselroade, 2012). P-technique factor analysis was done separately for each burst. A one-factor model was adopted for each burst (with idiographic factor loadings for stressed, worried, sad, and lonely items) in order to facilitate comparison among bursts and participants and in order to avoid under-identification in measurement models with greater numbers of latent factors. Factor scores were computed for each burst according to the regression method. After these scores were obtained, time-series analysis was conducted on the 3-variate (SCC, impatience, and NA) time series. As in Study 1, a multivariate AR model was used as a baseline model, with SCC, impatience, and NA correlated at $t - 1$ and used to predict these states at time t. If fit was not satisfactory, cross-lagged regression parameters were added one-by-one until a well-fitting model was achieved. This process was conducted twice, once for each burst.

Once well-fitting models were achieved for each burst, the amount of model change from burst 1 to burst 2 was quantified as the SRMR when one burst's model was fit to the other burst's data for that person. The SRMR was recently identified as a quantitative index of model misfit in structural equation models (Maydeu-Olivares, 2017), but because it does not compensate for the complexity of models, the more parsimonious model was tested on the other burst's data (to avoid obscuring misfit through a high degree of model complexity).

Results and Discussion

Cross sectional examination of self-concept clarity's relationship with criterion variables

Mean scores for SCC, impatience, and negative affect variables were calculated for each participant. Correlation coefficients, means, standard deviations, and minimum and maximum scores for all six variables can be seen in Table 2. Consistent with previous cross-sectional research, SCC showed negative interindividual correlations with negative affect and impatience (Bond, Ruaro, & Wingrove, 2006; Campbell et al., 1996; Ellison & Levy, 2012; Lear & Pepper 2016; Lee-Flynn, Pomaki, DeLongis, Biesanz, & Puterman, 2011). Furthermore, participants' scores at burst 1 were positively correlated with their scores at burst 2, showing stability of mean values from one month to the next.

P-technique factor analyses

Results from the preliminary p-technique factor analysis of the NA items in these 72 separate time series revealed substantial individual differences in the covariance of worry, stress, sadness, and loneliness states within persons. In general, a one-factor model showed good to excellent fit across participants. However, for 13 participants, a one-factor model contained negative error variances in one of the two bursts, suggesting that this model was misspecified. For an additional seven participants, this problem held for both bursts. Examination of the original time series suggested that, in all of these cases, "stressed" was the only item with substantial variability (whereas the participants did not report much sadness, worry, or loneliness on these days). Therefore, the series of "stressed" values was used in the multivariate time series models for these cases; for all other participants, NA factor scores were used. Whether "stressed" scores or p-technique NA factor scores were used did not relate to the overall level of self-reported stress at either lab visit (burst 1: $t[55] = .25$, $p = .80$, 95% CI: -.15.59 to 12.09, $d = .07$; burst 2: $t[33] = .66$, $p = .52$, 95% CI: -8.98 to 17.50, $d = -.23$).

Dynamic factor analyses

Dynamic factor analyses revealed a similar picture as in Study 1: of the 36 burst-1 time series, eighteen were modeled with excellent fit by a multivariate autoregressive model. The remaining eighteen required a partial vector autoregressive model for adequate fit, and the cross-lagged regression parameters appearing in these models were diverse. At burst 2, cross-lagged parameters were somewhat more common, appearing in 25 of 36 models. Each of these parameters was present in roughly the same number of models; the least common, appearing in 11 models, was the parameter in which impatience was regressed onto negative affect at the previous occasion, and the most common (in which negative affect was regressed on impatience at the previous occasion) appeared in 15 models. Thus, results provide a conceptual replication of the results of study 1, in that links between SCC and criterion variables were heterogeneous in form, direction, and sign.

Month-to-month stability in dynamic factor models

The average SRMR when one month's model was applied to the other month's data for that person was .09, a value close to widely used cutoffs for adequate fit (Hu & Bentler, 1999). Thus, some participants' models remained relatively consistent across bursts, whereas for others, there was substantial incongruity between bursts. In addition, there was substantial variability in the SRMR value across participants (*SD* = .04), which also suggests that some participants changed more than others. A qualitative comparison of good-fitting models across bursts showed that only four participants out of the 36 showed structurally identical models from one month to the next (Table 3), with some individuals changing only slightly in terms of model parameters and parameter values, and some individuals changing a great deal. Two individuals' burst-1 and burst-2 models are presented in Figures 1 and 2.

We further investigated the extent of model change by comparing model parameters across bursts. This is particularly important because some apparent changes between bursts may have been due to sampling error, given the relatively small number of observations upon which these models are based (k = 64). In order to characterize the extent to which imprecision in parameter estimates contributed to the picture of model change in Table 3, we examined how many parameter estimates in burst-2 models were within the 95% confidence intervals around the corresponding parameter estimates for the same person at burst 1. Excluding parameters involving NA when the measurement model for NA changed between bursts, the parameter "match" ranged from 0% to 67% across participants. An average of 25.1% of the parameters in burst 2 were within the confidence intervals around the corresponding parameters in burst 1. Thus, 75% of parameters had changed to a degree that was not accounted for by sampling error.

Differences in measurement models for NA may have also accounted for some month-to-month differences in the models' structure. Because 14 individuals had p-technique factor models for NA at one burst, but NA characterized entirely by "stress" in the other burst, their overall model change might have been due in part to this difference. Therefore, we also considered whether model change was an artifact of changes in the measurement model of NA between bursts. Individuals whose measurement models changed did not show more overall model change (M = .085, SD = .04) than those whose measurement models did not change (M = .085, SD = .03), $t(34)$ = .034, p = .97, 95% CI: -.03 to .03, d = .01. Finally, the length of the interval between bursts was not related to the extent of model change, $r(34)$ = .259, p = .13, d = .54, 95% CI: -0.076 to 0.541.[1]

Stress change as a correlate of model change

On average, a similar amount of "overall stress," as reported in lab visits before the initiation of ESM sampling, was evident for participants before burst 1 (M = 51.53, SD = 21.20) and before burst 2, one month later (M = 56.44, SD = 21.66), $t(42)$ = 1.69, p = .098, d = .23, but there were ample differences in individuals' stress change. We examined changes in self-reported "overall stress," as reported in lab visits before the initiation of ESM sampling, as a correlate of model changes. Stress change was related to model change: the more individuals' overall stress level changed from one month to the next, the more their dynamic factor models changed as measured by the SRMR, $r(33)$ = .474, p = .004, d = 1.08, 95% CI: 0.168 to 0.697. Figure 3 shows the relation between these two variables. This correlation did not appear to result from stress-related changes in model complexity, as the amount of stress participants were experiencing was not related to the complexity of their models (as measured by the number of parameters) at burst 1, $r(34) = -.056$, $p = .75$, 95% CI: -.377 to .277, $d = .11$, or at burst 2, $r(33) = -.137$, $p = .43$, 95% CI: -.449 to .205, $d = .27$.

General Discussion

Considered together, the results of the two studies suggest differences, both between and within persons, in the dynamic patterns among momentary self-concept clarity, impatience, and negative affect. Results of both studies suggest that substantial variability exists in whether relationships between state SCC, state impatience, and state negative affect exist, and if so, in the direction and sign of these relationships. Most relevant for theories of SCC, this variable predicted impatience and negative affect states for some participants, supporting the theory that SCC can serve as a resource enabling people to better regulate their behavior and emotions (Campbell et al., 1996). For others, state NA or impatience predicted state SCC, suggesting that SCC might be the outcome of behavioral and emotional experience for them (Bem, 1967; McConnell, Rydell, & Leibold, 2002; Sedikides & Skowronski, 1995). Thus, overall results support both theories of SCC's relation to emotion and behavior regulation, but for different individuals. On the other hand, in many individuals no short-term relationship between SCC and impatience, or between SCC and negative affect, was observed. These results are not consistent with any theory of SCC and suggest that nomothetic findings of relationships between SCC and self-regulation variables may not represent the "general" dynamics of SCC (in the sense that a general model would apply to all individuals). This is because these models represent averages across individuals for whom SCC has a strong role in self-regulation and individuals for whom SCC is largely unconnected to self-regulation.

One possible explanation for this heterogeneity is that it reflects diversity of self-concept among the participants. For example, negative affect and impatience might be congruent with some individuals' self-concepts, incongruent with other individuals' self-concepts, and irrelevant to the self-concepts of others. Self-concept clarity might then increase with negative affect and impatience in the first group, decrease in the second, and be unrelated to these variables in the third. This proposition awaits further study. Another possible explanation for the positive SCC-impatience and SCC-NA links, which were unexpected based on prior theory, is that a feeling of negative affect or impatience may sometimes result when an individual is engaged in a task that is not congruent with his or her self-concept and is thus eager to switch to a preferred activity. In these instances, their self-concept might be easily called to mind and relatively clear, even as they feel impatient or anxious. A third possibility is that NA or impatience initially leads to decreases in SCC, but these decreases are followed by explicit or implicit compensatory processes (e.g., Dewall et al., 2011; Koole & Jostmann, 2004; Rudman, Dohn, & Fairchild, 2007), so that SCC appears increased for some participants after a 15-minute interval. Because the speed of such processes is unknown (and may itself even vary among participants), future research with different sampling intervals will be needed to investigate these more complicated hypothetical dynamics.

Study 2 showed that the patterns describing the covariation of SCC, NA, and impatience were somewhat fluid from one month to the next. The changes in these patterns across this period did not appear to be the result of random variation, measurement error, or an artifact of data processing or modeling. Instead, the extent of the changes varied along with the amount of self-reported stress change over this interval. Thus, we construe these patterns as meaningful and the changes as examples of “lawful discontinuity” (e.g., Belsky & Pensky, 1988) in the dynamic relationships among SCC, impatience, and negative affect.

In other papers using “measurement burst” designs (e.g., Carstensen et al., 2011; Sliwinski, Almeida, Smyth, & Stawski, 2009), which mostly concern changes in intraindividual patterns that take place over years or decades as individuals age, changes across bursts are often interpreted as natural maturation. Indeed, most longitudinal research on SCC to date has operated on this timescale; accordingly, changes in relations between SCC and other variables in these studies are interpreted as indications of gradual processes of identity and personality development (Lodi-Smith & Crocetti, 2017). However, the relatively brief window between bursts in the current study, along with the fact that the participants were not mature adults but mostly students in their first year of college, suggests a different interpretation for the current results. We think that these patterns may represent temporary “snapshots” of the dynamics among SCC, NA, and impatience. That is, the dynamic factor models do not characterize stable SCC-behavior and SCC-emotion relations but rather a fluid, flexible organization that is possibly related to salient environmental factors. The fact that the extent of changes correlated with changes in stress level supports this interpretation. We might also speculate that a given individual might oscillate among a limited set of different patterns according to the relative presence or absence of particular environmental characteristics. These propositions await further study.

A few limitations of the current set of studies deserve mention. One limitation is that, given the idiographic nature of the analyses, results cannot be assumed to apply to a broader population of individuals. We consider this to be a considerable strength, however, as the results illustrate the extent to which nomothetic research on SCC dynamics may not itself apply at the individual level. Another potential limitation is the frequency of the observations taken during ESM sampling. Although the current study used a relatively high-frequency sampling design compared to other ESM studies (most participants returned surveys every 15 minutes in Study 1, and all participants did so in Study 2), it is possible that important processes among self-concept clarity, impatience, and negative affect occur at a higher frequency and thus were missed (or that lagged relations at a higher frequency were misinterpreted as contemporaneous relations). There is also the possibility that sampling participants as frequently as we did could have limited their participation in identity-relevant activities or led to reactivity as they began to anticipate or be influenced by the measurement protocol. A third limitation concerns measurement. SCC and impatience states were measured with one item each, which certainly limits their reliability. There is a well-recognized tradeoff in ESM studies between accurate measurement and participant burden (Bolger, Davis, & Rafaeli, 2003; Csikszentmihalyi & Larson, 1987; Shiffman et al., 2008), and we chose to err on the side of lowering burden (and thus increasing ecological validity). This approach is consistent with prior studies on state SCC, which have often used one-item SCC measures (Ayduk, Gyurak, & Luerssen, 2009, Study 2; Scala et al., 2018; Schwartz et al., 2011). However, multi-item measures of these constructs would certainly be desirable. Fourth, dynamic factor modeling assumes “weak stationarity” of the time series data (Molenaar, 1985), or the equality across the survey period of the means and of the covariances between equally-spaced observations. We have no reason to believe that this assumption was violated, especially as most participants completed their 64 surveys within a roughly 36-hour period of time. However, as Study 2 showed that these models do change from one month to the next, shifts in these parameters within a 36-hour period cannot be ruled out. Finally, although these models can show (through the presence of cross-lagged parameters) whether one variable is a

Granger cause of another for a given person (Granger, 1969), we could not show causal influences in a strict sense in the current study. Doing so may require an experimental design.

It would be particularly helpful at this stage to investigate specific correlates of different dynamic factor models, whether between different individuals or at different times for a single individual. It is not uncommon for heterogeneity in person-specific models of longitudinal data to go unexplained (e.g., Burg et al., 2017), and it is difficult to select potential static moderator variables *a priori* given the shared variance among measures of stress, depression, anxiety, well-being, and the like (Tennen & Affleck, 2002). However, we find the multivariate nature of the current investigation to be a considerable strength, as the results easily generate further theorizing. In addition, it would be beneficial to determine the content of the self-concept for each individual participant. Doing so would allow researchers to examine whether fluctuations in thoughts, feelings, or behaviors relevant to each individual's self-concept would predict changes in their SCC, as well as test whether relationships exist between certain self-concept content and specific models of self-concept clarity's relationships with behavioral and emotion constructs. In planning future research, studies employing an experimental design in conjunction with ESM should be considered. This design would give the researcher the ability to manipulate SCC (Boyce, 2008; Setterlund & Niedenthal, 1993), or other emotion and behavior variables to more directly assess the causal relationship between SCC and various constructs.

It would also be very important to replicate the current results in populations other than undergraduate students. Many undergraduates are at an age of rapid development of self-concept and self-regulation abilities (Lodi-Smith & Crocetti, 2017). This may mean that the study of the connections between self-concept clarity and other important variables is particularly relevant and important in this population. However, this may also mean that the dynamic connections between self-concept clarity and emotion or behavior may be different in other populations, just as trait self-concept clarity has different implications for individuals in different cultures (Campbell et al., 1996). Studies of SCC dynamics in groups with different ages, ethnicities, and socioeconomic characteristics would be particularly desirable given the limited range of these variables in the current sample, and indeed in the extant SCC literature in general.

Overall, results suggested that there exists substantial variability among individuals in the kinds of parameters required to describe the covariance of their self-concept clarity and impatience states. The heterogeneity of these models is also evident from the diversity in the direction and size of model parameters. This in turn suggests that a single model does not describe the dynamic relations between these variables equally well for all persons. Furthermore, lack of model stability from month to month indicates that a single model does not adequately describe one individual at all times. Thus, we believe the most plausible explanation for our results is that these models represent temporary states of a dynamic functional relationship between SCC, NA, and impatience. As a consequence, interpreting groupwise models of the relationships between SCC and putatively related correlates as indications of general psychological processes that hold at the within-person level, or indeed assuming that within-person models represent processes that are stable over time, would be ill-advised. We believe the results highlight the importance of examining self-concept clarity from a longitudinal and person-specific perspective.

Author Contributions.

William D. Ellison: study conceptualization, data collection, data preparation, data analysis, report writing

Megan E. Gillespie: data collection, data preparation, data analysis, report writing

Alec C. Trahan: data analysis, report writing

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Table 1

Parameter Estimates for 41 Participants' Time-Series Models (Study 1)

	Parameter				
Participant	ψ	β_{II}	β_{SS}	β_{IS}	β_{SI}
1	0.14	0.05	0.33**	-	-
2	0.02	0.25	0.19	-0.15	-
3	0.18	-0.05	0.52***	-	-
4	0.58***	0.75***	0.30**	0.13	0.38**
5	0.29*	0.32**	0.23	0.25*	
6	-0.19	0.37**	0.35**	-	-
8	-0.18	0.58***	0.33*	-	-
9	0.01	0.32**	0.35**	-	0.25*
10	-0.11	0.25*	0.15	0.20	
11	0.05	0.51***	0.54***	-	-
13	-0.07	0.26*	0.41**	-	-
14	0.35*	0.32*	0.90***	0.17	0.10*
16	0.05	0.40***	0.43***	-	-0.25*
17	-0.18	0.24	0.39***	-	-0.20
18	0.10	0.40**	0.39**	-	-
19	-0.22	0.70***	0.36**	-	-
20	0.48**	0.00	0.37***	-	-
21	0.15	-0.06	0.26*	-	-
23	0.13	0.33*	0.12	-	-
24	0.09	-0.02	0.40**	-	-
25	-0.40**	0.06	0.16	-	-
33	0.24	0.46***	0.33**	-	-
34	-0.11	0.51***	0.39**	-	-
39	-0.01	0.47***	0.44***	-	-
40	-0.10	0.58***	0.58***	-	-
41	0.06	0.29*	0.34**	-	-
43	-0.05	0.53***	0.68***	-	-0.18*
44	0.19	0.44***	0.22	0.21	-
45	-0.12	0.57***	0.32*	-	-
46	0.56***	0.40***	-0.01	-	0.31*
47	0.26	0.34**	0.36**	-	0.24*
49	-0.28	0.09	0.50***	-	-
51	0.13	-0.09	0.41***	-	0.25*
52	0.16	0.41***	0.44***	0.21	-
53	0.06	0.60***	0.41***	-	-
54	-0.12	0.61***	0.63***	-	-
55	0.23	0.02	0.21	0.26	-
59	-0.31*	0.61***	0.12	-	-
61	-0.19	0.19	0.11	-	-

63	-0.11	0.15	0.48***	-	-
66	0.17	0.19	0.19	-	-

Note. ψ = correlation of impatience and self-concept clarity at time *t - 1*. β_{II} = autoregression relating impatience at time *t - 1* to impatience at time *t*. β_{SS} = autoregression relating self-concept clarity at time *t - 1* to self-concept clarity at time *t*. β_{IS} = cross-lagged regression relating self-concept clarity at time *t - 1* to impatience at time *t*. β_{SI} = cross-lagged regression relating impatience at time *t - 1* to self-concept clarity at time *t*. Dashes indicate that the parameter was not required for good fit. Correlations between impatience and self-concept clarity residuals at time *t* were also included in all models but are omitted here.

*p < .05. **p < .01. ***p < .001

Table 2

Descriptive statistics and correlations among mean SCC, impatience, and negative affect scores (study 2)

	1	2	3	4	5	6	7	*M*	$SD_{between}$	SD_{within}
1 SCC	**.834****	-.071	-.295	-.043	-.338*	-.304	-.334*	57.59	26.58	8.38
2 Impatient	.111	**.648****	.482**	.695**	.618**	.528**	.303	23.68	17.39	12.12
3 Sad	-.271	.501**	**.548****	.739**	.806**	.699**	.438**	16.37	19.27	8.38
4 Lonely	-.189	.471**	.931**	**.616****	.628**	.554**	.195	14.63	17.15	8.24
5 Worried	-.337*	.508**	.610**	.536**	**.617****	.853**	.479**	26.51	21.13	10.68
6 Stressed	-.381*	.584**	.507**	.478**	.832**	**.549****	.460**	36.61	20.79	13.47
7 Baseline stress	-.149	.146	.254	.124	.358*	.283	**.607****	52.04	21.70	
M	59.95	23.35	12.34	13.45	25.05	36.13	56.44			
$SD_{between}$	23.81	17.99	12.52	14.61	17.57	18.80	21.66			
SD_{within}	9.52	13.08	9.16	9.55	11.94	14.79				

Note. SCC = self-concept clarity. $SD_{between}$ = interindividual standard deviation; standard deviation of individual participant means from the group mean. SD_{within} = intraindividual standard deviation; standard deviation of individuals' responses from their mean, averaged across participants. Statistics for burst 1 are presented below the diagonal, and correlations for burst 2 are presented above the diagonal. Boldface correlation coefficients on the diagonal represent correlations between participants' mean levels of each variable at burst 1 and mean levels at burst 2.

Table 3

Parameter Estimates for 36 Participants' Time-Series Models (Study 2)

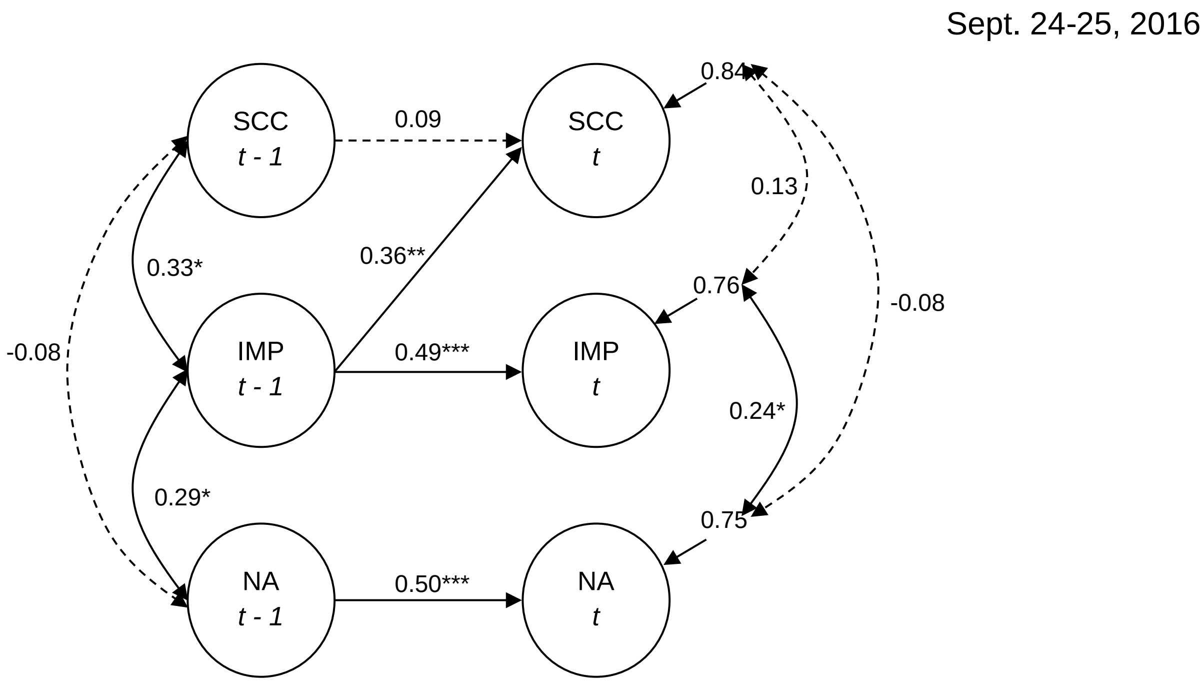
		Parameter											
Part.	burst	ψ_{SI}	ψ_{SN}	ψ_{IN}	β_{SS}	β_{II}	β_{NN}	β_{SI}	β_{SN}	β_{IS}	β_{IN}	β_{NS}	β_{NI}
1	1	-.22	-.23	.03	.63***	.48***	.82***	-	-	-	-	-	-
	2	-.19	-.41**	.44**	.31**	.41***	.63***	-	-	-	-	-	-
2	1	-.16	.14	.02	.04	.31*	.66***	-.28*	.22	-	-	-	-
	2	.28*	.05	.18	.19	.22	.03	-	-	-	-	-	-
5	1	.54***	-.01	.14	.83***	.54***	.61***	-	-	-	-	-	-
	2	.06	-.39**	-.07	.27*	.21	.10	-	-	.24*	-	-.30*	-
8	1	-.14	-.28	.02	.33*	.48***	.58***	-	-	-	-	-	-
	2	.22	.28*	.45**	.25*	.05	.69***	-	-	-	-	-	-
9	1	.02	.11	.18	.45***	.04	.44***	-	-	-	-	-	-
	2	.25	-.29*	-.08	.21*	.24*	.51***	-	-	-	-	-	-
10	1	-	-.46**	.57***	.61***	.49***	.56***	-	-	-	-	-.22*	-
	2	.15	.30*	.42**	.26*	.68***	.65***	-	-	-	-	-	-
11	1	.06	.12	-.12	.24	.26*	.67***	-	-	-	-	-	-
	2	.08	.02	.69***	.19	.67***	.08	-	-	-	-	-	.56***
12	1	.33*	-.08	.29*	.09	.49***	.50***	.36**	-	-	-	-	-
	2	.20	.25	.62***	.20	.09	.02	.40**	-.38**	-	-	-	-
13	1	-.15	-	.50***	.33**	.39***	.48***	-	-.31*	-	.37**	-.29**	.20*
	2	.13	-.44**	-.13	.23*	.32*	.04	-	-	-	-	-	-
16	1	.08	.26	.28*	.46***	.12	.52***	-	-	-	-	-	-
	2	-.21	.16	-.37**	.25*	.13	.42***	-.19	-.30*	-	-.22	-.17	-
17	1	.35*	.06	-.16	.24*	.61***	.48***	-	-	-	-	-	-
	2	-.06	.08	-.09	.22	.35**	.17	-.22	-	-	-	-	-.25*
18	1	-.27	-.06	.57***	.29*	.68***	.51***	-.33*	.27	-.16	.12	-	.27*
	2	.08	-.06	-.07	.06	.30*	.38**	-	-	-	-	-	.20
19	1	-.04	-.45**	.23	.12	.00	.18	-	-	-	-	-	-
	2	-.14	.10	.41**	.05	.23	.34**	-.23	-	-	-	-	-

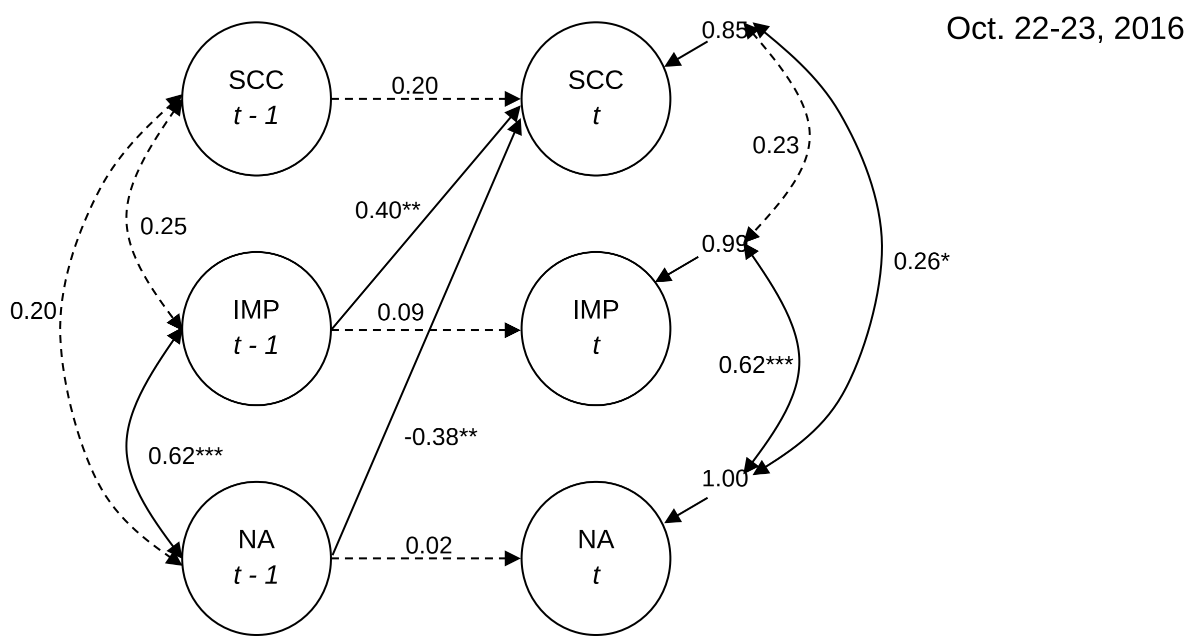
		Parameter											
Part.	burst	ψ_{SI}	ψ_{SN}	ψ_{IN}	β_{SS}	β_{II}	β_{NN}	β_{SI}	β_{SN}	β_{IS}	β_{IN}	β_{NS}	β_{NI}
20	1	-.05	-.11	.17	.33**	.15	.52***	-	-	-.29*	.28*	-	-
	2	-.06	.17	.40**	-.02	.14	.49***	-	-	-	-	-	-
24	1	-.26	-.30*	.48**	-.11	.18	.44***	-	-	-	-	-	-
	2	-.10	-.05	.29*	.06	.15	.53***	-	-	-	-	-	-
25	1	-.12	.06	.10	.03	.52***	.25*	-	-	-	-	-	-
	2	.22	.30*	.43**	.07	.08	.53***	-	.36**	-	-	-	-
26	1	.36*	.49**	.30	.25	.20	.35*	-	.34*	-	.38**	.34*	-
	2	.66***	.28	.15	.54***	.21	.19	-	-	.44**	-	-	-
27	1	.04	.02	.09	-.05	.52***	.18	-	-.25	-	-.16	-	-
	2	-.22	-.43**	.24	.28*	.29*	.60***	-	-	-	-	-	-.20*
28	1	-.07	.05	.18	-.09	.39**	.44***	-	-	-	-	-	-
	2	.28*	-.27	-.22	.42***	.32**	.41***	-	-	-	-	-.28*	-
29	1	-.21	.02	.66***	.33**	.50***	.19	.62***	-	.18*	.35**	-	.54***
	2	-.38**	-.33*	.70***	.47***	.44***	.44***	-	-	-.23*	-	-	.38**
30	1	-.19	-.30*	.57***	-.05	.23	.91***	-	-.32*	-.32**	.33*	-	-
	2	.28*	-.11	.34*	.05	-.17	.39**	-	-	-	-	-	-.26*
31	1	.16	.36**	.15	.31*	.20	.28*	-.19	-.21	-	-	.33**	-
	2	.20	.32*	.13	.23	.02	.20	-.32*	-	-	.21	.43***	-
33	1	-.45**	.07	.51***	.18	.15	.39***	-	-	-	-	-	-
	2	.21	-.06	.55**	.49***	.19	.72***	-	-	-	.43**	-	-
35	1	-.06	.00	.11	.34**	.22	.46***	-	-	-	-	-	-
	2	-.16	-.36*	.34*	.28*	.38**	.43***	-	-	-	-	-	-
37	1	-.15	-.05	-.45**	.04	.50***	.63***	-	-	-	-.30**	-	-
	2	-	-	.80***	.27*	.39***	.62***	-	-.37**	-	.51***	-	.31***
38	1	.32*	.06	.10	.16	.17	.24	-	-	-	-	-	-
	2	.07	.00	.18	.27*	.22	.41***	-.24	-	-	-	-	-
41	1	.08	-.10	.61***	.50***	.27*	.27*	-	-	-	-	-	-
	2	-.21	-.49	.35	.64***	.58***	.67***	-	-	-	-	-.19	-
43	1	.32*	-.13	.06	.40***	.07	.32*	-	-	-	-	-	-
	2	.07	-.34*	.32*	.74***	.28*	.55***	-	-	-	.25*	-	-

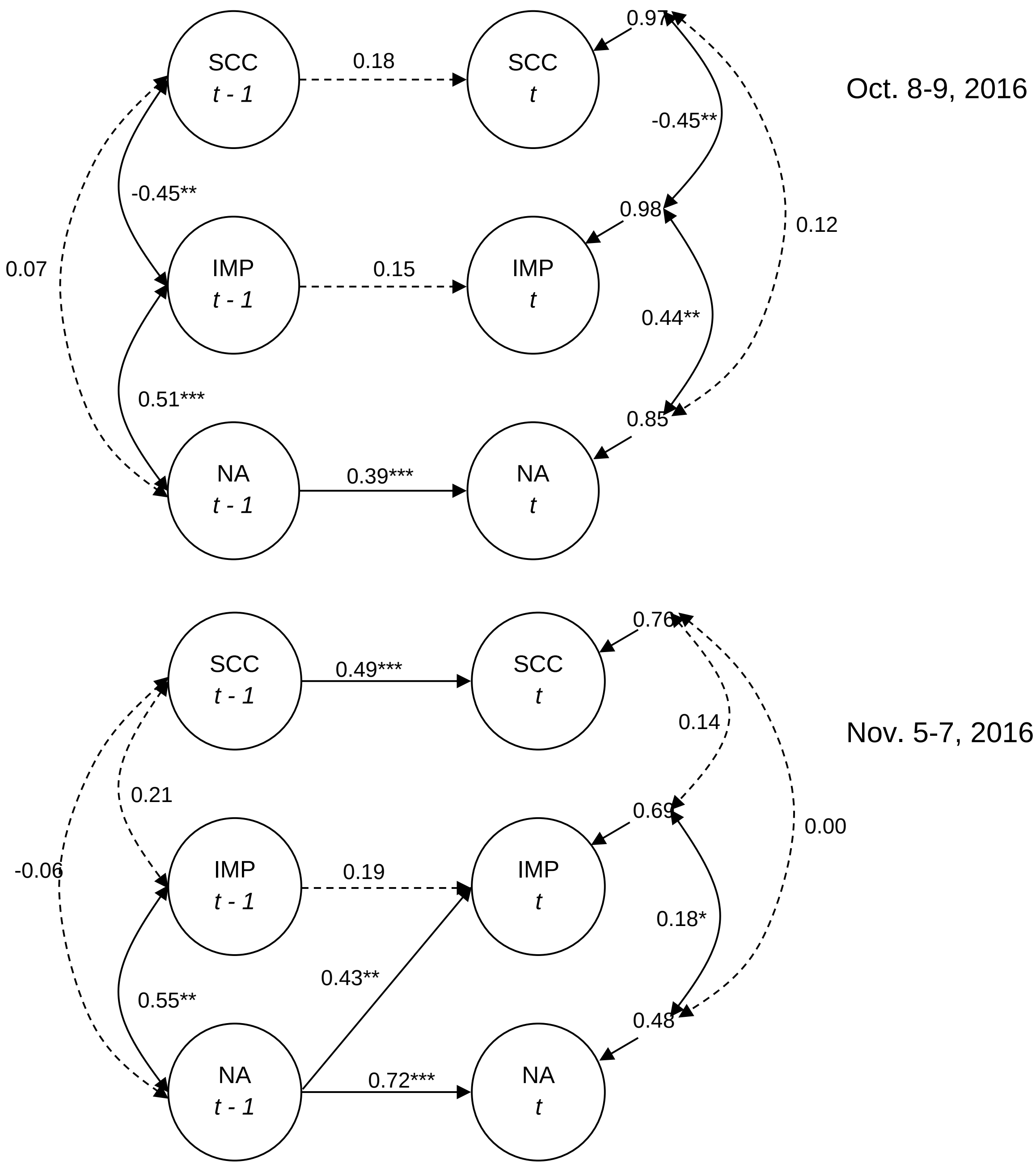
		Parameter											
Part.	burst	ψ_{SI}	ψ_{SN}	ψ_{IN}	β_{SS}	β_{II}	β_{NN}	β_{SI}	β_{SN}	β_{IS}	β_{IN}	β_{NS}	β_{NI}
46	1	.03	.04	.18	-.05	.16	.24	-	-	-	-	-	-
	2	-.16	-.32*	-.06	.84***	.17	.28*	-.15*	-	-	-	-.20	-
49	1	-.17	-.19	.58***	.63***	.12	.27*	-.23*	-	-	-	-	-
	2	-.04	-.24	.04	.09	.39**	.40***	-	-	-	-	-	-
50	1	-.31	.15	.41	.26*	.05	.75***	-	-	-.19	.35**	-.23**	-
	2	.59***	-.11	.24	.29**	.33**	.17	-	-	-	-	-	-
53	1	-.23	-.21	-.02	.00	.09	.73***	-	-	-	-	.24*	-
	2	.03	-.04	-.10	.29*	.06	.33**	-	-	-	-	-	-
54	1	.36*	-.04	.20	.52***	.16	.74***	-	-	.27*	-	-	-
	2	.09	-.12	.37**	.57***	.31**	.61***	-	-	-.26*	-	-.23*	-
55	1	-.31*	.18	.17	.49***	.41***	.64***	-	-	-	-	-	-
	2	-.09	.19	.21*	.79***	.53***	.79***	-	-	-	-	-	-
63	1	.10	-.32*	-.08	.28*	.05	.71***	-	-	.51***	-.26*	.20	-
	2	.11	.18	-.12	.41***	.44***	.46***	-	-	-	-	-	-.25*
66	1	-.09	.12	.44**	-.12	.20	.15	-	-	-	-	-	-
	2	-.02	.27*	.31*	.34**	.39***	.73***	-	-	.31**	-	-	-

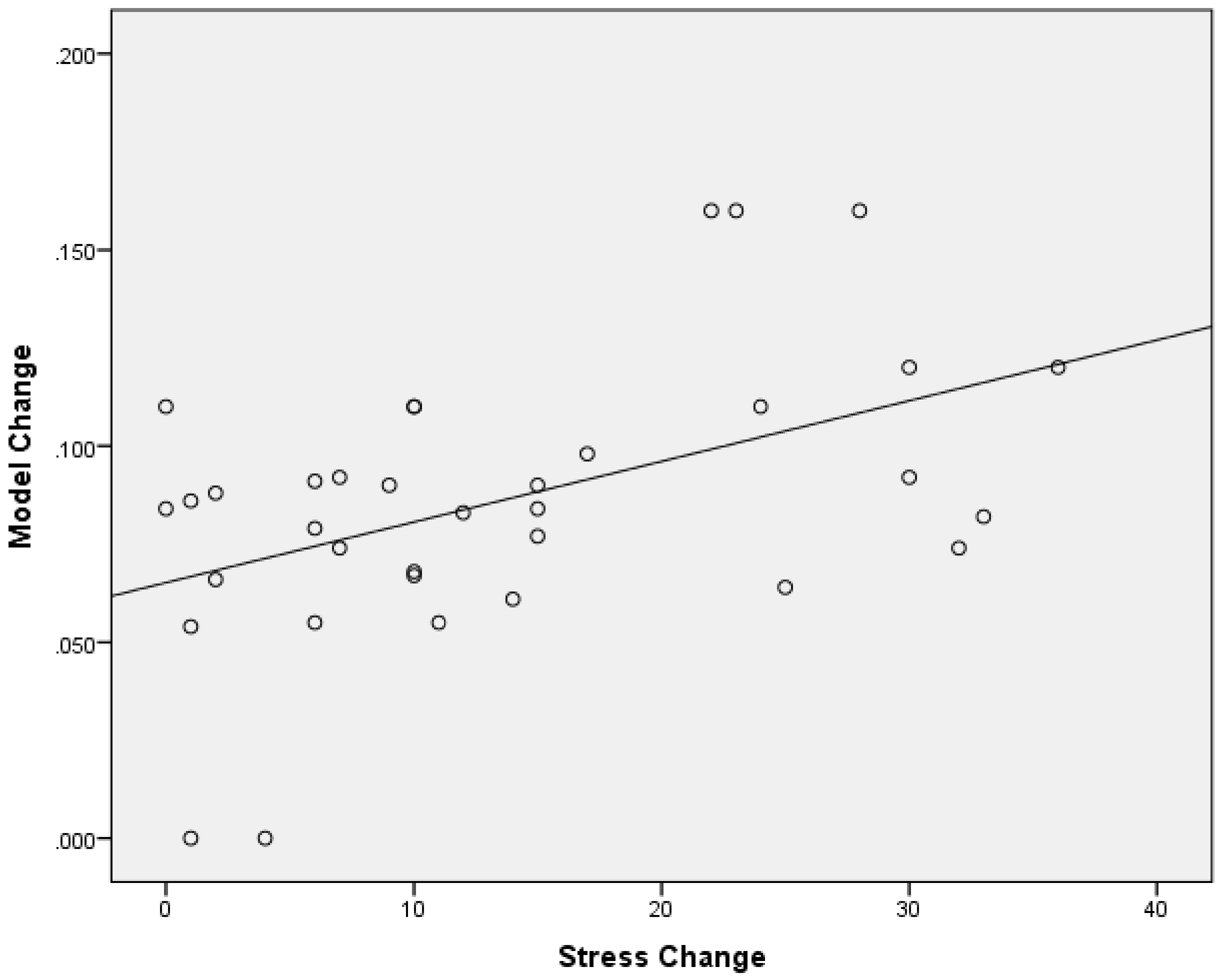
Note. ψ_{SI} = correlation of impatience and self-concept clarity at time t - 1. ψ_{SN} = correlation of negative affect and self-concept clarity at time t - 1. ψ_{IN} = correlation of impatience and negative affect at time t - 1. β_{SS} = autoregression relating self-concept clarity at time t - 1 to self-concept clarity at time t. β_{II} = autoregression relating impatience at time t - 1 to impatience at time t. β_{NN} = autoregression relating negative affect at time t - 1 to negative affect at time t. β_{SI} = cross-lagged regression relating self-concept clarity at time *t* to impatience at time t – 1. β_{SN} = cross-lagged regression relating self-concept clarity at time *t* to negative affect at time t – 1. β_{IS} = cross-lagged regression relating impatience at time *t* to self-concept clarity at time t – 1. β_{IN} = cross-lagged regression relating impatience at time *t* to negative affect at time t – 1. β_{NS} = cross-lagged regression relating negative affect at time *t* to self-concept clarity at time t – 1. β_{NI} = cross-lagged regression relating negative affect at time *t* to impatience at time t – 1. Dashes indicate that the parameter was not required for good fit. Correlations between impatience, negative affect, and self-concept clarity residuals at time *t* were also included in all models but are omitted here.

$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.


Sept. 24-25, 2016
SCC t - 1
IMP t - 1
NA t - 1
SCC t
IMP t
NA t
0.09
0.36**
0.49***
0.50***
0.33*
0.29*
-0.08
0.84
0.76
0.75
0.13
0.24*
-0.08


Oct. 22-23, 2016
SCC t - 1
IMP t - 1
NA t - 1
SCC t
IMP t
NA t
0.20
0.40**
0.09
-0.38**
0.02
0.25
0.62***
0.20
0.85
0.99
1.00
0.23
0.62***
0.26*


SCC
t - 1
0.18
SCC
t
0.97
Oct. 8-9, 2016
-0.45**
-0.45**
0.98
0.12
0.07
IMP
t - 1
0.15
IMP
t
0.44**
0.51***
0.85
NA
t - 1
0.39***
NA
t
0.76
SCC
t - 1
0.49***
SCC
t
0.14
Nov. 5-7, 2016
0.21
0.69
0.00
-0.06
IMP
t - 1
0.19
IMP
t
0.18*
0.43**
0.55**
0.48
NA
t - 1
0.72***
NA
t



.200
.150
.100
.050
.000
Model Change
0
10
20
30
40
Stress Change

Figure captions.

Figure 1. Dynamic factor models describing the relationship between self-concept clarity, impatience, and negative affect, simultaneously and at successive time points, for participant #12 in September and October 2016 (structural model only). Numbers represent completely standardized maximum likelihood parameter estimates. Dashed lines indicate nonsignificant parameters retained in the final model (p > .05). SCC = self-concept clarity; IMP = impatience; NA = negative affect. Interval between $t - 1$ and t is 894s for September and 898s for October.
* $p < .05$. ** $p < .01$. *** $p < .001$.

Figure 2. Dynamic factor models describing the relationship between self-concept clarity, impatience, and negative affect, simultaneously and at successive time points, for participant #33 in October and November 2016 (structural model only). Numbers represent completely standardized maximum likelihood parameter estimates. Dashed lines indicate nonsignificant parameters retained in the final model (p > .05). SCC = self-concept clarity; IMP = impatience; NA = negative affect. Interval between $t - 1$ and t is 922s for October and 970s for November.
* $p < .05$. ** $p < .01$. *** $p < .001$.

Figure 3. Scatter plot relating change in the amount of stress from one month to the next to overall degree of change in dynamic factor models.

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[1] Most individuals took exactly four (n = 9) or five (n = 10) weeks in between bursts, but there was a fair amount of variability around these two modes due to scheduling eccentricities (SD = 6.24 days, range = 21 days to 49 days).