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RESEARCH PAPER

One Size Does Not Make All Happy: Idionomic Links Between Striving for Positive States and Happiness in Experience Sampling

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Abstract
Striving for happiness can sometimes increase happiness but can also backfire and reduce it. To explore this paradox, we used idionomic methods—balancing individual-level analysis with group-level generalization—to examine how striving for happiness influences momentary happiness. Our data included ecological momentary assessment (EMA) surveys ($n = 2251$) from 167 participants (75.6% female; M age = 23.96, SD = 8.7). Each individual's data were first modelled separately, producing their own estimate and standard error for the association between each striving item and each affect item. These idiographic estimates were then submitted to a multivariate random-effects meta-analysis, which revealed high, non-random heterogeneity. The type of striving—prioritizing positivity (PP) versus experiential attachment (EA) to enjoyment moderated the overall effect. Due to high heterogeneity in the overall effect, we applied group-based multivariate trajectory modelling. This revealed two distinct groups with nonlinear patterns across striving and affect. Multilevel vector autoregressive models showed that EA consistently dampened happiness within-person, despite no between-person association. In contrast, PP was linked to higher happiness in one group, but in the other, it had no direct benefit and indirectly reduced happiness via its connection to EA. The dampening effects of EA held even when accounting for stress, positive events, loneliness, and social connection. Our findings underscore the importance of combining within-person and between-person analyses by replicating known nomothetic effects and highlighting complex subgroup dynamics. This dual approach is a crucial and necessary advancement for modern happiness research.

Keywords Happiness · Experiential attachment · Affect · Ecological momentary assessment · Network analysis · Idionomic analysis

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1 Introduction

We all want to be happy. However, the deliberate pursuit and experience of happiness are not always beneficial across different levels, contexts, types of happiness, reasons, or persons (Gruber et al., 2011). Research shows that striving for happiness can lead to happiness (Catalino & Tov, 2022), but it can also backfire by decreasing happiness (Mauss et al., 2011). Shedding new light on such a divergent pattern of results requires new methods. We explored the possible utility of high-temporal density ecological momentary assessment data examined through an idionomic lens that combines idiographic and nomothetic analyses into a cohesive whole (Hayes et al., 2022; Sahdra et al., 2024). We used idionomic analyses balancing individual-level analysis with group-level generalization to evaluate the links between different forms of striving for positive states and hedonic well-being in daily life both within person and between persons.

1.1 The Promise and Pitfalls of Pursuing Happiness

The deliberate pursuit of happiness has long been thought to paradoxically reduce happiness. For example, Mauss et al. (2011) found that a stronger pursuit of happiness correlated with decreased positive affect, increased negative affect, lower life satisfaction, and heightened depressive symptoms. Similarly, valuing happiness—defined as wanting to be happy most of the time—has been linked to greater loneliness in adults, particularly in stressful conditions (Mauss et al., 2012), and depressive symptoms in adolescents (Gentzler et al., 2019) and individuals with prior depression (Ford et al., 2014).

However, these findings largely rely on the Valuing Happiness Scale (VHS), which has been criticized for its methodological and conceptual limitations. Recent research has highlighted significant issues with the VHS, including its lack of unidimensionality and problematic item wording. For instance, Luhmann et al. (2016) demonstrated that the VHS is not a single construct but comprises multiple factors, only one of which—concern about happiness—consistently correlates with lower well-being. Other factors, such as aspiring to happiness, show null or even positive associations with well-being. Similarly, Zerwas et al. (2024) found that concern about happiness, characterized by excessive monitoring and judgment of one's happiness, is the primary driver of the negative associations between valuing happiness and well-being.

Adding to this complexity, Huang (2024) conducted a large longitudinal study of Dutch adults and found that valuing happiness generally exhibited positive associations with well-being, including higher life satisfaction, more positive affect, and less negative affect. However, increases in valuing happiness did not result in long-term changes in life satisfaction and had mixed emotional consequences, such as heightened positive and negative affect.

Building on these critiques, Krasko et al. (2020) introduced the concept of Happiness Goal Orientations (HGO) as a multidimensional construct to better understand the pursuit of happiness and its effects on well-being. Their research identified two distinct dimensions of HGO: Happiness-Related Strivings and Happiness-Related Concerns. Happiness-Related Strivings represent the active and persistent pursuit of happiness, characterized by approach-oriented behaviors and positivity. This dimension was found to be positively associated with well-being, including higher life satisfaction and positive affect. In contrast, Happiness-Related Concerns reflect a tendency to worry about and focus on threats to one's happiness, which aligns with avoidance-related constructs and anxiety. This dimension was consistently negatively associated with well-being, including lower life satisfaction and heightened negative affect.

These findings underscore the importance of distinguishing between different dimensions of happiness pursuit. While active striving for happiness can enhance well-being, excessive concern about achieving happiness can lead to emotional rigidity, negative meta-emotions, and disappointment during positive experiences, ultimately reducing well-being (Krasko et al., 2020; Zerwas et al., 2024). Relatedly, the literature on experiential attachment to positive states also suggests that clinging to happiness is not conducive to lasting happiness, and the opposite quality of ‘nonattachment’ or release from such fixations is more effective for promoting genuine well-being (Ciarrochi et al., 2024a, 2024b; Sahdra et al., 2010). Experiential attachment (EA) is defined as our tendency to pursue and rigidly cling to pleasant internal states, including feelings of comfort, being in control, feeling capable, having high social status, and maintaining power over others (Ciarrochi et al., 2024a, 2024b). It has been found to be negatively related to hedonic and eudemonic well-being (Sahdra et al., 2016), and positively related to psychological distress (Ho et al., 2022) and symptoms of depression and anxiety in clinical and nonclinical samples (Whitehead et al., 2021; Yang et al., 2020). In youth, it has been shown to be a precursor to poor mental health (Ciarrochi et al., 2020) and to be linked to less prosocial behavior as observed by peers (Sahdra et al., 2015).

While clinging to happiness can be counterproductive, striving for happiness may not always be self-defeating. Catalino et al. (2014) found cross-sectional evidence that higher levels of prioritizing positivity (PP) in daily life correlated with more positive emotions and less depressive symptoms. In a three-wave longitudinal study, Datu and King (2016) reported that prioritizing positivity predicted future positive emotions, which in turn, predicted subsequent life satisfaction. In a daily diary study, Catalino and Tov (2022) found that individuals who prioritized positivity in daily life reported higher levels of well-being, including more positive emotions, satisfaction, and meaning in life. In the context of coping with crises, prioritizing positivity has been linked to posttraumatic growth, active coping strategies, and deliberate rumination (Zięba et al., 2022). However, the effectiveness of PP may vary across different life stages and individuals, suggesting that personalized strategies may be necessary to optimize well-being (Littman-Ovadia & Russo-Netzer, 2019).

1.2 An Idionomic Assessment of Happiness: Combining Idiographic and Nomothetic Approaches

The studies reviewed above used different designs—cross-sectional, experimental, cross-lagged panel, or daily diary—but they all focused on nomothetic effects assessed across collections of particular people (whether that be specific individuals, or particular couples, families, or groups). Nomothetic effects observed using standard statistical procedures are called “group” approaches but not typically in the sense of analyzing intact groups. Rather, effects are observed based on differences between people within a collective. Such effects often fail to apply to particular people assessed over time, which is not surprising because the mathematical assumptions needed to assume that kind of generalization are rarely met (Molenaar, 2008). A growing literature has documented the very large gap between within-person effects and between-person effects drawn from the same datasets (e.g., Sahdra et al., 2024). To better address these challenges, an idionomic approach has been proposed, which combines the insights from idiographic and nomothetic approaches in a coordinated fashion that protects idiographic effects without needless homogenization (Hayes et al., 2022; Sahdra et al., 2024; Ciarrochi et al., 2024a, 2024b). High-frequency temporal data is subjected to idiographic analyses, which are then meta-analyzed or otherwise combined to yield group-level insights that are designed to build upon and help explain the idiographic findings. For example, in the context of high idiographic heterogeneity of effects, subgroups of particular people with relatively similar patterns may be further explored to clarify the dynamic interrelations between different processes and outcomes using both between- and within-level networks of variables.

An idionomic approach seems especially applicable to happiness studies because the field itself has long viewed happiness as a highly personal human life journey, not an analytic abstraction that "should" or "must" apply to all. For example, in her book, "The How of Happiness," Lyubomirsky (2008) argued forcefully that strategies for increasing happiness needed to be fitted to the person's goal, strengths, circumstances and preferences, concluding that "There is no magic one-size-fits-all strategy for becoming happier" (p. 70). Previous nomothetic findings of negative effects of valuing happiness (e.g., Mauss et al., 2011) raise a question of significant practical and theoretical importance: which particular individuals experience detrimental versus positive effects of particular methods of striving for happiness, and why? Some studies have found moderators that partially explain the individual variability in the nomothetic effects of valuing happiness in particular ways. For instance, individuals with strong emotion regulation and overall functioning capacities may experience beneficial outcomes from valuing happiness (Mauss et al., 2011). Lower acceptance of emotions may exacerbate the positive link between striving for happiness and depressive symptoms (Zhao et al., 2020). The different methods individuals use to pursue happiness—whether by trying to manage the valence of an emotional experience or by seeking experiences that foster positive emotions—can influence their well-being (Hansenne, 2021). By re-evaluating known nomothetic effects through an idionomic lens, we can potentially uncover new insights about the individual subtleties in the links between striving for positive states and hedonic well-being.

1.3 Purpose of the Present Study

The current study employed ecological momentary assessment (EMA) data and idionomic analyses to generate idiographic and nomothetic insights about the interconnections between different forms of striving for happiness and affective states in daily life. In line with the preregistration of the study (blinded for peer review: https://osf.io/fwv6j/?view_only=6732e9316da64227bfc3f89885789a00), our hypotheses were as follows:

1. Based on the past studies reviewed above, on average, we expected the striving items to be positively correlated to negative affect and negatively correlated to positive affect.
2. We also expected substantial idiographic heterogeneity in the nomothetic effects. Specifically, we hypothesized that individuals who substantially deviate from the norm, relative to the rest of the sample, would show a different pattern of within-person associations between variables.
3. Based on recent research on network analysis using idionomically defined groups (Sahdra et al., 2024), we expected the within-person networks to vary from the between-person networks of strivings and happiness.
4. There are no prior idionomic studies teasing apart the within- and between-person longitudinal associations between these variables to our knowledge. Therefore, we did not have specific a priori hypotheses about the form of idiographic effects and their role

in refining nomothetic conclusions; we instead intended to explore the structure of the within-person and between-person networks of variables in this study.

5. We hypothesized that contextual events might influence the relationship between striving for positive states and happiness at the within-person level, though we could not prespecify the exact nature of this influence in the networks due to a lack of prior idionomic studies in this area.

2 Method

2.1 Participants and Procedure

This study involved a pre-registered secondary analysis of ecological momentary assessment (EMA) data (anonymized link of pre-registration: https://osf.io/fwv6j/?view_only=6732e9316da64227bfc3f89885789a00) of a previously published study (citation blinded for peer review). The original study had 201 participants, but not all completed all measures. Of the participants, 167 provided data for the strivings and affect-related variables relevant to the current study. (There was an error in the preregistration about the total number of participants as 168.) The data comprised EMA surveys ($n = 2251$) completed by 167 college students at a large public university in Western United States. Participants were eligible if they were 18 or older, enrolled in college, and owned an Android or iPhone to respond to EMA surveys. EMA surveys were administered via text message three times daily over the course of one week, alongside pre- and post-assessments. Participants were recruited via the university's online research platform. They received up to three research credits towards their courses. Participants received three random prompts daily during these time windows: 9 AM–1 PM, 1–5 PM, and 5–9 PM. A minimum of 2 h separated each prompt, and participants had a 2 h window to respond. To ensure data quality and minimize careless responses, only responses that took 72 s or longer—calculated by allowing 2 s per item—were included in the analyses. Of the participants, 75.60% were women, and 7.14% were persons of color (as indicated by self-reported race other than White). Participants' average age was 23.96 ($SD = 8.7$).

2.2 EMA Measures

Striving for positive states was assessed by five items adapted from the Valuing Happiness Scale (VHS; Mauss et al., 2011) and Experiential Approach Scale (EAS; Swails et al., 2016). See Table 1 for the wording of all items. *Positive and negative affect* were evaluated using ten items from the Positive and Negative Affect Schedule (PANAS; Watson et al., 1994). Four items measured positive affect (happy, joyful, confident, excited), while six assessed negative affect (sad, angry, irritable, guilty, ashamed, nervous). *Contextual variables* were evaluated using four items: stressful events: "Since the last prompt, how much did you experience stressful events and situations?"; positive events: "Since the last prompt, how much did you experience positive events and situations?"; loneliness: "Right now, how lonely do you feel?"; and connectedness: "Right now, how connected do you feel to other people?" All EMA items were rated on a 5-point Likert scale from 1 (not at all) to 5 (very much so). The reliability of each EMA item was assessed using the intraclass correlation coefficient-2 (ICC(2)) from a one-way analysis of variance model (Bliese, 2000).

Table 1 The ICC(2) reliability estimates of the EMA items

		ICC(2)	95% Confidence Interval	
			Lower	Upper
Strivings items	EA_Fading	0.97	0.96	0.98
	EA_Distressed	0.97	0.96	0.97
	EA_Worry	0.97	0.96	0.98
	PP_Happy	0.98	0.97	0.98
	PP_Hang-On-To	0.98	0.97	0.98
Affect	Happy	0.94	0.93	0.95
	Excited	0.95	0.94	0.96
	Joyful	0.95	0.94	0.96
	Confident	0.96	0.95	0.97
	Nervous	0.94	0.93	0.95
	Ashamed	0.95	0.94	0.96
	Sad	0.94	0.93	0.96
	Angry	0.91	0.89	0.93
	Guilty	0.94	0.93	0.96
	Irritable	0.94	0.93	0.95
Contextual variables	Stressful events	0.92	0.91	0.94
	Positive events	0.94	0.92	0.95
	Loneliness	0.96	0.95	0.97
	Connectedness	0.94	0.93	0.96

ICC(2): intraclass correlation coefficient-2 reliability estimate from a one-way analysis of variance model; EA: Experiential attachment related items; PP: Prioritizing positivity related items. The wording of the strivings EMA items was as follows: EA_Fading: "Since the last prompt, I worried about my positive emotions fading"; EA_Distressed: "Since the last prompt, I got distressed if I didn't feel happy"; EA_Worry: "Since the last prompt, if I didn't feel happy, I worried about it"; PP_Happy: "Since the last prompt, I did my best to stay happy all the time"; PP_Hang-On-To: "Since the last prompt, I tried to hang on to feelings I enjoyed."

ICC(2) of all items were above 0.90 (range: 0.91 to 0.98), suggesting that all items were highly reliable (see Table 1).

2.3 Planned Analyses

Analysis was conducted in R version 4.4.1 (R Core Team, 2024). See the Supplementary Information for the R script on the analyses. We followed our pre-registered (https://osf.io/fwv6j/?view_only=6732e9316da64227bfc3f89885789a00) analysis plan, which we summarize here. We first examined the EMA items' missing data pattern, revealing that 33% of the data were missing (see Fig. S1 top panel). Longitudinal imputation was used to handle missing data (Genolini et al., 2013). The data were then subjected to idionomic analyses that combined idiographic and nomothetic insights (Ciarrochi et al., 2024a, 2024b; Sahdra et al., 2024). First, an idiographic analysis of each of the five strivings EMA items relating to each of the ten affect items was conducted by using the idiographic autoregressive integrative moving average models with an exogenous variable (i-ARIMAX). Details on i-ARIMAX models may be found in Sahdra et al. (2024); in brief, a time series model was generated for each individual in a dataset which included autoregression (i.e., the outcome was regressed on its prior values), allowed residual error from a moving-average model of the previous timepoints to predict later timepoints, and included a predictor variable (a striving item) that may predict the outcome (an affect item). The effect size estimates and standard errors from these idiographic models were then subjected to a random-effects meta-analysis (RE-MA) to calculate estimates of the nomothetic bivariate association between each striving and affect pair of items and the heterogeneity of the pooled effects. Moderation analyses using experiential attachment (EA) and prioritizing positivity (PP) related items, and demographic variables, were conducted to account for the heterogeneity of the effects.

We next examined the data's clustering tendency. We conducted K-means cluster analysis of the i-ARIMAX estimates. We also conducted group-based multivariate trajectory modeling (Nagin et al., 2016), where individuals were assigned to groups based on a multivariate polynomial (non-linear) regression model of time of all striving and affect variables. This latter method was not explicitly prespecified in the preregistration but was consistent with our prespecified plan for using idiographic data for identifying subgroups. Finally, we conducted multilevel-vector autoregression modeling (multilevel-VAR; Borsboom et al., 2021) to build networks of variables and examine how EA and PP items were dynamically related to happiness at the within-person and between-person levels in the different groups.

3 Results

3.1 Preliminary Analyses

Preliminary analyses of the strivings EMA items (reported in Tables S1 and S2 in Supplementary Information) indicated that the items of Fading, Distress, and Worry were correlated with each other more strongly than they were correlated with the items of Happy and Hang-on-to. However, as shown in Table S2, there was a wide range of within-person correlations for each bivariate association. For instance, the average within-person correlation between the Fading and Hang-on-to item was 0.09 but the range was −1.00 to 1.00. As another example, the Distressed and Worry items' mean correlation was 0.53, but the range was −0.61 to 1.00. That is, even though, on average, the two items showed a strong positive correlation, the correlation was strongly negative for some people but extremely positive for others. Tables S3 and S4 report the descriptives of raw within-person correlations of the striving items with positive and negative affect items, respectively. These within-person correlations also showed a wide range, indicating heterogeneity in the associations of the striving items with the affect items.

Three striving items indicated tendencies to cling to positive experiences; we tentatively labelled these items as experiential attachment (EA; Ciarrochi, et al, 2024a, 2024b). Worrying about positive emotions fading (EA_Fading), feeling distressed when not happy (EA_distressed), and worrying when not feeling happy (EA_Worry) often signal attachment or unhealthy fixations to ideas about how life 'should' be (Ciarrochi et al., 2024a, 2024b; Sahdra et al., 2010). The remaining two striving items were tentatively labelled as prioritizing positivity (PP). Doing one's best to stay happy all the time (PP_Happy) and trying to sustain enjoyable feelings (PP_Hang-On-To) indicate prioritizing happiness in daily life and nurturing positive emotions, which are considered to be essential elements of prioritizing positivity (Catalino & Boulton, 2020).

The labels of the items, EA or PP, were used solely for descriptive purposes and not for creating scale scores. When we used the generalizability theory of psychometrics of intensive longitudinal data (Bolger & Laurenceau, 2013), the five striving items taken together did not reliably capture between-person differences on any given day. An intercept-only multilevel model was conducted, and the variance estimates of the person by time and residuals were used to calculate the reliability coefficient, *Rc* of 0.63, which fell short of being satisfactory. The Rc of the three items of EA was 0.71 and the two items of PP was 0.68. An idionomic lens requires looking at group-level effects while preserving and elucidating idiographic information as much as possible. The *Rc* values of the EA and PP items almost reached satisfactory levels of reliability for capturing between-person differences on a given day. However, the raw within-person associations (Table S2) showed wide ranges between people. Rather than assuming that combining the different EA (or PP) items would be appropriate for each person, we followed best practices in idionomic methods and analyzed each EMA item separately (Sahdra et al., 2024). This conservative approach allowed us to see how the interrelations among, and across, the EA and PP items, as well as their associations with happiness, varied between and within individuals.

3.2 Idionomic Analysis: i-ARIMAX and RE-MA

The within-person correlations of the striving items with the affect items (Tables S3 and S4) discussed above provided preliminary evidence of heterogeneity of the bivariate associations of the strivings and affect items. To account for the temporal nature of the data, we conducted i-ARIMAX time-series models of the links between each striving and affect items for each person. The models were run using the R package, *idionomics* (Hernández et al., 2025). A total of 50 ARIMAX models were run separately for each person, where each of the five strivings items predicted each of the ten affect items. For each bivariate pair, a random-effects meta-analysis was conducted to estimate the pooled (nomothetic) effect and the heterogeneity of the idiographic effects, as indicated by 95% prediction intervals and the I^2 estimate of heterogeneity.

Prediction intervals provide a range for where the effect size of a future study might lie, or, in the case of our study, where the effect size of additional individuals may fall (Higgins & Thompson, 2002). Prediction intervals reflect the combined impact of random variability and what might be called "true heterogeneity" as the term "heterogeneity" is understood in meta-analysis (Higgins, Thompson, Deeks, & Altman, 2003). In a meta-analytical context, "heterogeneity" refers specifically to the degree of variability in effect estimates that is due to systematic or non-random differences between studies rather than due to mere sampling error or "chance" (Higgins & Thompson, 2002). The difference between these two sources of variability is measured by I^2, expressed as a percentage of the total variance that is non-random, or truly "heterogeneous" (Higgins et al., 2008). Because outside of meta-analysis "heterogeneous" has a strong connotation of mere variability, in the present paper when speaking of I^2 values we will occasionally use the term "non-random heterogeneity" to remind the reader what this percentage means in a more technical sense. An I^2 value of 75%, for example, means that three-quarters of the homogeneous effect is due to systematic, non-random differences among particular people in the sample. In guides to meta-analysis, such as the *Cochrane*

Handbook for Systematic Reviews of Interventions (Higgins et al., 2022), values that large generally lead to cautions in interpreting pooled effect sizes and calls to explore and identify the sources heterogeneity.

Table S5 summarizes the results of the RE-MA models. The mean of the I^2 estimates of the 50 models was 89.67% (Range = 81.02 to 98.51%), indicating very substantial non-random heterogeneity of the bivariate associations between the striving and affect variables across participants. Each of the 95% prediction intervals of the models showed a wide range, including negative and positive values. For example, the pooled (nomothetic) effect of the bivariate link between the Worry item of EA and the Sad item of affect was 0.18, a positive effect estimated with relatively high precision (95% confidence interval of 0.12 to 0.24). However, the 95% prediction interval of the same effect was −0.51 to 0.87, indicating that a new person in a fresh sample may have a negative estimate for this bivariate pair or a positive estimate. The results suggest that the pooled effects should be interpreted cautiously, given the extremely high (non-random) heterogeneity of the idiographic effects. In sensitivity models, we compared RE-MA models with and without using the number of EMA completed as a weighting variable, which showed comparable results.

Table 2 details the number and percentage of individuals showing different patterns of i-ARIMAX associations between EA/PP items and happiness. For EA items predicting happiness, while the pooled effects were negative, only 22.16 to 23.95% of participants showed significant negative within-person associations, and 7.19 to 12.42% actually showed significant positive associations. The majority of cases (63.98 to 70.66%) showed null within-person effects. Similarly, despite positive pooled effects for PP items predicting happiness, approximately half of the sample showed no statistically significant within-person effects. At the same time, 35.33% to 40.36% demonstrated positive associations, and 7.78% to 8.43% showed negative effects.0

Figure 1 visualizes this heterogeneity for EA_Worry ('If I didn't feel happy, I worried about it') and happiness. Despite the significant negative pooled effect (indicated by blue vertical line), a substantial number of participants showed no significant association (black horizontal lines), and several individuals even demonstrated significant

Table 2 Summary of i-ARIMAX estimates for each of the EA and PP items predicting happiness

Model	Pooled effect	*SE*	I^2	Number (%) of Individuals with different effects		
				Negative	Null	Positive
EA_Fading predicting Happiness	−0.08	0.03	85.03	38 (23.60%)	103 (63.98%)	20 (12.42%)
EA_Distressed predicting Happiness	−0.09	0.03	88.51	37 (22.16%)	118 (70.66%)	12 (7.19%)
EA_Worry predicting Happiness	−0.15	0.03	86.35	40 (23.95%)	114 (68.26%)	13 (7.78%)
PP_Happy predicting Happiness	0.20	0.04	92.43	14 (8.43%)	85 (51.20%)	67 (40.36%)
PP_Hang-On-To predicting Happiness	0.22	0.03	88.58	13 (7.78%)	95 (56.89%)	59 (35.33%)

I^2 = Estimate of heterogeneity

Table S5 in Supplemental File summarizes the results of RE-MA of i-ARIMAX estimates for all 50 bivariate pairs of striving and affect items. Refer to Figs. 1 and 2 for visualizations of i-ARIMAX estimates of EA_Worry and PP_Happy, respectively. Figures S2 to S4 in Supplemental File contain visualizations for the remaining EA and PP items predicting happiness.

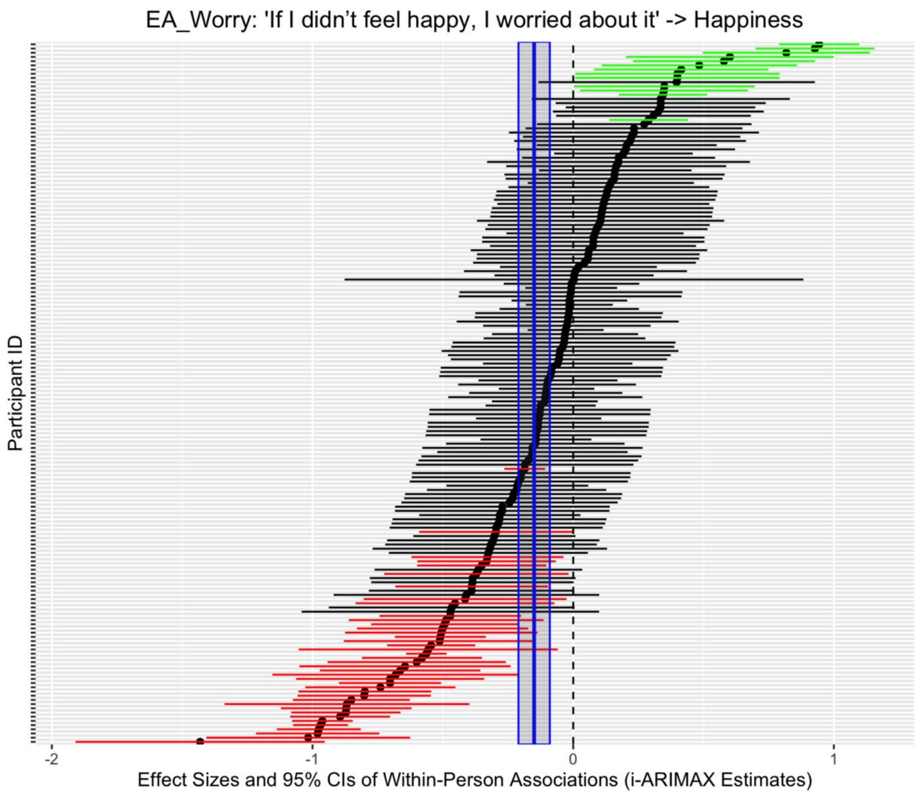

Fig. 1 Visualization of the pooled effect and heterogeneity of the i-ARIMAX estimates showing within-person associations between EA_Worry and happiness. Note. Blue vertical lines represent the pooled (nomothetic) effect in the middle and the lower and upper bounds of the 95% confidence interval of the pooled effect. Green horizontal lines indicate 95% confidence intervals of positive associations, red lines indicate negative ones, and black ones represent associations not different from zero

positive associations (green horizontal lines). Figure 2 provides a similar visualization for PP_Happy and happiness. Figures S2 to S4 in Supplemental File contain similar visualizations for the remaining EA and PP items predicting happiness.

We next tested whether the type of striving items, EA or PP, might moderate the overall association of striving for positive states and affect. We ran multivariate random-effects meta-analysis (MV RE-MA) models in which the effects of the strivings items on the affect items were nested within persons. The negative affect items were reverse scored so that all affect items had the same directionality of effect. These models allowed summarizing the overall pooled effects and heterogeneity estimates concisely, reducing the total number of tests for moderation analysis. A log-likelihood ratio test was conducted to compare the fit of a 3-level MV RE-MA model that allowed the effects at all levels to vary with the fit of a 2-level model where the person level was fixed. A 3-level model fit the data better than a 2-level model ($p < 0.001$). MV RE-MA also allowed partitioning of total variance into within and between components. The within-person heterogeneity, when high, suggests that different process variables relate differently to the outcomes within persons. The between-person heterogeneity, when high, indicates that the effect of processes on

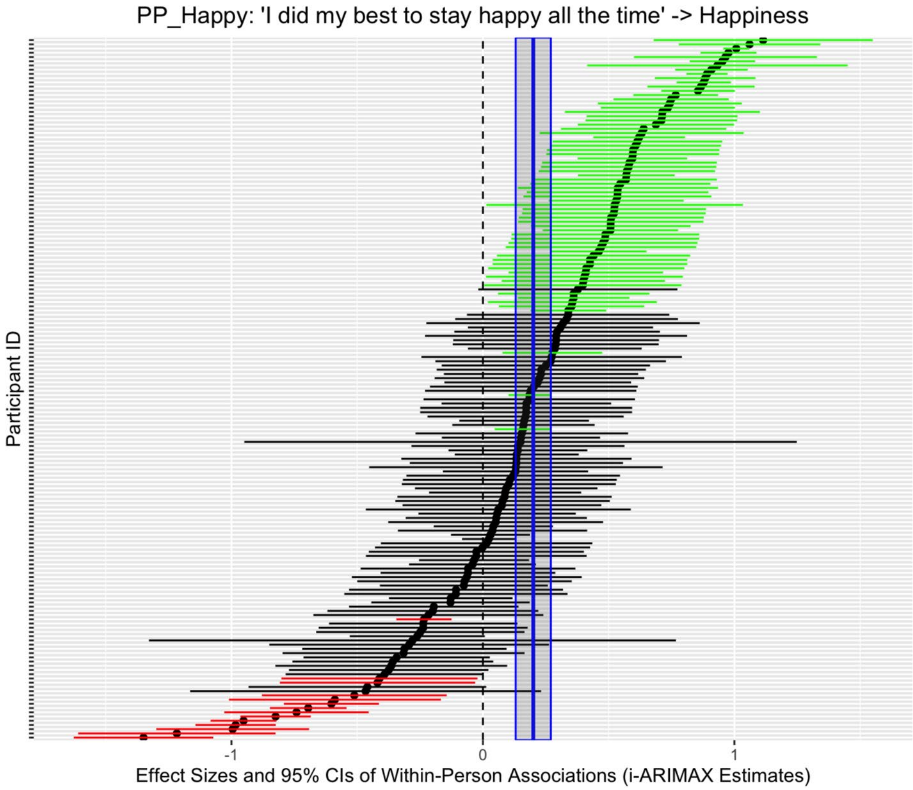

Fig. 2 *Visualization of the pooled effect and heterogeneity of the i-ARIMAX estimates showing within-person associations between PP_Happy and happiness. Note*. Blue vertical lines represent the pooled (nomothetic) effect in the middle and the lower and upper bounds of the 95% confidence interval of the pooled effect. Green horizontal lines indicate 95% confidence intervals of positive associations, red lines indicate negative ones, and black ones represent associations not different from zero

outcomes differ between people, considering all process-outcome combinations in the model. As shown in Table 3, the overall pooled effect of striving for positive states on hedonic well-being was negative but almost negligible, -0.03 (95% CI: -0.05 to -0.002). The prediction interval ranged from -0.75 to 0.70, and total I^2 was 94.02%, suggesting that the vast majority of the variance in how striving for positive states impacted hedonic well-being was due to systematic non-random idiographic differences.

The test of moderation of the overall effect by the type of EA vs. PP items was statistically significant: F (1, 8171) = 543.23, $p < 0.0001$. When we ran separate MV RE-MA models for the PP and EA items, the results showed that the pooled effect of the PP items on affect was positive and that of the EA items was negative, as reported in Table 3. However, in both cases, the total I^2 remained high (>90%) and the 95% prediction intervals remained wide, including both negative and positive values. We also ran MV RE-MA models of the i-ARIMAX effects of either PP or EA items predicting either positive or negative affect items separately, yielding high heterogeneity in all cases (see Tables S6 and S7). The pooled effects showed that the PP striving items negatively predicted negative affect and positively predicted positive affect. The EA items showed the opposite pattern.

Table 3 Summary of the MV RE-MA Results

Model	Pooled effect	*SE*	95% Confidence interval		95% Prediction interval		I^2		
			Lower bound	Upper bound	Lower bound	Upper bound	Total (%)	Within (%)	Between (%0
Overall model	−0.03	0.01	−0.05	−0.002	−0.75	0.70	94.02	82.48	11.54
PP model	0.11	0.02	0.07	0.14	−0.65	0.86	90.69	68.01	22.69
EA model	−0.11	0.01	−0.14	−0.09	−0.78	0.55	94.35	74.38	19.97

The overall model consisted of all i-ARIMAX effects of all striving items on all affect items. The PP model focused on the effects of the prioritizing positivity related items of striving and the EA model focused on the effects of the experiential attachment related items of striving

However, all models showed high heterogeneity and contained numerous cases that did not conform to the norm represented by the average effect (see Table S7; Total $I^2 > 89\%$; 95% prediction intervals included negative and positive values).

The prediction interval indicates that in 95% of the individuals in a fresh sample, the true effect size will fall in that interval. The results reported above show that the effect size could be negative, zero, or positive. At one extreme, there would be individuals for whom striving for positive experiences, reflecting EA or PP, could be linked to highly adverse effects on well-being. At the other extreme, striving could be linked to highly positive hedonic well-being. And there may be many individuals for whom striving may have little impact on hedonic well-being in daily life. In sum, even though the type of striving items (EA vs. PP) was a statistically significant moderator of the nomothetic effect, it failed to reduce the total heterogeneity of the idiographic effects, and adequately represent the individuals constituting the sample.

3.3 Identifying Subgroups

Next, we attempted data-driven approaches to identify meaningful subgroups in the data. We first focused on the relationship between variables, and tested the clustering tendency in the data of 50 i-ARIMAX estimates per person. There was no meaningful structure in the data, suggesting a lack of non-random clustering of individuals (Hopkins statistic of 0.66 indicating a lack of meaningful clusters), which we confirmed through visual inspection (see Figures S5 and S6 in Supplementary Information). When we compared different types of validation methods to determine the optimal number of clusters, different methods gave different solutions (see Fig. S7), which further confirmed that K-means cluster analysis did not help identify meaningful clusters.

For each of the 50 models, we examined individuals with statistically significant i-ARIMAX effects with the opposite sign to the corresponding pooled effects. No single individual overlapped in the list of ‘opposites’ across the 50 models; rather, different models showed different people who had such notably deviant effects. Put another way, individual A may have an effect similar to the nomothetic effect in one model, a slightly deviant effect in another model, and a drastically deviant effect in yet another. There was no universally “normal” or “anomalous” individual nor group of individuals across all 50 models.

Based on these findings, we redirected our focus from bivariate time-series associations to the functional form of the original longitudinal trajectories of the striving and affect variables. By examining the multivariate non-linear trajectories of the five striving variables and ten affect variables, we sought to identify meaningful groups of individuals exhibiting similar patterns over time. We used the *gbmt* package in R (Magrini, 2022) to conduct group-based multivariate trajectory modeling. The method involves conducting models with different numbers of groups and varying degrees of polynomial to select the optimal number of groups and the degree of polynomials that best fit the data (Nagin et al., 2016). The models with two groups and polynomial 3 (cubic) showed the best fit (see Table S8 for fit indices of different models, and Fig. S5 for the multivariate group trajectories of the two groups of the best fitting model).

Table S8 reports fit indices for models with varying numbers of groups and polynomial terms. We used several fit indices available in the *gbmt* package to determine the optimal model parameters (Magrini, 2022). The Akaike Information Criterion (AIC) balances model fit and complexity with a lighter penalty term, while the Bayesian Information Criterion (BIC) applies a stronger penalty based on sample size. The Consistent AIC (CAIC) adds an extra penalty term for consistency. The Sample-Size Adjusted BIC (SSBIC) modifies the BIC formula to handle smaller samples better, and the Hannan-Quinn Information Criterion (HQIC) provides a middle ground between AIC and BIC with a logarithmic penalty term. In our sample, the two-group model consistently showed the lowest CAIC value (indicating best fit) across all polynomial variations, compared to models with more groups. When comparing two-group models with different polynomial terms, the model with polynomial = 3 had the lowest values across all indices—AIC, BIC, CAIC, SSBIC, and HQIC—making it clearly the best fitting model. Therefore, we selected the model with two groups and polynomial = 3 as our final model.

As a sensitivity test of whether the 2-group solution was robust to differential completion rates, we conducted the same tests on a restricted sample by removing all cases with fewer than 10 complete observations. This reduced the sample from 167 to 109 participants and decreased missingness from 33 to 16% (see Fig. S1 bottom for missingness map). The results of the various *gbmt* solutions with the restricted sample are reported in Table S9. Consistent with our original findings,the models with 2 groups showed better fit than models with three or more groups, regardless of the number of polynomials, which was consistent with the group-based multivariate trajectory modeling using the full sample reported in Table S8. All subsequent analyses were conducted using the full sample rather than the restricted sample.

As shown in Fig. S8, Group 1 ($n = 121$) tended to lack multivariate temporal trends and showed high variation across individuals, whereas Group 2 ($n = 46$) had relatively pronounced multivariate polynomial trends and relatively low variation. For several variables (e.g., PP_Happy, PP_Hang-on-to, EA_Distressed, EA_Worry, and Sad), Group 2 showed an overall initial decline in the level of the variable, which plateaued somewhat, followed by a trend of further lowering of the levels. Despite being a smaller group, the trajectories of variables in Group 2 had lower variation than that of Group 1. This was also reflected in a MV RE-MA of i-ARIMAX effects, which showed that Group 1, relative to Group 2, had higher between-level heterogeneity (see details in Table S10; the total heterogeneity remained high in both groups). A linear mixed model of survey response time regressed on group membership, with random intercepts for individuals, showed that the two groups did not differ in the average time taken to complete EMA surveys, which was used as a proxy of quality of responses (see Table S11 for details.) This finding suggests that the differences between the two groups are not likely attributable to variations in potentially careless responding. Type III multivariate analysis of variance test showed that the two groups did not differ in terms of the mean (averaged across measurement occasions) levels of all the EMA variables, including all striving items, affect items, and the contextual variables: $F(1, 19) = 1.45$, $p = 0.11$, *Wilk's lambda* = 0.84. Therefore, the two groups did not differ in terms of the *level* of the variables across time but in terms of the *shape* of the multivariate non-linear trajectories of striving and affect over time.

3.4 Multilevel-VAR Networks of Subgroups

We examined whether group membership, identified through group-based multivariate trajectory modeling, would help us understand the dynamic links between striving variables and affect at both within-person and between-person levels—our final pre-registered study goal. To ensure model convergence and interpretability, our main network models focused on the striving items and the single affect item of happiness, with separate network models incorporating contextual variables. While we had not pre-specified which affect item to use in the network, selecting the "happy" item aligned with our theoretical focus on happiness studies and helped keep the network size computationally tractable and interpretable. Figures 3 and 4 report the networks of the striving items with happiness. Figure S9 shows the networks of the striving and happiness items with the contextual variables of positive and stressful events. Figure S10 shows the networks of striving, happiness, and the contextual variables of loneliness and connectedness.

As shown in Figs. 3 and 4, the two groups differed in terms of the impact of EA and PP on happiness. Taking into account the links of the EA items with all items in the networks, the links of the PP items with happiness showed the following pattern of results: In Group 1, both the PP items were positively linked with happiness in the within-person contemporaneous network, and the PP_Hang-on-to item was positively related to happiness in the between-person network as well. Prioritizing positivity was contemporaneously linked with happiness for Group 1. None of the PP items were related to happiness in Group 2 in either their within-person contemporaneous network or their between-person network. Interestingly, happiness had a downstream temporal (lag-1) effect on one of the prioritizing positivity variables in both groups.

Accounting for the links of the PP items with all items in the networks, the links of the EA items with happiness showed the following pattern of results: Experiential attachment to positive states had negative contemporaneous link with happiness in both groups, at least at the within-person level which focused on day-to-day life. But this effect was not evident in the between-person networks, which focused on the links in means collapsed across all time points. The temporal (lag-1) networks showed no links between the EA items and happiness.

The network effects reported in Figs. 3 and 4 held mainly in the networks where we added the contextual effects, as shown in Figs. S9 and S10. That is, at least one of the EA variables had a negative link with happiness in the within-person contemporaneous networks in both groups in the networks with contextual variables. The PP items negatively linked with happiness in Group 1 but not in Group 2 within-person networks. As shown in Fig. S9, not surprisingly, positive events were linked with happiness at both within- and between-person networks of both groups. Interestingly, stressful events were unrelated to happiness in the between-person networks but were negatively related to happiness in the within-person networks. The between-person networks also showed that stress had a positive effect on EA in both groups but had a negative effect on PP only in Group 2. Positive events were positively linked to the PP items in the within-person network of Group 1, but not in their between-person network. Group 2 showed the opposite pattern: positive events were positively related to a PP item in the between-person network but not related to any PP item in the within-person network.

Finally, Fig. S10 showed a strong negative association between connectedness and loneliness, and a positive link of connectedness with happiness in all networks. Further, for Group 1, happiness was negatively related to an EA item and positively related to the PP items in the within-person network but was unrelated to EA or PP in the between-person network. For Group 2, happiness was negatively related to an EA item in the within-person network but unrelated to EA and PP in the between-person network. The pattern of results was largely similar to that in the networks without the contextual variables.

In summary, the key similarities of both groups suggested that experiential attachment was linked to lower happiness within persons. The key difference was that PP was positively linked to daily happiness for Group 1 but not Group 2. Further, Group 2 was characterized by nonlinear decreasing use of PP strategies. We therefore tentatively referred to the first and second groups as PP-linked and PP-unlinked, respectively. Importantly,

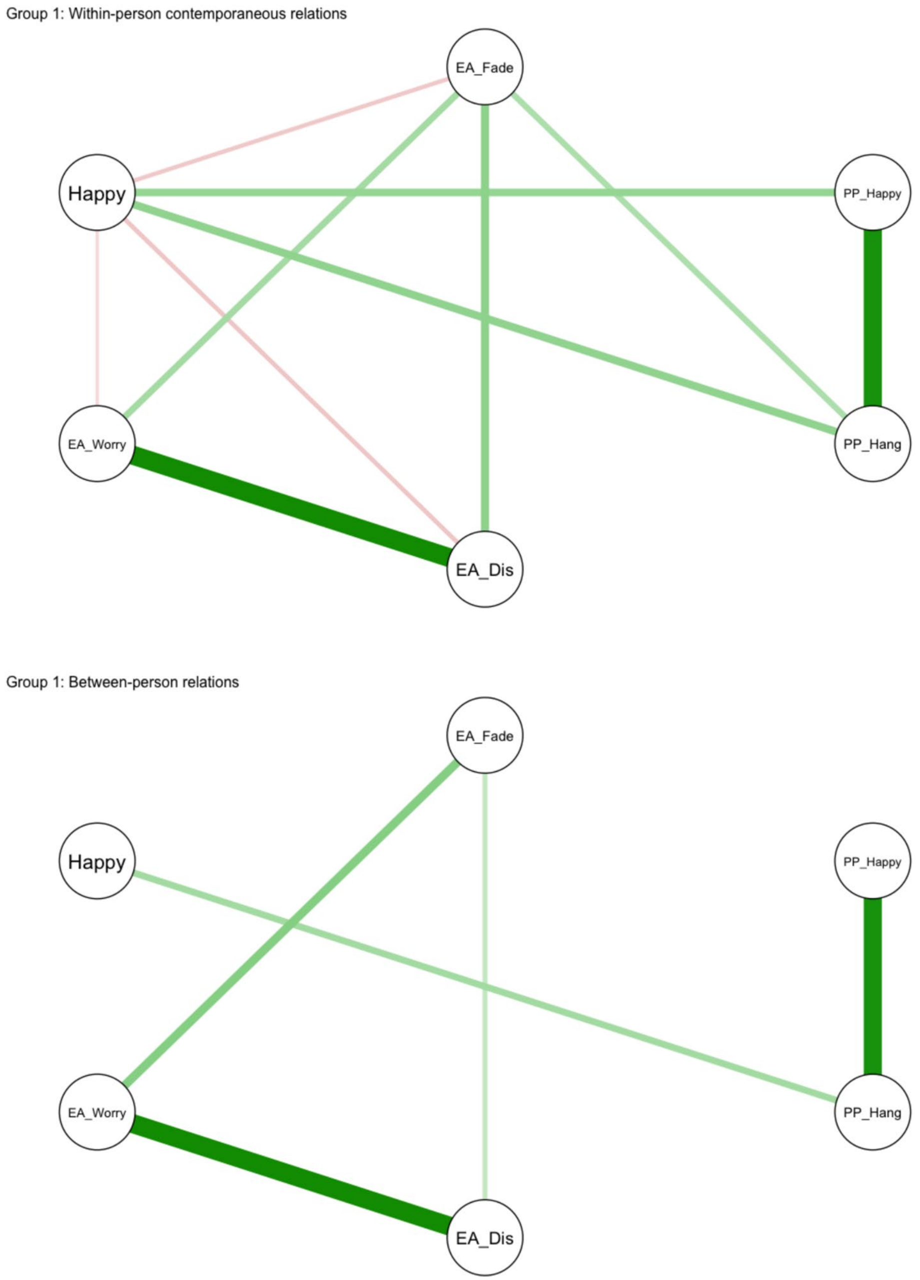

Fig. 3 *Multilevel-VAR networks of Group 1. Note*. Green links indicate positive effects, while red links indicate negative effects. Line thickness shows the strength of each effect. EA: Experiential attachment-related items; PP: Prioritizing positivity-related items. EA_Fading: "Since the last prompt, I worried about my positive emotions fading"; EA_Distressed: "Since the last prompt, I got distressed if I didn't feel happy"; EA_Worry: "Since the last prompt, if I didn't feel happy, I worried about it"; PP_Happy: "Since the last prompt, I did my best to stay happy all the time"; PP_Hang-On-To: "Since the last prompt, I tried to hang on to feelings I enjoyed."

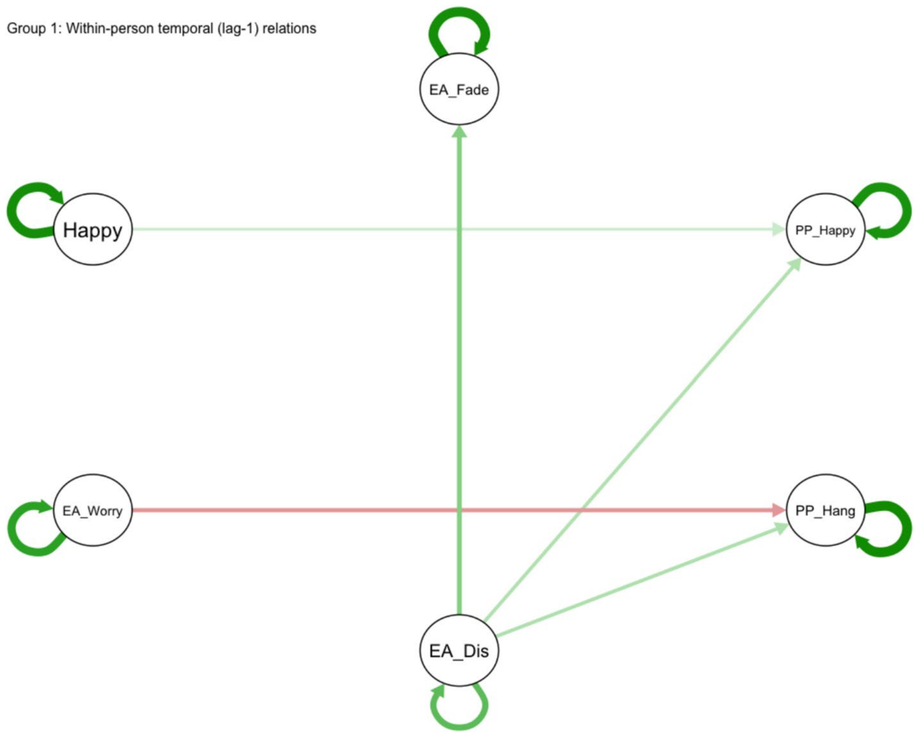

Fig. 3 (continued)

these differences between subgroups would have largely been invisible in the absence of idiographic analysis. Said more directly, it would not have been possible to understand how happiness interacts with different methods or levels of striving for it while remaining within traditional normative statistical analytic strategies alone. While replicating previously known nomothetic effects about PP and EA linking to happiness differently at the group level, the findings add to the happiness literature by clarifying the complex within- and between-person effects at the subgroups level and documenting extremely high non-random heterogeneity of idiographic effects.

4 Discussion

We examined the links between different forms of striving for positive states—experiential attachment (EA) vs. prioritizing positivity (PP)—with hedonic well-being. Using ecological momentary assessment data, we used an idionomic analytical approach combining idiographic and nomothetic insights. We first examined idiographic bivariate associations between the different types of striving and affect, which we subjected to meta-analytical models to yield pooled nomothetic effects and estimates of heterogeneity of the idiographic effects. The overall pooled effect of striving on affect was "equisyncratic" (Ciarrochi,et al, 2024a, 2024b), a neologism created to describe findings in which nomothetic effects between given variables are null or nearly so, while extremely high non-random

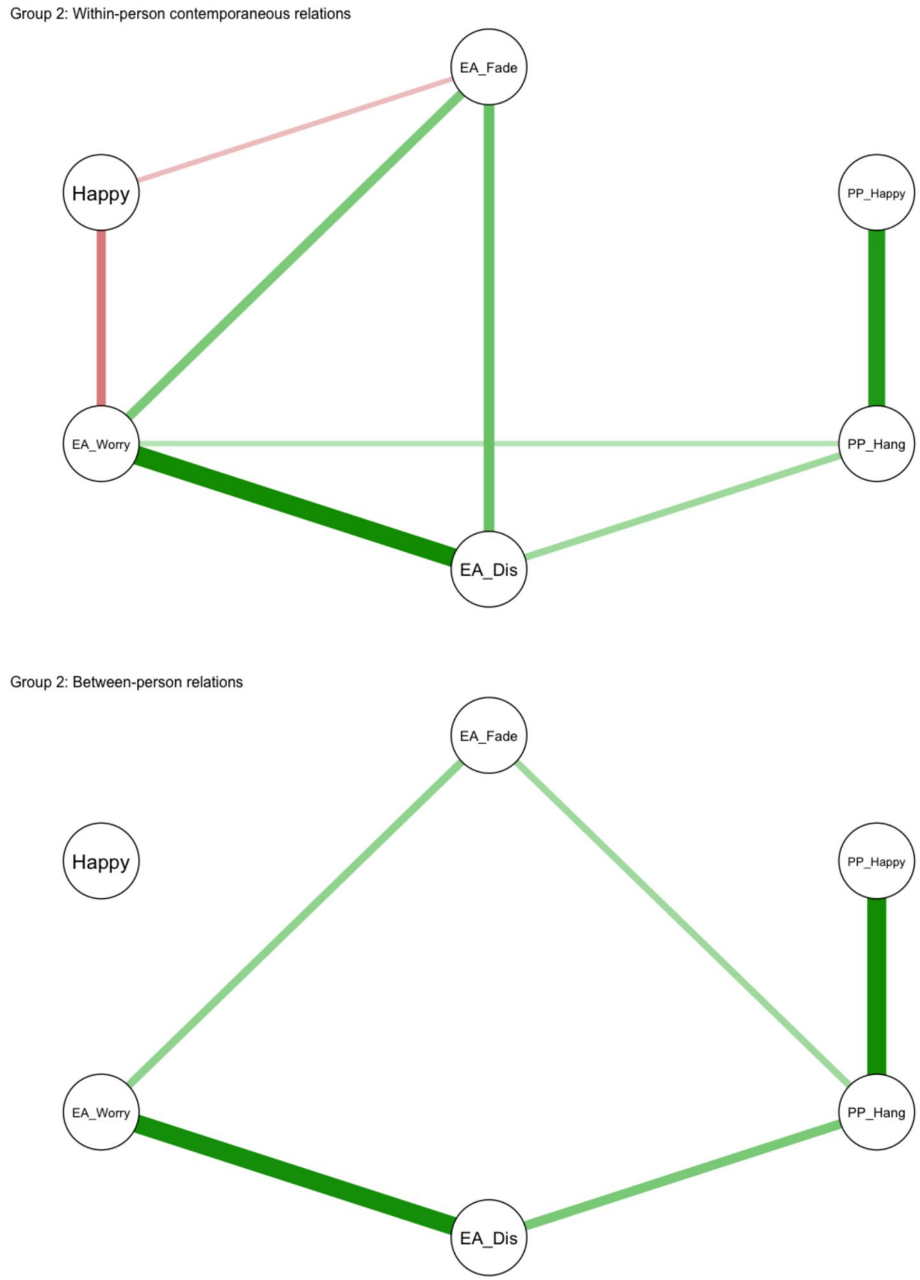

Fig. 4 *Multilevel-VAR networks of Group 2. Note*. Green links indicate positive effects, while red links indicate negative effects. Line thickness shows the strength of each effect. EA: Experiential attachment-related items; PP: Prioritizing positivity-related items. EA_Fading: "Since the last prompt, I worried about my positive emotions fading"; EA_Distressed: "Since the last prompt, I got distressed if I didn't feel happy"; EA_Worry: "Since the last prompt, if I didn't feel happy, I worried about it"; PP_Happy: "Since the last prompt, I did my best to stay happy all the time"; PP_Hang-On-To: "Since the last prompt, I tried to hang on to feelings I enjoyed."

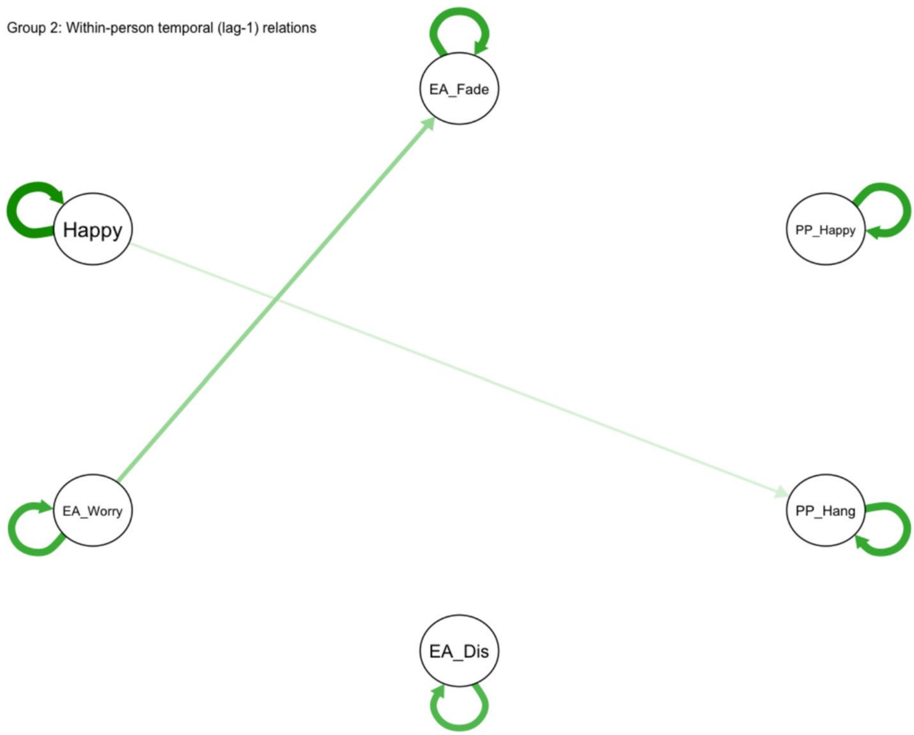

Fig. 4 (continued)

heterogeneity of idiographic effects lead to relationships among these same variables that are reliably negative for some people and positive for others. A wide prediction interval of the nomothetic effect including both negative and positive values suggested extremely high uncertainty in estimating the effect for a new person in a fresh sample based on the results of this study.

For EA items predicting happiness, our analyses revealed a striking pattern: while pooled effects were negative, only a minority of participants displayed significant negative within-person associations, with a smaller subset actually showing positive associations. Most participants exhibited no statistically significant within-person effects. Likewise, for PP items predicting happiness, despite positive pooled effects, roughly half the participants showed no significant within-person effects, while a substantial portion demonstrated positive associations, and a small fraction exhibited negative effects.

The type of striving items, EA vs. PP, moderated the overall effect: the pooled effect of EA items on affect was negative. This nomothetic finding is consistent with past literature documenting the paradoxical effect of pursuing happiness when it is tainted by worries about failure to achieve happiness (Mauss et al., 2012). The pooled effect of the PP items on hedonic well-being was positive, which replicates recent findings from a daily diary study which showed that daily variation in PP predicted higher levels of daily well-being (Catalino & Tov, 2022). In both EA and PP models, however, idiographic effects showed high non-random heterogeneity, indicating that the means poorly represented a substantial subset of people.

These findings substantially advance theoretical understanding of happiness-related strivings in several ways. First, they directly challenge the prevailing nomothetic paradigm that presupposes uniform effects across individuals. Instead, our results convincingly demonstrate that relationships between experiential avoidance/positive pursuit strategies and happiness outcomes are far more nuanced and person-specific than conventional theories suggest. Second, this marked heterogeneity provides a compelling explanation for the inconsistent effectiveness of well-being interventions—approaches beneficial for some individuals may prove ineffective or even counterproductive for others. Finally, these findings strongly support the need for developing personalized, idiographically-informed approaches to well-being enhancement rather than applying one-size-fits-all interventions based on average effects.

There were no discernible clusters of relatively homogenous subgroups of people in the data of the idiographic bivariate associations. Therefore, group-based multivariate trajectories modeling of the variables was used to identify two subgroups, which did not differ in the mean levels of striving or affect but in the shape of the temporal trends. Group 2, more so than Group 1, tended to show multivariate polynomial trends over time, nonlinear decreases in PP, and relatively low variation across people.

Finally, we examined the dynamic links between the different forms of striving and happiness in within-person and between-person networks of the variables in the two groups. Overall, the results showed that the effects observed at the between-person level did not necessarily hold at the within-person level, and vice versa. Our study therefore highlights the potential importance of examining within-person effects in addition to the between-person effects in happiness studies. The network modeling results revealed that had we only looked at between-person effects, we would surmise that the happiness of Group 1 individuals was linked with PP but that of Group 2 individuals was not affected by EA or PP. This was not the case when within-person contemporaneous networks were examined: they revealed the pernicious effects of EA for both groups. Furthermore, PP was not beneficial for the happiness of Group 2 either at within-person or between-person level. These results are consistent with the polynomial trends for the PP variables in Group 2: the group started with relatively high levels of PP, followed by decline that plateaued somewhat before slightly declining further. These individuals might have developed some awareness that PP was not benefiting them and might have abandoned that strategy.

Successful striving for happiness involves tracking the effectiveness of one's strategies. It is possible that some individuals may be more self-aware than others and may realize when a strategy is not working for them. In the context of an EMA design, repeatedly responding to the items related to striving for happiness may increase awareness, at least in some people, regarding when a strategy may or may not be working for them. Future research with both quantitative and qualitative data may help clarify this possibility.

Tracking the effectiveness of one's strategies in the pursuit of happiness may also be an important goal in clinical interventions. On average, excessively valuing happiness is associated with increased symptoms of depression, as evident in both community samples and individuals with a history of major depressive disorder, indicating that the cultural value placed on happiness can be a risk factor for depression (Ford et al., 2014). Understanding the paradoxical effects of valuing happiness can inform therapeutic approaches. Interventions focusing on improving emotional regulation, enhancing psychological flexibility, and fostering acceptance may help mitigate the negative outcomes associated with the pursuit of happiness (Valdivia-Salas et al., 2022).

Further, the extremely high degree of non-random heterogeneity in the effects observed in the current study highlights the importance of collecting high frequency temporal data to yield data-driven understanding of the dynamics of striving for happiness in clients, which would be necessary for personalization of interventions. Some people, for example, had counter normative effects such as feeling happier when higher in EA, and/or worse when higher in PP. Interventions would need to identify, and then address these counter-normative effects to decrease the risk of adverse effects, which are often under-reported (Honkalampi, et al., 2024). There is growing evidence that personalization of clinical interventions tends to be more effective than a one-size-fits-all approach (Li et al., 2024). Systematic tracking is needed for clinicians and clients to see which strategy is important for predicting an outcome like happiness, whether it is working reliably and consistently over time, and whether it improves the client's functionality.

Psychological intervention more generally is moving toward a more personalized and process-based approach that considers how all complex systems evolve through healthy variation that is selected, retained, and fitted to different contexts (Hayes et al., 2022). An intervention, by definition, introduces changes in how challenges are addressed in a person's life (variation). EMA assessment can help monitor the key processes of change over time so that the clinicians and clients can determine which processes are worth abandoning and which ones are worth pursuing (selection) for particular individuals, couples, or families, thus helping clients choose to invest more of their time into making particular strategies more likely and habitual (retention) in the contexts in which they are most needed.

Nomothetic information, such as pooled mean effects, may be used as a heuristic for estimating client dynamics but that information needs to be tempered by analyses that fit its actual use case. The pooled effects were relatively precise in the present study, but the prediction intervals were very wide, reflecting substantial variability among individuals. This could be represented in a Bayesian framework (van de Schoot et al., 2021), for instance, by setting the prior mean to the pooled effect and using a relatively large variance to capture the wide prediction intervals. In concrete terms, this would imply that if no information about a given client is available, the best guess would be to assume, for example, that PP would likely increase the experience of happiness, while the clinician-analyst remains vigilant that the impact may vary from the norm in size and even direction as more information about the individuals become evident and adapting the course of intervention accordingly. A flow of such information happens routinely in applied work as cases unfold but often without much scientific help about what to do with it. At the very minimum, knowing about the existence of cases that do not conform to the norm may help individuals adopt a more flexible approach when designing interventions.

As idionomic methods gain attention, more data will be available to use pooled effects as Bayesian priors, while clinicians remaining adaptable as idiographic data such as experience sampling are gathered. Unlike traditional approaches like multilevel modeling, where individual estimates are constrained by fixed effects of the group mean (Sahdra et al., 2024), the Bayesian approach allows the individual estimate to deviate significantly—or even entirely—from the prior mean when sufficient evidence from the individual's data supports this (ve dan Schoot et al., 2021). Such a combination of nomothetic and idiographic approaches would thus provide a robust framework for achieving generalizability while dynamically tailoring interventions to suit each individual.

4.1 Limitations and Future Directions

We acknowledge the limitations of our striving items adapted from the VHS, which has been criticized in previous research using factor analytical methods (e.g., Luhmann et al., 2016). Instead of using traditional factor analysis—where observed variables are treated as linear combinations of latent variables—we analyzed each striving item individually and examined its relationships with happiness and other affect items. A potential limitation concerns the EA items specifically, as they contain the words “worry” and “distressed.” These terms inherently imply negative experience, which somewhat confounds the interpretation of links between EA items and negative affect items. However, the presence of negative correlations between EA and negative affect in some individuals suggests that these constructs are not redundant. In some cases, higher EA was associated with lower negative affect, indicating counter-normative relationships and highlighting individual variability in how EA relates to emotional experience.

Some might criticize our study for being potentially underpowered due to a relatively short EMA design. Standard power analyses are not readily applicable to idionomic statistics since nomothetic conclusions in this framework derive from meta-analytical models. For examining effects in idiographic time series, our study met the threshold of having at least 20 observations (Jebb et al., 2015). While longer time series would be necessary for forecasting future data points, this was not an aim of our study. To generate nomothetic insights, we employed RE-MA. Though there is no universal consensus on the minimum number of studies needed for meta-analyses, Cochrane guidelines suggest at least 5 studies, with 10 or more providing reliable pooled estimates. Our RE-MA far exceeded these recommendations, including estimates from 167 individuals. Furthermore, our sensitivity analyses compared RE-MA models with and without EMA completion counts as a weighting variable. These analyses confirmed that our results remained robust regardless of variations in participant survey completion rates.

We acknowledge the limitation that careless responding cannot be entirely ruled out, despite implementing minimum response time thresholds. However, potential noise from careless or inconsistent responding is unlikely to explain the high I^2 values observed in our study. Although it may seem intuitive that more random noise would increase heterogeneity, I^2 actually decreases with greater randomness. This is because I^2 quantifies the proportion of variance that exceeds what would be expected by chance — that is, variance not attributable to random sampling error. The formula $I^2 = \max(0, (Q—df) / Q) \times 100\%$ (where Q is Cochran’s heterogeneity statistic and df is degrees of freedom) shows that when most variability is due to random noise, Q will be close to df, (Q—df) will be small, and I^2 will approach 0%.Therefore, the high I^2 values we observed reflect meaningful between-person heterogeneity, not random variation alone.

The study’s short timeframe and EMA methodology raises questions about capturing long-term happiness processes. Krasko et al.’s (2020) Happiness Goal Orientations framework distinguishes between “Happiness-Related Strivings” and “Happiness-Related Concerns,” which operate on different timescales. While EMA effectively captures immediate patterns, happiness pursuit outcomes depend on whether individuals show strivings (approach-oriented behaviors) or concerns (avoidance tendencies). Strivings link to rapid positive outcomes through happiness-enhancing activities, while concerns relate to slower-emerging negative outcomes like anxiety and emotional rigidity. Our study’s timeframe was suitable for capturing momentary experiences but misses the longer-term impacts of concerns. The relationship between happiness orientations and well-being unfolds through complex processes over time. Future EMA studies combined with longer-term, less frequent observations may help clarify these patterns.

Our results are based on an undergraduate sample. The results may be different in samples of older people. Research on lifespan differences in striving for happiness by Littman-Ovadia and Russo-Netzer (2019) indicates that prioritizing positivity is associated with increasing positive emotions in older adulthood, but not in young adulthood, and more with decreasing negative emotions in young adulthood than in older adulthood. Their content analysis of qualitative data revealed that interpersonal interaction was critical in both increasing positive and reducing negative emotions, across age groups. However, young adults were more likely to prioritize pleasurable activities as triggers of positive emotions, whereas older adults focused on avoiding unfulfilling situations, due to the negative emotions that they trigger (Littman-Ovadia & Russo-Netzer, 2019). Future EMA studies with people of all ages are needed to document the degree of heterogeneity in the within-person effects of striving for happiness.

We further acknowledge that the insights from the current study will remain limited until similar research is conducted in non-western cultures and until the network of the striving and happiness variables are expanded to include other relevant processes. Past studies show that valuing happiness is linked to lower well-being among U.S. students, but higher well-being among Russian and East Asian students (Ford et al., 2015). In most of the western societies, the emphasis on individualism and personal achievement can intensify the pressure to attain happiness, which can create a destructive cycle of guilt and dissatisfaction (Krueger, 2022). In contrast, in cultures that emphasize acceptance and mindfulness, valuing happiness can enhance well-being (Zhao et al., 2020), which suggests that the pursuit of happiness may be more successful when individuals adopt a balanced approach that includes accepting negative emotions and setting realistic expectations. It may be essential to approach any strategy—valuing happiness or prioritizing positivity—with an understanding of its nuances and potential limitations, ensuring that it is applied in a way that aligns with individual needs and circumstances.

Some individuals, especially those in Group 2 in our study, might have developed an awareness of PP, used it less frequently, and found it less beneficial. This decreased engagement could be attributed to several factors. First, the repeated exposure to questions about "happiness" in the survey may have led to heightened self-consciousness about PP usage. Additionally, participants might have developed resistance to PP when frequently reminded about it, and the repeated focus on happiness through PP might have led to saturation or habituation effects. This process ultimately resulted in devalued or decreased use of PP among these participants, suggesting that excessive focus on happiness-promoting strategies might paradoxically reduce their effectiveness. These are speculations that need to be rigorously tested in future research.

We acknowledge that the findings of this study require replication. Replication is a critical objective when we aim to make population-level inferences about nomothetic findings, as it helps validate the generalizability of observed effects across different contexts and samples. However, in extremely high heterogeneity, where findings fail to reveal a universally applicable nomothetic effect, the utility of replication becomes more nuanced. High heterogeneity often indicates that the assumptions of homogeneity underlying nomothetic approaches are violated, making it challenging to identify consistent effects across diverse populations. In such cases, the null hypothesis significance testing framework does not inherently require replication to confirm the absence of a universal effect. Instead, repeated failures to reject the null hypothesis across studies may reflect the reality of heterogeneity rather than a failure of the research process itself. This suggests that the focus should shift from attempting to replicate findings under the assumption of universal applicability to exploring the sources and implications of heterogeneity. By doing so, researchers can better understand the conditions under which specific effects emerge and identify subpopulations or contexts where nomothetic effects may hold true (Beltz et al., 2016). Ultimately, until a universally acceptable nomothetic population-level effect about striving and happiness is identified, replication efforts should be complemented by approaches that account for heterogeneity, such as idiographic analyses or mixed-method frameworks. These approaches can provide deeper insights into the variability of effects and help bridge the gap between nomothetic and idiographic perspectives, as we have attempted in the current study.

5 Conclusion

The degree of heterogeneity of any nomothetic effects regarding striving for happiness within any culture may currently be vastly underestimated due to the dearth of EMA designs with sufficiently long time series needed to clarify between-person heterogeneity of within-person effects, and the relative dominance of normative statistical methods over a more bottom up, idionomic approach. As more and more EMA studies on striving for happiness are conducted across different cultures and a more diverse set of individuals, a high degree of non-random idiographic heterogeneity in effects may come to be viewed as commonplace once a more idionomic, analytic approach is taken. This does not mean that nomothetic generalizations cannot be found. To the contrary, methods for nomothetic clustering of non-random heterogeneous effects at the level of the particular person are rapidly evolving, as the present study shows; we did replicate previously known nomothetic effects. The point is rather that nomothetic insights need to be built upon data and analyses that fit the use case for that information.

The pursuit of happiness has long been viewed as a personal journey by many if not most of the scholars in the area. In that context, we cannot be satisfied with analytic methods that fail to address the non-random heterogeneity of those personal pathways to well-being. We cannot allow poorly grounded nomothetic generalizations to overshadow the ability of idiographic insights drawn from high-intensity temporal data at the level of the individual to yield personalized recommendations for promoting lasting happiness. If increasing happiness is a legitimate goal of happiness studies, its analytic methods need to focus on the needs of particular people. Ours is not a “one-size fits all” field, and one size does not make all happy.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10902-025-00933-0.

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Declarations

Conflict of interest This study involved pre-registered (https://osf.io/fwv6j) secondary analyses of ecological momentary assessment data of a previously published study (Klimczak et al., 2023). The university’s Institutional Review Board approved the study, and informed consent was obtained from all participants. Informed consent did not include a statement regarding sharing de-identified data on open science platforms, preventing us from making the data open access. However, the data are available upon reasonable request. Generative artificial intelligence tools were not used in the writing of the initial draft. They were used during the editing of the manuscript to improve readability. We have no conflicts of interest to disclose.

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