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Research Article

Spread the Joy: How High and Low Bias for Happy Facial Emotions Translate into Different Daily Life Affect Dynamics

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There is evidence that people commonly show a bias toward happy facial emotions during laboratory tasks, that is, they identify other people's happy facial emotions faster than other people's negative facial emotions. However, not everybody shows this bias. Individuals with a vulnerability for depression, for example, show a low happy bias compared to healthy controls. The main aim of this study was to acquire a better understanding of laboratory measures of happy bias by studying how these translate to people's daily life. We investigated whether stable high and low happy bias during a laboratory task were associated with different daily life affect dynamics (i.e., effects from one time interval of 6 hours to the next). We compared the daily life affect dynamics of young adults (age 18–24) with a high bias toward happy facial emotions ($N = 25$) to the affect dynamics of young adults with a low bias toward happy emotions ($N = 25$). Affect and related measures were assessed three times per day during 30 days. We used multilevel vector autoregressive (VAR) modelling to estimate lag 1 affect networks for the high and low happy bias groups and used permutation tests to compare the two groups. Compared to their peers with a low happy bias, individuals with a high happy bias more strongly sustained the effects of daily life reward experiences over time. Individuals with a high happy bias may use their reward experiences more optimally in daily life to build resources that promote well-being and mental health. Low reward responsiveness in daily life may be key to why individuals who show a low happy bias during laboratory tasks are vulnerable for depression. This study illustrates the potential benefits of a network approach for unraveling psychological mechanisms.

1. Introduction

It is an interesting phenomenon that some people have a tendency to be relatively fast in identifying other people's happy facial emotions while others are relatively fast in identifying other people's negative facial emotions. Happy bias is an implicit bias of which people are probably unaware themselves; therefore, it is commonly assessed with standardized laboratory tasks. There is consistent evidence from studies using these laboratory tasks that people generally show a bias toward happy facial emotions, that is, they commonly identify other people's happy facial emotions faster than other people's negative facial emotions [1]. However, not everybody shows this bias. Depressed individuals, for example, show a low happy bias compared to healthy controls [2–4], and there are indications that a low happy bias is already present before onset of depression and predicts onset of depression [5, 6]. Given these findings and the accumulating evidence that the smallest building blocks of an individual's adaptive and maladaptive affect patterns are found in daily life affect dynamics [7–9], one would expect that high and low happy bias also reflect differences in daily life affect dynamics. However, to date this has not been investigated. In the present study, we looked at daily life correlates of laboratory measures of happy bias. We investigated how happy bias during a standardized laboratory task translates to daily life affective dynamics by comparing the daily life affect dynamics (i.e., effects from one time interval of 6 hours to the next) between young adults with a stable high happy bias and young adults with a stable low happy bias. The main aim of this study was to acquire a better understanding of the importance and scope of laboratory measures of happy bias in people's daily life. Our findings are expected to facilitate the interpretation of laboratory measures of happy bias and, because of our focus on adaptive and maladaptive affect dynamics, may possibly also provide clues to why a low happy bias is associated with an increased risk for depression.

Indications of which daily life affect dynamics promote mental health (i.e., are adaptive) and which ones are associated with depressive problems (i.e., are maladaptive) can be found in both laboratory studies and in studies based on ecological momentary assessments (EMA). Evidence from laboratory tasks suggests that the inability to sustain positive emotions [10, 11], the inability to sustain activation in neural circuits underlying positive affect and reward over time [12], and the incapability to disengage from negative self-referential rumination [13] are associated with depressive symptoms and clinical depression. It was further found that positive affect facilitates recovery from negative emotional experiences [14, 15]. EMA studies also indicate that the inability to sustain positive affect over time in daily life is associated with depressive symptoms (e.g., anhedonia), in general as well as in clinically depressed populations [16, 17]. Additionally, the ability to generate positive affect from pleasant experiences in daily life predicted fewer symptoms of depression and anxiety in individuals with a history of depression [18] and in individuals who had been exposed to childhood adversity or recent stressful life events [19]. Taken together, this evidence suggests that the following types of affect dynamics are adaptive and promote mental health:

(1) The ability to sustain positive affect and positive experiences over time [10–12, 16, 17], that is, the carry-over of positive affect and positive experiences from one time interval to the next

(2) The ability to use positive experiences to generate positive affect and vice versa [18, 19], that is, the carry-over of positive experiences to positive affect and vice versa from one time interval to the next

(3) The ability to use positive affect and positive experiences to dampen negative affect, negative thoughts (i.e., rumination), and negative experiences [13–15].

In the present study, we investigated whether a high happy bias as compared to a low happy bias during a laboratory task is associated with (1) enhanced responses to positive affect and positive experiences over time in daily life, with more carry-over over time (i.e., from one 6-hour time interval to the next), and more carry-over from one type of positive affect or positive experience to another, and a stronger dampening effect on negative affect, thoughts, and experiences; and (2) diminished responses to negative affect, thoughts, and experiences in daily life, with less carry-over over time (i.e., from one time interval of 6 hours to the next), less carry-over from one type of negative affect, thoughts, or experience to another, and weaker dampening effects on positive affect and positive experiences.

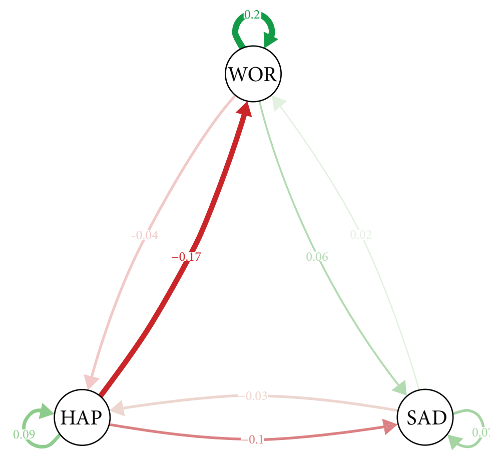

Figure 1: Fictitious example of a temporal network containing three nodes. The green edges represent positive directed associations; for example, on average high levels of worrying during one assessment predict high levels of sadness during the next assessment. The red edges represent negative directed associations; for example, on average high levels of happiness during one assessment predict low levels of worrying during the next assessment. The self-loops represent autocorrelations (i.e., the effect of the node on itself from one assessment to the next).

We used a network approach to affect dynamics, which entails that psychological symptoms or constructs are represented as interacting components of a complex dynamic system [20, 21] and that these dynamics define the very nature of the psychological phenomena we study (i.e., mental disorders, well-being) [22]. This approach can be used to investigate cross-sectional associations between symptoms at a specific point in time, but also, as in the present study, to investigate the temporal dynamics of affect over time. These temporal networks consist of "nodes" (i.e., the variables in the network) and "edges" (i.e., the directed associations between these nodes from one assessment to the next). See Figure 1 for a fictitious example of a temporal network containing the three nodes "happiness" (HAP), "sadness" (SAD), and "worrying" (WOR). In this network model, as well as in the models we used, each node is predicted by the lag (i.e., $t-1$) of all other variables and itself. SAD at time t is, for example, predicted by HAP_{t-1}, WOR_{t-1}, and SAD_{t-1}. Temporal networks can be used to study how different affect components interact as a dynamic system over time. They provide insightful visualizations of the interplay of the network components, and it is also possible to compute centrality indices indicating the importance of each of the components in the network.

We compared the daily life dynamic affect networks (i.e., effects from one time interval of 6 hours to the next) of two groups of young adults with extreme and stable biases to happy facial emotions during a laboratory task. We selected a high happy bias group, consisting of individuals who were considerably more sensitive to happy emotions than to negative emotions, and a low happy bias group, who showed considerably less bias toward happy emotions, or even a bias toward negative emotions.

The affect dynamics of the high and low happy bias groups were compared on nodes that are associated with reward responsiveness, emotion regulation, and depressive symptoms. We selected three nodes that were related to positive affect and positive experiences (for the sake of brevity and readability hereafter referred to as positive nodes): "feeling joyful," "pleasant experiences," and "feeling interested"; and four nodes related to negative affect, negative thoughts, and negative experiences (for the sake of brevity and readability hereafter referred to as negative nodes): "feeling sad," "feeling irritated," "worrying," and "unpleasant experiences." The nodes feeling interested, feeling sad, and feeling irritated closely resemble core symptoms of depression according to the Diagnostic and Statistical Manual of Mental Disorders [23], and feeling interested also reflects openness to new experiences and an inclination to actively approach and explore the outside world. The nodes feeling joyful and pleasant experiences are particularly relevant in the light of indications that high transference of positive emotions over time in daily life [17] and the ability to generate boosts of positive affect from pleasant daily life experiences [19] may protect against affective problems. As opposed to feeling interested, feelings of joy and pleasant experiences are by definition rewarding at the very moment they are experienced. To illustrate the difference, people may cheer because they feel joy or pleasure, but not because they feel interested. More than the other nodes, "pleasant experiences" and "unpleasant experiences" reflect not only affective states but also the type of events individuals are involved in and their ability to seek out rewarding experiences or escape from a cascade of negative events. The term "worrying" was used for both negative thoughts about the past, often referred to as "rumination", and negative thoughts about the future, commonly referred to as "worrying" [24, 25]. "Worrying" was included for its associations with depressive disorder [26], positive and negative affect [24], and reduced cognitive control [27]. It was explored how these different nodes interact as dynamic systems and if these dynamics differed between the high and the low happy bias group.

We expected that an increase in positive affect and positive experiences, particularly of the directly rewarding positive nodes joy and pleasant experiences, would have larger and longer-lasting effects in the high happy bias group than in the low happy bias group. More specifically, we expected that the high happy bias group would more easily sustain and act upon pleasant experiences and feelings of joy to enhance positive affect and positive experiences and dampen negative affect, negative thoughts, and negative experiences. We also expected that pleasant experiences would generalize or carry over to feelings of joy and the other way around. We thus hypothesized that pleasant experiences and feelings of joy would be stronger predictors in the network of the high happy bias group than in the network of the low happy bias group (hypothesis 1) and that the nodes pleasant experiences and joy would more strongly predict themselves (i.e., pleasant experiences and feelings of joy would be more easily sustained) and each other (i.e., more carry-over between pleasant experiences and feelings of joy) over time in the high happy bias group than in the low happy bias group (hypothesis 2) and that joy and pleasant experiences would more strongly predict the negative affect nodes over time (i.e., a larger dampening effect on negative nodes) in the high happy bias group than in the low happy bias group (hypothesis 3). Further, because of the hypothesized reduced reward responsiveness in the low happy bias group, we expected the negative affect nodes to be stronger predictors in the network of the low happy bias group than in the network of the high happy bias group (hypothesis 4) and that the negative affect nodes would more strongly predict themselves and each other over time in the low happy bias group than in the high happy bias group (hypothesis 5) and more pronounced negative associations between negative nodes and positive nodes over time (i.e., a larger dampening effect on positive nodes) in the low happy bias group than in the high happy bias group (hypothesis 6). Although feeling interested is a positive node, we did not expect it to have a similar role as joy and pleasant experiences as we consider feelings of joy and pleasure as intrinsically rewarding, whereas feeling interested is a more instrumental node, which only potentially leads to reward. More specifically, rather than group differences in the way in which feeling interested influenced other nodes, we expected that joy and pleasant experiences would more strongly predict interest in the high than in the low happy bias group (hypothesis 7).

2. Methods

2.1. Sample. Data were collected as part of the "No Fun No Glory" (NFNG) study, in which we investigated anhedonia in young adults. The study was approved by the Medical Ethical Committee from the University Medical Center Groningen (no. 2014/508) and registered in the Dutch Clinical Trial Register (NTR5498). Participants were treated in accordance with the Declaration of Helsinki and indicated their informed consent prior to enrollment in the study. The project started with a large online screening survey in the northern part of the Netherlands among 2937 young adults between 18 and 24 years old. Participants were recruited through advertisements on electronic learning environments of university and higher and intermediate vocational education institutes, pitches during lectures and classes, flyers, and advertisements on social media. After subscribing on the study website (http://www.nofunnoglory.nl), participants received an email with the link to the online survey. The survey contained questionnaires about, for example, pleasure, psychiatric problems, and stress, as well as a facial emotion identification task. From the screening survey, 69 young adults who suffered from persistent anhedonia and 69 controls were selected for the part of the study in which momentary assessments were completed. For a description of the selection procedure for the anhedonia and control group in the NFNG project, see Section 1 of the online Supplementary Material or van Roekel et al. [28]. From the 138 participants who completed the momentary assessments during the first month, we selected 25 participants with a high happy

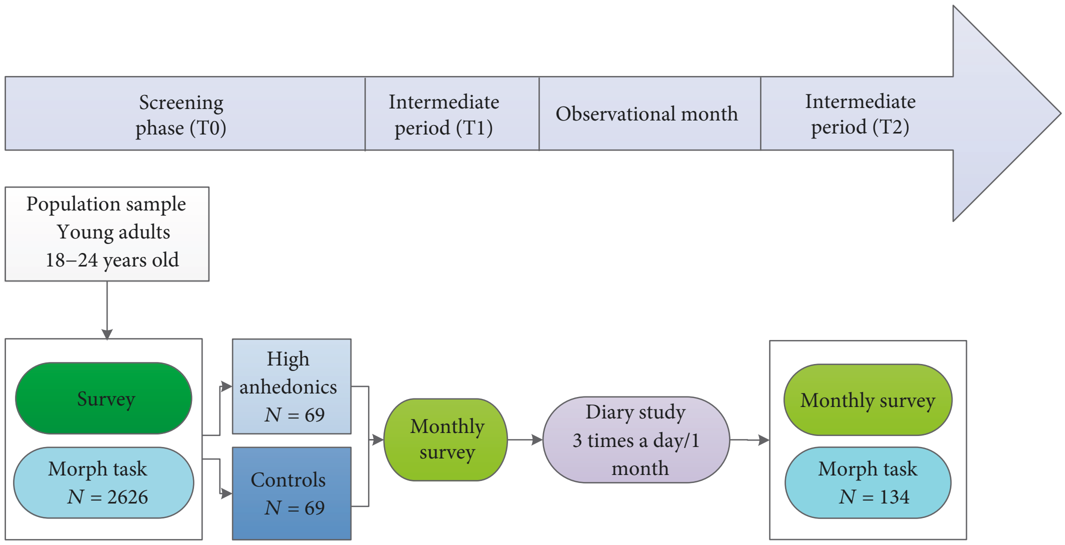

Figure 2: Flowchart of morph tasks and diary study month (i.e., momentary assessments) used in the current study.

bias and 25 participants with a low happy bias for the present study.

2.1.1. Selection of High and Low Happy Bias Groups. We used extreme bias groups rather than the full happy bias continuum because of both conceptual and methodological considerations. First and foremost, the extreme-group approach more closely fitted our supposition that mainly happy biases in the extremes of the distribution distinguish between adaptive and maladaptive affective mechanisms [29]. Second, a particular strength of network analyses is that these can be used to explore group differences in overall patterns of affect dynamics rather than investigating single effects only. Estimating and plotting the networks for each of the groups separately yields more insight into the affect dynamics within these groups than a single network based on the total sample, while it is still possible to test statistically whether specific affect patterns differ between the groups.

We selected participants for the high and low happy bias groups without taking into account whether participants belonged to the anhedonia or the control group. The selection was based on scores on a facial emotion identification morph task participants completed for the first time as part of the online screening survey (T0) and a second time after the first month of momentary assessments (T2); see Figure 2 for a flowchart.

We excluded four participants who did not complete the morph task at T2. During the morph task, participants were shown 24 10-second movie clips of neutral faces which slowly changed into one of four emotions: happy, sad, angry, or fearful. The participants had to press the spacebar as soon as they identified the emotion the neutral face turned into. For a more detailed description of the morph task, which was a shortened version of a task developed at Radboud University Nijmegen, the Netherlands [30], see Section 1 of the Supplementary Material or Vrijen et al. [29]. For each participant, the mean reaction time (RT) of correctly identified trials was calculated per emotion, resulting in RT Happy, RT Sad, RT Angry, and RT Fearful. We excluded one participant with less than 50% correct answers at T2. Separate happy bias scores were calculated at T0 and T2 by dividing the average of RT Sad, RT Angry, and RT Fearful by RT Happy. A higher happy bias means being faster in identifying happy emotions than in sad, angry, and fearful emotions.

We were interested in the affect dynamics associated with trait high and low happy bias and compared the average affect dynamics during 30 days of individuals with a stable high happy bias (i.e., stable during these 30 days) to the affect dynamics of individuals with a stable low happy bias. Because stable happy bias and state fluctuations can only be unraveled by using happy bias at two time points, we selected an extreme high stable and an extreme low stable happy bias group based on the ranked happy bias scores at T0 and T2. Happy bias at T0 and Happy bias at T2 were each ranked from low (ranking 133) to high (ranking 1), and selection of the two happy bias groups was based on the summed ranks for T0 and T2. The 25 participants with the highest summed rank were selected for the high happy bias group, and the 25 participants with the lowest summed rank for the low happy bias group. An additional advantage of this approach was that part of the measurement error is also parceled out because a participant is only selected for the high happy bias group if scores on both tasks are high. (Please note that we do not mean to suggest that all differences between happy bias at T0 and T2 are due to measurement error. We acknowledge that there may well be state happy bias fluctuations within a person between T0 and T2, but in the present study, we are interested in the daily life affect dynamics associated with more stable high and low happy bias.) To ensure that high (or low) scores reflected a high (or low) score relative to the rest of the group on both tasks, we used summed rank scores rather than summed mean scores. In this way, scores on both tasks count equally even in the case of general learning effects of the whole group. The middle group, which consisted of participants with moderate or unstable happy bias scores, was excluded from the main analyses.

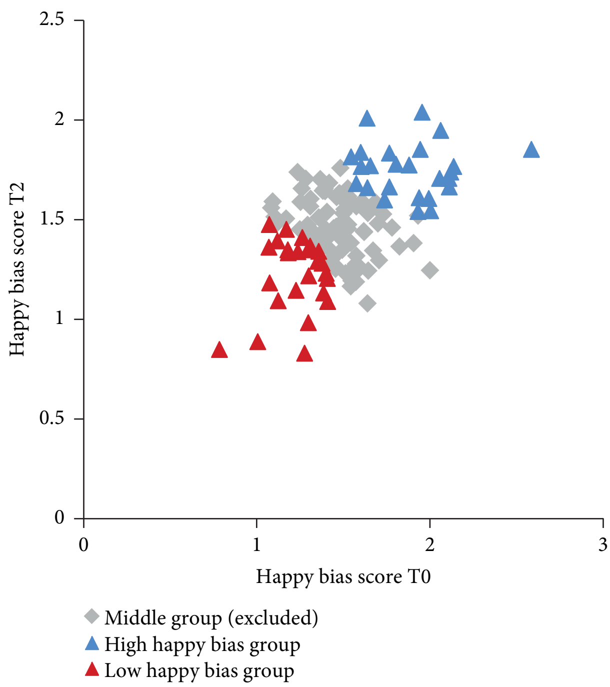

Figure 3: Happy bias scores T0 and T2 and selection high and low happy bias group.

This group was taken into account in part of the post hoc sensitivity checks (see Section 4 of the Supplementary Material). See Figure 3 for the individual happy bias scores at T0 and T2 for the high happy bias group, the low happy bias group, and the middle group.

2.2. Ecological Momentary Assessments. In the online questionnaire participants filled out three times a day, we included items to measure positive affect and positive experiences, negative affect, negative thoughts, and negative experiences, social company, activities, etc. See van Roekel et al. [28] for a detailed description of all momentary items that were assessed as part of the No Fun No Glory Study. Starting point as well as times of receiving the questionnaires during the day were personalized to the schedule and preference of the participants. They received a text message on their smartphone with the link to the questionnaire three times a day on fixed times with 6-hour intervals in between (e.g., 10:00 AM, 4:00 PM, and 10:00 PM). The questionnaire had to be completed within 2 hours after the first notification. If necessary, reminders were sent after 1 hour and again after 1.5 hours. Completion of the questionnaires took on average 3 minutes.

We included the following items in the present study: Since the last assessment I felt joyful (JOY); Think about the most pleasant event you experienced since the last assessment: how pleasant was this experience for you? (POS); Since the last assessment I felt interested in the things around me (INT); Since the last assessment I felt sad (SAD); Since the last assessment I felt irritated (IRR); Since the last assessment I have been worrying (WOR); Think about the most unpleasant event you experienced since the last assessment: how unpleasant was this experience for you? (NEG). Because we considered JOY, INT, SAD, and IRR to be sensitive to overnight recall bias, the morning assessments of these items were phrased more momentarily, that is, into "I feel joyful," "I feel interested in the things around me," "I feel sad," and "I feel irritated." Participants indicated their endorsement to these items by means of a slider on a Visual Analogue Scale (VAS), with "not at all" as its left anchor and "very much" as its right anchor. The position of the slider was transformed into a score between 0 ("not at all") and 100 ("very much").

2.3. Statistical Analyses. We provided descriptive statistics for gender, age, education, and anhedonia status; calculated mean levels of all variables used in this study; and showed them for the high and low happy bias group separately. We used R package psych version 1.6.12 [31, 32] to calculate the group and individual mean squared successive differences (MSSDs) for each node, as these indicate the amount of variability from one assessment to the next. We also indicated per node how many participants had an MSSD < 50, which was used as a criterion for insufficient variability from one assessment to the next, following Van Der Krieke et al. [33]. If one group shows a higher average MSSD than the other or contains more participants with an acceptable MSSD, it is possible that this results in more power for this group. Therefore, we decided that if more or stronger significant associations were found for this group, we would address the possibility that these differences were driven by differences in MSSD in the discussion.

We used multilevel vector autoregressive (VAR) modelling in R package mlVAR version 0.4 [34, 35] to explore the daily life dynamics between JOY, POS, INT, SAD, IRR, WOR, and NEG for the high and low happy bias groups. One of the main advantages of mlVAR was the availability of tools that, in combination with the R packages igraph [36] and qgraph [37], allowed not only visualization of networks and centrality indices on a group level but also visualization of individual variation within groups.

Although exact power calculations are not possible for VAR analyses, a minimum of 50 assessments per person has been recommended for individual VAR analyses [38]. We performed multilevel VAR analyses for which power is influenced by both the number of assessments and the number of persons. Our analyses were based on three assessments per day for a period of 30 days, that is, 90 assessments per person (with an average of 6 missings per person), and our high and low happy bias groups consisted of 25 participants each. We ensured sufficient power by limiting the number of parameters estimated in mlVAR; that is, we focused mainly on within-subject processes, refrained from investigating the influence of between-subject predictors, and did not estimate correlations between random effects (see below for further details). We have performed a simulation study based on the present study's effect sizes and number of subjects and data points. Eight hundred datasets were simulated in which the individual network models we found were generated as the "true" models. Fixed and random effects were estimated with the same method and number of nodes as in our main mlVAR analyses. In the present study, we used on average 84 time points per subject, and for this number of time points the simulation study showed high correlations between the true and the estimated fixed and random effects of the simulated datasets (see Figure S1 in the Supplementary Material). This indicates that the method we used is appropriate for our effect sizes, number of subjects, and number of time points. Additionally, because all of our hypotheses were based on network patterns rather than on specific effects of a single variable, our findings do not rely on single paths in the network models.

As a first preparatory step, we removed linear time trends from the data, because time trends violate the stationarity assumption of VAR analyses and may bias parameter estimation [39]. We also removed cyclic time of day trends prior to VAR analysis, because mlVAR does not allow controlling for time of day. Linear and cyclic time trends were removed by regressing each variable on time and on dummy variables for afternoon and evening, within each individual. The residuals from these analyses were used as input for the VAR models.

For estimating networks containing both autoregressive and cross-lagged effects, it has been recommended to person-mean center all predictors prior to the analyses in order to separate within-subject from between-subject effects [40, 41]. Because our main interest was to grasp daily life psychological processes which take place within individuals, we separated within-subject from between-subject effects even further by within-person standardization of all network variables prior to the VAR analyses. For comparing the relative strengths of different predictors within and between networks, standardization of the coefficients has been recommended because differences in coefficients may be due to differences in variance [42, 43]. Using raw coefficients to compute centrality indices has been discouraged as well [42].

In mlVAR, separate lag 1 networks were estimated for the high and low happy bias groups, by means of the lmer function from the linear mixed-effects R package lme4 version 1.1-15 [44]. The networks were constructed by performing seven univariate multilevel VAR analyses, one for each dependent variable, and combining the results into a network. In each of the univariate multilevel VAR analyses, the dependent variable was predicted by the lag (i.e., $t-1$) of all other variables and itself. This means that, for example, feeling irritated (IRR) at time t was predicted by INT_{t-1}, JOY_{t-1}, SAD_{t-1}, WOR_{t-1}, POS_{t-1}, NEG_{t-1}, and IRR_{t-1}. The unique direct temporal effects were modeled [22, 42]. Random effects were estimated to account for individual differences. We assumed no correlations between random intercepts and random slopes (orthogonality specification in mlVAR), as the person-mean of each variable was equal to 0 after within-person standardization.

The above-described procedure resulted in a network for the high happy bias and a network for the low happy bias group. For each node of these networks, we calculated two centrality indices, outstrength and instrength. The outstrength of a node represents the summed strength, that is, the absolute value of the coefficients, of all outgoing paths from this node at $t-1$ to other nodes at time t, and as such reflects how strongly the node predicts other nodes over time. The instrength reflects how strongly a particular node is predicted by other nodes over time and is computed by the summed strength of all its incoming paths at time t from other nodes at $t-1$. In mlVAR, the packages igraph version 1.1.2 and qgraph version 1.4.4 were used to plot the networks and to compute and visualize the centrality indices. Autoregressive components were not included in the outstrength and instrength [37]. We compared the group network models and centrality indices of the high and low happy bias group by means of visual inspection. Next, we explored individual differences within the two groups by plotting the instrength and outstrength for each person separately, based on the person-specific effects.

In addition to the visual comparisons of the networks and centrality indices, we performed seven permutation tests to test the hypothesized differences between the high and low happy bias groups. Significant results on the permutation test suggest differences between high and low happy bias in the population. The permutation tests compared the observed differences of interest to distributions of possible differences under the null hypothesis of no differences between the groups. Distributions of possible differences were derived from reshuffling the groups randomly 10,000 times, also called Monte Carlo sampling. For each reshuffle, differences between the two reshuffled groups were estimated with the lmer function of R package lme4, that is, in the same way as the original models had been defined in mlVAR. If an observed difference between the high and low happy bias groups was within 2.5% on either side of the distribution of the 10,000 possible differences, the difference between the high and low happy bias group was considered significant (i.e., $p < 0.05$). We used an adapted version of the permutation test developed by Snippe et al. [45] to test differences between the high and low happy bias groups which match our hypotheses as described in the Introduction. See Table 1 for a description of the seven hypotheses and their operationalization for the permutation tests.

All of the tested difference scores were based on the fixed effects of the group models. For permutation tests (1) and (4), we used absolute edge weights in order to avoid that expected positive and expected negative associations cancel each other out. All of our hypotheses and therefore also all permutation tests applied to outstrength. We explored possible differences in instrength between the high and low happy bias groups by visual comparison of the networks and centrality plots and did not use permutation tests because we did not have clear hypotheses in advance.

Finally, we performed multiple sensitivity analyses to explore the robustness of our findings. First, we repeated the mlVAR analyses in Mplus version 8 [46], which allowed multivariate mlVAR analyses with a Bayesian estimator. Second, although the decision to use extreme groups rather than continuous happy bias measures was driven by valid conceptual and methodological considerations, there were no clear criteria on how extreme the groups should be and therefore the exact number of individuals selected for each group (i.e., 25) was somewhat arbitrary. To assess the robustness of the results based on groups of 25 individuals, we estimated the networks, computed the centrality indices, and performed the permutation tests for bias groups of 20, 30, 35,

Table 1: Description and operationalization of the seven hypotheses tested with the permutation tests.

	Description	Permutation test
Hypothesis 1	JOY and POS are stronger predictors in the network of the high happy bias group than in the network of the low happy bias group	(1) The total summed absolute edge weight of all outgoing edges from JOY and POS at time $t-1$ to all nodes in the network at time t (including autoregressive edges) is larger for the high happy bias group than for the low happy bias group
Hypothesis 2	JOY and POS more strongly predict themselves (i.e., are more easily sustained over time) and each other (i.e., more carry-over between JOY and POS) over time in the high happy bias group than in the low happy bias group	(2) The total summed edge weight of all outgoing edges from JOY and POS at time $t-1$ to JOY and POS at time t (including autoregressive edges) is larger for the high happy bias group than for the low happy bias group
Hypothesis 3	JOY and POS more strongly predict the negative nodes (i.e., larger dampening effect on negative nodes) over time in the high happy bias group than in the low happy bias group	(3) The total summed edge weight of all outgoing edges from JOY and POS at time $t-1$ to SAD, IRR, WOR, and NEG at time t is larger for the high happy bias group than for the low happy bias group
Hypothesis 4	The negative nodes are stronger predictors in the network of the low happy bias group than in the network of the high happy bias group	(4) The total summed absolute edge weight of all outgoing edges from SAD, IRR, WOR, and NEG at time $t-1$ to all nodes in the network at time t (including autoregressive edges) is larger for the low happy bias group than for the high happy bias group
Hypothesis 5	The negative nodes more strongly predict themselves (i.e., are more easily sustained over time) and each other (i.e., more carry-over between the negative nodes) over time in the low happy bias group than in the high happy bias group	(5) The total summed edge weight of all outgoing edges from SAD, IRR, WOR, and NEG at time $t-1$ to SAD, IRR, WOR, and NEG at time t (including autoregressive edges) is larger for the low happy bias group than for the high happy bias group
Hypothesis 6	More pronounced negative associations between negative nodes and JOY and POS (i.e., larger dampening effect on JOY and POS) over time in the low happy bias group than in the high happy bias group	(6) The total summed edge weight of all outgoing edges from SAD, IRR, WOR, and NEG at time $t-1$ to JOY and POS at time t is larger for the low happy bias group than for the high happy bias group
Hypothesis 7	JOY and POS more strongly predict INT in the high than in the low happy bias group	(7) The total summed edge weight of all outgoing edges from JOY and POS at time $t-1$ to INT at time t is larger for the high happy bias group than for the low happy bias group

JOY = feeling joyful; POS = pleasant experiences; INT = feeling interested in the things around me; SAD = feeling sad; IRR = feeling irritated; WOR = worrying; NEG = unpleasant experiences.

and 40 individuals. We used the same mlVAR methods as in the main analyses. As a third check, to adjust for anhedonia status, we computed subject-specific centrality indices based on the random estimates of the edges of the low and high happy bias networks and subsequently regressed the subject-specific centrality indices on anhedonia status and happy bias. See Sections 3–5 in the Supplementary Material for further details.

3. Results

3.1. Descriptive Statistics General Demographics. The high and low happy bias groups were quite comparable in terms of age, gender, and education (see Table 2). Although in the low happy bias group more participants attended university, in both groups all participants were enrolled in higher education. The groups differed considerably in symptoms of anhedonia.

The descriptive statistics for the facial emotion identification variables are presented in Table 3. The high happy bias group had a mean happy bias score of 1.82, which means that happy facial emotions were identified on average 1.82 times faster than the negative facial emotions sadness, anxiety, and fear. The low happy bias group had a mean happy bias score of 1.23, which indicates that this group is on average

Table 2: General demographics and anhedonia status.

	High happy bias group ($n = 25$) Mean (SD)/count (%)	Low happy bias group ($n = 25$) Mean (SD)/count (%)
Age	21.64 (1.77)	20.69 (2.05)
Females	20 (80%)	22 (88%)
University education	13 (52%)	18 (72%)
Higher vocational education	12 (48%)	7 (28%)
Anhedonic[a]	8 (32%)	13 (52%)
Control[a]	17 (68%)	10 (40%)
Switcher[a]	0 (0%)	2 (8%)

[a]Participants were classified as anhedonic or control if they met all criteria at T0 and did not change in pleasure levels from one group to the other at either T1 or T2. Otherwise, they were classified as switcher.

Table 3: Descriptive statistics of facial emotion identification scores.

	High happy bias group ($n = 25$)		Low happy bias group ($n = 25$)	
	Mean	SD	Mean	SD
RT Total	5522.61	574.66	5236.69	848.37
RT Happy	3449.08	377.55	4550.20	1034.25
RT Sad	6797.62	801.18	6051.65	1014.42
RT Angry	5761.44	705.29	5189.62	916.74
RT Fearful	6094.69	883.37	5168.86	821.34
Happy bias score	1.82	0.14	1.23	0.13
Happy bias rank	36.84	18.92	218.96	22.25

RT = reaction time; RT Total = mean score on RT Happy, RT Sad, RT Angry, and RT Fearful; happy bias score = mean score on RT Sad, RT Angry, and RT Fearful divided by RT Happy; happy bias rank = summed rank of happy bias score at T0 and T2.

Table 4: Descriptive statistics of the momentary assessment items used as nodes in the networks.

	Mean		Average within-person SD		Average within-person MSSD (n with MSSD < 50)	
	High bias $n = 2094$	Low bias $n = 2095$	High bias	Low bias	High bias	Low bias
JOY	60.27	56.07	12.98	12.38	237 (0)	248 (0)
POS	63.35	60.06	14.76	14.02	302 (0)	312 (0)
INT	58.31	53.30	13.28	13.35	263 (0)	275 (1)
SAD	13.96	18.49	11.16	12.34	225 (5)	262 (3)
IRR	15.42	19.87	13.02	15.03	302 (2)	384 (1)
WOR	21.88	22.88	13.75	15.26	291 (0)	310 (2)
NEG	32.82	39.27	18.75	18.79	565 (1)	554 (0)

JOY = feeling joyful; POS = pleasant experiences; INT = feeling interested in the things around me; SAD = feeling sad; IRR = feeling irritated; WOR = worrying; NEG = unpleasant experiences; MSSD = average within-person mean squared successive difference. *Note*. These descriptive statistics are based on data from which linear time trends, and cyclic time of day trends have already been removed.

still faster in identifying happy facial emotions, but the difference between happy and the negative emotions is only small.

Table 4 presents the descriptive statistics of the network variables. On average, the high happy bias group scored higher than the low happy bias group on the positive nodes (JOY, POS, and INT) and lower on the negative nodes (SAD, IRR, WOR, and NEG). Within-person SDs were quite similar across the groups, with the largest differences for IRR and WOR. MSSDs of all nodes were larger in the low happy bias group than in the high happy bias group and in both groups for all nodes MSSD ≥ 50 for almost all participants; that is, in the high happy bias group 5 participants had an MSSD < 50 on SAD, 2 on IRR, and 1 on NEG, and in the low happy bias group, 3 participants had an MSSD < 50 on SAD, 1 on INT, 1 on IRR, and 2 on WOR. Both the high and low happy bias group showed low numbers of missings per person on the momentary assessments; for both groups, the mean number of missings per person was 6.2 (out of 90), with min = 1 and max = 17.

3.2. Descriptive Statistics Network Models. The network models for the high happy bias group and the low happy bias group are visualized in Figure 4; only the significant edges with p values < 0.05 are depicted (see Table S1 in the Supplementary Material for the exact coefficients and significance levels of all paths). Green edges represent positive, and red edges represent negative associations from one node at time $t-1$ to another node at time t; the thickness of the edges indicates the strength of the associations. As we within-person standardized all variables, the edge coefficients represent the change in terms of within-person SD in the outcome variable based on one within-person SD increase in the predictor variable.

3.2.1. Associations between Positive Nodes at Time $t-1$ and Positive Nodes at Time t. For both groups, all autocorrelations of the positive nodes JOY, POS, and INT were significant. Autocorrelations of JOY and POS were higher, and JOY, POS, and INT were more densely connected to each other in the high happy bias group than in the low happy bias group. The positive edges suggest that an increase in one of the positive nodes is associated with an increase in the others at the next measurement.

3.2.2. Associations between Negative Nodes at Time $t-1$ and Negative Nodes at Time t. For both groups, we found significant autocorrelations of the negative nodes WOR, NEG, and SAD, with a higher autocorrelation for WOR in the low happy bias group than in the high happy bias group. The autocorrelation of IRR was only significant in the low happy bias group. The negative nodes SAD, IRR, WOR, and NEG showed several positive temporal interrelations in both groups.

3.2.3. Associations between Positive Nodes at Time $t-1$ and Negative Nodes at Time t. For the high happy bias group, a higher score on POS predicted a lower score on WOR, and a higher score on JOY predicted lower scores on IRR and NEG. For the low happy bias group, we did not find negative edges from POS and JOY to negative nodes at the next measurement.

3.2.4. Associations Between Negative Nodes at Time $t-1$ and Positive Nodes at Time t. A higher score on negative nodes was significantly associated with a lower score on positive nodes at the next measurement for the low happy bias group only; that is, WOR and IRR showed negative associations with JOY and INT.

3.3. Descriptive Statistics Centrality Indices

3.3.1. Centrality Plots on Group Level. Centrality plots for outstrength and instrength are presented in Figure 5(a). JOY and POS had the highest outstrength in the high happy bias group and the lowest outstrength in the low happy bias group, indicating that JOY and POS most strongly predicted the other nodes in the high happy bias group and least strongly predicted the other nodes in the low happy bias

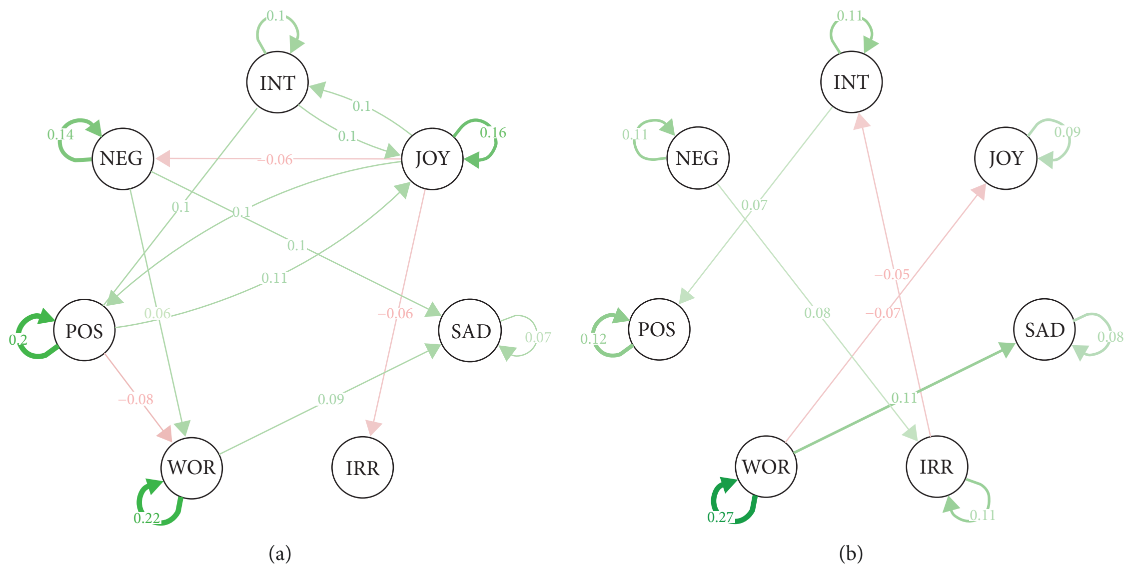

FIGURE 4: Significant association networks high happy bias group (a) and low happy bias group (b). JOY = feeling joyful; POS = pleasant experiences; INT = feeling interested in things around me; SAD = feeling sad; IRR = feeling irritated; WOR = worrying; NEG = unpleasant experiences.

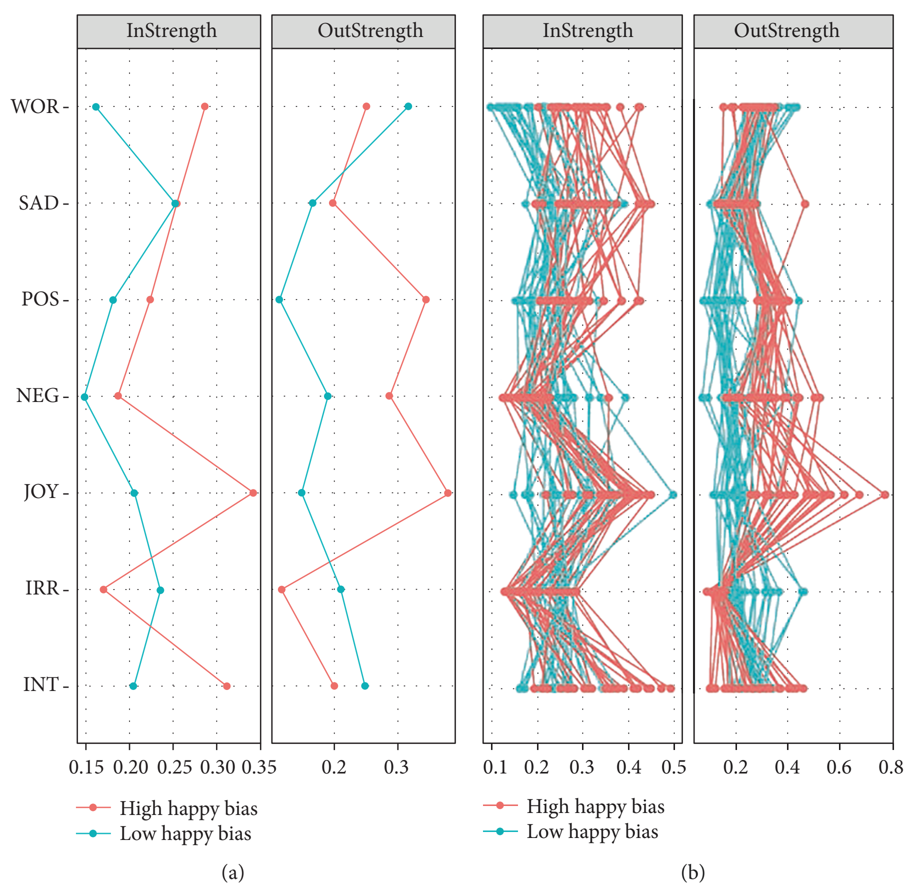

FIGURE 5: Centrality indices instrength and outstrength based on the complete network models. In panel (a) the indices are plotted for the high and low happy bias groups, and panel (b) illustrates the individual variation within these groups. JOY = feeling joyful; POS = pleasant experiences; INT = feeling interested in things around me; SAD = feeling sad; IRR = feeling irritated; WOR = worrying; NEG = unpleasant experiences. *Note.* Estimations for panel (b) are based on multilevel group models (fixed effects) and individual variation within these groups (random effects). No separate individual models were estimated, and the lines in panel (b) should not be interpreted as such.

group. We found the largest differences in instrength between the high and low happy bias group for WOR, JOY, and INT, all of which were more strongly predicted by other nodes in the high happy bias group than in the low happy bias group.

3.3.2. Individual Variation in Centrality Indices. Individual variation in outstrength and instrength within the two happy bias groups is presented in Figure 5(b). In general, instrength showed more individual variation than outstrength. Regardless of the individual variation, the ranges of the high and low happy bias groups hardly overlapped on the outstrength of JOY, indicating that the low and high happy bias groups could be most clearly discriminated on the outstrength of this node.

3.4. Permutation Tests of Differences between the Low and High Happy Bias Group. As a brief reminder, the following seven hypotheses were tested: (1) JOY and POS are stronger predictors in the network of the high happy bias group than in the network of the low happy bias group; (2) JOY and POS more strongly predict themselves and each other over time in the high happy bias group than in the low happy bias group; (3) JOY and POS more strongly predict the negative nodes over time in the high happy bias group than in the low happy bias group; (4) the negative nodes are stronger predictors in the network of the low happy bias group than in the network of the high happy bias group; (5) the negative nodes more strongly predict themselves and each other over time in the low happy bias group than in the high happy bias group; (6) more pronounced negative associations between negative nodes and positive nodes over time in the low happy bias group than in the high happy bias group; and (7) JOY and POS more strongly predict INT in the high than in the low happy bias group. See Table 1 for a more detailed description of the hypotheses and their operationalization for the permutation tests.

Only permutation tests 1 and 2 reached significance at $p < 0.05$. The observed difference of the total absolute strength of all outgoing edges from JOY and POS between the high and low happy bias groups was 0.61, $p < 0.01$ (permutation test 1). The observed difference between the two groups of the total strength of all outgoing edges from JOY and POS to JOY and POS was 0.31, $p < 0.01$ (permutation test 2). We found no significant differences between the two groups for the total strength of all outgoing edges from JOY and POS to negative nodes (observed $\text{difference} = -0.24$, $p = 0.13$; permutation test 3), the total absolute strength of all outgoing edges of the negative nodes (observed $\text{difference} = -0.14$, $p = 0.57$; permutation test 4), the total strength of all outgoing edges from negative nodes to negative nodes (observed $\text{difference} = -0.15$, $p = 0.36$; permutation test 5), the total strength of all outgoing edges from negative nodes to JOY and POS (observed $\text{difference} = 0.14$, $p = 0.18$; permutation test 6), and the total strength of all outgoing edges from JOY and POS to INT (observed $\text{difference} = 0.12$, $p = 0.06$; permutation test 7).

3.5. Sensitivity Analyses. The multivariate Mplus multilevel VAR analyses showed minor differences for several of the network model estimates, but general patterns and main findings were confirmed (for more details, see Section 3 of the Supplementary Material). Networks, centrality indices, and permutation tests for extreme happy bias groups of 20, 30, 35, and 40 individuals showed the same patterns as the ones based on the original groups of 25 individuals. As expected, group differences became less pronounced as groups became larger and for $N = 40$ one of the two permutation tests was no longer significant. For more details, see Section 4 of the Supplementary Material. Finally, controlling for anhedonia status did not change our findings (see section 5 of the Supplementary Material for more details).

4. Discussion

Our study is the first to investigate what a bias for happy facial emotions as assessed by a standardized laboratory task pertains to in daily life. We found that feelings of joy and pleasant experiences were stronger predictors in the network of the high happy bias group than in the network of the low happy bias group (hypothesis 1) and that in the high happy bias group joy and pleasant experiences more strongly predicted themselves and each other over time (hypothesis 2). These were robust findings based on both visual inspection of the networks and centrality indices and permutation tests. Other group differences were only found by visual comparison but could not be corroborated by the permutation tests: joy and pleasant experiences dampened the negative nodes (i.e., sadness, irritation, worrying, and unpleasant experiences) in the high but not in the low happy bias network (hypothesis 3); the negative nodes dampened joy and pleasant experiences in the low but not in the high happy bias network (hypothesis 6); and joy and pleasant experiences predicted interest in the high but not in the low happy bias network (hypothesis 7). These group differences were present in the study sample, but since the permutation tests were not significant, it is not possible to draw inferences about group differences in the population. The fact that the permutation tests did not reveal group differences regarding these hypotheses may be due to large individual differences or small effects. We found no support that negative nodes more strongly predicted the overall affect network or the negative network in the low happy bias group than in the high happy bias group (hypotheses 4 and 5). Although the high and low happy bias groups differed considerably in symptoms of anhedonia, the differences we found between the high and low happy bias groups seem to be driven primarily by happy bias status and could not be (fully) explained by anhedonia status.

Our more specific results may be discussed in terms of the extent to which a certain node predicts other nodes at the next time point (outstrength) or in terms of the extent to which a certain node is predicted by other nodes at the previous time point (instrength). Because our hypotheses applied to outstrength and we did not have clear hypotheses about instrength in advance, our methodological approaches toward outstrength and instrength differed. For outstrength, we focused more on hypothesis-testing by means of permutation tests, whereas we used a more exploratory approach based on visual inspection for instrength. Both perspectives will be discussed, starting with the outstrength.

We found that joy and pleasant experiences more strongly predicted affect over time in the high happy bias group than in the low happy bias group. This suggests that individuals with a high happy bias show a bias toward positive affect and positive experiences in their daily lives and may be better capable of sustaining positive affect and positive experiences over a longer period of time and generalizing it to other positive components than individuals with a low happy bias. This is particularly important because these same mechanisms, that is, the inability to sustain positive affect over time [10–12, 16, 17] and the inability to generate positive effect from pleasant experiences [18, 19], have been associated with depression in previous studies. In the present study, we also found indications that the same specific daily life affect dynamics that are associated with a low happy bias are also associated with depressive symptoms. That is, we found that for individuals suffering from anhedonia, which is one of the two core symptoms of depression, joy and pleasant experiences were weaker predictors of affect in the next six hours (see Section 5 of the Supplementary Material). Furthermore, daily life momentary positive affect during one month has been found to predict life satisfaction and a higher ability to adapt to changing environments after this month [47], which suggests that positive affect in the moment broadens one's attentional scope and facilitates building valuable cognitive and social resources essential to well-being [47, 48]. If feelings of joy can be sustained longer and spread to other positive experiences, their beneficial influence may be prolonged too. The savoring of positive affect, which includes the anticipation as well as the prolongation of positive affect, has been found to be associated with more life satisfaction and happiness and with lower levels of neuroticism, depression, and anhedonia [49]. In previous studies, it has also been found that positive affect facilitates recovery from negative experiences [14] and that resilient individuals use positive affect to downregulate negative affect [15]. This is in accordance with our findings that joy and pleasant experiences dampened negative nodes in the high but not in the low happy bias network and suggests that individuals with a high happy bias may be better equipped to use positive experiences and positive affect to regulate negative affect, thoughts, and experiences than the low happy bias group. However, caution is warranted in interpreting this finding because, although in all different sensitivity analyses joy and pleasant experiences dampened negative nodes in the high but not in the low happy bias group, the permutation test did not reach statistical significance. Therefore no conclusions can be drawn about group differences in the population. It is possible that the permutation test was not significant because of large individual variation in edges from joy and pleasant experiences to negative nodes, but this is only speculation. The regulation of negative nodes by means of positive nodes may also essentially occur on a shorter time frame, for example, 2 hours. If this is indeed the case, then the current method only picked up what was still left of the initial effect several hours later.

With regard to instrength, that is, the extent to which a certain node is predicted by other nodes at the previous time point, we found the largest differences between the high and low happy bias group for worrying, joyfulness, and feeling interested, all of which were more strongly predicted by other affect components in the high happy bias group than in the low happy bias group. A possible explanation is that this reflects psychological flexibility, such that for individuals with a high happy bias, worrying, joyfulness, and feeling interested are more dependent on context. How this might work can be illustrated by comparing the high and low happy bias networks in Figure 4. The level of worrying is influenced by pleasant and unpleasant experiences in individuals with a high happy bias, whereas for individuals with a low happy bias worrying seems to be less dependent on context, has a higher autocorrelation, and consequently tends to lead its own life. As psychological flexibility has been found to be highly important for optimal functioning in many situations, and psychological rigidity has been associated with depression as well as other forms of psychopathology [50, 51], the high happy bias group seems to be better off.

Sensitivity analyses were performed to explore the effects of different estimators, statistical packages, group sizes, a multivariate approach, and controlling for anhedonia status. All of these sensitivity analyses but one supported the original main findings completely; for the largest happy bias groups ($N = 40$), only partial support was found in the sense that one of the two original main findings was no longer significant. As expected, group differences became less pronounced as groups became larger. Two plausible explanations are, first, that for the happy bias groups of $N = 40$ the stability assumption of mlVAR analysis was not met, and second, that only happy bias in the extremes of the distribution may be associated with the development of adaptive versus maladaptive affective patterns in daily life.

Strengths of our study are, first of all, that we combined the best of two worlds by using a multilevel approach in which within-subject effects were separated from between-subject effects by within-person standardization of all variables prior to the analyses. This enabled us to explore dynamic processes that take place within individuals; at the same time, it allowed us to compare the two happy bias groups [43]. Secondly, following recent developments in the field [45, 52], in addition to visual comparison of the affect networks and centrality indices, we used permutation methods adapted to our specific hypotheses to test statistically whether the happy bias groups differed in their affect dynamics. A third strength of this study is its high ecological validity, as we assessed affect and related measures three times a day in daily life situations, for a period as long as 30 days, and achieved compliance rates of at least 80%. Additionally, the use of a morph task allowed us to assess the identification of more subtle traces of emotions, which is assumed to give a more ecologically valid perspective than static full-intensity facial emotion identification tasks, as in daily life static full-intensity facial emotions are quite rare. Finally, we repeated the facial emotion identification task and based our selection of the happy bias groups on individuals' scores on both tasks. This enabled us to select only those participants with a stable happy bias. This was necessary because the daily life affect networks were estimated over a period of 30 days and participants showing large shifts in happy bias from one happy bias group to the other during this period would have added noise to the network models.

Evidently there are also limitations to our study. First, our sample largely consisted of higher educated females, which may limit the generalizability of our findings because gender and level of education may moderate the associations we investigated [53–58]. Second, the selection of extreme and stable happy bias groups resulted in small groups of 25 participants, which limits generalizability and resulted in insufficient power to correct for anhedonia status or use multivariate multilevel analysis, which would require the estimation of additional parameters. The disadvantage of the univariate approach is that correlations between the dependent variables and between random effects of the dependent variables were not taken into account. We presented sensitivity analyses to show the effects of a multivariate approach, different group sizes, and controlling for anhedonia status. However, most of these alternative approaches required multiple conceptual and methodological concessions and can only be interpreted as proxies to our original models. Third, we offered a network approach in which only unique direct temporal effects were studied, and no shared effects [22, 42]. As such, our approach should be regarded as complementary to approaches that take into account shared variance. Fourth, our results were based on assessments that were on average six hours apart. We were unable to grasp dynamic processes that took place within a shorter time frame. Finally, a limitation of our study that applies to all nonexperimental study designs is that we cannot make inferences about true causality; our conclusions are confined to "Granger" causality, that is, if a variable at time $t-1$ contains unique information to predict a second variable at time t, it is said to Granger cause this second variable [59]. We investigated the directed associations between different affect components over time, and it is plausible that other factors that were not included in our models explain part of these dynamics and therefore no true causal claims can be inferred from our network models.

Further research is required, first of all to confirm our findings by replication in other samples. Because of the present study's small group sizes, the conclusions are tentative awaiting attempts to replicate. Second, the specific conditions in which happy bias influences daily life affect dynamics need to be explored, for example, how extreme the bias needs to be before predicting positive or negative outcomes regarding well-being or mental health. Third, although our findings are promising, it should be noted that the ability to sustain positive emotions has been operationalized in many different ways in previous studies and there are also inconsistencies and unresolved issues, for example with respect to autocorrelation. It has been found that a stronger daily life autocorrelation of positive emotions over time protects against depression [17] but also that strong autocorrelations, for positive as well as negative emotions, predict depression [51, 58]. Further research is needed to investigate adaptive and maladaptive effects of strong autocorrelations versus psychological flexibility. It seems plausible that strong autocorrelations may indicate resistance to change and thereby limit psychological flexibility, but equally plausible that no carry-over of positive affect and positive experiences over time (weak autocorrelation) may also not be very adaptive. It may be important to consider different time scales [60], to look at proportions of autocorrelation in relation to cross-lagged paths (relative influence of other nodes) and to distinguish between high autocorrelation with respect to low and high levels of positive and negative affect and experiences. Finally, depression is a heterogeneous construct and specific subtypes of depression may be differentially associated with affect dynamics. A low happy bias could reflect such a subtype, and our study suggests that it can be useful to take happy bias into account when studying affect dynamics. Depressed individuals with a low happy bias may show different affect dynamics compared to depressed individuals with a high happy bias, but this remains to be investigated.

5. Conclusions

We compared young adults with a high bias for happy facial emotions during a standardized laboratory task to peers with a low bias for happy facial emotions on their daily life affect dynamics, using a highly personalized approach in which we separated within-subject from between-subject effects. Our most important and robust finding was that joy and pleasant experiences more strongly predicted the affect network of the high happy bias group than that of the low happy bias group. These findings tentatively suggest that individuals with a high happy bias are more responsive to positive, rewarding, experiences, and emotions, and more easily sustain them, whereas positive experiences and emotions seem to be more short-lived in the daily life of individuals who lack this happy bias. We propose that high reward responsiveness may be reflected in both a high happy bias during facial emotion identification and the ability to sustain and generalize positive experiences and positive affect in daily life. This may be key to why individuals with a bias toward happy facial emotions are potentially more resilient to developing depression. By using a network approach to compare the daily life affect dynamics of individuals with a high and with a low happy bias, we came closer to understanding the daily life mechanisms behind high and low happy bias during a laboratory task. This novel perspective is valuable for interpreting facial emotion processing tasks, as are often assessed in clinical research and practice. The present study illustrates the potential benefits of a network approach for unraveling psychological mechanisms.

Data Availability

Data and syntax have been made publicly available via the Open Science Framework and can be accessed at https://osf.io/4czv3/.

Disclosure

Preliminary results of the present study were presented in April 2017 at the biennial conference of the Society for Research in Child Development (SRCD; poster), in June 2017 at the biennial conference of the Society for Ambulatory Assessment (SAA; oral presentation), and in May 2018 at the 30th annual convention of the Association for Psychological Science (APS; poster).

Conflicts of Interest

The authors have no conflicts of interest.

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Supplementary Materials

Section 1: descriptions of the No Fun No Glory (NFNG) selection procedures and the facial emotion identification morph task. Section 2: the exact coefficients and significance levels of the main analyses, and the results of a simulation study which was used to assess the reliability of mlVAR for our specific sample size, number of time points, and model specifications. Sections 3–5: results of the sensitivity analyses performed to assess the robustness of our findings. *(Supplementary Materials)*

References

[1] J. M. Leppänen and J. K. Hietanen, "Positive facial expressions are recognized faster than negative facial expressions, but why?," *Psychological Research*, vol. 69, no. 1-2, pp. 22–29, 2004.

[2] C. Bourke, K. Douglas, and R. Porter, "Processing of facial emotion expression in major depression: a review," *Australian & New Zealand Journal of Psychiatry*, vol. 44, no. 8, pp. 681–696, 2010.

[3] J. Joormann and I. H. Gotlib, "Is this happiness I see? Biases in the identification of emotional facial expressions in depression and social phobia," *Journal of Abnormal Psychology*, vol. 115, no. 4, pp. 705–714, 2006.

[4] S. A. Surguladze, A. W. Young, C. Senior, G. Brébion, M. J. Travis, and M. L. Phillips, "Recognition accuracy and response bias to happy and sad facial expressions in patients with major depression," *Neuropsychology*, vol. 18, no. 2, pp. 212–218, 2004.

[5] J. Joormann, L. Talbot, and I. H. Gotlib, "Biased processing of emotional information in girls at risk for depression," *Journal of Abnormal Psychology*, vol. 116, no. 1, pp. 135–143, 2007.

[6] C. Vrijen, C. A. Hartman, and A. J. Oldehinkel, "Slow identification of facial happiness in early adolescence predicts onset of depression during 8 years of follow-up," *European Child & Adolescent Psychiatry*, vol. 25, no. 11, pp. 1255–1266, 2016.

[7] M. L. Pe, K. Kircanski, R. J. Thompson et al., "Emotion-network density in major depressive disorder," *Clinical Psychological Science*, vol. 3, no. 2, pp. 292–300, 2015.

[8] T. J. Trull, S. P. Lane, P. Koval, and U. W. Ebner-Priemer, "Affective dynamics in psychopathology," *Emotion Review*, vol. 7, no. 4, pp. 355–361, 2015.

[9] J. T. W. Wigman, J. van Os, D. Borsboom et al., "Exploring the underlying structure of mental disorders: cross-diagnostic differences and similarities from a network perspective using both a top-down and a bottom-up approach," *Psychological Medicine*, vol. 45, no. 11, pp. 2375–2387, 2015.

[10] M. S. Horner, G. J. Siegle, R. M. Schwartz et al., "C'mon get happy: reduced magnitude and duration of response during a positive-affect induction in depression," *Depression and Anxiety*, vol. 31, no. 11, pp. 952–960, 2014.

[11] D. L. McMakin, C. D. Santiago, and S. R. Shirk, "The time course of positive and negative emotion in dysphoria," *The Journal of Positive Psychology*, vol. 4, no. 2, pp. 182–192, 2009.

[12] A. S. Heller, T. Johnstone, A. J. Shackman et al., "Reduced capacity to sustain positive emotion in major depression reflects diminished maintenance of fronto-striatal brain activation," *Proceedings of the National Academy of Sciences of the United States of America*, vol. 106, no. 52, pp. 22445–22450, 2009.

[13] L. M. Hilt and S. D. Pollak, "Characterizing the ruminative process in young adolescents," *Journal of Clinical Child & Adolescent Psychology*, vol. 42, no. 4, pp. 519–530, 2013.

[14] B. L. Fredrickson and R. W. Levenson, "Positive emotions speed recovery from the cardiovascular sequelae of negative emotions," *Cognition and Emotion*, vol. 12, no. 2, pp. 191–220, 1998.

[15] M. M. Tugade and B. L. Fredrickson, "Resilient individuals use positive emotions to bounce back from negative emotional experiences," *Journal of Personality and Social Psychology*, vol. 86, no. 2, pp. 320–333, 2004.

[16] V. E. Heininga, E. Van Roekel, J. J. Ahles, A. J. Oldehinkel, and A. H. Mezulis, "Positive affective functioning in anhedonic individuals' daily life: anything but flat and blunted," *Journal of Affective Disorders*, vol. 218, pp. 437–445, 2017.

[17] P. Höhn, C. Menne-Lothmann, F. Peeters et al., "Moment-to-moment transfer of positive emotions in daily life predicts future course of depression in both general population and patient samples," *PLoS One*, vol. 8, no. 9, article e75655, 2013.

[18] M. Wichers, F. Peeters, N. Geschwind et al., "Unveiling patterns of affective responses in daily life may improve outcome prediction in depression: a momentary assessment study," *Journal of Affective Disorders*, vol. 124, no. 1-2, pp. 191–195, 2010.

[19] N. Geschwind, F. Peeters, N. Jacobs et al., "Meeting risk with resilience: high daily life reward experience preserves mental health," *Acta Psychiatrica Scandinavica*, vol. 122, no. 2, pp. 129–138, 2010.

[20] D. Borsboom and A. O. J. Cramer, "Network analysis: an integrative approach to the structure of psychopathology," *Annual Review of Clinical Psychology*, vol. 9, no. 1, pp. 91–121, 2013.

[21] L. F. Bringmann, N. Vissers, M. Wichers et al., "A network approach to psychopathology: new insights into clinical longitudinal data," *PLoS One*, vol. 8, no. 4, article e60188, 2013.

[22] L. F. Bringmann, M. L. Pe, N. Vissers et al., "Assessing temporal emotion dynamics using networks," *Assessment*, vol. 23, no. 4, pp. 425–435, 2016.

[23] American Psychiatric Association, *Diagnostic and Statistical Manual of Mental Disorders*, American Psychiatric Association, Arlington, VA, USA, 5th edition, 2013.

[24] K. A. McLaughlin, T. D. Borkovec, and N. J. Sibrava, "The effects of worry and rumination on affect states and cognitive activity," *Behavior Therapy*, vol. 38, no. 1, pp. 23–38, 2007.

[25] S. Nolen-Hoeksema, "Responses to depression and their effects on the duration of depressive episodes," *Journal of Abnormal Psychology*, vol. 100, no. 4, pp. 569–582, 1991.

[26] S. Nolen-Hoeksema, B. E. Wisco, and S. Lyubomirsky, "Rethinking rumination," *Perspectives on Psychological Science*, vol. 3, no. 5, pp. 400–424, 2008.

[27] M. Beckwé, N. Deroost, E. H. W. Koster, E. De Lissnyder, and R. De Raedt, "Worrying and rumination are both associated with reduced cognitive control," *Psychological Research*, vol. 78, no. 5, pp. 651–660, 2014.

[28] E. van Roekel, M. Masselink, C. Vrijen et al., "Study protocol for a randomized controlled trial to explore the effects of personalized lifestyle advices and tandem skydives on pleasure in anhedonic young adults," *BMC Psychiatry*, vol. 16, no. 1, p. 182, 2016.

[29] C. Vrijen, C. A. Hartman, G. M. A. Lodder, M. Verhagen, P. de Jonge, and A. J. Oldehinkel, "Lower sensitivity to happy and angry facial emotions in young adults with psychiatric problems," *Frontiers in Psychology*, vol. 7, 2016.

[30] G. M. A. Lodder, R. H. J. Scholte, L. Goossens, R. C. M. E. Engels, and M. Verhagen, "Loneliness and the social monitoring system: emotion recognition and eye gaze in a real-life conversation," *British Journal of Psychology*, vol. 107, no. 1, pp. 135–153, 2016.

[31] R Core Team, "R: a language and environment for statistical computing," 2013, https://www.R-project.org/.

[32] W. Revelle, "psych: procedures for psychological, psychometric, and personality research," 2016, May 2017, https://cran.r-project.org/web/packages/psych/index.html.

[33] L. Van Der Krieke, B. F. Jeronimus, F. J. Blaauw et al., "HowNutsAreTheDutch (HoeGekIsNL): a crowdsourcing study of mental symptoms and strengths," *International Journal of Methods in Psychiatric Research*, vol. 25, no. 2, pp. 123–144, 2016.

[34] S. Epskamp, M. K. Deserno, and L. F. Bringmann, "mlVAR: multi-level vector autoregression," R package version 0.4, 2017, https://CRAN.R-project.org/package=mlVAR.

[35] S. Epskamp, L. J. Waldorp, R. Mõttus, and D. Borsboom, "Discovering psychological dynamics: the Gaussian graphical model in cross-sectional and time-series data," 2016, https://arxiv.org/abs/1609.04156v2.

[36] G. Csárdi and T. Nepusz, "The igraph software package for complex network research," *InterJournal, Complex Systems*, vol. 1695, 2006.

[37] S. Epskamp, A. O. J. Cramer, L. J. Waldorp, V. D. Schmittmann, and D. Borsboom, "Qgraph: network visualizations of relationships in psychometric data," *Journal of Statistical Software*, vol. 48, no. 4, 2012.

[38] G. E. P. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, *Time Series Analysis: Forecasting and Control*, John Wiley & Sons, 2015.

[39] M. J. Rovine and T. A. Walls, "Multilevel autoregressive modeling of interindividual differences in the stability of a process," in *Models for Intensive Longitudinal Data*, Oxford University Press, 2006.

[40] E. L. Hamaker and R. P. P. P. Grasman, "To center or not to center? Investigating inertia with a multilevel autoregressive model," *Frontiers in Psychology*, vol. 5, 2015.

[41] S. W. Raudenbush and A. S. Bryk, *Hierarchical Linear Models: Applications and Data Analysis Methods*, SAGE, 2002.

[42] K. Bulteel, F. Tuerlinckx, A. Brose, and E. Ceulemans, "Using raw VAR regression coefficients to build networks can be misleading," *Multivariate Behavioral Research*, vol. 51, no. 2-3, pp. 330–344, 2016.

[43] N. K. Schuurman, E. Ferrer, M. de Boer-Sonnenschein, and E. L. Hamaker, "How to compare cross-lagged associations in a multilevel autoregressive model," *Psychological Methods*, vol. 21, no. 2, pp. 206–221, 2016.

[44] D. Bates, M. Mächler, B. Bolker, and S. Walker, "Fitting linear mixed-effects models using lme4," *Journal of Statistical Software*, vol. 67, no. 1, pp. 1–48, 2015.

[45] E. Snippe, W. Viechtbauer, N. Geschwind, A. Klippel, P. de Jonge, and M. Wichers, "The impact of treatments for depression on the dynamic network structure of mental states: two randomized controlled trials," *Scientific Reports*, vol. 7, no. 1, article 46523, 2017.

[46] L. K. Muthén and B. O. Muthén, *Mplus User's Guide*, Muthén & Muthén, Los Angeles, CA, USA, 1998.

[47] M. A. Cohn, B. L. Fredrickson, S. L. Brown, J. A. Mikels, and A. M. Conway, "Happiness unpacked: positive emotions increase life satisfaction by building resilience," *Emotion*, vol. 9, no. 3, pp. 361–368, 2009.

[48] B. L. Fredrickson, "What good are positive emotions?," *Review of General Psychology*, vol. 2, no. 3, pp. 300–319, 1998.

[49] F. Bryant, "Savoring Beliefs Inventory (SBI): a scale for measuring beliefs about savouring," *Journal of Mental Health*, vol. 12, no. 2, pp. 175–196, 2003.

[50] T. B. Kashdan and J. Rottenberg, "Psychological flexibility as a fundamental aspect of health," *Clinical Psychology Review*, vol. 30, no. 7, pp. 865–878, 2010.

[51] P. Kuppens, L. B. Sheeber, M. B. H. Yap, S. Whittle, J. G. Simmons, and N. B. Allen, "Emotional inertia prospectively predicts the onset of depressive disorder in adolescence," *Emotion*, vol. 12, no. 2, pp. 283–289, 2012.

[52] A. Klippel, W. Viechtbauer, U. Reininghaus et al., "The cascade of stress: a network approach to explore differential dynamics in populations varying in risk for psychosis," *Schizophrenia Bulletin*, vol. 44, no. 2, pp. 328–337, 2018.

[53] B. H. Strand, O. S. Dalgard, K. Tambs, and M. Rognerud, "Measuring the mental health status of the Norwegian population: a comparison of the instruments SCL-25, SCL-10, SCL-5 and MHI-5 (SF-36)," *Nordic Journal of Psychiatry*, vol. 57, no. 2, pp. 113–118, 2003.

[54] L. R. Demenescu, A. Stan, R. Kortekaas, N. J. A. van der Wee, D. J. Veltman, and A. Aleman, "On the connection between level of education and the neural circuitry of emotion perception," *Frontiers in Human Neuroscience*, vol. 8, 2014.

[55] E. B. McClure, "A meta-analytic review of sex differences in facial expression processing and their development in infants,

children, and adolescents," *Psychological Bulletin*, vol. 126, no. 3, pp. 424–453, 2000.

[56] S. Nolen-Hoeksema and A. Aldao, "Gender and age differences in emotion regulation strategies and their relationship to depressive symptoms," *Personality and Individual Differences*, vol. 51, no. 6, pp. 704–708, 2011.

[57] R. P. Bagozzi, N. Wong, and Y. Yi, "The role of culture and gender in the relationship between positive and negative affect," *Cognition and Emotion*, vol. 13, no. 6, pp. 641–672, 1999.

[58] M. Houben, W. Van Den Noortgate, and P. Kuppens, "The relation between short-term emotion dynamics and psychological well-being: a meta-analysis," *Psychological Bulletin*, vol. 141, no. 4, pp. 901–930, 2015.

[59] C. W. J. Granger, "Investigating causal relations by econometric models and cross-spectral methods," *Econometrica*, vol. 37, no. 3, pp. 424–438, 1969.

[60] P. Koval, M. L. Pe, K. Meers, and P. Kuppens, "Affect dynamics in relation to depressive symptoms: variable, unstable or inert?," *Emotion*, vol. 13, no. 6, pp. 1132–1141, 2013.