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Idiographic personality networks: Stability, variability and when they become problematic

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ABSTRACT

Idiographic personality networks are gaining popularity for modeling individual differences, but their validity requires stability, which seems contradicted by theory and empirics. This study employs conventional idiographic network analysis to evaluate inter- and intra-individual variation in youngsters with a mild intellectual disability ($N = 26$; $M_{age} = 23$) who completed 60 daily self-reports. Results show high between-person heterogeneity in network structures, even within subgroups with a similar personality profile. Repeatedly estimating idiographic networks in a sliding 30-day window revealed within-person network variability throughout the 60 days. Both theory and our study suggest non-stationarity, which invalidates aggregated network estimates. This is problematic because capturing individuals' stable personality networks is required to subsequently assess individual differences. We discuss implications for modeling and theory building.

1. Introduction

Personality is traditionally conceptualized in terms of traits that are relatively stable across situations and over time (Allport, 1937; cf. Mischel & Shoda, 1995). Observations of within-person temporal patterns, however, show far more variability than stability over time. In fact, few if any people respond to stimuli completely equally across different and seemingly similar situations over time (Shoda et al., 1994). To account for these idiosyncrasies, personality processes ought to be modeled for each individual separately. Recently this became possible through the introduction of statistically estimated idiographic personality networks (Beck & Jackson, 2020; Costantini et al., 2019; Lazarus et al., 2020; Springstein & English, 2023). Idiographic network models are estimated from intensive longitudinal within-person data, such as ecological momentary assessments (EMA), which are visualized as a person-specific network of statistical associations between different personality components and their interdependencies. Yet, the degree to which idiographic network structures can inform personality theory and research remains unclear. This paper will employ conventional idiographic personality network analysis, with the aim to demonstrate that the stability of these networks is not just theoretically unlikely but also empirically dubious, which may pose a problem for studying individual differences. Stability, in this paper, exclusively implies time-invariance within-persons, not across persons. We first introduce how idiographic personality networks are employed in studies of individual differences, before we elaborate on potential disconnects between personality theory and the assumptions of this new type of model.

Idiographic personality networks are intuitively understandable graphs in which various personality components are represented as nodes, and pairwise interdependencies between them are represented as edges; connections between these nodes (Cramer et al., 2012). Personality components are self-reported behaviors, cognitions and emotions derived from personality surveys, which are taken to be constitutive of traits (Cramer et al., 2012). It is worth noting that idiographic network analysis differs from psychometric network analysis of personality trait surveys (e.g., Borsboom et al., 2021; Chen et al., 2023; Christensen et al., 2020) in the sense that it applies to one individual and does not aim to map out the population-level personality structure. That is, in

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idiographic network analysis the interdependency between nodes is estimated with pairwise partial correlations between time-series of one individual. Statistically estimating the edges is done on two timescales: contemporaneous and lag-1 associations (Epskamp & Fried, 2018), which respectively are 1) covariances of each personality component at time-point *t* with other personality components at the *same* time-point *t* and 2) covariances between each personality component with itself and other components at the *previous* time-point *t*-1. Personality networks thus represent either contemporaneous or delayed interdependencies between various personality components. Idiographic network models thereby enable studying individual differences in personality bottom-up, by first estimating each individual's personality network structure separately and then comparing individuals' networks.

Such comparisons of different individuals have demonstrated high between-person personality heterogeneity – even within sets of variables and samples where larger homogeneity may have been expected based on shared sample characteristics. For instance, Beck and Jackson (2020) showed that estimated idiographic networks of identical personality-related items were highly heterogeneous in a student sample. Most of the research that reveals between-person heterogeneity of idiographic networks, however, has looked samples that share a clinical diagnosis. Dotterer et al. (2020) used idiographic networks to assess the interrelations between negative affect, detachment, impulsivity, and hostility in 91 clients with various personality disorders. Using a procedure that searches for commonalities between edges in idiographic networks (i.e., group iterative multiple method estimation (GIMME)), they found no edge that was significantly present for more than 75 % of the sample, indicating high between-person heterogeneity. Lane et al. (2019) reanalyzed the same dataset to explore idiographic networks for the 35 participants included with a borderline personality disorder, identifying only one association as a group-level edge, once more revealing high between-person differences. Similar heterogeneity was found in various other clinical samples (e.g., Fisher et al., 2017; Reeves & Fisher, 2020).

While between-person network comparisons indicate substantial heterogeneity, there is far less evidence on the stability of idiographic networks within-persons over time. Beck and Jackson (2020) found that some individuals' networks were relatively consistent over two years while other individuals showed vastly different structures across the two waves (cf. Beck & Jackson, 2021; Jackson & Beck, 2021). The lag-1 estimates even demonstrated odd–even and split-half unreliability within-waves (Beck & Jackson, 2020), indicating structural variability over time within a timeframe of two weeks. A small body of psychopathology network studies found similar within-person variability (Nemesure et al., 2022; Wichers et al., 2016). This preliminary evidence of within-person network variability prompts the question what network (in)stability exactly tells us, and what could theoretically be expected.

Theoretical models highlight that assuming stability may be a fool's errand. The Cognitive–Affective Personality System (CAPS; Mischel & Shoda, 1995) and the Knowledge and Appraisal Personality Architecture (KAPA; Cervone, 2005) provided the theoretical incentive for considering idiographic personality network to be informative, while the method also has clear parallels later dynamic systems accounts of personality (Danvers et al., 2020; DeYoung, 2015; Fajkowska, 2015; Nowak et al., 2005; Read et al., 2017; Sosnowska et al., 2019). Their core theoretical claim is that personality is best perceived as a complex system of interacting cognitions and emotions, which is continuously influenced by situational features in ways unique to individuals. The priority of dynamic systems theories is to understand both stability and variability, making them fundamentally different from 'traditional' research in personality that emphasizes trait-based stability and treat any within-person variability as error or situation-induced noise (cf. Mischel & Shoda, 1995; Sosnowska et al., 2019). According to the CAPS and KAPA, the internal personality system always interacts with specific situational features, producing behavioral patterns which are variable across different situations but stable within (similar) situations. Personality stability across situations can best be perceived through *if-then* contingencies (Mischel & Shoda, 1995). For example, *if* John is at a party with friends, *then* he tends to blurt things out, but *if* he is at work *then* he is restrained. The system of internal processes producing such behavioral patterns can vary between people, even when the observed patterns are identical. For one person, lack of self-esteem may cause an *if-then* pattern like John's, whilst for another the cause may be a strong professional self-schema (Cervone, 2005).

Due to the stability of such personality-relevant internal processes (e.g., self-schema's do not change quickly) we perceive stable personality traits. Hence, dynamic systems theories do not posit that the trait impulsivity 'begets' acting without thought (as may appear from latent variable models, e.g., Whiteside & Lynam, 2001), but that acting without thought emerges from a complex interplay between situational features and a relatively stable system of internally interacting personality components. Notably, the stability of traits here comes from self-reinforcement; a synchronized stability of the personality system resulting from the person's tendency to maintain a state of homeostasis relative to the environment (Mischel & Shoda, 1995; Fajkowska, 2015). More simply put, internal personality processes like self-schema's (Cervone, 2005) are not stable of themselves, but cause people to actively seek out situations that strengthen self-schema's. For example, excitement at parties leads John to blurt things out, leading to laughter with friends that reinforces this tendency due to positive feedback and a resultant lack of a (social) need to question this behavior. This feedback loop in turn contributes to more stable, high impulsivity self-assessments (Borsboom & Cramer, 2013). In the network, this is expected to be evidenced by a strong average interrelatedness between relevant personality components (Cramer et al., 2012). When an idiographic network model captures this stable personality system, these models thus can be used to study individual (differences in) personality structures.

However, to successfully capture the individual's personality structure we require theory about the timescale at which personality dynamics occur, because it is unlikely that John's restlessness on Monday 10:00 AM will equally cause him to blurt out things at Monday 11:00 AM, Tuesday 10:00 AM or Friday 7:00 PM. Problematically, neither theory nor empirical evidence indicate which timescale should be selected to track the influence of situational change on the personality system. Moreover, personality processes unfold not at singular but at multiple timescales (Hopwood et al., 2022; Wrzus & Roberts, 2017), which further complicates the matter. Neuroticism, for example, emerges from within-day processes such as neurons firing within seconds (Read et al., 2017) or emotional changes by the minute or hour (Verduyn & Lavrijsen, 2015). Similarly, weekly or monthly processes (e.g., a depressive episode or a romantic relationship) and even processes that may fluctuate across decades (e.g., occupational status) all contribute to neurotic behavior at a certain point in time (Jeronimus, 2015). The current state of the personality as a complex system, at any given moment, self-organizes out of interactions between many processes across different timescales (Wrzus & Roberts, 2017; cf. Olthof et al., 2023; Wallot & Kelty-Stephen, 2017; Wijnants, 2014). Dynamic systems approaches to personality even suggest that the personality system and its reactivity to situational features may change within people over time as a consequence of learning and updating self-relevant beliefs (Cervone, 2005; Mischel & Shoda, 1995). Hence, massively varying idiographic personality networks (e.g., Beck & Jackson, 2021) may theoretically be expected as a consequence of either the chosen timescale, changing situations, learning processes, or a combination of all three.

Idiographic network variability over time relates to stationarity: an important theoretical assumption about the processes that generate the time-series from which networks are estimated (Molenaar, 2004). Contemporary network models assume weak stationarity (Bringmann et al., 2018), which means that the time-series used to estimate the network may be variable over time but may not change in how they vary over time. In other words, the dynamic properties of the patterns (average, lag-1 covariance) need to remain stable over time (Manuca & Savit, 1996). Consider a time-series in which the average changes halfway from 0 in the first half to 6 in the second half. This non-stationarity invalidates a summary statistic like the total average (3), which does justice to neither the first half, second half nor the whole process. Similar to the average in this univariate example, average network estimates are invalid when the weak stationarity assumption is violated. The consequence is that they could gravely misrepresent the actual dynamic process. Weak stationarity is thus necessary to interpret an idiographic personality network as representative of the underlying personality processes.

However, examining (non–)stationarity in networks is not straightforward, because it is possible that a linear combination of multiple non-stationary time-series results in stable average relations between them (cf. cointegration; Hamilton, 1994; Ryan et al., 2023). Currently there is not enough empirical research to verify whether the (weak) stationarity assumption holds in idiographic personality networks. Findings from the few available research (i.e., within-person network variability found in Beck & Jackson, 2021) points in the opposite direction: non-stationarity in the data-generating processes. Examining (non)stationarity further is imperative because we rely on idiographic networks to provide a valid description of someone's personality system, which then forms the basis of inferences about differences in personality structures between people.

The current study will explore how variable personality network structures are *between* individuals and *within* individuals over time. This illustrative study is based on a sample of adolescents and young individuals with a mild intellectual disability or borderline intellectual functioning who participated in a 60-day daily diary study. We first explore the degree of homogeneity of idiographic networks between individuals. Second, we explore homogeneity within subgroups of individuals who, based on traditional personality screening, share a personality profile. Third, we explore network homogeneity within-persons. More specifically, for each individual we assess 1) how variable or stable the networks are over time and 2) whether there is stability in its variability (i.e., stationarity). Based on these three research questions we discuss implications for network modeling and theory building.

2. Methods

2.1. Setting

Participants were recruited in Dutch residential care facilities specialized for youngsters with a mild intellectual disability in combination with complex behavioral problems. According to the DSM-5, a mild intellectual disability is characterized by an intelligence quotient (IQ) between 50 and 69, combined with problems in reasoning, learning, problem solving, and adaptive behavior, impeding a range of everyday social and practical skills (American Psychiatric Association, 2013). Persons with borderline intellectual functioning have an IQ that typically ranges between 70 and 85. Just like their peers with an IQ below the 70 cut-off, they often struggle with the adaptive skills to meet the demands of everyday life. For some people (including our participants) this means that they are in need of care that is considerate of their limited adaptive skills and intellectual functioning (American Psychiatric Association, 2013; Wieland & Zitman, 2016). Due to the shared deficiencies, persons with mild intellectual disability or borderline intellectual functioning have access to the same specialized care in the Netherlands and researchers consequently study them as one group. In this care setting, treatment protocols are tailored to the individuals' specific personality traits (cf. personality-targeted treatment, Gosens et al., 2021; O'Leary-Barrett et al., 2016; Schijven et al., 2021).

2.2. Procedures

Information folders about the daily diary study were distributed to care professionals and youngsters. Youngsters who were interested contacted the researcher, after which they were further briefed about study procedures. Informed consent was then obtained from the participant and – when under age or under legal custody – from the parents or legal guardian. During the intake, the researcher screened the participant's personality profile and explained the daily diary procedure. Participation was rewarded with a gift card worth maximally 75 euros. The Ethical Committee Social Sciences of Radboud University approved current study procedures (ECSS–2020–105).

2.2.1. Personality profiles

Personality-targeted interventions are becoming increasingly popular, particularly in substance use interventions in school- and care settings (e.g., Gosens et al., 2021; O'Leary-Barrett et al., 2016). In such programs the Substance Use Risk Profile Scale (SURPS; Woicik et al., 2009) is administered at intake to evaluate which personality-targeted intervention protocol would fit each individual best. The best fitting protocol targets the personality dimension on which the participant scores highest (i.e., highest z-score). In practice, this protocol is typically referred to as the participant's profile (e.g., John receives intervention for personality profile "Impulsivity"). As such, we similarly administered the SURPS – translated in simplified Dutch wording and with added pictorial stimuli (Poelen et al., 2017 –at intake. This adapted version of the SURPS has demonstrated reliability and validity in people with a mild intellectual disability or borderline intellectual functioning (Pieterse et al., 2020; Poelen et al., 2017). The SURPS consists of four personality dimensions: anxiety sensitivity, negative thinking, impulsivity, and sensation seeking. The questionnaire includes 23 items – seven measuring negative thinking, six for sensation seeking, five for impulsivity and five for anxiety sensitivity. A 4-point Likert scale ranging between (0) 'strongly disagree' and (3) 'strongly agree' was used to score each item.

2.2.2. Daily diaries

During the intake, the researcher helped the participant to install the app Ethica (Ethica, n.d.) on their mobile phone. Through Ethica, surveys were promoted once per day for 60 consecutive days. All participants received this prompt in the evening. The exact evening time was tailored to each participant's convenience, but did not change within individuals throughout the 60 days, ensuring equidistant time intervals within-persons. For example, some participants' diaries prompted at 8:00 PM each day and for some this was at 9:30 PM. All surveys included eight items that the participants self-rated daily. The choice of diary items was guided by both theory about personality network components and appropriateness for EMA. Cramer et al. (2012) suggest items from personality-trait inventories are the best starting points for components of the personality system. We therefore chose two items per construct of the Dutch version of the SURPS (Poelen et al., 2017; Woicik et al., 2009) that were also most pragmatic to answer on a daily basis. That is, items that had the potential to fluctuate between days. "Did you feel happy?" (reverse coded) and "Did you worry about your future?" were indicative of the day's negative thinking. Daily anxiety sensitivity was measured with the items "Did you feel fearful?" and "Did you feel nervous?". "Did you do things that you later regretted?" and "Did you do things without thinking?" reflected daily impulsivity. "Did you do things purely for kicks?" reflected sensation seeking of that day. The seven aforementioned items were derived from the SURPS. Because other sensation seeking items of the SURPS were deemed not appropriate to measure daily in this target group, the last (sensation seeking) diary item "Did you feel restless today?" was derived from the Brief Sensation Seeking Scale (van Dongen et al., 2021). All eight items were self-rated on a slider with five answer options, ranging between (0) "not at all" and (4) "very strongly". The exact wording of the eight items was finetuned to the target group based on input from four youngsters with a mild intellectual disability who piloted the items. Throughout the 60-day diary period, self-ratings of participants on these items were channeled back to their care professionals, to be used as feedback for the treatments they received. The fact that care professional and participant discussed their answers in clinical settings speaks to the validity of the responses given.

2.3. Participants

The current study was part of a larger feasibility study for a personality-targeted substance use prevention program for adolescents and young adults with a mild intellectual disability or borderline intellectual functioning (Hulsmans et al., 2023). In total, 50 participants – which were both substance users and non-users – enrolled in this daily diary study. From these 50, we excluded 20 participants who completed less than 75 % of their diaries (a criterion consistent with Beck & Jackson, 2020). Non-zero variance on each person's variables is essential for idiographic networks. Because the items "Did you feel fearful?" and "Did you do things purely for kicks?" demonstrated zero variance over time for respectively 20 % and 40 % of the 30 participants, these were excluded from analyses. There were four participants who were then excluded due to zero variance on one of the remaining six items, resulting in a final sample of 26 participants that were analyzed.

2.4. Analyses

All analyses were performed in RStudio-2022.02.2-458 (RStudio Team, 2022), which runs on R software (version 4.2.0; R Core Team, 2020). The dataset is available upon request from 10.17026/dans-z92-yv4x and R scripts are publicly available via 10.17605/OSF.IO/TFBPS. There were five distinct aspects to this study's analytic strategy that are described below.

2.4.1. Attributing personality profiles

Per participant, we computed a z-score for each of the four SURPS dimensions (i.e., negative thinking, anxiety sensitivity, impulsivity, and sensation seeking). The normative M and SD that were used to calculate z-scores were derived from SUPRS data of 275 other individuals with a mild intellectual disability (obtained from Pieterse et al., 2020; Poelen et al., 2017; Schijven et al., 2021). A participant's personality profile was then determined based on the highest z-score (cf. O'Leary-Barrett et al., 2016).

2.4.2. Autocorrelation structures

Before we estimate idiographic personality networks, we explored the full autocorrelation structure with R function *acf* of each participant's multivariate timeseries. Whereas networks can only estimate dynamic patterns across two timescales (lag-0 and lag-1), autocorrelation functions reveal interactions across all possible timescales. For example, whether happiness is correlated with restlessness seven days ago (lag-7) or a month ago (lag-30). Exploring this is important, because when theoretical support for a single timescale of personality-related dynamics is lacking (see Introduction) then an informed decision about which timescale to (not) model should be data-driven. If the dynamics manifest predominantly at lag-0 and lag-1 but not beyond, then conventional networks on these two timescales are justified. To assess this within our sample, we counted statistically significant autocorrelations (evaluated at $p < 0.01$) per lag and divided by the maximum number of evaluated autocorrelations. This provides the percentage of statistically significant autocorrelations for one lag across participants, relative to all meaningful bivariate comparisons. At lag-1 and beyond, all variables may meaningfully covary with their own and others' previous values. At lag-0, each variable may meaningfully covary with other's but not with itself (i.e., per definition correlation of 1), which is why these same-variable same-timepoint autocorrelations were not considered when calculating this relative percentage for lag-0.

2.4.3. Estimating idiographic networks

We then estimated idiographic network models. Because network analyses cannot handle missing data, missing data-points were first imputed using a structural model fitted by maximum likelihood and Kalman smoothing (Moritz & Bartz-Beielstein, 2017). We iterated through each of the 26 participants, employing a Gaussian graphical vector autoregression model (GVAR) with functionality from R package *graphicalVAR* (Epskamp et al., 2018). GVAR essentially entails estimating a sparse contemporaneous and lag-1 partial correlation matrix. One such matrix is 6 rows and 6 columns, such that all 6 variables are compared to one another. All parameters (i.e., edges) in the contemporaneous model (lag-0) are estimated after conditioning for all other associations between variables at lag-0 and lag-1. To control for model complexity, they are constrained with the graphical least absolute shrinkage and selection operator (LASSO: Friedman et al., 2008, cf. Morosan et al., 2020). This is a regularization technique appropriate for ordinal data – making weak and likely spurious associations to be estimated at exactly zero. GVAR does both model parameter estimation and model selection. That is, all possible models are iteratively estimated and the best fitting one (i.e., the one with the lowest Extended Bayesian; Chen & Chen, 2008) is selected. The model with the optimal model fit is then visualized as a network using functionality from R package *qgraph* (Epskamp et al., 2012). For more detail on GVAR and regularization, see Epskamp et al. (2018) or Epskamp and Fried (2018). We present networks only on the contemporaneous timescale and not on a lag-1 timescale. This was done because 1) the lag-1 personality networks previously demonstrated within-person unreliability (Beck & Jackson, 2020), 2) we deemed it unlikely that the processes we measured map onto one day-to-day timescale (e.g., Johns feeling restless on day 1 is more likely to make him blurt things out the same day than tomorrow) and 3) preliminary data-explorations confirmed the previous, showing long-term autocorrelations beyond lag-1 in various idiosyncratic ways (explicated in Section 3.2).

2.4.4. Between-person heterogeneity in within-person associations

In the iterative process of estimating each of the idiographic networks, we generated 6x6 data matrices that contained the counts of all non-zero (i.e., significant) bivariate partial correlations at the individual level. These matrices provide the input for comparing within-person associations within the sample and within subgroups with the same personality profile. In each matrix the rows and columns reflected each of the six variables. Statistically significant positive partial correlations were saved in one diagonal of the matrix and the significant negative partial correlations in the other diagonal, so that heterogeneity in direction of partial correlations could also be assessed. One matrix contained the counts of all statistically significant associations between individuals of the whole sample, while the other matrices only contained counts of statistically significant associations for individuals within a specific subgroup. For example, one matrix reflects the counts of all sensation seekers. Functionality from *qgraph* (Epskamp et al., 2012) was used to visualize group-level networks that reflect the degree of homo- or heterogeneity within the sample and subgroups.

2.4.5. Within-person network variability and change

In this last step we aimed to quantify and visualize within-person variability and change in the idiographic network structures over time. Using a sliding day window technique, we repeatedly estimated the idiographic network structure in segments of 30 consecutive days along the participant's 60-day timeline. This means the network was first computed based on data-points between day 1 and day 30, then again between day 2 and day 31, and so on. For each participant, within each window, we calculated the node strength using package *qgraph* (Epskamp et al., 2012). Node strength quantifies how strongly a node is connected to other nodes in the network and is thereby indicative of the overall network structure, equivalent to how items with high loadings explain a lot of variance in factor analysis (Christensen & Golino, 2021;

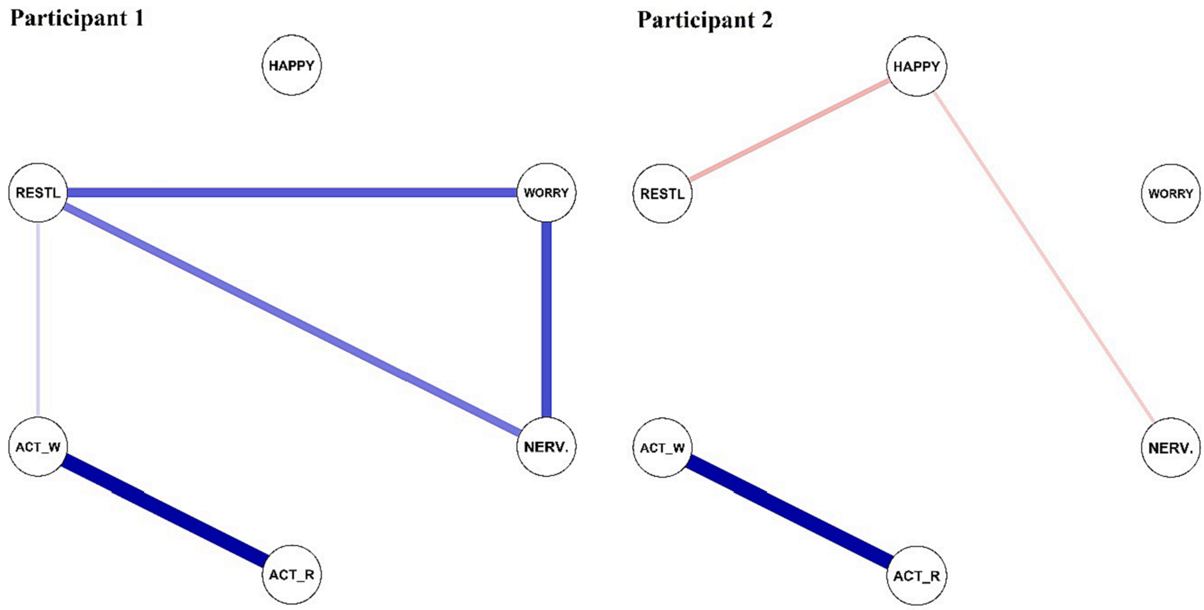

Fig. 1. Idiographic networks of the 60-day dairy data from two participants. Note. Nodes reflect the six measured diary variables. HAPPY = happiness. WORRY = worrying about the future. NERV. = nervousness. ACT_R = acts that lead to regret. ACT_W = acts without thinking. RESTL = restlessness. Edges reflect significant associations within that individual over time. Blue edges are positive partial correlations. Red edges are negative partial correlations. Thicker edges reflect a higher partial correlation coefficient, relative to that participant. Non-significant edges are pruned.

Hallquist et al., 2021). To obtain the variability between estimated idiographic network structures across the 30 windows, we calculated the standard deviation between these 30 node strengths. We present these per participant, per node and averaged across nodes. To exploit the intuitiveness of networks we decided to visualize within-person variability. To do so, we counted all within-window statistically significant edges and presented these counts in summarizing networks of idiographic homogeneity. However, this only indicates variability between idiographic networks, but it does not show how stable network variability is over time (i.e., (non)stationarity). To illustrate change over time, the temporal sequence of networks was plotted in an animated video through the *graph.animate* function (Epskamp et al., 2012). These videos were created separately for each participant. Visual inspection of dynamic network videos provided us with a first impression on network changes over time and how this occurred. That is, some variability of networks that is inconsistent over time would indicate non-stationarity. Lastly, Kernel change-point analysis, as implemented in *kcpRS* (Cabrieto et al., 2022), was used to examine changes in the original idiographic network's correlation structure within overlapping 30-day windows statistically differed from those of 1000 permutations at $p < 0.05$. This was done for each individual, allowing us to evaluate if (and when) there was at least one statistically significant change-point in the estimated idiographic network structure. Such a sudden change from one stable network structure to another stable structure would provide more conclusive evidence of non-stationarity and indicate that idiographic network change was potentially meaningful.

3. Results

3.1. Sample description

The sample ($N = 26$) consisted of adolescents and young adults with a mean age of 22.7 years ($SD = 5.5$; range 15–33). Their average IQ was 72.3 ($SD = 10.4$). There were slightly more women ($n = 15$, 58 %) than men. The case records of 21 participants (81 %) showed one or more DSM-5 based diagnoses comorbid to their intellectual disability. We counted 14 unique comorbidities, of which posttraumatic stress disorder ($n = 7$) and autism spectrum disorder ($n = 4$) were the most recurring. A personality profile was estimated for each participant, based on the relative difference of their scores on the SURPS (Woicik et al., 2009) compared to a norm group. There were 9 individuals (35 %) with negative thinking as the most prominent profile, 8 had anxiety sensitivity (31 %), 6 impulsivity (23 %), and only 3 had a sensation seeking personality profile (12 %).

3.2. Autocorrelation structures

We now explore the autocorrelation functions of each participant. These analyses do not evaluate network structures, but rather characterize the dynamics across all possible timescales within the time-series that will be the input for idiographic network models in the next steps. Appendix A shows the counts and percentages of autocorrelations that were significant at $p < 0.01$ across all 26 participants, across all possible timescales (lag-0 to lag-59). Autocorrelation functions further demonstrate associations on both short time-lags (e.g., 11.9 % at lag-1 and 5.7 % at lag-2) and longer time-lags. For example, 3.5 % at lag-7 (exactly one-week) and 2.2 % at lag-14 (exactly two weeks). Most within-person bivariate correlations (38.7 % of all bivariate comparisons) can be found at the same-day timescale (lag-0), supporting the contemporaneous timescale as the most appropriate for estimating the networks.

3.3. Idiographic networks

For each participant, an idiographic network model was estimated over the complete 60-day timescale. In Fig. 1 we present the contemporaneous networks of two participants as an illustrative example. Participant 1 had five bivariate partial correlations that were significantly non-zero. Worrying about the future was positively associated with nervousness ($r = 0.09$)[1] and restlessness ($r = 0.08$). Restlessness was also positively associated with nervousness ($r = 0.07$) and acting without thinking ($r = 0.02$). The latter showed a relatively strong

[1] Please note that partial correlation coefficients have been shrunk due to the LASSO regularization technique, so interpretation differs from that of r in traditional linear regression.

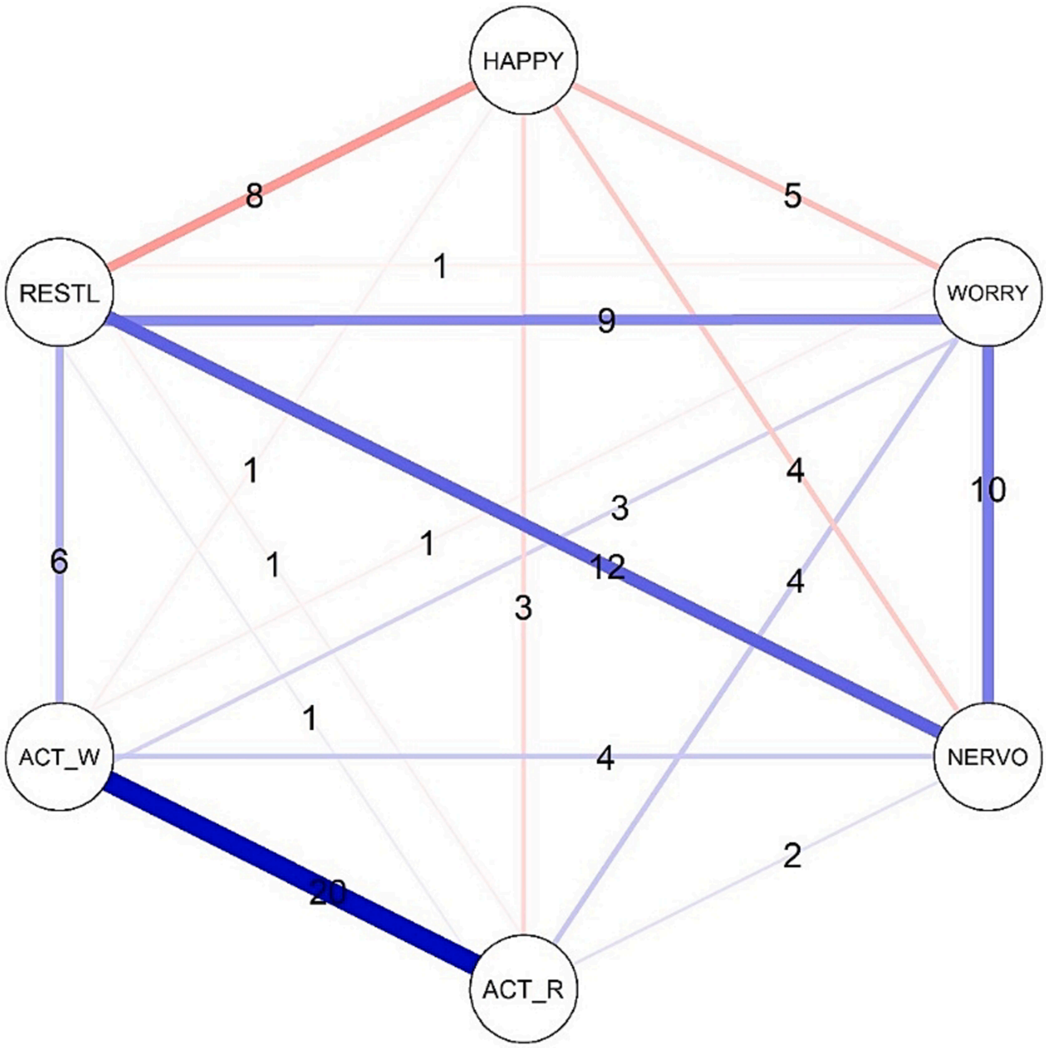

Fig. 2. Network visualization of between-person heterogeneity in whole sample (N = 26). Note. Nodes reflect the six measured diary variables. HAPPY = happiness. WORRY = worrying about the future. NERVO = nervousness. ACT_R = acts that lead to regret. ACT_W = acts without thinking. RESTL = restlessness. Edges reflect the count of all significant associations in idiographic networks. Blue edges are the counts of positive partial correlations. Red edges are the counts of negative partial correlations. Thicker edges reflect a higher number of individuals who had a particular bivariate association significant.

association with doing things that were later regretted (r = 0.13). Similar to participant 1, the association between doing things that were later regretted and acting without thinking was the strongest association for participant 2 (r = 0.26). Daily levels of happiness were negatively associated with restlessness (r = −0.08) and nervousness (r = −0.05).

3.4. Between-person differences in networks

After estimating idiographic networks for all 26 participants, we evaluated (dis)similarities between them. Fig. 2 presents these (dis) similarities in one summarizing network. The interpretation of the edges here is different from Fig. 1. Whereas edges in each of the idiographic networks (Fig. 1) reflect significant partial correlation coefficients, the edges in Fig. 2 reflect the count of significant edges across each of the idiographic networks. A small number of thick edges would reflect between-person homogeneity and the presence of many thin edges indicates high degree of between-person heterogeneity. Some edges were common amongst individuals. For example, 20 participants (77 %) had a significant positive association between doing things that were later regretted and doing things without thinking. Other edges were less common between individuals, for example, nervousness was positively associated with restlessness (n = 12, 46 %) and worrying about the future (n = 10; 38 %). Moreover, the many thin edges in Fig. 2 reflect a high degree of between-person heterogeneity in our sample. This was also reflected in the direction of bivariate associations in the different idiographic networks (negative vs. positive). For instance, there were three participants who, on average, worried more about their future on days when they reported *higher* levels of acting without thinking (three blue edges between the nodes in Fig. 2), but there was also one participant who tended to report *less* worrying about the future on days when self-report about acts without thinking were higher (1 red edge between these two nodes).

The summary networks with edge counts for each personality profile (Woicik et al., 2009) can be found in Fig. 3 and on https://hulsmans.shinyapps.io/IdiographicNetworks/. There was heterogeneity in idiographic network structures within all subgroups of individuals who share the same personality profile.

3.5. Within-person network variability and change

To further explore (non)stationarity of the process that generates idiographic network models, we evaluated the degree to which they each changed in structure over time. Table 1 presents the variability of node strengths between each idiographic 30-day window network. This

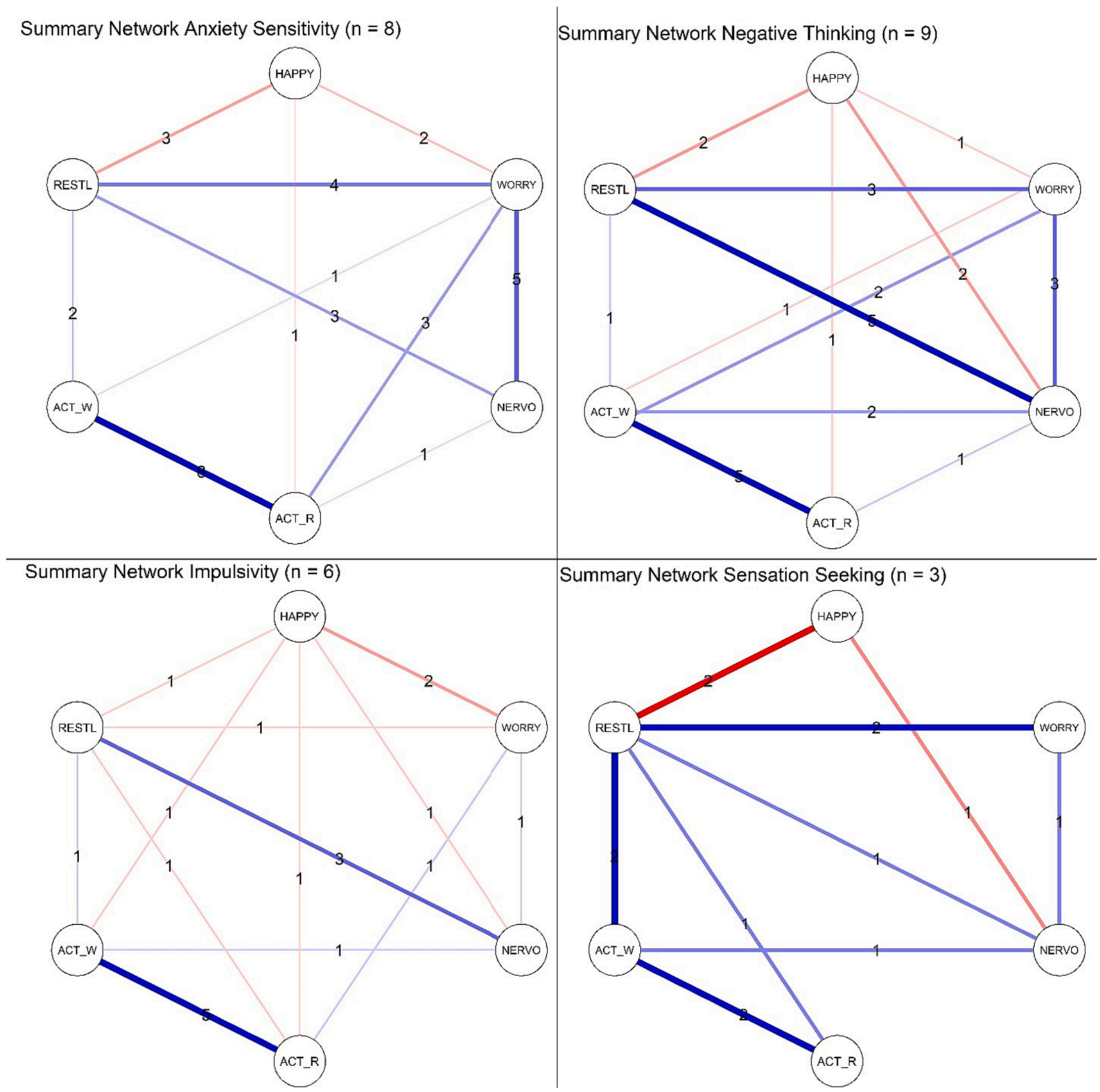

Fig. 3. Network visualization of between-person heterogeneity in each of the four personality-risk profiles Note. Nodes reflect the six measured diary variables. HAPPY = happiness. WORRY = worrying about the future. NERVO = nervousness. ACT_R = acts that lead to regret. ACT_W = acts without thinking. RESTL = restlessness. Edges reflect the count of all significant associations in idiographic networks. Blue edges are the counts of positive partial correlations. Red edges are the counts of negative partial correlations. Thicker edges reflect a higher number of individuals who had a particular bivariate association significant.

shows that some participants' network estimations were more variable than others. For example, participant #23's network model was relatively variable over time (average *SD* of all node strengths = 3.92). For this participant, in particular nervousness was extremely variable (*SD* node strength = 12.79). The most time-invariant network structures in our sample were those of participant #24 and #29 (average node strengths *SD* of 0.17 and 0.18, respectively). There was no correlation between idiographic network variability (i.e., average *SD* of all node strengths) with any of the four trait levels (anxiety sensitivity, negative thinking, impulsivity, sensation seeking as measured with the SURPS).

What does this idiographic network variability over time look like? So far, all idiographic networks (e.g., the two examples in Fig. 1) summarize partial correlations for the entire 60-day timeline. Now, we estimate partial correlations between the six variables, per individual, within each 30-day epoch on that 60-day timeline, and visualize these as networks. Fig. 4 shows the idiographic network structures for day 1–30, day 16–45, and day 31–60 for the same two participants as depicted in Fig. 1.

Based on the SURPS, Participant 1's personality profile (i.e., the highest dimension *z*-score) was anxiety sensitive. Associations with nervousness – an item derived from the anxiety sensitivity scale in the SURPS – changed throughout her 60-day timeline. On average, between day 1 and day 30, she reported higher levels of nervousness on days with higher levels of restlessness evidenced by the blue edge between those nodes. When estimating the network in other window (day 16–45 or 31–60), the association with restlessness had disappeared. In the last time window (day 31–60), the positive association between nervousness and worrying appears. From all five bivariate associations of this participant in Fig. 1, none occur in each of the 30 windows. That is, the rightmost panel in Fig. 4 shows no count of statistically significant edges across all windows that adds up to 30.

Scores on the SURPS of Participant 2 resulted in personality profile impulsivity. Fig. 4 demonstrates that, in three example 30-day windows, he had a positive association between the two impulsivity items (doing things without thinking and doing things that were later regretted). In fact, these were significant across all 30 windows (see rightmost panel Fig. 4). The overall structure of the network is very similar between the windows 1–30 and 16–45. However, the connectivity between all six variables substantially increased in the network that reflects day 31 to day 60. The structure of his networks changed over time, albeit to a lesser extent than for Participant 1. Nevertheless, we reach the same conclusion: the network that summarizes his 60 days (Fig. 1) differed

Table 1
Standard deviations of all node strengths of idiographic networks across all 30-day windows.

Participant ID	Happy node strengths SD	Worrying node strengths SD	Nervous node strengths SD	Act without thought node strengths SD	Act later regret node strengths SD	Restless node strengths SD	Mean of all six node strengths SDs
# 2	0.19	0.30	0.18	0.16	0.31	0.20	0.22
# 4	0.44	0.70	0.46	0.74	0.59	0.26	0.53
# 8	0.47	0.34	0.15	0.23	0.26	0.20	0.28
# 9	0.22	0.24	0.23	0.34	0.23	0.28	0.26
# 10	0.38	0.27	0.09	0.37	0.22	0.34	0.28
# 12	0.29	0.12	0.23	0.24	0.24	0.15	0.21
# 18	0.61	0.27	0.27	0.60	0.22	0.15	0.35
# 19	1.55	0.30	0.21	0.32	0.14	0.52	0.51
# 20	0.53	0.44	0.23	0.45	0.21	0.45	0.39
# 22	0.16	0.12	0.19	0.22	0.20	0.26	0.19
# 23	2.32	0.48	12.79	1.17	5.06	1.70	3.92
# 24	0.21	0.14	0.12	0.28	0.10	0.19	0.17
# 25	0.20	0.25	0.16	0.11	0.22	0.26	0.20
# 26	0.24	0.20	0.43	0.17	0.16	0.23	0.24
# 28	0.19	0.44	0.19	0.40	0.33	0.35	0.32
# 29	0.25	0.18	0.17	0.14	0.13	0.22	0.18
# 30	0.25	0.26	0.30	0.32	0.15	0.20	0.25
# 31	0.20	0.22	0.23	0.20	0.23	0.31	0.23
# 32	4.36	0.41	0.27	3.74	0.29	0.26	1.55
# 35	0.54	0.28	0.22	0.19	0.27	0.30	0.30
# 36	0.49	0.59	0.38	0.51	0.42	0.29	0.45
# 37	0.64	0.23	0.11	0.64	0.14	0.26	0.34
# 38	6.19	1.00	0.78	1.53	0.32	0.53	1.73
# 42	0.16	0.20	0.48	0.48	0.27	0.23	0.30
# 44	0.15	0.36	0.22	0.22	0.23	0.40	0.26

Note. Each cell reflects the SD of the node strengths for that item across each 30-day window. A higher SD indicates high variability in the connections of that node over time. The last column shows mean of all six item node strength SDs and is thereby indicative of the overall consistency of the network structure. A value here indicates that the network was more variable over time.

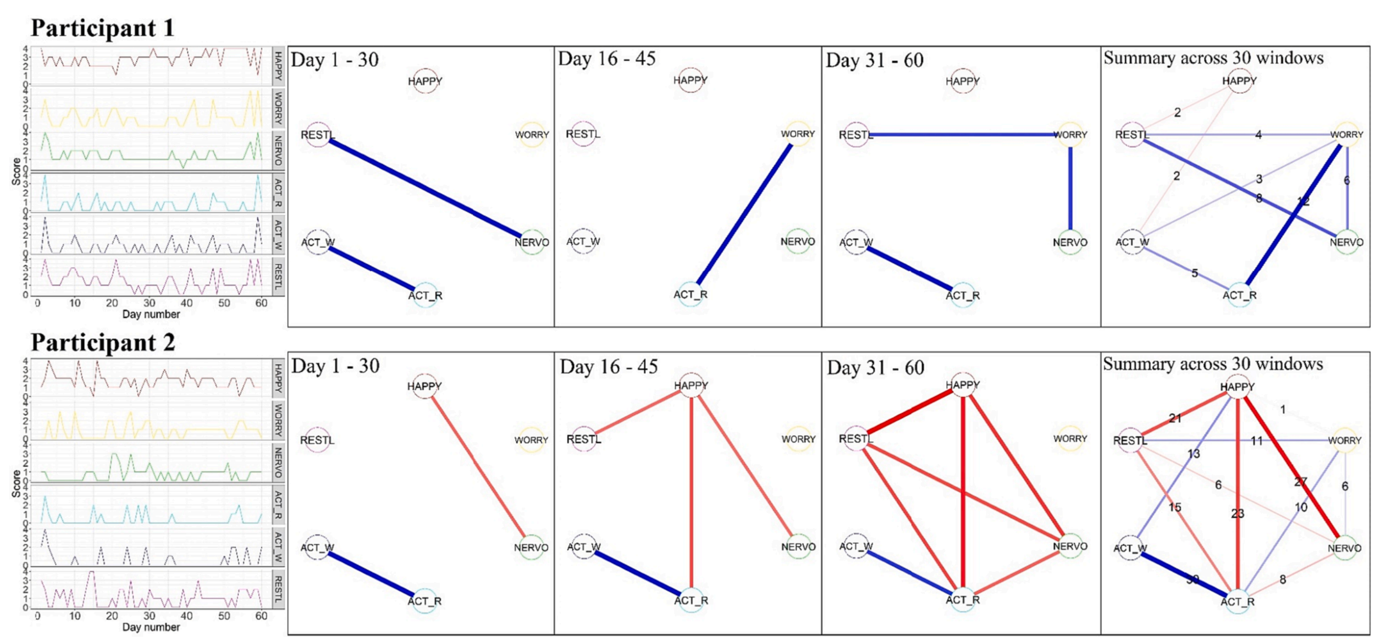

Fig. 4. *Two participants' raw timeseries, idiographic networks of three example 30-day windows, and a summary network of their within-person homogeneity across all possible 30-day windows (30) on the 60-day diary period. Note.* The left panel visualizes raw timeseries of happiness, worrying about the future, nervousness, later regretted acts, acts without thinking, and restlessness. Colors of these timeseries correspond to edge circles in idiographic networks. Idiographic networks show partial correlations in three 30-day windows that summarize, from left to right, day 1–30, day 16–45 and day 31–60. All edges here reflect significant partial correlations within that individual over time. Blue edges are positive partial correlations. Red edges are negative partial correlations. Non-significant edges are pruned. Thicker edges reflect a higher partial correlation coefficient. The rightmost networks show the counts of all significant edges across all possible windows (30) on the timeline. Thicker edges here indicate a higher count of significant edges across the windows. For example, a count of 30 thus indicates that this edge was significant across all windows. Alternatively, if there is no edge in the summary plot then this edge was not significant in any window.

from that of the 30-day epochs within his entire timeline.

The dynamic network videos of each of the 26 participants can be found on https://hulsmans.shinyapps.io/IdiographicNetworks/. These videos visualize how the sequence of idiographic network structures changes between all possible overlapping 30-day windows along each participant's 60-day timeline. Although the network structures of some individuals changed more drastically over time than for others (e.g., the videos and Table 1 show that there is more consistency over time for participant #24 than for participant #23), *some* non-stationarity was evident in all participant's network structures. Nevertheless, Kernel change-point analyses revealed no statistically significant change-points in pairwise correlations between windows for all but one participant (except #28). This indicates that – although different time-windows for each person yield (sometimes vastly) different network structures (see dynamic network videos) – this within-person heterogeneity cannot be reduced to a single time-point that marks a change from one stable phase to another.

4. Discussion

The current study explored idiographic network structures of adolescents and young adults with a mild intellectual disability or borderline intellectual functioning who completed a personality-related daily diary for 60 days. More specifically, we evaluated how variable personality networks were *between* individuals and *within* individuals over time. We found high between-person heterogeneity in network structures across the sample. Comparisons of the idiographic networks among individuals with a similar personality profile (Woicik et al., 2009) reveal similarly high levels of between-person heterogeneity. These findings are in line with the heterogeneity that is repeatedly found in other idiographic networks in various samples (e.g., Dotterer et al., 2020; Fisher et al., 2017; Reeves & Fisher, 2020). Our results further show that networks structures were not only variable between persons, but also varied within persons over time. Repeatedly estimating idiographic personality networks in a sliding 30-day window showed the structures to be variable throughout the 60-day timeline for all participants – although the degree of within-person network variability differed between persons (Table 1). This echoes the within-person network inconsistencies that Beck and Jackson (2020) found between EMA waves two years apart and even within a two-week EMA wave.

How to interpret network variability over time is connected to one's conceptualization of personality. Under the theoretical assumption that the personality system is time-invariant, time-varying idiographic networks can be considered the result of unreliably estimating that 'true' average personality system (e.g., split-half network unreliability in Beck and Jackson (2020, 2021)). However, dynamic systems theories expect structural variability when learning takes place and when situations significantly differ (e.g., Mischel & Shoda, 1995). The variability we find at the n = 1 level over time, visualized with dynamic network videos, showcases non-stationarity. The consequence is that averaged network estimates (i.e., edges) misrepresent the actual dynamic process. For studying individual differences this is detrimental, because it casts doubt on the validity of the summary statistics (i.e., average relations between personality components) upon which between-person comparisons are based.

Yet, there are several theory-informed explanations for the non-stationarity. First, Mischel and Shoda (1995) indicate that the personality system can change due to learning or updating self-beliefs. Participants in our study received treatment, possibly inducing learning and updating self-beliefs, which would explain the non-stationarity. Indeed, interventions are associated with changes in personality traits (Roberts et al., 2017). However, if this was the case, we would have expected to see change-points from one stable network to another stable network over time, which our change-point analyses did not reveal. We therefore deem it unlikely that intervention-induced learning was responsible for the variability in the idiographic networks over time. The second explanation, being that unobserved situational changes underlie non-stationarity, is more probable. Dynamic systems approaches to personality all stress the inseparability between the internal personality system and situational features (Cervone, 2005; Danvers et al., 2020; DeYoung, 2015; Fajkowska, 2015; Mischel & Shoda, 1995; Nowak et al., 2005; Read et al., 2017; Sosnowska et al., 2019). However, current idiographic personality network studies (Beck & Jackson, 2020; Costantini et al., 2019; Lazarus et al., 2020) – our study included – did not model the situations. Previously, the situational *if-then* signatures (e.g., *if* John is excited at a party with friends, *then* he tends to blurt things out, but *if* he is excited at work *then* he is restrained; Mischel & Shoda, 1995) have even been projected on a temporal lag-1 personality network structure (*if* John is excited now *then* he blurts things out later; Beck & Jackson, 2020), without including variable coding for situational features. Notably, empirical studies into situational *if-then* signatures (e.g., Shoda et al., 1994) relied on psychological perceptions of situations, which of course also differs between persons (what is exciting for John may not be exciting for someone else). The CAPS, KAPA and other dynamic systems theories posit that the internal personality system – in continuous interaction with the situations – produces behavioral patterns which are variable across different situations but relatively stable within (similar) situations (Cervone, 2005; Mischel & Shoda, 1995). As such, the non-stationarity we found most likely shows that an idiographic network does not capture (changes in) the underlying personality system, but rather reflects unobserved changes in situational features from day to day.

This does not mean that networks in principle cannot capture the underlying (relatively stable) personality system. What we need is theory to inform research about three crucial elements. Firstly, we need to know the timeframe within which a stable personality network can be found. With our once-per-day measurement frequency and duration of two months, we found high variability of estimated idiographic network structures over time. Had we measured longer, would that have resulted in a stationary pattern? The evidence for long-term trait-stability is not entirely clear-cut. Life events (e.g., graduation, marriage, parenthood) have been associated with within-person changes at the trait-level (Bleidorn et al., 2018; Wrzus & Roberts, 2017). Thus, over a lifespan, the mean-level of personality traits change within-persons (Roberts & Mroczek, 2008) and these change trends differ between-persons (Schwaba & Bleidorn, 2018). Given this, theory should inform research about the duration of the timeframe.

Secondly, within any timeframe, we need to know at which timescale (s) the dynamics should be summarized in a network. By only estimating contemporaneous networks (i.e., the same day), we refrained from attributing temporality to lagged effects in networks. Within-day dynamics, however, remain hidden due to diary surveys not being momentary (e.g., there can be multiple impulsive moments during a day). Nevertheless, temporality manifests within a myriad of different short and long timescales, as evidenced by the autocorrelation functions in Appendix A. Not estimating lagged effects is not a solution to the non-stationarity problem per se, but at least avoids (implicitly) suggesting that dynamics manifest on one (lag-1) timescale only. Instead, the dynamics of complex systems interact across multiple timescales. Many fast and slow processes are interdependent and, in interaction with their environment, lead to the emergence of behavior (Olthof et al., 2023; Wallot & Kelty-Stephen, 2017). This interdependence across multiple timescales is not entirely new to research in personality (Hopwood et al., 2022; Wrzus & Roberts, 2017), but it is incongruent with the common practice of summarizing idiographic dynamics within a network at one or two time-lags. A theoretical account about how to understand interactions among personality processes on multiple timescales in networks is lacking.

Thirdly, we need to know what the to-be-modeled personality network components are. Cramer et al. (2012) suggested to use items from personality-trait surveys as a starting point for selecting the personality components, so we derived our variables from a personality-trait inventory (Woicik et al., 2009) that were also appropriate for a daily diary (i.e., having the potential to fluctuate from day to day). Selecting items from trait-inventories as nodes in idiographic personality network estimation is standard practice (Beck and Jackson, 2020, 2021). According to Cramer et al. (2012), individual differences can be assessed by "allowing for individual differences in components and the strengths of the connections among them" (p. 420). Empirical science has only achieved the latter, as standardizing the set of variables across participants is common practice. That is, we compare between-person differences in edges – not components. Pressing theoretical paucities are thus is 1) which personality components to model and 2) whether these differ between individuals. The most significant theoretical implication within dynamic systems accounts lies in the necessity of explicitly incorporating *if-then* contingencies. People are relatively stable within situations, but the behavioral pattern is highly variable as a result of encountering different situations over time (Cervone, 2005; Mischel & Shoda, 1995). Recent idiographic research using machine-learning has shown considerable between-person differences in which situational features are personally relevant and the degree to which situations were predictive of behavior (Beck & Jackson, 2022). Thus, when estimating idiographic personality networks, researchers need to identify which situational features and internal components need to be modeled, and whether that differs between individuals. As a preliminary step, Bringmann et al. (2022) recently suggested conditions for selecting the network's components. They pointed out that, in theory, nodes of psychological networks should be separately identifiable (i.e., able to be assessed separately) and independently malleable (i.e., outside influences should be able to have an effect on a node without it affecting any other nodes).

Instead of trying to theorize non-stationarity away, it also possible to embrace non-stationarity as a feature of the personality system. Most analytical advances, however, characterize it as a to-be-overcome challenge (Ryan et al., 2023). It is worth noting that statistical timeseries analyses advance quickly, now allowing for some non-stationarity in the form of gradual mean-shifts (Bringmann et al., 2018) or a-priori specifications of the number of stable states the system has (e.g., Haslbeck & Ryan, 2021). Most of these models still assume that interactions among the variables are linear. There are, however, methodologists that move away from the linearity assumptions of statistical models and develop nonlinear analytical toolboxes. Nonlinear dynamics can for example be modeled with recurrence networks, in which the nodes represent time points, the edges connect recurring values, and the weights of the distance in time between two recurring values (Hasselman & Bosman, 2020). Although this descriptive method does not assume stationarity, it is considerably harder to intuitively interpret these networks. In terms of intuitiveness, linear models have an advantage, which is perhaps why they are more popular. However, our study demonstrates that this intuitiveness may be misleading. We therefore encourage future research to employ alternative network models (e.g., Bringmann et al., 2018; Hasselman & Bosman, 2020; Haslbeck & Ryan, 2021) when estimating idiographic personality structures. Importantly, this study showed that the GVAR model (Epskamp et al., 2018) did not accurately grasp stable personality within our sample. Also (more) advanced linear network analyses should not automatically be assumed to yield valid aggregated network estimates. Stationarity should always be examined.

Our primary recommendation for future research is to include situational information in the data collection. With information about the context it is possible to model personality as consisting of multi-level networks, where quick-varying situational features and behaviors, intermediately varying moods and/or evaluations and slow-changing internal processes are placed in separate but interacting layers of the model (Kivelä et al., 2014; cf. de Boer et al., 2021). This would allow the multiple relevant timescales to be studied at once. Importantly, the solution to non-stationarity is not just statistical but also theoretical. Estimating a stable idiographic personality network may never be achieved when the timeframe, timescale(s) and situational features (Cervone, 2005; Mischel & Shoda, 1995) remain unspecified. It is our contention that even the most advanced statistical models will not solve the problems demonstrated in this study. Therefore the ultimate challenge for personality researchers who wish to employ idiographic networks to study individual differences is to start with further theory building.

The current study has some limitations. Particularly around idiographic network variability over time we build on limited evidence, which warrants cautious conclusions. That is, we cannot automatically assume our non-stationarity findings are generalizable, because we do not know how representative our sample is for the population in terms of personality network stability. Current personality theory, on the other hand, also does not inform us about which demographic variables influence personality stability. Future research should explore this further in different samples with different demographics. Second, we based our networks on 60 time-points per individual. A recent simulation study suggest that this may be underpowered, which makes for an increased possibility we mistake noise for true between- or within-person heterogeneity (Hoekstra et al., 2022). Future research is encouraged to compare idiographic networks estimated from sufficiently large segments (e.g., assuming it is feasible, windows with 300 data-points within a timeseries with 600 time-points). Importantly, when the data-generating processes are in fact non-stationary, variability over time remains a realistic prospect and it will still be unclear what inferences we can derive from the average network.

In a more general sense, the current paper illustrates that conclusions about personality based on between-person structures (such as the attributing of SURPS profiles) and within-person structures (idiographic network models) are not compatible (cf. Brose et al., 2015). This stresses the need for an idiographic perspective complementary to the nomothetic perspective that dominates research on personality. Idiographic networks are one intuitive route to grasping the complex dynamics of personality. However, both theory (Cervone, 2005; Mischel & Shoda, 1995) and our empirical study demonstrated non-stationarity in the data-generating processes, which invalidates aggregated network estimates. This is problematic because capturing the individual's stable personality network is required to subsequently assess individual differences. Advances in network analysis currently outpace the theory, while it should be theory that informs analyses about the phenomena they are trying to model. We therefore hope our findings encourage further theory building.

5. Open practices

The current paper is based on a data collected as part of a larger project. Data collection procedures relevant for this paper, such as personality screening and daily diaries, were pre-registered at https://doi.org/10.17605/OSF.IO/7T2YX. The current paper's research questions and analyses were largely exploratory and were therefore not pre-registered.

CRediT authorship contribution statement

Daan H.G. Hulsmans: Conceptualization, Data curation, Investigation, Methodology, Writing – original draft, Writing – review & editing, Formal analysis. **Freek J.W. Oude Maatman:** Conceptualization, Methodology, Writing – review & editing. **Roy Otten:** Conceptualization, Funding acquisition, Methodology, Supervision, Writing – review & editing. **Evelien A.P. Poelen:** Conceptualization, Funding acquisition, Methodology, Project administration, Supervision, Writing – review & editing. **Anna Lichtwarck-Aschoff:** Conceptualization, Methodology, Supervision, Writing – review & editing.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The dataset is available upon request from https://doi.org/10.17026/dans-z92-yv4x and R scripts are publicly available via https://doi.org/10.17605/OSF.IO/TFBPS.

Appendix A. Supplementary material

The supplementary table that presents results of the autocorrelation analyses can be found online at https://doi.org/10.1016/j.jrp.2024.104468.

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