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Day-to-day variation in perceived causal networks: a feasibility study in two psychiatric settings

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Abstract

Purpose

The network approach conceptualizes psychopathology as systems of causally interacting problems of living, more or less unstable over time. Longitudinal Perceived Causal Networks (L-PECAN) is a self-report method designed to capture day-to-day variability in patients' perceived causal relations between problems. We examined the feasibility of an L-PECAN procedure in two clinical settings and explored within-person variability in structures.

Methods

Patients in two psychiatric clinics first completed a training week using a generic item list. Based on this, personalized items were formulated and used for at least three additional weeks. Feasibility was evaluated via recruitment rates and adherence. Within-person variability was examined using saturation and drift analyses.

Results

Eight patients completed the protocol. As expected, daily assessments were completed quickly, and participants largely perceived their personalized nodes as being caused by the other nodes. Some causal relations were perceived across days, but overall network structures showed substantial day-to-day variability.

Conclusions

An L-PECAN procedure, with a training week and personalized nodes, appears feasible in higher-functioning psychiatric patients and offers a structured way to examine within-person variability in perceived causal problem networks. Such variability may be clinically informative when investigating cyclical (e.g. menstrual) or context-dependent patterns. Further research is needed to evaluate validity and clinical utility.

Background

Diagnostic categories in psychiatry are broad constructs that encompass substantial heterogeneity across individuals (Allsopp et al., 2019). Precision psychiatry aims to identify clinically meaningful differences between patients and to use this information to tailor treatment to the specific problems and needs of the individual, with the goal of improving treatment outcomes (Fernandes et al., 2017).

According to the network approach, psychopathology can be understood as a stable state in a network of causally entangled variables of behavioral, emotional, somatic and contextual variables (Borsboom, 2017). The network approach is particularly compatible with the goals of precision psychiatry. Rather than assuming that symptoms reflect a single latent disorder that is similar across individuals, the network approach conceptualizes psychopathology as a system of directly interacting symptoms and other factors that may differ substantially between individuals (Robinaugh et al., 2020). It is assumed that the relevant variables, i.e. nodes in the network, should cover symptoms irrespective of current diagnostic categories, and that these networks are to some extent person-specific (Vogel et al, 2025). Following this conceptualisation, the network of a particular person can be seen as shifting between different distinct states, between healthy and pathological.

Although originating from different intellectual backgrounds, the network approach is similar to case conceptualizations in psychotherapy. In case conceptualizations, therapists and patients try to figure out how the context, behaviors and feelings of the patient are related to one another, in order to change central processes to maximize downstream effects (Kuyken, Padesky, & Dudley; 2008). In other words, the therapist and patient work together to capture both the day-to-day variability and which factors are consistently causing other problems. Such analysis is an important clinical skill for therapists, but typically relies on somewhat unsystematic data collection and qualitative analysis (Haynes et al, 2018).

The network approach might contribute with better methods for both data collection and analysis, i.e. for personalizing treatment (Hofmann, 2025; Lavefjord et al, 2026). The network approach is primarily a conceptual model of psychopathology, but it has also given rise to a growing set of empirical methods for assessing, estimating, and visualizing individual networks (Scheffer et al, 2024). Networks are visualized as “nodes” (variables) connected by “edges” that reflect statistical or perceived relations between variables (Borsboom, 2017). Edges can be undirected (“these nodes tend to co-occur”), or directed (“variability in this node predicts or is perceived to cause variability in this other node”). A concept that follows from this is idea of differing importance or influence of nodes within a network: i.e. “centrality”. Different centrality metrics are used to summarize how much a given node is connected to other nodes, for example by quantifying how many and how strong connections it has to other parts of the network (Bringmann et al, 2022). Such central nodes are often interpreted as potentially influential points for intervention, under the assumption that changes in central nodes may have downstream effects on other problems (Vogel et al, 2025). Note however that this has also been critiqued (e.g. Bringmann et al, 2019).

The network approach does not rely on a specific method for data collection, or a particular analysis. Rather, the approach is a way of thinking about psychopathology as a system of interacting problems, where the structure of causal relations may vary across persons and over time. From a clinical perspective, this offers a formalized language for ideas that are already familiar in psychotherapy, and opening up possibilities to investigate them in a more rigorous manner.

Person-specific networks are typically estimated using dense repeated measures over several weeks (Ecological momentary assessment; EMA), which can be analysed using e.g. VAR (Vector Autoregression; for an overview see Bringmann et al, 2022). In a network estimated from such data, the directed edges between nodes in the network represent how much variation in one node predicts variation in the other nodes at the next assessment point (typically 2–3 hours later). This method has been used widely to map between-person heterogeneity and inform intervention foci, for a wide range of patient populations, e.g. depression (Siepe et al, 2024), eating disorders (Levinson et al, 2021) and post-traumatic stress (Bridges-Curry, 2025). Some studies use idiosyncratic nodes (for an overview, see Andreoli et al, 2025).

However, time-series analyses comes with risk of missing relations because processes operate on multiple timescales within the same network, which makes alignment with sampling densities difficult (Bringmann et al, 2022). Further, such time-series analyses are necessarily very data-hungry, limiting their clinical feasibility (Mansueto et al, 2023: Hall et al, 2025). Another technique, Perceived Causal Networks (PECAN; Klintwall et al, 2023; Vogel et al, 2025), creates a person specific network by simply asking the patient which causal relations he or she perceives between the nodes. This has the benefit of being able to capture processes of varying speed, but is obviously reliant on patient self insight and memory. The PECAN has been used in clinical settings (Andreasson et al, 2023), and in both self-guided questionnaire formats (Bångstad et al, 2022) and as a structured interview (Kaariniemi et al, 2025; Klintwall et al, in preparation; Reichert et al, 2025).

Both these methods assume that the network structure of a particular patient is stable across time, or at least across the time period of investigation. Indeed, there are empirical papers that find that at least for a majority of patients, this is true (e.g., van der Tuin et al, 2023). Other studies by contrast find that networks change quite quickly (e.g., Cusack et al, 2025; Hulsman et al, 2024; Siepe et al, 2024). Some of this variation might plausibly be considered “noise,” i.e., random daily events affecting mood and behaviors, but e.g. for women some variation is likely due to hormonal cycles (see for example Tauseef et al, 2024) or important contextual factors such as weekdays vs weekends.

A method that bridges EMA and PECAN is Longitudinal PECAN (L-PECAN). In this method, the patient is asked each day which symptoms were experienced that day, and how these symptoms were perceived to causally influence one another. This approach avoids both the timescale misalignment of EMA and decreases the recall bias of PECAN. Daily assessments can be aggregated into an averaged network to highlight the most frequently perceived causal relations. Crucially, this method moreover allows an analysis of how the perceived causal links fluctuate from day to day. This offers insight into both the variability and the stability of node interactions. By examining these two aspects together, we can identify nodes that are not only consistently central across time but also understand when and how their causal influence changes. This information may be useful for tailoring interventions to individual patients (Rubel et al, 2018; Hall et al, 2025).

In the study by Burger et al. (2024), participants recruited through social media completed four weeks of daily assessments in which they selected the problems they had experienced that day from a predefined list (covering common symptoms, behaviors, and emotions) and rated how these symptoms influenced one another (i.e., both their causes and effects). For each participant, a *core set* of nodes was defined as those reported on at least one third of the days, and an aggregated network was created to identify consistent causal links within this core. For each participant, the rate of *causal saturation* was computed, defined as the number of assessed days needed to aggregate a stable network (i.e., when collecting more assessment days no longer changed the aggregated network). *Distance plots* were also visualized for each participant, showing whether days tended to be more alike the closer they were to each other in time. While this study demonstrated that individuals can indeed provide daily reports on perceived causal relations over extended periods, there were several limitations noted. The self-selected, non-clinical sample limited generalizability to clinical settings. The predefined node-list was experienced as limiting by respondents, and excluded contextual factors altogether (e.g., *financial problems*; an issue pointed out previously, e.g. von Klipstein et al, 2025). Interestingly, only about half the sample reached *causal saturation*, that is, consistent causal links over days, raising the question whether a stable network is to be expected, and whether L-PECAN could be used to investigate this within-person variability further.

The aim of the present study was to build on the previous L-PECAN study by improving on the method (e.g., individualized items), and evaluate the clinical feasibility with actual psychiatric patients of differing severity. Importantly, we also aim to make the within-person variability the focus, in order to investigate whether L-PECAN can be used to analyze such day-to-day fluctuations. We report how we determined our sample size, all data exclusions, all manipulations, and all measures in the study.

Methods

Design and Setting

We use a within-subject observational design in which patients provide repeated daily assessment of perceived causal relations between personalized nodes over a three-week period. Each patient serves as their own unit of analysis, allowing both analysis of day-to-day variability and aggregation of person-specific networks. Data were collected in two clinical settings aimed at adult patients, but differing in symptom severity. The first setting is a university psychotherapy training clinic, i.e., outside of the public health care system, offering cognitive-behavioral therapy for adults with mild to moderate psychological problems such as anxiety, depression, or stress. The second setting is a specialist psychiatric outpatient clinic, part of routine secondary care, treating patients with severe and often comorbid conditions, including affective and neurodevelopmental disorders. Due to differing organizational requirements, L-PECAN was implemented in Qualtrics for the university clinic setting, and in RedCAP for the specialist psychiatry setting. Data collections has correspondingly two separate ethical approvals from the national Ethical Review Authority (reg. nrs. 2022–03141 and 2024–04165 respectively). To ensure patients are impossible to identify, we report no data on gender or age. The university clinic part of the

study was preregistered at https://aspredicted.org/CY9_7WN. All data and code can be found at: https://osf.io/hma3e/overview?view_only=2fa0f1f341434be98dca8774bc930950. No funding was received for the conduct of this study or the preparation of this manuscript.

Procedure

Recruitment

Recruitment was done during a phase of 6 months at the two participating clinics. During this time-period, all patients filling inclusion criteria were approached with information about the study, which stressed that participation was both voluntary and that findings could be used to personalize their subsequent care. Interested patients were sent a brief psychoeducational video introducing the purpose of L-PECAN, explaining the purpose of the method and how to interpret the causal question in the daily assessments. The video illustrated concrete examples to ensure the patients understood the purpose and setup of the method before they consented to participation, thus hopefully reducing the dropouts observed in the Burger et al (2024) study. Patients still interested were given written study information and give their verbal and written consent.

Training Week

Patients completed one week of daily assessments using a generic list of 18 common problems (e.g., overthinking, sleep problems, financial issues, see appendix A). This predefined list was an updated version of the list used in Burger et al (2024), expanded to include contextual factors. Each evening, patients received a text message at a timepoint decided beforehand (between 18:00 and 20:30). The text message contained a link to the L-PECAN survey. Participants could complete the assessment the following morning, but they were instructed that answering at the end of the day in question was to be preferred (the proportion of responses that were in fact made the next morning is seen in Table 2). They reported which items they had experienced that day, and described the selected items in their own words (e.g., “You selected *overthinking*, what did you think about?”). Importantly, respondents picked which of the other items (whether experienced on that day or not) had contributed to the experienced problem (i.e., ingoing edges). Patients were also allowed to write causes other than the other items.

Collaborative Item Individualization

At the end of the training week, each patient met with a clinician (authors K.L. or G.A. in the university clinic, or Ä.T. or R.F. in the specialist clinic) to review their week-one data. The clinician had prepared a summary of the freetext answers (item specifications and causes) and quantitative data (i.e., item frequencies and out-degree centralities), and prepared a suggestion for a shortened item-list with not more than ten items. This was collaboratively edited so that each item was relevant and made sense to the patient. In practice, this procedure worked by both combining and splitting items to find a good level

of abstraction, and add idiosyncratic information provided by the patient in free-text boxes. We were particularly careful to avoid content overlap by formulating items on a more abstract level (e.g., combining “pain” and “tired” into one item if these were hard to distinguish). Items were prioritized if they were perceived to be causing other items, or were experienced as important by the patient. This finalized list was used to create a personalized for the L-PECAN for the remainder of the study for each patient. Finally, the patient could choose to change the timepoint each evening the text-message with a link to the survey was sent out.

L-PECAN phase

Patients in the university clinic completed at least three weeks of daily assessments using the L-PECAN. Patients from the specialist clinic could respond for a longer period, depending on their planned sessions. In each assessment, the patient was first shown the individualized list of items and asked to select those that were experienced that day (note that for item “insomnia”, the respondent was asked to answer about the previous night; meaning that for responses delayed to the next morning, the patient was answering about a night two nights distant). Next, contributing causes for each selected item was asked about (e.g., “Today, what contributed to <staying home from work>?”) with the other individualized items as potential contributing causes. The patient could select as many contributing causes as he or she wished, including none. An option “other causes” was also available. As compared to the Burger et al (2024) version, the present study asked only about the causes (i.e., edges going into the node), not their effects (i.e., edges going out from the node). Another difference was that items were available as causes even though that item had not been reported as experienced that day (i.e. all items were always available as causes). The latter was changed to allow causal relations for time-scales longer than that day (e.g., being *tired* due to *drinking alcohol* the previous day). For each item, pictograms were created and used throughout to reduce cognitive load and make the repeated assessments less tedious. Note that responses were binary: an item was either selected as a cause or not (i.e., there was no grading of the causal strength or certainty of the perception). For the university sample, some extra questions were asked in the L-PECAN, described in appendix B.

Other measures

Depressive symptoms were assessed with the *Patient Health Questionnaire–9* (PHQ-9; Kroenke, Spitzer, & Williams, 2001). The PHQ-9 consists of nine items corresponding to the diagnostic criteria for major depressive disorder. Each item is rated on a 4-point scale from 0 (*not at all*) to 3 (*nearly every day*), yielding a total score between 0 and 27. Higher scores indicate greater depressive symptom severity.

Anxiety symptoms were assessed with the *Generalized Anxiety Disorder–7* (GAD-7; Spitzer, Kroenke, Williams, & Löwe, 2006). The GAD-7 contains seven items measuring the frequency of core anxiety symptoms during the past two weeks, rated from 0 (*not at all*) to 3 (*nearly every day*). Total scores range from 0 to 21, with higher scores reflecting higher levels of anxiety.

Participants

University Psychotherapy Clinic

Patients self-referred to the university training clinic by completing an online intake form, which included the PHQ-9 (Kroenke et al., 2001) and the GAD-7 (Spitzer et al., 2006) for symptom screening. The university clinic routinely excludes individuals with psychosis, acute suicidality, substance dependence, or other conditions judged unsuitable for student-provided therapy. All patients are required to have sufficient proficiency in <redacted language > for psychotherapy. Our pre-registered criteria (requiring patients to have PHQ9 and GAD7 scores both over 5) were not applied, as inclusion was slower than we had expected. Nine patients were approached with information about the study. Two declined participation after having been given written information about the study. Another two declined participation after having been given verbal information about the study and seen the inclusion video. Thus, five out of nine approached patients were included in this setting. Descriptives in Table 1.

Specialist Psychiatric Clinic

Patients were recruited by clinicians during the early stages of their psychiatric evaluation before intervention initiation. Twelve patients were approached with study information. Four declined participation after receiving detailed information, primarily because the daily ratings were perceived as demanding. Two were excluded due to unclear technical difficulties that prevented completion of any of the daily assessments (i.e., could not get the link to work). Thus, six patients initially consented participation in the study. Of these, three dropped out during data-collection for unclear reasons. Thus, three out of twelve patients were included from this setting. Descriptives in Table 1.

Table 1
Descriptives of included patients

Patient	PHQ-9	GAD-7	Given reason for seeking therapy
University clinic			
Patient 101	7	5	Anxiety, relationship issues
Patient 102	10	18	Anxiety, depression
Patient 103	5	4	Performance anxiety, social anxiety
Patient 104	1	6	Obsessive thoughts and compulsive behaviors
Patient 105	16	11	Anxiety, depression
Specialist psychiatric clinic			
Patient 106	17	15	Depression, relationship issues
Patient 107	13	13	Anxiety, anger
Patient 108	missing		Trouble focusing, restlessness

Data Analysis

Feasibility and adherence metrics

For each participant, we calculated the percentage of completed daily assessments (i.e., percentage of days answered in between the first and last assessments), and the median time needed to complete the daily assessments. The typical time of completion (type response hour) was derived from time stamps of submitted surveys. Finally, we calculated the proportion of causal questions on which the “other causes” response option was used. All of the above are presented individually for each patient.

Saturation analysis

With the aim of quantifying day-to-day variation and to what extent assessing more days would eventually saturate a stable aggregated network for each patient, this analysis was a slight adaptation to the same analysis in Burger et al (2024). For each participant, we constructed one directed daily adjacency matrix (0/1) per assessment day, where each cell was coded as 1 if the perceived causal relation between the corresponding ordered pair of nodes was reported that day. To quantify how many assessment days were required for a participant’s network to stabilize, we repeatedly drew random sets of *a* assessment days from the participant’s available data without replacement and randomly partitioned each set into two equal-sized subsets of days. For each subset, daily adjacency matrices were aggregated to form a weighted network reflecting the proportion of days on which each causal relation was reported. Similarity between the two aggregated networks was quantified using the Spearman correlation between their edge weights. This procedure was repeated 1,000 times for each value of *a*, with *a* ranging from four days to the participant’s total number of available days in steps of

two. The resulting distributions of correlations were summarized across values of *a* to obtain a saturation curve. In contrast to Burger et al. (2024), these analyses were not restricted to a core set of nodes, because nodes could be indicated as causes even if they were not reported as experienced on a given day; accordingly, all personalized nodes were retained for each participant. Also, pilot studies using individualized nodes indicated that this approach ensured nodes with adequate day-to-day frequency, avoiding the problem seen in Burger et al (2024), with most nodes having zero frequency.

Causal drift analysis

As in Burger et al (2024), we aimed to identify whether individual patients exhibited trends in their daily network structures. This was assessed by quantifying the extent to which similarity between daily perceived causal networks changed as a function of distance between assessment days. For each participant, all unique pairs of daily adjacency matrices were identified. Similarity between each pair was computed using the phi coefficient, reflecting the binary nature of the daily adjacency matrices (Burger et al 2024 used spearman correlations). Temporal distance was defined as the absolute difference in assessment day indices. For each participant, day to day trend was summarized descriptively as the regression slope obtained by regressing network similarity on temporal distance, with more negative slopes indicating greater divergence of network structure with larger distance between assessed days. Slopes were not subjected to inferential statistical testing.

Network visualization and centrality measures

Personalized causal networks were visualized using aggregated networks constructed across all available assessment days for each participant, with edge weights representing the proportion of days on which a directed causal relation was reported. To examine temporal variability in perceived causal structure, daily networks were also visualized for each participant, presented as a table with each cell representing the network for that day.

To characterize the relative importance of individual nodes within aggregated networks, we computed outstrength centrality, defined as the sum of outgoing edge weights for each node. Outstrength values were standardized by the number of possible outgoing edges for each node to account for differences in number of nodes in the individual networks. Centrality measures were computed on the aggregated networks and interpreted descriptively as indicators of nodes with relatively strong perceived causal influence.

Data were analyzed with R (version: 4.3.0, R Core Team 2023) in R-Studio (version: 2023.06.1, Posit team 2023) using the following packages: PECAN2 (v0.1.0, Reichert & Vogel. 2024), visNetwork (v2.1.2, Almende & Thieurmel, 2022), ggplot2 (v3.5.1, Wickham 2016), chromote (v0.5.1, Aden-Buie et al., 2025), htmlwidgets (v1.6.4, Vaidyanathan et al., 2023), webshot (v0.5.5, Chang et al., 2023), jaccard (v0.1.0, Chung et al., 2018), stringr (v1.5.1, Wickham, 2023), psych (v2.4.6.26, Revelle, 2024), car (v3.1-3, Fox et al., 2012), tidyr (v1.3.1, Wickham et al., 2024)), janitor (v2.2.0, Firke, 2023), dplyr (v1.1.4, Wickham et al., 2023), and readxl (v1.4.3, Wickham & Bryan, 2023).

Results

Feasibility and adherence

As can be seen in Table 2, all five patients from the university clinic completed the 21-day L-PECAN protocol with good adherence. The number of completed assessments ranged from 15 to 21, corresponding to 71–100%. Median response duration per day ranged from 2 to 6 minutes. The “other causes” response option was used on 11 to 28% of causal questions, indicating that most perceived causal relations were captured within the network. The three patients from the specialist psychiatric clinic showed lower levels of adherence, ranging from answering 60% to 83% of days (note that the length of the L-PECAN phase varied for these patients). Response durations were similar to the university sample: ranging from 1 to 8 minutes. Also similar was the use of the “other causes” response alternative, which varied from 7% to 28%. Proportion of responses that were made the next day varied substantially, from none to almost three quarters.

Table 2
Feasibility and adherence metrics

Patient ID	**101**	**102**	**103**	**104**	**105**	**106 = HS**	**107 = PJ**	**108 = DS**
Days responded	18	15	21	21	21	15	29	25
Response rate	86%	71%	100%	100%	100%	83%	79%	60%
Response duration (median minutes)	3.6	2.1	5.1	5.9	2.7	3.0	1.0	8.0
Response hour (type value)	9 pm	1 am	8 pm	10 pm	8 pm	9 pm	12am	8 pm
Responses next morning	6%	13%	0%	0%	19%	0%	3%	72%
Average “other causes”	28%	13%	17%	11%	12%	28%	7%	20%

Networks

Individualized items can be found in Appendix C. Two example aggregated networks, one from the university clinic sample, and one from the specialized psychiatric clinic, can be seen in Fig. 1 (all aggregated patient networks can be found in Appendix D). Outdegree centralities for these two networks can be found in Fig. 2.

Saturation and drift

As expected, networks tended to saturate (i.e., stabilize) the more days were included in aggregations. As expected, how quickly and to what extent networks saturated varied from patient to patient. Two “saturation plots” for two patients are shown in Fig. 3. Note that causal saturation was calculated using

all nodes for each participant (i.e., not limited to the core set, as in Burger et al, 2024). The plots of day to day trends (causal drift) for these two patients can be found in Fig. 4.

The day-by-day variability for patient 103 can be seen in Fig. 5. In this figure, note how initially only a few nodes are selected each day as seen in red. Starting day 11, more nodes are selected each day, and with them more perceived causal relations are reported. One interpretation is that the increase of experienced nodes is maintained by a direct loop between “stuck worrying” and “negative emotions”. After a week, on day 18, the network winds down.

Clinical utility

Although clinical utility was not assessed systematically, anecdotal observations from patients and clinicians are worth noting. One patient in the university clinic sample commented: “The first week, the assessments made me feel worse. But that was probably because I had to accept the bad state I’m in. It made it more tangible how I actually felt. But after week one, it got better.” The same patient also noted that while the aggregated network itself was not particularly useful, the process of answering the questions was helpful: “Thinking about the causes did me good. It helped me understand that things are in fact connected. So when I saw the network, it was not a big surprise.” Similar reactions were reported by another patient in the university clinic, who described the network as largely consistent with her expectations and gave her no new insights. Therapists described the method as a potentially useful complement to clinical assessment, while also noting the trade-off between the burden of daily monitoring and help with identifying consistently central problems.

Discussion

Main findings

We examined the feasibility of using daily perceived causal ratings to construct idiographic symptom networks before the start of psychiatric treatment in two clinical settings: five patients in a university clinic, and three from a specialist psychiatric clinic. Whereas the original demonstration of the method (Burger et al, 2024) relied on a self-selected, online-recruited sample which showed substantial attrition (making it impossible to know how representative the final analyzed sample was), we tested the method in routine clinical contexts with a known recruitment process, and patients who knew their responses might be used for their own care planning. We also updated the method by adding a training week to ensure the respondents understood the purpose and setup of the method, and adding a data-informed method for formulating idiosyncratic nodes. Further, we simplified the assessments by asking only about edges going into the node (not edges going out from the node).

The results suggest that the updated method is feasible in a university clinic with relatively high-functioning patients, but more challenging to implement in specialist psychiatric care. In the university clinic, roughly half of those approached about participation in the study agreed to participate, and none discontinued after enrolling. Compliance was high, with three of five patients completing all assessment

days and the lowest completion rate being 71%. By contrast, recruitment in the specialist setting was more difficult: of the patients approached about participation, only a quarter completed the full protocol, and adherence among these completers was still lower than in the university sample (60–79%). These findings suggest that, at least in its current form, daily causal self-ratings may not yet be realistic for patients with more severe or complex psychiatric presentations.

For patients who did complete the protocol, the method functioned as intended. Daily assessments were short, between one and eight minutes on average. Patients largely stayed within their personalized item sets when assigning causes, suggesting that patients did view the constructed items as causally entangled (in line with the network approach to psychopathology).

The within-person aggregated networks suggested that influence was unevenly distributed across problems: some nodes showed higher outgoing centrality (outstrength), indicating that they were perceived as affecting many other nodes on many days. These centrality patterns are descriptive and should be treated as hypothesis-generating rather than evidence of causal effects, but they may still be clinically useful for prioritizing potential treatment targets when planning interventions.

Day-to-day variability in perceived causal relations was large. This is illustrated by the example in Fig. 3, and by the slow causal saturation observed for most participants. Even with many days of observations, no patient had an aggregated network that was representative of all days. In other words, while some idiosyncratic problems were consistently present for a patient, the perceived causal structure connecting them varied across time, and there was little evidence that networks for patients converged toward a stable network with many days of data. These findings suggest that perceived causal structures are variable across time within individuals. From a methodological perspective, this highlights the value of explicitly examining fast acting temporal change in networks. As showcased in the present study, the causal drift metric can be used detect trends or phase shifts over time, e.g. over a menstrual cycle or important contextual changes. L-PECAN may be particularly well suited to an idiographic approach in which variability in problem networks is treated as information rather than noise.

Finally, preliminary patient feedback in the university sample suggested that the procedure was acceptable but that the resulting network summary was not experienced as particularly informative. Patients engaged with the daily questions without difficulty, yet seeing the aggregated network did not seem to add insight beyond what they had already reflected on during the rating period.

Limitations

This study was small and designed for feasibility rather than generalizability, so the results should be viewed as preliminary. We did not evaluate whether the networks actually informed differential diagnostics, case formulation or treatment decisions, and importantly we also do not know whether the perceived causal relations correspond to actual causal relations. The method therefore remains unvalidated.

The added value of the longitudinal procedure, with repeated small assessments, over a simpler single-timepoint PECAN interview is unknown. The initial training week may be helpful for learning the task and providing data for individualizing items, but simpler procedures might be sufficient. Importantly, the problems with using the method in a specialist psychiatric clinic is a notable limitation, since patients with more complex presentations are exactly those where idiographic networks may be most useful.

Finally, the finding that perceived edges varied from day to day. This could reflect genuine fluctuation (i.e., true causal relations), but it could also arise from a tendency to report *contrasts* rather than absolute causes: one can easily imagine a patient who is always sad due to rumination, but instead of consistently reporting that cause, the patient each day reports causes that differ from day to day (e.g., one day conflicts at work, another day financial issues). Without external validation, it is difficult to know how to interpret this variability. Another issue is to what extent the observed within-person variability in network structures can be explained by variability in the symptoms, not the edges (e.g. worry is infrequently reported, but when it is the perceived contributing cause might consistently be conflicts with spouse). This could be explicitly analysed.

Future directions

Most importantly, clinical utility needs to be evaluated. Future studies should ask patients and clinicians how findings from a person-specific L-PECAN can be integrated with current practices of case conceptualization, either as data to be discussed together (e.g. Hall et al, 2025) or used as part of an algorithm to choose treatment foci (e.g. Rubel et al, 2018). Validity can be assessed after some treatment has taken place, i.e., “retrospective validity” (Andreasson et al, 2023). Ultimately, the utility should be measured in terms of improved or faster treatment outcomes (for a planned such study, see Lai et al, 2025).

The substantial day-to-day variation in perceived edges should be explored more systematically. It may be useful to distinguish between stable influences and day-specific fluctuations, for example by prompting patients to indicate whether a reported edge reflects a general pattern or something unique about that day. Importantly, L-PECAN could be used to investigate cyclical patterns (e.g., symptoms linked to the menstrual cycle) or important contextual factors (e.g., different network structures on weekdays as opposed to weekends).

Another possible extension would be to better capture the time-scales of different perceived causal relations. For every causal relation reported, the system could ask something like “Your said X contributed to Y today, how long after X did Y occur?” (phrased differently whether X and Y are discrete events or longer phenomena). Another possibility is that when a respondent indicates that X contributed to Y today, the patient could be asked when X occured. Possibly, the L-PECAN could use information about when X last occurred, so that the system could ask targeted follow-up questions. For example, if a respondent reports rumination today and selects a cause that was not experienced on the same day, the prompt could refer to the most recent occurrence of that symptom (e.g., “You reported symptom X four days ago. Is this what contributed to your rumination today?”). Such an approach could help distinguish

short- from longer-term perceived influences while minimizing respondent burden, and may provide useful guidance for setting EMA sampling schedules aimed at estimating the same relations more objectively.

The collaborative co-creation of nodes by patients and a clinician might seem atheoretical, but was obviously influenced by the predefined items used in the training week, and by the theoretical leanings of the researchers and clinicians who were all trained in CBT. This can be seen in for example in the university clinic sample, where all five patients had some variant of the three nodes “negative thoughts”, “physically inactive” and “tired” (i.e., a classic CBT triad of cognitions, behaviors and emotion/somatic). Since patients likely need guidance to formulate distinct nodes, it might make more sense to make the theoretical framework explicit. Indeed several network studies have used the framework of process based therapy (Hoffmann, 2025; Ong et al, 2025). Another interesting avenue might be to combine L-PECAN with a diagnosis specific model. An example of this can be found in Hertz-Palmor et al (under review), a study in which patients diagnosed with PTSD completed daily assessments about perceived causal relations between nodes which were personalized from a predefined model of PTSD. Only causal relations “allowed” by the model were asked about, thus decreasing the burden on participants at the cost of limiting the network to a specific diagnosis (e.g. precluding psychiatric comorbidities). In other words, focusing the data-collection or the analysis using priors about the specific patient (Burger et al, 2022) or the patient population (Bellander et al, under review) might decrease participant burden.

Conclusion

L-PECAN with personalized nodes is a structured method for assessing day-to-day variability in perceived causal networks. In this study, patients undergoing psychiatric evaluation were carefully involved in setting up their own data collection by first making sure they were on board with the purpose and idea of the study, e.g. by use of a psychoeducational video, and then trying out the method during an initial “training week”. Based on this, patients collaboratively formulated their personalized items. Evaluated under these relatively robust conditions, both some recurring causal relations and day-to-day variability were observed, pointing to the limitations of aggregated (i.e. assumed stable) person-level networks. Identifying both stability and fluctuation may be helpful when deciding on intervention targets and possibly timing.

Declarations

Author Contribution

JR ran data analyses and edited manuscript. TB supervised and edited manuscript. TA supervised. ÄT, RF , KL and GA collected data. NJL and JB edited manuscript. LK initiated project and wrote first draft of maniscript. All authors reviewed the manuscript.

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Data Availability

https://github.com/JR-psych/R_code_publications/tree/main/code%20and%20data%20lpecan

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Figures

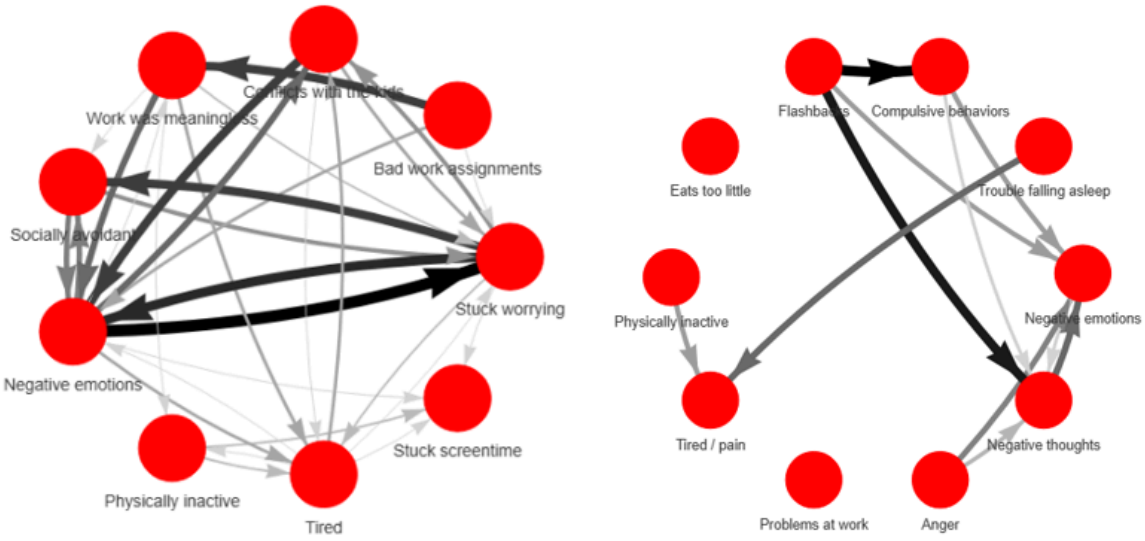


Figure 1

Aggregated networks for patients 103 (left) and 107 (right). Edge weight corresponds to the proportion of days the relation was perceived. Most reported edge by patient 103 ("negative emotions" causing "stuck worrying") was reported 52 % of days. Most reported edge by patient 107 ("Flashbacks" causing "Compulsive behaviors") was reported 46 % of days. Note that these network visualizations do not take node frequency into account (e.g. node sizes are all equal, edge weights are not adjusted by source or target node frequency).

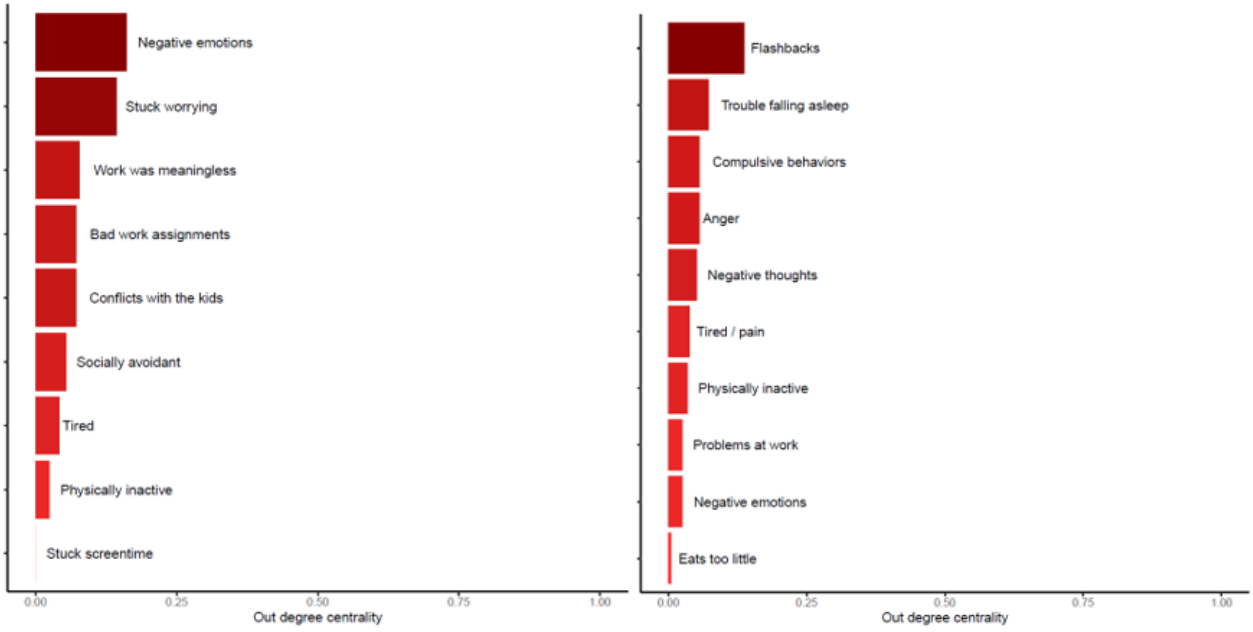


Figure 2

Out-degree centralities from the aggregated networks for patients 103 and 107

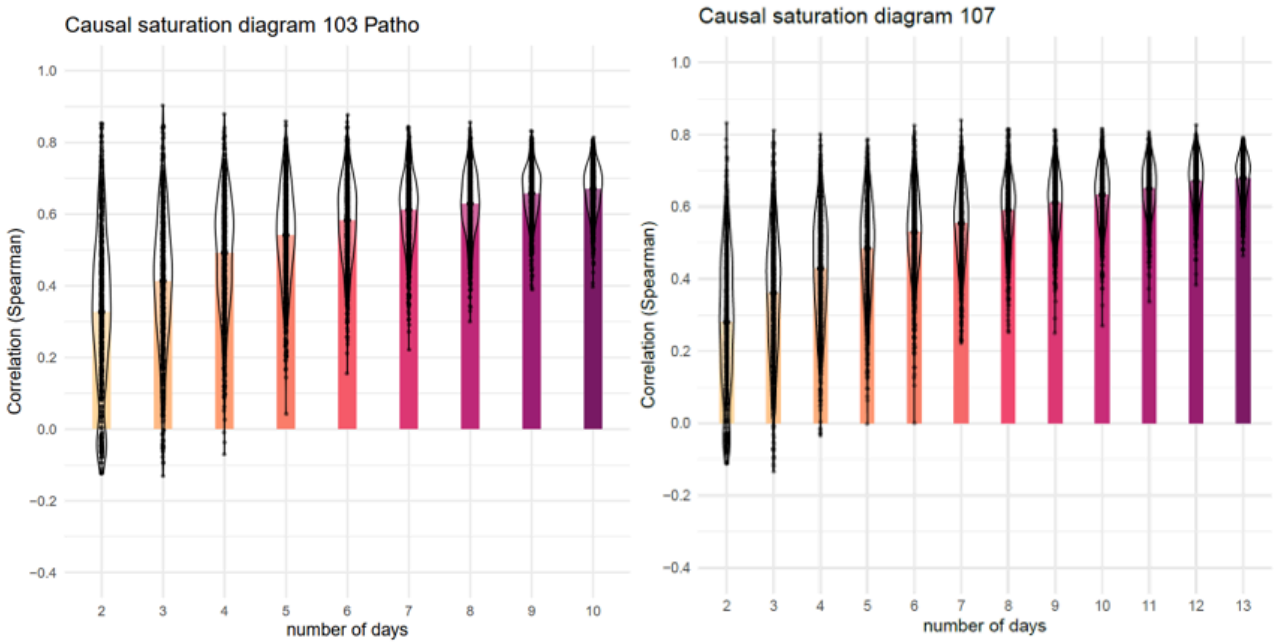


Figure 3

Causal saturation plots for patients 103 and 107. Violins indicate distribution of spearman correlations between two repeatedly drawn samples, with x-axis indicating the size of the drawn samples. Colored bar indicates average across all bootstrapped samples.

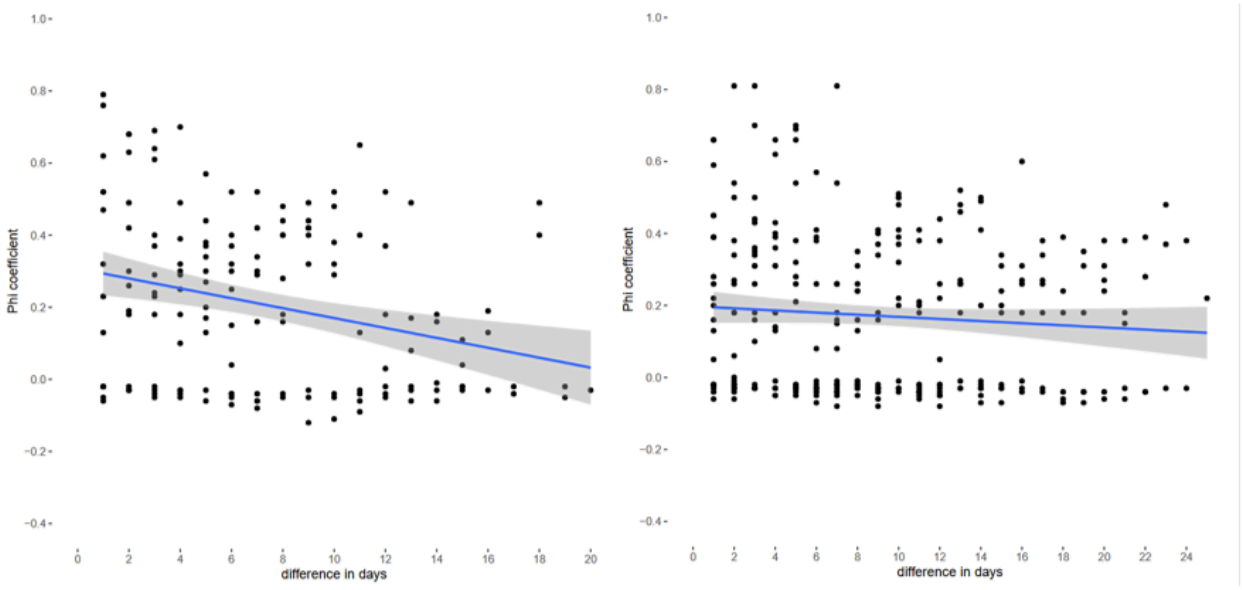


Figure 4

Causal drift plots for patients 103 and 107. A slope indicates that daily network structures tend to be more dissimilar the further away two days are two one another, i.e. the patient exhibits differing phases across the assessment period (evident in 103 and not 107).

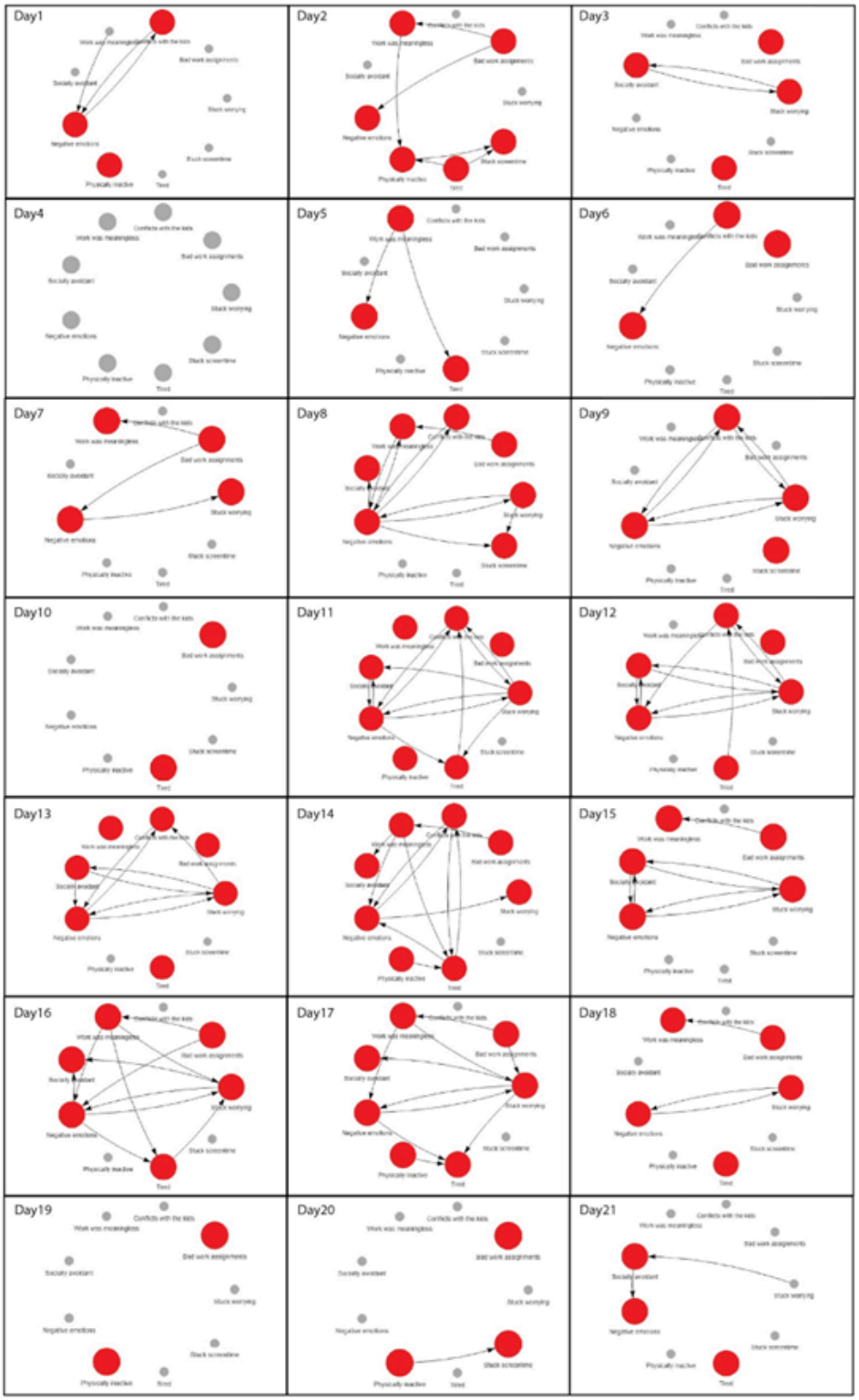


Figure 5

Separate frames for days, patient "103". Animated GIF in online supp.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- AppendixA.docx