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REVIEW

A Systematic Scoping Review of Fully Idiographic Network Analysis in Mental Health

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Abstract

Background The network analysis (NA) approach has predominantly relied on cross-sectional data, to characterize the relationships between symptoms across individuals at a single time point. In contrast, fully idiographic network analysis (FINA) allows for a more personalized perspective by estimating symptom networks at the individual level using intensive data collection. The aim of this scoping review is to map current practices in FINA in mental health research, identify methodological trends and gaps, and offer recommendations to support future studies in planning, data collection, analysis, and reporting.

Methods We searched MEDLINE, PsycINFO, Scopus, and Web of Science for peer-reviewed journal articles (published until January 2025). The initial search identified 12,586 articles, of which 43 were included in the review. Information was extracted on study and sample characteristics, data collection methods, and data analytic techniques.

Results We observed high heterogeneity between the studies. Commonly employed data collection methods included experience sampling and ecological momentary assessment, and the FINA model most frequently employed was graphical vector auto-regressive. Most studies estimated both contemporaneous and temporal networks, and fewer than half shared their data following open science practices.

Conclusions FINA is a promising tool for mental health research, but future studies need to adopt greater scientific rigor. To support this goal, we provide a set of recommendations and a structured checklist to guide researchers in conducting FINA studies.

Keywords Network analysis · Scoping review · Idiographic · Personalized mental health care

Introduction

The nomothetic approach in psychological science examines interindividual differences to uncover general laws applicable to entire populations (Lyon et al., 2017; Molenaar, 2004). Conversely, the idiographic approach focuses on intraindividual variation across time and contexts to make person-specific predictions (Lyon et al., 2017). Traditional mental health research predominantly employs nomothetic methods involving large groups, but there is growing recognition of the value of idiographic, case-based designs (Piccirillo & Rodebaugh, 2019; Piccirillo et al., 2019). This shift reflects the primary goal in mental health: to apply effective, personalized interventions tailored to individual patients (Howard et al., 1996). However, the nomothetic-idiographic debate is still open, exemplified by "the therapist's dilemma"—treating individuals using group-level information (Levine et al., 1992; Piccirillo & Rodebaugh, 2019).

Nomothetic research, despite its long-standing tradition, faces limitations, particularly in its inability to capture within-individual dynamics due to the nonergodic nature of psychological processes (Molenaar, 2004). This limitation is evident in the substantial heterogeneity within diagnoses and symptom trajectories across individuals (Yaroslavsky et al., 2013). By aggregating data across multiple individuals,

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nomothetic methods fail to reflect dynamic and interconnected symptoms within individuals over time (Fisher et al., 2011, 2017). Addressing these limitations requires a shift towards idiographic approaches that emphasize repeated assessments of symptoms within the same individual, allowing for a more accurate representation of personal symptom dynamics (Lyon et al., 2017).

The rise of the network approach to psychopathology has intensified the nomothetic-idiographic debate, offering a compelling framework that views mental disorders as complex networks of causally interconnected symptoms (Borsboom, 2017; Hofmann et al., 2016). The success of the network approach to psychopathology has been facilitated by the development of network analysis (NA) (Borsboom & Cramer, 2013). NA allows estimation of symptom networks, where nodes represent symptoms and edges depict causal connections (Borsboom & Cramer, 2013). Through centrality indices, NA can identify key nodes, helping to guide interventions by targeting the most central symptoms first (Fried et al., 2016). NA techniques have been successfully applied to describe various mental disorders and identify targets for prevention and intervention (Contreras et al., 2019; Fried & Cramer, 2017).

NA has predominantly been applied to cross-sectional data, where symptoms are assessed from the entire sample at a single point in time (Burger et al., 2023). However, such group-level networks provide only a "snapshot" of psychopathology (Bystritsky et al., 2012), and are unable to capture dynamic relationships between symptoms or track symptom progression within individuals over time (Jordan et al., 2020). Understanding individual symptom dynamics is crucial in clinical practice, as symptoms can rapidly shift from mild to severe impairment (Wichers et al., 2016), and individuals may transition between different diagnoses over time (Garke et al., 2019).

To address the need for personalization in mental health research (Piccirillo & Rodebaugh, 2019), the network approach has increasingly embraced an idiographic perspective, applying NA to intensive longitudinal data to explore how symptoms interact over time (Bringmann et al., 2022). Networks based on intensive longitudinal data reveal symptom influences across time points and can identify those symptoms most predictive of others (Jordan et al., 2020). While this is a relatively novel approach and further research is needed to establish its clinical utility, it holds promise for informing case conceptualization and offering preliminary insight into the persistence of psychopathology in specific individuals (Borsboom & Cramer, 2013; Burger et al., 2022a; Hofmann et al., 2016; Scholten et al., 2024). A "fully idiographic" approach can be adopted within the network framework, which examines relationships between variables within a single individual over multiple occasions (Piccirillo & Rodebaugh, 2019).

Fully idiographic network analysis (FINA) refers to the estimation of symptom networks that are both constructed and interpreted exclusively at the level of the individual. These models rely on intensive longitudinal data to capture the dynamic interplay between symptoms and their progression over time within a single person. While the broader category of idiographic network approaches includes methods that incorporate both person-specific and group-level information (such as multilevel vector autoregressive models or Group Iterative Multiple Model Estimation), FINA is conceptually distinct in that it excludes any form of data aggregation or inference across individuals. We therefore use the term 'fully idiographic' to specifically refer to $n = 1$, person-specific analyses that are strictly individual-focused, in contrast to hybrid approaches that combine idiographic and nomothetic elements (Bringmann et al., 2013; Piccirillo & Rodebaugh, 2019).

FINA requires intensive data collection methods, such as ambulatory assessment (AA), which gathers data in natural environments. AA includes methodologies such as experience sampling methods (ESM; Larson & Csikszentmihalyi, 1983), which traditionally focus on the intensive measurement of internal affective states, and ecological momentary assessment (EMA; Shiffman et al., 2008), which typically also includes behaviors and physiological variables. While EMA and ESM are technically forms of self-report questionnaires, they differ from traditional self-reports in their use of frequent, brief, and momentary assessments. Traditional self-reports are typically retrospective and less frequent in their administration, making them more susceptible to recall bias (i.e., the tendency to alter past experiences when recalling them) (Shiffman et al., 2008). Other data collection methods include routine outcome monitoring (ROM), which involves session-by-session administration, often conducted by clinicians. ROM shares the limitations of traditional self-report questionnaires but is widely used to provide immediate feedback to both clinician and patient, supporting real-time treatment adjustment (Barkham et al., 2023). Advances in digital technologies have increased the use of AA for monitoring psychological processes in daily life (Stange et al., 2019), but an overview of the data collection methods used in FINA is still lacking.

The choice of data collection methods is linked to the requirements of the statistical models used in FINA. Most FINA studies use time series models, which capture how psychological variables influence each other within an individual over time (Bringmann et al., 2022). These models can rely on important assumptions that affect their validity and interpretation. For instance, stationarity assumes that every variable maintains a stable mean, variance and relationship

with other variables and itself over time. This condition is essential in many time series models but is rarely met in practice (Epskamp, 2020). Another common assumption is that data are collected at equidistant intervals (Janssens et al., 2018), which is often violated by overnight lag, where a larger time difference occurs between the last assessment of one day and the first of the next. These assumptions underscore the importance of methodological decisions related to data collection, missingness, and model selection, therefore playing a crucial role in the validity and interpretability of FINA-derived networks.

Among the various time series models used in FINA, the graphical vector auto-regressive (GVAR) model is one of the most frequently applied (Epskamp et al., 2018c). This model extends the basic lag-1 VAR, which estimates how variables at one time point predict variables at the next time point, by modeling the residuals within time points to estimate a partial contemporaneous network (Wild et al., 2010). However, an overview is lacking of the analytical techniques for constructing these networks.

FINA-derived networks can be "temporal" or "contemporaneous" depending on the measurement window. Temporal networks represent predictive associations between symptoms, depicting how one node at a time t predicts itself or another node at the next window of measurement t + 1. In contrast, contemporaneous networks represent associations between symptoms within the same measurement window, showing how nodes are linked to one another at a single time point. In temporal networks, edges are directed, indicating which variables predict others at the subsequent time point. In contemporaneous networks, edges represent partial correlations between two nodes, controlling for all other nodes within the same measurement window as well as for temporal effects (Thonon et al., 2020).

FINA is a relatively new analytical approach that started to emerge only in recent years, and some methodological issues remain in its application. Key challenges include variability in the rationale for using FINA, limited descriptions of the participants and recruitment settings, variability in data collection protocols (including measures used), unclear analytic choices for data preparation and network estimation, heterogeneous reporting practices, and limited implementation of transparent open science practices.

FINA is increasingly used in psychological research, with growing efforts to implement FINA-derived networks in mental health settings (Burger et al., 2020). For clinicians, understanding individual psychopathology is vital, and FINA is a promising tool for clinical practice. However, no established guidelines currently exist for conducting FINA studies, and existing research varies widely in methodologies and analytic strategies to answer different research questions. Indeed, researchers adopting an idiographic approach must consider individual differences. For instance, some individuals struggle with intensive data collection while others engage readily. Additionally, some researchers may prioritize the dynamic evolution of symptoms within the patient over time and others emphasize contemporaneous interactions among symptoms. Given this variability, there is a need for comprehensive guidance to support the implementation of FINA in mental health research.

While previous reviews have focused on broader applications of NA (Blanchard et al., 2022; Contreras et al., 2019; Robinaugh et al., 2019), none have specifically examined how FINA has been used to study individuals with mental health conditions. This review aims to fill that gap by reviewing empirical research on FINA in clinical populations. A scoping review approach was chosen as it is particularly well suited to mapping diverse methodological approaches in rapidly evolving fields (Munn et al., 2018). Specifically, this review describes current FINA practices, highlights trends, and identifies areas for improvement, ultimately providing guidance for future researchers in planning, data collection, analysis, and reporting. Our review systematically maps existing FINA studies across eight core domains: (1) study planning; (2) participant characteristics; (3) recruitment procedures; (4) data collection; (5) measures; (6) data analysis; (7) reporting practices; (8) open science. To promote reporting standards and support transparency, we also provide a structured checklist to guide researchers in conducting FINA studies.

Methods

Search Strategy

To conduct our scoping review, we followed the PRISMA extension for scoping reviews guidelines (PRISMA-ScR; Tricco et al., 2018). Searches were conducted in MEDLINE, PsycINFO, Scopus, and Web of Science, using keywords related to NA and idiographic approaches, with a time restriction from January 2011 to March 2022. We updated the search until January 2025. Search strings included variations of terms like "network analysis", "idiographic", "single subject", and "person specific", applied to title, abstract and keywords (Online Resource 1).

Inclusion and Exclusion Criteria

Included studies were: a) original peer-reviewed research studies, b) written in English, Spanish, or Italian, c) applying fully idiographic analytical methods to time-series data for estimating FINA-derived networks, and d) involving participants with a mental health condition. Exclusions

were: a) non-original research articles (e.g., reviews, protocols), b) qualitative studies, c) validation studies, and d) modelling/simulation studies without real-world application, e) studies not involving humans, f) studies including participants without a mental health condition, g) studies not addressing psychological variables or using non-psychological networks (e.g., social NA, thematic NA), h) studies with cross-sectional designs, i) studies applying NA methods without a fully idiographic approach (e.g., multilevel VAR), j) studies applying fully idiographic methods without a network approach (e.g., P-technique), and k) studies not adopting a fully idiographic approach nor using NA methods (e.g., time-lagged hierarchical linear modeling).

Study Selection Process

Two independent reviewers screened the titles and abstracts, followed by full-text evaluations of selected papers. Any disagreements were solved through discussion until consensus.

Data Extraction

Following Blanchard et al. (2022), the information extracted to reach the present study aims included: (1) study planning (i.e., rationale for using FINA); (2) participant characteristics (i.e., demographic and clinical characteristics); (3) recruitment procedures (i.e., setting of recruitment, and incentives to participate); (4) data collection (i.e., method and device used, length of data collection, timescale, number of timepoints planned, sampling scheme adopted); (5) measures (i.e., measures used, number of items, type of response scale); (6) data analysis (i.e., missing data, check and correction of normality and stationarity, treatment of overnight lag, assessment of topological overlap, model selection to estimate the network, type of variables and number of nodes used for network construction, type of network estimated, centrality indices, network stability check, software used, network comparison); (7) reporting practices (i.e., number of timepoints completed, topological overlap among nodes, resulting estimated networks and centrality indices, network comparison provided, description of each individual analyzed); (8) open science (i.e., preregistration, data and code sharing). Two reviewers performed data extraction independently, resolving any disagreements by consensus.

Results

Database searches identified 12,586 articles, reduced to 8627 after removing duplicates. Following abstract and title screening, 189 full-text articles were assessed for eligibility, and 43 studies were included. The PRISMA flow diagram details the search and screening process (Fig. 1). Table 1 presents an overview of the studies included in the scoping review. Further details are available in Online Resource 3.

(1) Study Planning

Fifty-eight percent of the studies (n = 25 studies) used data from open repositories or reanalyzed pre-existing data. Studies show variability in their rationale for using FINA, for instance for examining dynamic processes within individuals, or to compare these with group-level networks.

(2) Participant Characteristics

Sample sizes varied from 1 to 1272 individuals, with 16.3% (n = 7 studies) being single-subject studies. The highest number of individuals analyzed with FINA was 255 (M = 41.5, SD = 63.8); however, the highest number of individuals analyzed with FINA whose FINA results were actually reported—either in the main text, supplementary material or open repositories—was 133 (M = 18.2, SD = 33.8). This discrepancy reflects the fact that, in some studies, FINA was applied to a broader sample but results were presented only for a subset of individuals. On average, 79.1% of the participants were included in FINA analyses, but in 36.1% of studies with n > 1 (n = 13 studies), FINA results were reported only for a subsample (10.4%, on average), primarily for illustrative purposes. The mean age of participants analyzed with FINA ranged from 12 to 69.8 and, on average, 65.4% of participants were female, calculated as the mean proportion across studies. In 37.2% of the studies (n = 16 studies), the most frequent diagnosis among participants was depression. An overview of participant characteristics is presented in Table S1 (Online Resource 2). Detailed information is available in Online Resource 3.

(3) Recruitment Procedures

Recruitment settings varied, with 30.2% of studies (n = 13 studies) recruiting participants only from the community and 25.6% (n = 11 studies) only from outpatient settings. Participants were compensated in 34.9% of studies (n = 15 studies).

(4) Data Collection

EMA and ESM were used in 65.1% of studies (n = 28 studies), with electronic devices employed in 96.4% of cases (n = 27 studies). Assessment frequencies varied, with four daily assessments in 32.1% of these studies (n = 9 studies) and five daily assessments also in 32.1% (n = 9 studies).

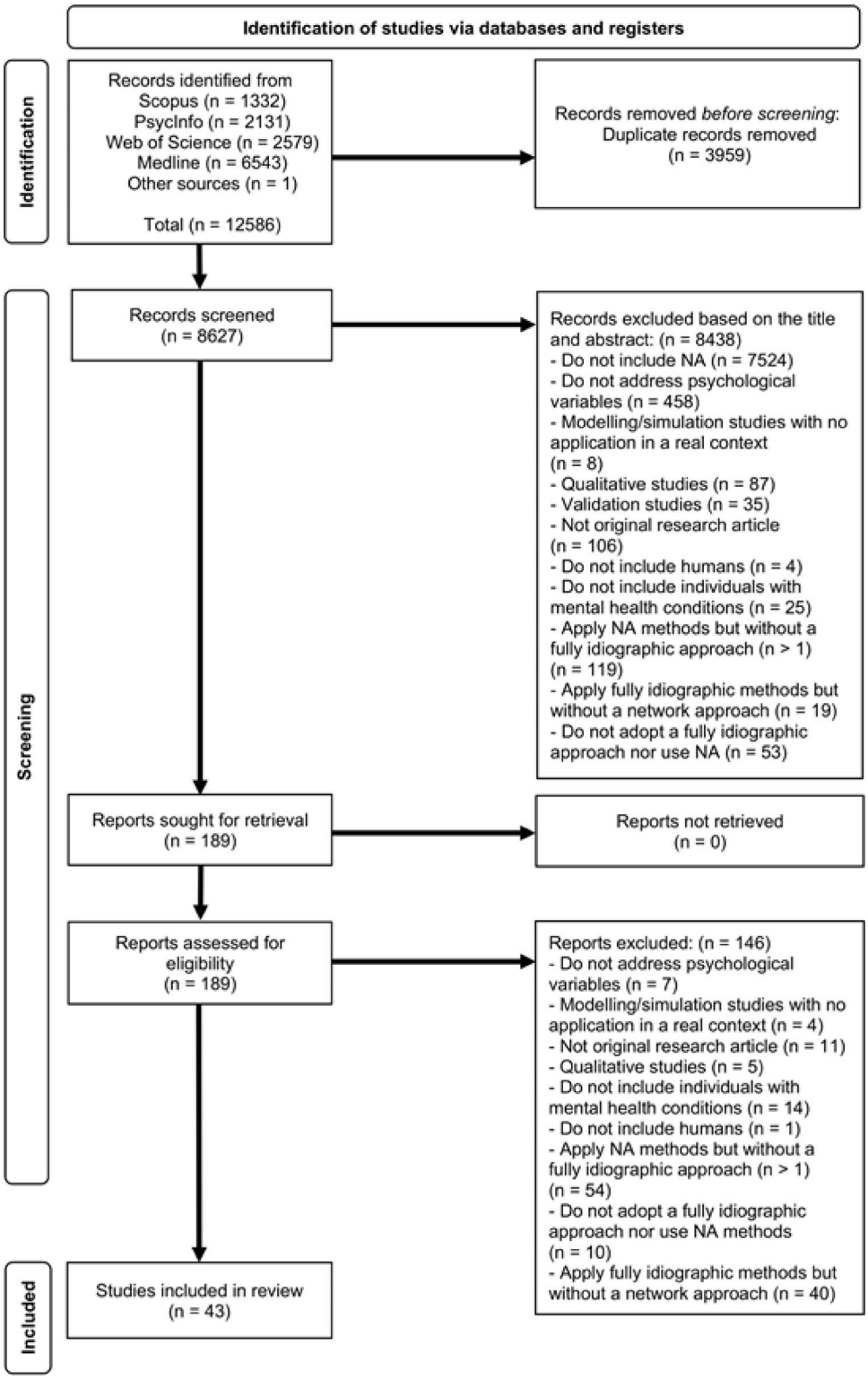

Fig. 1 PRISMA flowchart outlining the study selection process

Prompts were delivered at fixed intervals in 46.4% of cases (n = 13 studies) and at pseudo-random times (i.e., prompts sent randomly within a fixed interval) in 35.7% (n = 10 studies). Across all 43 studies, assessment frequency ranged from 10 times per day to 1 per 6 months, and the duration varied from 7 to 1529 days, with the total number of timepoints ranging from 6 to 1529 (M = 181.7). Among the studies reporting the percentage of completed timepoints, the average was 84.3%.

Table 1 Overview of the 43 studies included in the scoping review

1st author last name (Year)	N individuals analyzed with FINA	Mean age	% Females	Diagnosis	Setting of recruitment	Method used to collect data	Length of data collection	Timescale	Model used to estimate the networks
Bodner (2022)	158	NR	NR	Depression (100%)	Outpatient	Interview	1015 days	1 per week	ConNEcT
Booij (2021)	133	60.4	64.7	Depression (100%)	Inpatient	ROM	28–42 days[a]	1 per week	DTW
Bulteel (2018)	1	21	100	Depression (potential diagnosis) (100%)	Community	Self-report questionnaire	78 days	1 per day	PC-VAR
Burger (2022a)	1	31	100	Obsessive–compulsive disorder (100%)	NR	EMA	28 days	3 per day	Bayesian VAR (PREMISE approach)
Burger (2022b)	2	36.5	100	Eating disorder (100%)	NR	EMA	15 days	5 per day	Bayesian VAR (PREMISE approach)
Burger (2024)	20	36.1	NR	Depression (100%)	Community	Self-report questionnaire	28 days	1 per day	L-PECAN
Butler (2024)	18	30.7	94.4	Eating disorder (100%)	Inpatient, outpatients, and community	EMA	14 days	4 per day	GVAR
Cocx-Swiebel (2024)	148	50.4	62.2	Depression or bipolar disorder (100%)	Inpatient	ROM	14–15 weeks[a]	1 per 2 weeks	DTW
David (2018)	1	44	100	Comorbidity (100%)	NR	Self-report questionnaire	122 days	1 per day	DTSMLR
de Beurs (2024)	11	34.6	54.5	Depression (100%)	Outpatient	EMA	49–193 days[a]	3 per day	DTW
de Vos (2017)	54	34.7 (depression group); 34 (healthy group)	74.1 (depression group); 74.1 (healthy group)	Depression (50%)	NR	ESM	30 days	3 per day	sVAR
Ebrahimi (2024)	73	34.6	56.2	Depression (100%)	Outpatient	EMA	28 days	5 per day	GVAR
Epskamp (2018b)	1	53	100	Depression (100%)	Outpatient	ESM	2 weeks	5 per day	GVAR
Epskamp (2020)	1	57	0	Depression (100%)	NR	ESM	84 days	10 per day	ts-lvGVAR
Fisher (2017)	40	18 to 65	65	Generalised anxiety disorder (15%), major depressive disorder (10%), comorbidity (75%)	Community	ESM	29–35 days[a]	4 per day	DFA
Frumkin (2021)	12	33.7	58.3	Comorbidity (75%), adjustment disorder (8,3%), general anxiety disorder (8,3%), not available (8.3%)	Outpatient	EMA	21–24 days[a] for each wave (2 waves)	5 per day	GVAR
Gunther (2024)	87	NR	NR	NR	Community	Diary	28 days	1 per day	uSEM

Table 1 (continued)

1st author last name (Year)	N individuals analyzed with FINA	Mean age	% Females	Diagnosis	Setting of recruitment	Method used to collect data	Length of data collection	Timescale	Model used to estimate the networks
Hebbrecht (2020)	255	50.9	64.7	Depression (81.2%); bipolar disorder (18.8%)	Inpatient	ROM	2 weeks-16 months[a]	1 per 2 weeks	DTW
Hoekstra (2024)	2	NR	NR	Bipolar disorder (100%)	Outpatient	NR	42 days	5 per day	GVAR
Houtveen (2022)	10	42.8	90	Somatic symptom disorder (100%)	NR	ESM	112 days consecutively (study 1) or 70 days divided between pre and post treatment (study 2)	3 per day	RDSEM
Howe (2020)	45	37.6	65.2	Generalised anxiety disorder (51.1%), major depressive disorder (24.4%), comorbidity (24.4%)	Community	EMA	30 days	4 per day	Latent profile analysis (applied to individual time series) and mVAR
Levinson (2018b)	3	NR	NR	Anorexia nervosa (100%)	Inpatient and outpatients	EMA	7 days	4 per day	GVAR
Levinson (2020)	50	18.3	100	NR	Community	Interview	48 months	1 per month	GVAR
Levinson (2021)	34	34.5	91.2	Eating disorder (100%)	NR	EMA	15 days	5 per day	GVAR
Levinson (2022)	97	NR	NR	Eating disorder (100%)	Community	EMA	25 days	4 per day	GVAR
Lydon-Staley (2021)	2	NR	NR	Tobacco withdrawal (100%)	Community	EMA	14 days	4 per day	uSEM
Mariotti (2021)	1	12	0	Comorbidity (100%)	Outpatient	Self-report questionnaire	1 year (approximately)	1 per week; 1 per 2 weeks	GVAR
McGhie (2023)	52	30.1	76.9	Post-traumatic stress disorder (100%)	Community	EMA	14 days	5 per day	GVAR
Mesbah (2024)	141	49.1	60	Bipolar disorder (100%)	Outpatient	Self-report questionnaire, interview	2 years	1 per 6 months; 1 per 3 months	DTW
Nemesure (2024)	5	20 to 40	80	Depression (100%)	Community	EMA	90 days	3 per day	tv-VAR
Orzek (2023)	1	57	0	Depression (100%)	NR	ESM	41 days	10 per day	RCTSEM
Pagán (2023)	9	34.1	66.7	Comorbidity (100%)	NR	EMA	34–38 days[a]	2 per day; 3 per day	DTSMLR
Piccirillo (2022)	35	21.4	100	Comorbidity (100%)	Community	EMA	30 days	5 per day	GVAR
Raz (2024)	1	37	0	Post-traumatic stress disorder (100%)	NR	Diary	1529 days	1 per day	GVAR
Reeves (2020)	20	38.4	40	Post-traumatic stress disorder (100%)	Community	EMA	30 days (approximately)	4 per day	DFA

Table 1 (continued)

1st author last name (Year)	N individuals analyzed with FINA	Mean age	% Females	Diagnosis	Setting of recruitment	Method used to collect data	Length of data collection	Timescale	Model used to estimate the networks
Scholten (2022)	3	33	33.3	Depression (66.7%) and comorbidity (33.3%)	Outpatient	EMA	30 days	3 per day	GVAR
Scholten (2024)	8	31.8	62.5	Depression (25%), panic disorder (12.5%), comorbidity (62.5%)	Outpatient	EMA	30 days	4 per day	tv-VAR, tv-MGM
Siepe (2024a)	40	18 to 65	65	Generalised anxiety disorder (15%), major depressive disorder (10%), comorbidity (75%)	Community	ESM	29–35 days[a]	4 per day	Bayesian VAR
Siepe (2024b)	20	44.4	65	Depression (100%)	NR	EMA	154–539 days[a]	1 per day	tv-VAR
Thonon (2020)	3	34	66.7	Schizophrenia (100%)	Outpatient	ESM	2 weeks in the baseline and follow-up phases, 7 weeks in the intervention phase	5 per day; 3 per day	GVAR
van den Brink (2024)	28	35.7	65	Depression (100%)	Inpatient and outpatients	ESM	6 days	10 per day	DTW
van Zelst (2022)	182	69.8	68.7	Depression (100%)	Inpatient and outpatients	Self-report questionnaire	6 years	1 per 6 months	DTW
Wright (2015)	4	NR	NR	Personality disorders (100%)	NR	Diary	100 days	1 per day	uSEM

NR = not reported; EMA = Ecological Momentary Assessment; ESM = Experience Sampling Methods; ROM = Routine Outcome Monitoring; VAR = vector auto-regression; GVAR = graphical VAR; tv-VAR = time-varying VAR; PC-VAR = principal component-VAR; sVAR = sparse VAR; mVAR = mixed VAR; ts-lvGVAR = time series latent variables GVAR; uSEM = unified structural equation modeling; RDSEM = residual dynamic structural equation modeling; RCTSEM = regularized continuous time structural equation modeling; DTW = dynamic time warp analysis; DFA = dynamic factor analysis; DTSMLR = dynamic time series multiple linear regression; ConNEcT = contingency measure-based network; L-PECAN = longitudinal perceived causal problem networks; tv-MGM = time-varying mixed graphical model

[a]Depending on the participant

(5) Measures

The mean maximum number of items per assessment was 18.5, with items rated on ordinal scales in 48.8% of studies (n = 21 studies) and continuous scales in 46.5% (n = 20 studies). A summary of data collection methods and measures is provided in Table S2 (Online Resource 2), with further details available in Online Resource 3.

(6) Data Analysis

A summary of the data analysis methods used in the selected studies is presented in Table S3 (Online Resource 2). Detailed information is available in Online Resource 3.

Data Preparation

Three studies reported no missing data. Of the remaining studies, missing data were handled primarily using single imputation (20%, n = 8 studies). Among studies using FINA models that assumed data normality (79.1%, n = 34 studies), only 8.8% (n = 3 studies) tested normality and implemented corrective actions. Among studies using FINA models that assumed data stationarity (74.4%, n = 32 studies), stationarity was mostly checked by testing for linear trends (25%, n = 8 studies). Additionally, detrending was applied in 46.9% of cases (n = 15 studies) to correct for non-stationarity. Among EMA/ESM studies that reported treatment of overnight lag (75.9%, n = 22 studies), removal of the lag (i.e., the first measurement of a day was not regressed on the

last measurement of the previous day) was used in 68.2% of cases (n = 15 studies). Among studies that used individual items for network construction (86%, n = 37 studies), only six (16.2%) checked for topological overlap among nodes (i.e., when items measure similar constructs and are highly correlated), mostly using correlation analyses (83.3%, n = 5 studies).

Network Estimation

The most common model for estimating FINA-derived networks was GVAR (34.9%, n = 15 studies), followed by Bayesian VAR (7%, n = 3 studies) and time-varying VAR (tv-VAR) (7%, n = 3 studies). Other VAR models included principal component VAR (PC-VAR), sparse VAR (sVAR), mixed VAR (mVAR), and time series latent variables GVAR (ts-lvGVAR), each used in one study. Three studies (7%) used unified structural equation modeling (uSEM), one (2.3%) used residual dynamic structural equation modeling (RDSEM), one (2.3%) used regularized continuous time structural equation modeling (RCTSEM), seven (16.3%) used dynamic time warp analysis (DTW), two (4.7%) used dynamic factor analysis (DFA), two (4.7%) used dynamic time series multiple linear regression (DTSMLR), one (2.3%) used a contingency measure-based network (ConNEct), one (2.3%) used longitudinal perceived causal problem networks (L-PECAN), and one (2.3%) used time-varying mixed graphical model (tv-MGM). R was the primary software for FINA-derived networks estimation (93%, n = 40 studies). Variables for node representation were exclusively individual items in 69.8% of studies (n = 30 studies), and a mix of items and composites in 20.9% (n = 9 studies). The mean maximum number of nodes was 12.3.

Most studies (62.8%, n = 27 studies) estimated both contemporaneous and temporal networks, with 18.5% (n = 5 studies) combining them into a single plot. Centrality indices were estimated for both networks—strength for contemporaneous and instrength/outstrength for temporal networks—in 37% of these studies (n = 10 studies). Only five studies (11.6%) evaluated network stability (i.e., robustness to sampling error), mostly using a bootstrap method (60%, n = 3 studies). Visual comparisons of networks were made across participants in 41.9% of studies (n = 18 studies), within participants in 7% (n = 3 studies), and both across and within participants in 23.3% (n = 10 studies), with edge density (i.e., number of edges) frequently compared (18.8%, n = 8 studies).

(7) Reporting Practices

Among the studies that analyzed individuals with FINA whose FINA results are reported, 11 studies (25.6%) did not report participants' age, 12 studies (27.9%) omitted gender information, and four studies (9.3%) did not report diagnosis. Additionally, 12 studies (27.9%) did not specify the recruitment setting of participants, and 13 studies (30.2%) did not report the results for each estimated FINA-derived network.

Regarding data missingness, 29 studies (67.4%) did not report the percentage of completed timepoints. Among the 36 studies with n > 1, half (n = 18 studies) did not clarify whether any participants were excluded from statistical analysis due to missing timepoints. Of the 40 studies that did not explicitly rule out the presence of missing data, only one (2.5%) reported checking the type of missing data, while 14 (35%) did not report how missing data were handled.

With respect to data preparation, among the 37 studies that used individual items as node, topological overlap was not checked in 31 studies (83.8%). Among the 36 studies that estimated a contemporaneous network, two (5.6%) estimated but did not report centrality indices, and among the 34 studies that estimated a temporal network, two (5.9%) did the same.

More detailed information about reporting is provided in Online Resource 3.

(8) Open Science

Only three studies (7%) were preregistered. Data were shared in 13 studies (30.2%), and analysis code was shared in 25 (58.1%), either in supplementary materials or open science repositories.

Discussion

While reporting standards for cross-sectional NA have been established (Burger et al., 2023), no guidelines exist for FINA. This scoping review was conducted to map current practices, identify trends and gaps, and offer recommendations for planning, data collection, analysis, and reporting practices in FINA for mental health research.

The results highlight significant heterogeneity across studies in how FINA is applied in mental health research, likely due to the lack of clear guidelines. This heterogeneity encompasses study and participant characteristics, data collection, data analysis, and open science practices. Despite the idiographic nature of the method, only a few studies using FINA were single-subject, and among those with multiple participants, most reported only aggregated information on participants' characteristics. Data collection was typically intensive, often using electronic tools, though the amount of data collected varied considerably. Key statistical assumptions, such as normality, were seldom tested, while

the use of VAR models was widespread. As a relatively new area, FINA research shows limited adoption of open science practices: preregistration was rare, and data were less frequently shared than analysis code. Given the growing use of FINA in mental health research, providing guidance seems warranted. We have therefore provided recommendations and developed a structured checklist to guide researchers in conducting FINA studies (Table 2). The checklist is intended to enhance reporting standards and facilitate preregistration, ultimately promoting transparency in this emerging field.

Study Planning

The use of open repositories and the reanalysis of pre-existing datasets was common among the studies included in this review, with more than half adopting this approach. For example, both Orzek and Voelkle (2023) and Epskamp (2020) conducted secondary analyses on the dataset originally collected by Kossakowski et al. (2017), which included 1478 measurements across 239 consecutive days. The studies by Siepe et al. (2024a), and Siepe et al. (2024b), reanalyzed data from Fisher et al. (2017) and Lorenz et al. (2020), respectively. These examples illustrate that secondary analysis is a frequent strategy in FINA research, likely due to the challenges of collecting intensive longitudinal data. As such, open repositories represent a valuable resource for researchers aiming to apply FINA.

The decision to conduct FINA should align with research aims focusing on dynamic processes within individuals, addressing questions that aggregated group data cannot. For instance, Fisher et al. (2017) investigated the idiographic dynamics of mood and anxiety symptomatology, highlighting how individuals evolve over time–an aspect often missed in cross-sectional NA. FINA is also valuable for exploring differences between intraindividual and group-level networks, as shown by Levinson et al., (2018b) and de Vos et al. (2017), who noted the limitations of generalizing group-level symptom connections to individuals.

Participant characteristics

Despite the idiographic focus of FINA, most studies with $n>1$ reported only overall demographic and clinical characteristics, rather than individual-level information. For example, Levinson et al. (2018b), analyzed three individuals from an original sample of 66 patients with eating disorders but provided age, gender, and diagnosis information for the full sample only. Similarly, Lydon-Staley et al. (2021) conducted a secondary analysis on two individuals from a sample of 1210 participants, reporting demographic and clinical information only at the total sample level. In contrast, all single-subject studies included in the review (e.g., Burger et al., 2022a; David et al., 2018; Epskamp et al., 2018b; Epskamp, 2020; Mariotti et al., 2021; Orzek & Voelkle, 2023; Raz et al., 2024) provided detailed participant-level information.

Considering the idiographic focus of FINA, we recommend that researchers report detailed participant-level information (including age, gender, and diagnosis) not only for the overall sample (in studies with $n>1$) but also at the individual level, whenever possible. These details can be included in the main text or, more commonly, in supplementary materials. For example, Levinson et al. (2022) provided diagnostic information for all 97 participants in a supplementary file, along with their corresponding FINA-derived networks. Moreover, given the application of FINA in mental health, it is important that researchers specify the recruitment setting (inpatient or outpatient care). When participants are recruited from community samples, we recommend that researchers clearly describe how participants were recruited (e.g., Burger et al., 2024 reported enrollment through social media).

Data Collection

More than two thirds of the included studies used electronic devices to collect intensive data, primarily through EMA or ESM designs. Other methods, such as ROM, diaries, paper-and-pencil questionnaires, and interviews, were also used. A key difference among these methods is the timescale of assessments: EMA and ESM involve multiple daily assessments, while ROM, diaries, questionnaires, and interviews are typically conducted weekly or daily. For example, van den Brink et al. (2024) used an electronic device (PsyMate) to collect data 10 times per day using ESM. On the other hand, van Zelst et al. (2022) administered paper-and-pencil questionnaires once every six months.

EMA and ESM are widely recommended for collecting data from individuals in their natural environment, as they capture momentary states and reduce recall biases associated with traditional self-report questionnaires (Shiffman et al., 2008). While ESM has traditionally been used to measure affective states and EMA to track behaviors, the studies included in this review demonstrate flexible use of both methods across a variety of symptoms and experiences. Therefore, we recommend that researchers select the data collection method based primarily on the specific phenomena they aim to investigate. Importantly, since EMA/ESM rely on technological devices (all studies in this review used electronic tools) it is important to consider alternatives for patients with limited access to or difficulties using digital technologies, such as individuals from low-income populations or older adults. ROM can be a valuable alternative, particularly in clinical settings where immediate sharing

Table 2 Checklist for FINA in mental health research

Study planning

☐ Rationale for FINA: Motivations for choosing FINA over other approaches are clearly described
Note: FINA should be preferred in studies aimed to explore dynamic intraindividual processes that are not addressed by group-level analyses (Fisher et al., 2017)

Participant characteristics

☐ Participant(s): Age, gender and diagnosis are reported both for the total sample (in case of n > 1 studies) and for each individual analyzed using FINA

Recruitment procedures

☐ Setting of recruitment: The setting where participants were recruited (e.g., inpatient, outpatient, community) is clearly indicated
☐ Incentives: If incentives were provided to participants (e.g., monetary), this has been acknowledged. It is specified whether they were given based on a percentage of participation (e.g., completing 50% of timepoints)

Data collection

☐ Data collection method: The method (e.g., Ecological Momentary Assessment—EMA, Experience Sampling Method—ESM) and the device used for data collection (e.g., smartphone, paper and pencil) are clearly specified
☐ Length of data collection: The duration of data collection is clearly stated. If the length of data collection varies among participants, the individual-specific duration is indicated
☐ Timescale: The timescale of data collection (i.e., the frequency and number of assessments, such as per day or per week) is provided
Note. The timescale should match the variability of the clinical aspect under study (e.g., symptoms fluctuating daily or hourly) (Kasanova et al., 2020; Ram et al., 2017)*, and data collection frequency should be balanced to minimize participant burden* (Burke et al., 2017)
☐ Number of timepoints: The maximum possible number of timepoints is indicated
Note. The number of timepoints should be sufficient to ensure good sensitivity, meaning that a high proportion of true edges are accurately identified in the network (e.g., at least 75 timepoints for a network with up to 6 nodes) (Mansueto et al., 2023)
☐ Sampling scheme: In the case of using EMA/ESM to collect data, the sampling scheme (i.e., fixed, random, or pseudo-random) is indicated and justified
Note. A fixed design should be prioritized to facilitate equidistant data in case of using a model assuming that (e.g., VAR) (Janssens et al., 2018), *and to improve participant compliance* (Dejonckheere & Erbas, 2022)

Measures

☐ Measures used: The measures administered are specified, indicating whether they are pre-existing, drawn from an item repository, or created specifically for the study. It is clearly stated whether the validity and reliability of the measures were assessed
☐ Number of items: The number of items or questions asked at each timepoint is specified
☐ Response scale: The response scale for the administered items (e.g., ordinal, continuous) is indicated

Data analysis

☐ Missing data: The percentage of missing data is reported, the type of missing data (i.e., completely random, random, not random) is assessed, and the method for handling missing data (e.g., multiple imputation) is described. If participants are excluded due to missing timepoints, the minimum percentage of missingness for exclusion is stated
☐ Normality: If applicable, data normality is checked, and the adopted corrective measures (e.g., data transformations or robust estimation methods) are reported in case of non-normality
☐ Stationarity: If applicable, stationarity is checked, and the adopted corrective measures (e.g., detrending) are reported in case of non-stationarity
☐ Overnight lag: In the case of using EMA/ESM to collect data, treatment of overnight lag (e.g., removed, ignored) is detailed
☐ Node overlap: Node overlap is assessed (e.g., via correlation analyses), and methods used to handle overlap (e.g., creation of composites) are clearly indicated
☐ Model selection: The model used to estimate the networks (e.g., VAR, uSEM, DTW) is reported
Note. The choice of a model should be clearly justified by explaining how it can help answer the research question based on data characteristics (e.g., sampling scheme, type of variables) (Bringmann, 2021)
☐ Network construction: The type of variables used for node representation (i.e., individual item or composite scores) and the number of nodes in the network are clearly indicated
Note. The type of variables used for node representation and the number of nodes included in the network should be selected considering to balance the amount of information and network simplicity (Lafit et al., 2022; Mansueto et al., 2023)
☐ Type of networks: It is indicated whether temporal and/or contemporaneous networks are estimated
Note: The decision to estimate temporal or contemporaneous networks (or both) should be justified based on the type of information they provide (Epskamp et al., 2018b)
☐ Centrality indices: The estimated centrality indices (e.g., strength, instrength, outstrength, degree) are specified
☐ Network stability: The method used to assess network stability (e.g., data-dropping bootstrap) is reported, or the lack of assessment is justified
☐ Software used: The software and relevant packages used to estimate and plot the network are specified
☐ Network comparison: If more than one network is estimated, comparisons are conducted within and/or across participants, and the method used is clearly described
*Note. Visual comparison may overestimate heterogeneity due to sampling variations or power limitations. We therefore recommend statistical comparisons, such as the Individual Network Invariance Test (*Hoekstra et al., 2024*) to assess differences more rigorously*

Reporting practices

Table 2 (continued)

☐ Number of timepoints completed: The number or percentage of timepoints completed by participant(s) is reported
☐ Node overlap: The number of overlapping nodes and the statistics for their overlap (e.g., correlation indices) are provided
☐ Type of networks: All networks estimated, whether temporal, contemporaneous, or both, are reported in the results. If both types are estimated, details for each are provided
☐ Centrality indices: Values for all estimated centrality indices are reported
☐ Network comparison: If networks are compared, either within or across participants, the results detailing the differences and similarities between the networks are provided
☐ Individual-level description: Detailed results are provided for each individual analyzed with FINA

Open science

☐ Preregistration: Research questions, hypotheses, data collection methods, variables and analysis plans are preregistered (e.g., on the Open Science Framework or AsPredicted)
☐ Data and code sharing: Anonymized data and analysis scripts are made publicly available for replication and further exploration

of data with the clinician can support therapeutic decision-making (Barkham et al., 2023).

Regarding the timescale used in the reviewed studies, most were adapted to match the variability of the clinical aspect being investigated. For example, Wright et al. (2015) used diaries over 100 days to assess behaviors related to personality pathology, which are typically more stable over time. In contrast, Epskamp et al. (2018b) employed ESM over two weeks to monitor symptoms like sadness, tiredness, and rumination in a depressed patient, which fluctuate frequently throughout the day.

In line with the trends observed in the reviewed studies, we recommend adapting the length and timescale of data collection to the variability of the clinical phenomenon under investigation. More intensive sampling should be prioritized for symptoms that fluctuate rapidly throughout the day (Kasanova et al., 2020; Ram et al., 2017). However, there are currently no established guidelines to help researchers determine the optimal duration and timescale of data collection for specific mental disorders. This remains an important area for future research in N = 1 modeling (Nelson et al., 2017). To minimize participant burden during data collection, we recommend keeping high-frequency assessments brief (Burke et al., 2017; Wrzus & Neubauer, 2023).

In terms of sampling scheme, most EMA/ESM studies used fixed sampling, where assessments occur at consistent intervals. None of the included studies employed random sampling, where assessments are delivered at unpredictable times throughout the day. A fixed sampling scheme generally improves compliance (Dejonckheere & Erbas, 2022) and ensures equidistant data required by many FINA models, such as VAR (Janssens et al., 2018), and is therefore recommended. In contrast, random sampling schemes, where assessments are scheduled unpredictably throughout the day, can result in uneven data distribution and may not accurately capture the entire day. A pseudo-random design, where assessments are conducted randomly within fixed intervals, also violates the assumption of equidistant time-series data, but may be acceptable when the variation between timepoints is minimal (Bringmann et al., 2013).

The number of timepoints ranged from 6 to 1529 across studies, with a median of 99, while the maximum number of items per timepoint ranged from 4 to 56, with a median of 14. The included studies show that, when participant compliance is high, intensive assessments can improve understanding of psychological processes. For example, Scholten et al. (2022) conducted three daily assessments over 30 days, with up to 35 items per assessment, achieving a completion rate of 87.2% of the timepoints, with an average completion rate of 84.3%, among studies that reported this metric. This high level of compliance enabled the application of FINA to better understand individual functioning.

It has been recommended to use at least 75 time points when estimating a network with up to 6 nodes to ensure good sensitivity (i.e., the proportion of true edges correctly included in the network) (Mansueto et al., 2023). Although the absolute maximum number of timepoints for FINA remains unclear, it is advisable to plan as many as feasible. Recent work has also raised concerns about power limitations in FINA (Zhang et al., 2025), highlighting the risk of overfitting and issues concerning the replicability of individual edges. To address these concerns, we recommend that researchers plan the number of timepoints a priori whenever possible, using tools such as simulation-based power analysis and predictive accuracy analysis (Zhang et al., 2025). These methods can help determine the required number of observations per individual and assess the reliability of the resulting network structures. To improve compliance with intensive data collection protocols such as EMA/ESM, we also recommend the use of participant incentives, which have been shown to enhance adherence (Wrzus & Neubauer, 2023). While we do not prescribe a specific incentive amount, given the variability in study design and funding, researchers should indicate whether incentives were tied to specific participation thresholds. For example, Butler et al. (2024) offered a financial bonus to participants

who completed more than 75% of the assessments. Other methods to enhance compliance include personalized data collection protocols (Pieritz et al., 2021).

Measures

About half of the studies measured variables exclusively using ordinal, Likert-type scales, making this the most common measurement approach across the reviewed studies. Among them, Mesbah et al. (2024) used the highest number of response options, adopting a 9-point Likert scale to assess symptoms related to bipolar disorder. Only one study (Bodner et al., 2022) used a dichotomous scale to assess the presence or absence of depressive symptoms. Researchers should clearly specify the measures used to collect data, indicating whether they are pre-existing instruments or ad hoc items developed for the study. For EMA/ESM data collection, we recommend consulting open-access resources such as the ESM Item Repository (Kirtley et al., 2020) to inform item selection. We also recommend prioritizing the use of measures that have been evaluated for validity and reliability, in line with the growing emphasis on the importance of incorporating psychometric considerations into idiographic research. The number of items administered at each timepoint should be carefully balanced against participant burden, following the same logic used to determine the overall number of timepoints (Wrzus & Neubauer, 2023). Although about half of the studies measured variables exclusively using ordinal, Likert-type scales, continuous variables are preferable, as ordinal scales may limit variability in FINA (Piccirillo & Rodebaugh, 2019).

Data Analysis

Data Preparation

In most studies with $n > 1$, no specific criteria were defined for case inclusion based on the amount of missing timepoints. However, among the few that did, a common criterion was at least 80% completion of timepoints for inclusion in FINA analyses. Only one study (Scholten et al., 2022) reported examining the missing data mechanism. In general, most studies handled missing data through single imputation or omission. The most commonly used strategies included the Kalman filter (Levinson et al., 2018b) or the GVAR's "beepvar" function, which removes pairs of nonconsecutive responses (e.g., Epskamp et al., 2018b).

Following the recommendations of Mansueto et al. (2023), researchers should include participants who have completed a sufficient number of timepoints to ensure accurate identification of a high proportion of true edges, for example, at least 75 timepoints for a network with up to 6 nodes (Mansueto et al., 2023). Additionally, the minimum threshold of completed timepoints should be determined and stated, considering the characteristics of the study population, as compliance in longitudinal studies can be influenced by various factors such as specific psychological issues or low self-discipline (Schreuder et al., 2023).

Researchers should first assess the type of missing data to ensure compatibility with the selected handling methods, as different methods require specific assumptions (e.g. full-information maximum likelihood assumes that data are missing at random) (Cham et al., 2017). We also caution against the limitations of imputation techniques when handling missing data. While item-level missingness can often be addressed through imputation, EMA and ESM data are typically missing at the level of an entire timepoint (i.e., all items are missing for a specific assessment). In such cases, imputing entire timepoints may introduce bias, particularly in the estimation of contemporaneous networks where associations are inferred based on complete item responses at a given moment (Epskamp et al., 2018b). We therefore recommend mitigating this risk using techniques such as planned missingness, allowing some items to be omitted at each measurement, creating data missing completely at random or missing at random, thereby mimicking item nonresponse while managing participant burden (Mansueto et al., 2023). Researchers should specify how missing data were assessed and handled, using available checklists (Sidi & Harel, 2018).

Several FINA models, such as VAR-based ones, assume normality (Epskamp et al., 2018c). However, only six studies checked for this assumption, mostly using skewness and kurtosis. Of these, only three took corrective actions. For instance, de Vos et al. (2017) applied a quantile normalization procedure to adjust non-normal data. A variety of methods exists to address non-normality, and it is considered good practice to assess the distributional properties of data. We recommend that researchers address non-normality based on the specific statistical properties of their data (Pek et al., 2018). It is worth noting that, although violations of normality can occur for various reasons, there is no clear consensus on their impact on the estimation of person-specific networks (Epskamp, 2020).

Regarding stationarity, fewer than half of the studies that used models assuming stationarity actually tested this assumption. Common methods included visual inspection of time trends (e.g., Levinson et al., 2020) or statistical testing for linear trends (e.g., Ebrahimi et al., 2024). Most studies corrected for non-stationarity through detrending, by regressing the time-series on time and using the residuals for further analysis. In some cases, researchers assumed stationarity by selecting data from stable phases, such as

post-treatment periods (Epskamp, 2020). Detrending is recommended as a method to correct for non-stationarity, to avoid sensitivity issues (Epskamp, et al., 2018b).

In some FINA models assuming equidistant time points, this issue was addressed by removing the overnight lag (i.e., the first observation of the day was not regressed on the last of the previous day). Recommended approaches either treat nighttime as equidistant (e.g., using methods like cubic spline interpolation) or model it as missing data using continuous-time modelling (Ryan & Hamaker, 2022). However, unconstrained models are recommended, as they support interpolation, missing data treatment, removal of overnight lag (i.e., not regressing the first measurement of the day on the last of the previous day), and allow for testing overnight lag independently from daytime lag (Berkhout et al., 2024).

Finally, only six of the included studies assessed topological overlap, a phenomenon where individual items used as nodes in a network may reflect overlapping constructs and exhibit high intercorrelations, affecting network interpretation (Fried & Cramer, 2017). The common approach to detect overlap was examining inter-item correlations. To address it, most studies combined overlapping items into composite scores by averaging items targeting the same symptom (e.g., Piccirillo & Rodebaugh, 2022). To handle topological overlap, researchers should consider combining highly correlated variables or excluding redundant ones (Piccirillo & Rodebaugh, 2022; Scholten et al., 2022) using tools like the Goldbricker function in the 'networktools' R package (Jones, 2017). Alternatively, a theoretical approach can be used, where experts select items representing unique symptoms before analysis (Levinson et al., 2018a). Starting with a theoretical approach, followed by a data-driven one, is recommended.

Network Estimation

Various modeling approaches were used to apply FINA in the reviewed studies, and their choice should be justified based on the research question and the nature of the available data (Bringmann, 2021). Each model has its strengths and limitations, and model selection should align with research goals. VAR models were the most used in the FINA studies reviewed, particularly the GVAR model (e.g., Bulteel et al., 2018; de Vos et al., 2017; Epskamp, 2020; Howe et al., 2020; Levinson et al., 2022; Mariotti et al., 2021). As a result, researchers can rely on an extensive literature base and widely used software packages such as psychonetrics (Epskamp, 2021b) or graphicalVAR (Epskamp, 2021a) for applying these models. Although these models are widely used and recommended for FINA (Jordan et al., 2020), VAR's results depend on the duration of the measurement window, which may fail to capture symptom dynamics if it is too short (Epskamp et al., 2018b). We therefore recommend using VAR models only when the appropriate timescale for capturing symptom dynamics is well understood.

In addition to VAR models, other methods were used to estimate FINA. DTW analysis (Booij et al., 2021; Cocx-Swiebel et al., 2024; de Beurs et al., 2024; Hebbrecht et al., 2020; Mesbah et al., 2024; van den Brink et al., 2024; van Zelst et al., 2022) clusters symptoms based on the similarity of their temporal patterns: symptoms with similar severity trajectories exhibit smaller distances, whereas those with independent trajectories show greater separation. These distances are then organized into a matrix, which can be represented as a network graph. A key advantage of DTW is that it does not require fixed intervals between measurements, nor does it assume normality and stationarity. In addition, DTW allows the estimation of FINA-derived networks using a low number of timepoints (e.g., Mesbah et al., 2024 used only 6 timepoints). However, DTW is limited to identifying similarities between symptom trajectories and does not allow for inference of the direction of influence among symptoms. ConNEcT was used in one study (Bodner et al., 2022) to investigate symptom co-occurrence, offering a unique ability of handling dichotomous variables and operating without the assumptions of normality, stationarity, or equidistant measurements. Furthermore, unlike VAR models, the bivariate relations modeled by ConNEct remain unchanged when a variable is added or excluded. However, ConNEcT describes symptom co-occurrence without determining the directional influences between the symptoms. DTW and ConNEct are recommended when the research focus is on symptom co-occurrence rather than direct influences between symptoms. Both models rely on contemporaneous associations: DTW reveals how pairs of symptoms evolve similarly, while ConNEct is adept at studying pairwise associations in binary data. In addition, neither model relies on common assumptions of normality, stationarity, or equidistant measurements, which are often difficult to satisfy in clinical contexts.

Two studies used SEM approaches (Houtveen et al., 2022; Orzek & Voelkle, 2023), namely Residual Dynamic SEM (RDSEM) and Regularized Continuous Time SEM (RCTSEM). Both models are rooted in SEM, allowing for the inclusion of latent variables in the network structure. Although SEM models are not traditionally associated with network analysis, these models are increasingly adopted (Piccirillo & Rodebaugh, 2019) in FINA research to model within-person dynamics while addressing issues such as measurement error and irregular time intervals between observations. Their use highlights the integration of SEM frameworks into FINA research. RDSEM is suited for modeling dynamic relationships between residuals across time

within individuals. However, it can result in dense models that are difficult to interpret, especially when estimating a large number of parameters. In contrast, RCTSEM applies regularization techniques to reduce model complexity and improve interpretability by limiting the inclusion of unnecessary parameters. A shared limitation of both models is that they treat network variables as latent rather than observable. Four studies integrated SEM with VAR models, with three using uSEM (Gunther et al., 2024; Lydon-Staley et al., 2021; Wright et al., 2015) and one employing ts-lvGVAR (Epskamp, 2020). Combining SEM with VAR models enables the inclusion of both latent and observed variables, overcoming the limitation of relying solely on observed variables and assuming that all measurements are free of error. Both models also overcome SEM's constraints related to local independence (i.e., the assumption that variables are uncorrelated with each other after accounting for latent variables) (Epskamp et al., 2017). The main distinction between uSEM and ts-lvGVAR lies in their treatment of contemporaneous effects. ts-lvGVAR models these relationships as partial correlations, without assuming any specific direction of influence. In contrast, uSEM treats contemporaneous relationships as directed effects, interpreting relationships between variables at the same time point as causal effects. While uSEM enables the modeling of relationship directions within the same time point, determining the direction of these effects can be more challenging than working with the non-directional associations modeled by ts-lvGVAR (S. Epskamp, personal communication, October 3, 2024). Two studies (Fisher et al., 2017; Reeves & Fisher, 2020) used DFA to identify latent factors influencing observed variables over time. DFA combines elements of factor analysis with time series analysis, capturing both structural patterns and lagged relationships among latent factors. Unlike uSEM and ts-lvGVAR, which incorporate both observed and latent variables, DFA specifically focuses on modeling the dynamics of latent variables underlying time-series data. As a result, it does not prioritize the dynamics among observed variables, adhering to a latent variable approach, which is something network theory seeks to transcend.

In terms of recommendations, for studying latent factor dynamics, uSEM, ts-lvGVAR, RDSEM, RCTSEM, and DFA are preferable. uSEM and ts-lvGVAR are especially recommended when the research goal involves combining observed variables with latent constructs and exploring contemporaneous relationships. RDSEM and RCTSEM are well-suited for handling unequally spaced time intervals, with RCTSEM offering the additional advantage of reducing model complexity through regularization techniques, which can improve interpretability. DFA is recommended for examining dynamic relationships between latent constructs, particularly when working with short time-series data (Molenaar, 1985).

David et al. (2018) and Pagán et al. (2023) used dynamic time series multiple linear regression (DTSMLR) to obtain the partial correlation matrix of the network. This approach analyzes outcome-predictor relationships separately, which differs from VAR models that analyze the mutual influence of multiple variables simultaneously over time. Although the step-by-step linear regression process of DTSMLR is more computationally intensive, it offers more detailed insights into the individual contributions of each predictor. Additionally, this approach is particularly suitable in scenarios where VAR models are unsuitable due to the extent and pattern of missing data (David et al., 2018). For instance, David et al. (2018) successfully applied DTSMLR despite 26% of missing timepoints. L-PECAN was used in one study (Burger et al., 2024) to elicit symptom associations by directly asking patients about the causes and effects of their symptoms on a daily basis. This approach differs from other analytical models in the sense that it represents perceived relations among symptoms. Therefore, it captures subjective, perceived relations rather than statistically inferred associations from intensive longitudinal data. While L-PECAN does not involve statistical estimation, it overcomes some limitations of traditional EMA, such as those related to restricting symptom associations within predefined measurement windows. L-PECAN is recommended in situations where intensive EMA/ESM data collection is not feasible, or when the aim is to capture patients' or clinicians' perceived relationships among symptoms. This method may be especially useful in clinical practice, where subjective experience and clinical judgment are integral to case conceptualization (Burger et al., 2024).

Finally, three studies (Nemesure et al., 2024; Scholten et al., 2024; Siepe et al., 2024b) employed time-varying models to address the limitations associated with the assumption of stationarity in clinical contexts. These approaches allow for more accurate modeling of changes in symptom dynamics both within time points (tv-MGM) and across time points (tv-VAR). However, these models are computationally demanding and require a larger number of completed timepoints compared to simpler alternatives such as GVAR. These models are recommended when the research focus is on assessing changes in associations among variables over time, thereby relaxing the assumption of stationarity (Scholten et al., 2024). This is particularly useful in clinical settings when researchers aim to evaluate treatment effects over the course of an intervention.

In terms of nodes, most studies used individual items as nodes exclusively, with an average of 12 per network. Researchers should be aware that increasing their number can raise the risk of overfitting (Babyak, 2004) and reduce

predictive accuracy in FINA (Lafit et al., 2022). It is therefore advisable to maintain the network as simple as possible by limiting the number of nodes (Mansueto et al., 2023). Techniques such as dimension reduction (Bulteel et al., 2018) or the use of composite scores (e.g., Frumkin et al., 2021) are recommended to manage the number of nodes while balancing network complexity with interpretability.

The estimation of both contemporaneous and temporal networks was most common in the included studies: temporal networks capture relationships among variables over time, while contemporaneous networks capture associations occurring more rapidly. The choice of network type should match the research question and processes of interest, but using both contemporaneous and temporal networks provides a more comprehensive understanding of mental health dynamics (e.g., Levinson et al., 2021) and is recommended. For example, somatic arousal linked to the anticipation of a panic attack is captured in contemporaneous networks due to its immediacy, while the relationship between somatic arousal and avoidance behavior, which unfolds over time, is more likely to appear in temporal networks (Epskamp et al., 2018b).

Strength centrality (i.e., the sum of absolute edge weights connected to a node) was the most commonly used index for contemporaneous networks, while instrength (i.e., the sum of incoming absolute edge weights to a node) and outstrength (i.e., the sum of outgoing absolute edge weights from a node) were the most frequently estimated indices for temporal networks. When examining centrality, selecting the appropriate index is crucial for accurately capturing node importance, especially in mental health intervention science, where they can help identify personalized treatment targets (e.g., Levinson et al., 2020). However, researchers are advised to use centrality measures cautiously when informing treatment decisions and to consider them as exploratory tools rather than indicators of causal relevance. In particular, indices such as betweenness (i.e., the relative number of shortest paths passing through a specific node) and closeness (i.e., the number of edges that separate a specific node from the others) have been criticized for measuring node importance (Bringmann et al., 2019). Degree centrality (i.e., the total number of edges connected to each node) is generally considered more interpretable in this context. However, it should be re-estimated whenever a node is targeted in treatment to assess changes in its connectivity (Castro et al., 2024).

Regarding network stability, stability tests assess whether a network's structure remains consistent when estimated from subsets of the data, typically evaluating edge accuracy and centrality indices (Epskamp et al., 2018a). Only five studies in this review reported conducting stability assessments, reflecting the broader trend that, while bootstrap methods are standard in cross-sectional network research, approaches for evaluating stability in longitudinal networks remain under development (Reeves & Fisher, 2020). Researchers currently have limited methods available to assess the robustness of FINA-derived networks to sampling error. Of the reviewed studies, one (Epskamp, 2020) used a data-dropping bootstrap, which involves removing 25% of the data from a participant's dataset and re-estimating the model structure. This method is recommended for evaluating the stability of FINA-derived networks and is based on previous experience with case-drop bootstrap techniques commonly used in cross-sectional network analysis (Epskamp et al., 2018a). In addition to the statistical definition of stability used to assess the robustness of estimated networks, it is useful to consider a conceptualization of stability grounded in clinical interventions. In this context, stability is conceptualized as the resilience of a network (i.e., how quickly it recovers from disturbances). Highly connected and homogeneous networks tend to be more resilient, such that temporary disturbances (e.g., external stressors) may disrupt network equilibrium only briefly (Hofmann, 2025). Such networks can exist in either a pathological or non-pathological state and should therefore be interpreted in context. For example, in an adverse environment, a more stable network may make individuals less affected by negative events (Branchi, 2022). Nevertheless, reporting connectivity levels among nodes in FINA-derived networks in mental health can help distinguish between more and less stable networks (Hofmann et al., 2016). Although further empirical support is needed, this information may have important clinical implications. For instance, when psychotherapy is delivered during a period when the psychopathological network shows reduced resilience (i.e., lower stability), the system may be more likely to transition into a healthier alternative state (Hofmann, 2025).

Finally, about half of the studies compared networks either across participants or within the same individual using only visual inspection, while 12 studies used statistical procedures, often in combination with visual inspection. This suggests that, similar to stability testing, the use of formal statistical approaches for network comparison in FINA remains limited and represents an important area for future methodological development. When comparing networks within and/or across individuals, simplistic visual comparisons can overestimate heterogeneity due to sampling variability or power limitations (Hoekstra et al., 2023). Therefore, more rigorous methods, such as the Individual Network Invariance Test (Hoekstra et al., 2024) or Bayesian approaches (Siepe et al., 2024a), are recommended for testing individual differences in FINA.

Reporting Practices

Reporting practices varied considerably across the included studies and were often dependent on the specific variables considered. However, a general trend was the lack of information regarding the number of completed timepoints and whether participants were excluded based on missing data. The assessment and correction of topological overlap was not commonly reported, with fewer than half of the studies addressing this issue. Although centrality indices were often estimated, their results were not consistently reported. Another reporting practice concerned network comparisons, typically focused on descriptive accounts of individual networks without discussing differences or similarities across them. Finally, despite the idiographic focus of FINA, detailed reporting at the individual level, both in terms of participant characteristics and network results, was not consistently observed across the reviewed studies.

To enhance transparency, reproducibility, and replicability, authors should provide complete reporting of all relevant information. In particular, we strongly recommend reporting the number of timepoints completed by each individual, as this information is essential yet frequently omitted. We also recommend reporting whether topological overlap was assessed and how it was handled, as well as the type of network estimated (i.e., temporal, contemporaneous, or both), particularly in studies involving large samples. Centrality indices, and detailed similarities or differences across networks estimated using FINA should also be reported. FINA studies should prioritize individual-level reporting for each participant analyzed, and a similar principle applies to FINA-derived networks. However, given the potential difficulty of presenting detailed results for each individual in large samples, and depending on the study's objectives, we recommend a flexible approach. For example, graphical representations of all individual networks could be included, while detailed narrative or statistical summaries might be presented only for a representative subset (as done by Levinson et al., 2022).

Open Science

Preregistration remains uncommon in FINA research, with only three preregistered studies identified in this review (Gunther et al., 2024; Scholten et al., 2022; Siepe et al., 2024b). Approximately one third of the included studies provided access to their data, while just over half made their analysis code publicly available. These trends are consistent with those typically seen in emerging research areas, reflecting FINA's relatively recent development. Given that over half of the studies reanalyzed existing data, researchers should follow guidelines for pre-registering such studies (van den Akker et al., 2021). We recommend that researchers preregister their research questions, hypotheses, data collection procedures, variables, and analysis plans using platforms such as AsPredicted or the Open Science Framework (Nosek et al., 2022). Sharing data and code, especially in complex longitudinal approaches like EMA/ESM, enhances transparency, reproducibility, and collaboration. It allows others to validate findings, explore new questions, and build on existing work, ultimately advancing the field. In clinical research, data sharing is important but must be balanced with the need to protect patient privacy, particularly when working with intensive individual-level data. To address this, governance mechanisms can be implemented to reduce privacy risks while still enabling data accessibility. For instance, de-identification strategies, such as removing or masking sensitive information, or the use of AI-based tools to detect and anonymize personal identifiers can be effective solutions (Walsh et al., 2018).

Strengths and Limitations

To our knowledge, this is the first scoping review to systematically examine how FINA has been applied in mental health research. By identifying trends and areas for improvement, the review offers recommendations for researchers in study planning, data collection, data analysis, and reporting. We also developed a checklist and provided recommendations based on the results of this review and relevant literature that are focused on study planning, data collection, data analysis, and reporting.

In terms of limitations, despite our efforts, some relevant studies may have been missed. The search keywords may not have been exhaustive (e.g., the keyword "dynamic*" often used in person-specific network analysis was not included; the keyword "statistic*" could have retrieved studies unrelated to the research aim). Limiting the review to peer-reviewed studies may have introduced publication bias, overrepresenting positive findings and overlooking less favorable or unpublished research that could provide a more balanced view of the field. We did not assess the quality of the included studies, which could have offered insights into their methodological rigor and reliability. Consistent with the aims of a scoping review, we prioritized mapping the existing literature over answering specific research questions, which naturally led to a broad and descriptive synthesis.

Conclusion

This scoping review provided an overview of data collection and analysis methods used in studies applying FINA in mental health research. Future scoping reviews could investigate additional network analysis methods that assess dynamic relationships between symptoms within individuals, offering comparisons to fully idiographic approaches currently prevalent in clinical practice. One promising method is "idionomic networks" (Sanford et al., 2022), which model idiographic dynamics first and incorporate nomothetic information from a population only if it improves the idiographic model fit. A notable statistical approach for estimating idionomic networks is Group Iterative Multiple Model Estimation (GIMME; Gates et al., 2017), which detects individual-level network edges and, if sufficiently common, models these edges at the group level.

While the checklist we have provided synthesizes the key steps for conducting FINA studies, several methodological issues that limit its full applicability warrant further investigation. For example, although we recommend aligning the timescale of data collection with the variability of the clinical phenomena under study, no clear guidelines currently exist linking specific timescales to specific psychopathologies. This uncertainty also extends to the choice between temporal and contemporaneous networks, as it remains unclear which network type best captures symptom dynamics in different disorders. Future studies should directly compare various data collection timescales and network types across clinical populations to address these questions. Another important gap concerns the assessment of the validity and reliability of the measures used in FINA. While open-access item repositories are available to support item selection for intensive longitudinal data collection, the psychometric properties of these items remain underexplored. Addressing this issue would allow researchers to select items not only for their clinical relevance but also based on psychometric evidence.

Thorough reporting of FINA methodological details in mental health research can pave the way for future studies to accurately describe FINA procedures, thereby promoting replicability and enabling evaluation of its clinical validity and utility. For instance, providing specific information on data collection, missing data handling, and criteria for model selection can enhance the reproducibility of FINA studies. Detailed reporting also enables clinicians to evaluate whether the symptom networks estimated using FINA reflect the symptom patterns they observe in practice, including how one symptom may influence another.

We hope this overview encourages the rigorous planning and implementation of FINA, ultimately helping to bridge the gap between clinical practice and mental health research.

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Data Availability Data is provided within supplementary online resources.

Declarations

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