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nature reviews psychology

https://doi.org/10.1038/s44159-023-00218-4

Review article

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A review of approaches and models in psychopathology conceptualization research

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Abstract

Mental disorder classification provides a definitional framework that underlies applied clinical and research efforts to understand, assess, predict, prevent and ameliorate the burden of psychopathology. Many classification frameworks exist, perhaps most notable being the 'authoritative' systems of the fifth edition of the *Diagnostic and Statistical Manual of Mental Disorders* and the 11th revision of the *International Classification of Diseases*. However, numerous limitations of official classification systems have been identified, fostering the development of empirically derived, statistical and psychometric alternative classification approaches, which attempt to overcome those limitations. In this Review, we describe three such advances: transdiagnostic dimensional approaches (such as the Hierarchical Taxonomy of Psychopathology; HiTOP), network approaches and clinical staging approaches. We discuss their strengths, limitations, divergence, overlap, and scientific and clinical utility, with a focus on the potential synthesis and integration of disparate approaches towards better classification of mental disorders.

Sections

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Introduction

Mental disorder classification provides a definitional framework that underlies applied clinical and research efforts to understand, assess, predict, prevent and ameliorate the burden of psychopathology. A wide variety of such classification frameworks has emerged, differing in notable ways. Each takes a unique position on how mental disorders should be diagnosed, classified and assessed and on how psychopathology itself is structured.

'Official' classification systems (nosologies), such as the fifth edition of the *Diagnostic and Statistical Manual of Mental Disorders* (DSM-5)[1] and the 11th revision of the *International Classification of Diseases* (ICD-11)[2] are composed almost exclusively of very large sets of dichotomous (present/absent) diagnoses, each of which is itself composed of a set of diagnostic criteria. These are known as polythetic criterion sets: if a given person exhibits a pre-defined number of these criteria, and experiences related distress or impairment, that person is assigned that particular diagnosis. Because the DSM-5 and ICD-11 define disorders as independent of one another, one would expect their frequency of comorbidity due to chance to reflect the prevalence rates of the disorders. For example, based on reported national prevalence rates of major depression (13.3%) and generalized anxiety disorder (2.7%) in the USA,13.3% of individuals with generalized anxiety should also have major depression due to chance alone[3]. However, the observed rate of major depression in this population is closer to 53%[3]. Thus, a fundamental problem with these nosologies is that they do not account for the high rates of comorbidity (co-occurrence) among putatively distinct mental disorders.

The distinctions between categorical diagnoses are further obscured by symptom overlap[4]. Moreover, because arbitrary thresholds are used to demarcate the presence or absence of mental disorders (such as requiring the presence of at least five of nine diagnostic criteria to receive a diagnosis), two people with the same diagnosis might have only a single symptom in common. A further consequence of this 'checklist' approach is that one diagnosis often collapses hundreds or thousands of potential symptom presentations into a single 'present' versus 'absent' category[5–7], which is inconsistent with the continuous and dynamic nature of observed signs and symptoms that individuals experience in daily life[8]. In other words, the dominant models of mental disorder classification (such as discrete DSM-5 diagnoses) do not fit the data[9]. Consequently, comparing people 'with' and 'without' a diagnosis — for example, to identify risk factors or treatment effects — is often not a meaningful endeavour. Related to both symptom overlap and arbitrary thresholds, there is substantial unreliability in traditional diagnoses—there is low inter-rater reliability and instability in individual diagnoses over time[6,10,11].

Together with the misalignment between traditional diagnoses and key mechanisms in neuroscience, molecular genetics, biological psychiatry and clinical psychology[12,13], the limitations of official nosologies hinder progress in, for example, identifying biomarkers of mental illness and improving treatment outcomes[14–16]. Psychopathology classification is therefore facing a demonstrable paradigm shift in an attempt to overcome these limitations[17–22].

In this Review, we summarize progress in psychopathology classification to date emerging from three leading alternative approaches: transdiagnostic dimensional approaches, network approaches and clinical staging approaches. Each approach takes a different route to — and makes different theoretical assumptions about — the structure of mental disorder. First, we review the foundations, key research findings and limitations of each approach. Next, we consider how the three approaches can be applied to study within-person changes over time in both the short term and across the lifespan, and we discuss their potential clinical applications. We conclude with future directions for the classification of mental disorders at the intersection of the three approaches.

Transdiagnostic dimensional approaches

Transdiagnostic dimensional approaches apply continuous (versus categorical or dichotomous) dimensions to psychopathology data, which represent unbroken spectra (also referred to as factors) that range from very low to very high levels (and all levels in between). Further, these spectra are transdiagnostic: these dimensions are not simply continuous reflections of official dichotomous diagnoses but instead cut across the diagnostic boundaries separating disorders[23,24]. In doing so, these dimensions are interpreted as reflecting core 'building blocks' of variation that characterize multiple disorders. Thus, a single transdiagnostic dimension, such as 'internalizing', can include psychiatric phenomena from different diagnoses of the same type (in this case, major depressive disorder and dysthymic disorder, both of which are mood disorders) as well as from different groupings of disorders (in this case, mood disorders and anxiety disorders)[24].

Transdiagnostic dimensions overcome many of the problems with official nosologies. First, their dimensionality (versus a present/absent dichotomy) captures the structure of real-world data, where samples of individuals report levels of psychopathology that generally range widely — above and below DSM-5 diagnostic thresholds — and have no clear points of discontinuity across severity levels[25]. Further empirical support for dimensionality comes from taxometric research that finds little evidence for discrete groups within a spectrum[26], and genetic evidence suggests that liability to mental illness is continuously distributed[27].

Second, although diagnostic comorbidity is viewed as a problem in traditional classification frameworks, transdiagnostic dimensional models explicitly embrace comorbidity by modelling these relationships among mental health variables. These models explicitly allow for greater-than-chance correlations among different forms of psychopathology and for overlap among them.

Third, dimensionality overcomes the need for largely arbitrary diagnostic criterion thresholds. As an example, using the official nosologies' threshold of at least five of nine criteria being present to support the diagnosis of a given mental disorder, individuals with similar levels of psychopathology (such as a person meeting four criteria and another meeting five criteria) would be described as being totally different (in this case, diagnosis absent and diagnosis present, respectively), whereas individuals with notably different levels of psychopathology (such as a person meeting five criteria and another meeting nine criteria) would be described as exactly the same (both receiving a diagnosis). Thus, thresholds obscure important similarities and differences within diagnoses and across individuals by grouping individuals into one of two diagnostic groups (diagnosis present versus diagnosis absent). Because transdiagnostic dimensions have no thresholds, the similarity (or dissimilarity) between two individuals is fully characterized by their levels (or scores) on the underlying dimension(s). This dimensional view of psychopathology addresses the well known failure of traditional nosologies to recognize subthreshold manifestations of psychopathology, which are associated with high rates of suicidal behaviour, health service utilization, public assistance costs, and impairment and disability[28,29].

Key classification findings

Transdiagnostic dimensionsional approaches generally fall into two groups: those that arose specifically to organize personality disorder variation, and those that arose to organize psychopathology more broadly. This grouping stems from early work on the part of personality disorder researchers to move toward dimensional models to overcome problems with official personality disorder diagnoses. Informed by this earlier work, psychopathologists began applying similar methodologies to broader types and numbers of disorders, sometimes still including personality disorders in their analyses. These models are remarkably congruent despite their unique origins. Further, they build upon, and converge with, findings from research on the structure of normal-range personality variation, and they outperform models from official nosologies with regard to superior model fit to observed data and structural validity[30–34].

Fundamental dimensions of general personality were examined to organize all of the stable personality-related attributes that can describe people. They were shaped by comprehensive analyses of adjectives abstracted from dictionaries[35] and separately by hypothetically derived lists of items[36]. Such research programmes independently identified five dimensions of personality, often referred to as domains: neuroticism (versus emotional stability), extraversion, agreeableness, conscientiousness and openness[37,38]. Multiple subdimensions (facets) were identified as nested within each dimension, producing a hierarchical organization of personality traits with increasing levels of generality, ranging from narrow habits (for example, 'frequency of tooth brushing') at the base and broad predispositions (for example, 'conscientiousness') at the apex. This Five-Factor Model, and the very similar Big Five (see Fig. 1a), are the best established frameworks of dispositional traits.

Dimensional research on the structure of personality pathology has been largely based on personality disorder symptoms included in the DSM-5. These studies consistently revealed five domains of maladaptive personality: negative affectivity (versus emotional stability), detachment (versus extraversion), antagonism (versus agreeableness), disinhibition (versus conscientiousness) and psychoticism[39]. The first four pathological domains map closely onto their normal-range Five-Factor Model counterparts[40,41]. The link between psychoticism and openness is unsettled[42]. As in the Five-Factor Model, the higher-order domains of personality pathology subsume a set of narrow traits (for example, 'risk taking'). This hierarchical organization was included in the DSM-5 Alternative Model for Personality Disorders[1,43] (Fig. 1b), and

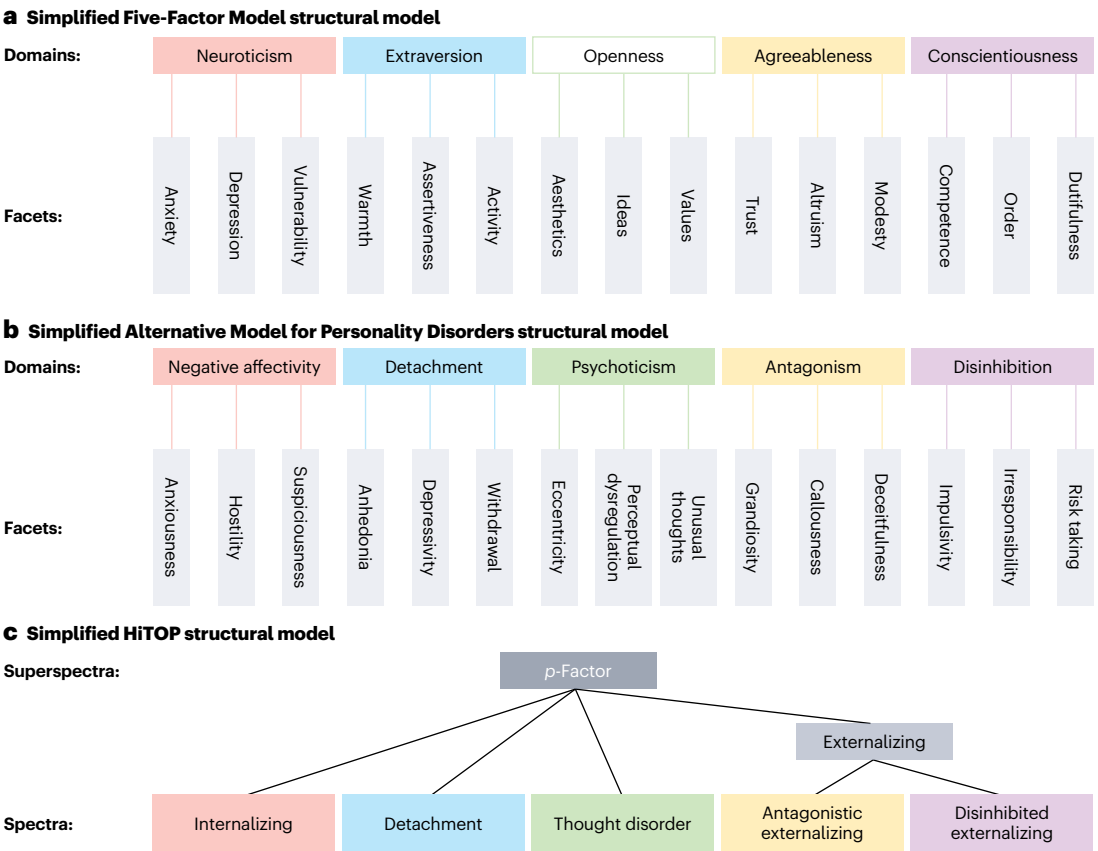

Fig. 1 | Links between factors in dimensional models. a, Simplified Five-Factor Model structural model. **b**, Simplified DSM-5 Alternative Model for Personality Disorders structural model. **c**, Simplified Hierarchical Taxonomy of Psychopathology (HiTOP) structural model. Domain and spectrum boxes are shaded by colour to show their corresponding domains and spectra across the three models. The unfilled box around the five-factor model openness domain indicates that its associations with the Alternative Model of Personality Disorders psychoticism domain and the HiTOP thought disorder spectrum are unresolved. For simplicity, not all facets of each domain of the Five-Factor Model and Alternative Model for Personality Disorders are depicted. Only the highest-order portion of the full HiTOP model is depicted (see Supplementary Fig. 1 for the full model), and the somatoform spectrum is not included on account of ongoing questions about its optimal placement in the model.

Box 1

Relationships among transdiagnostic dimensions and other approaches

A common question is how transdiagnostic dimensional approaches, such as HiTOP, relate to approaches such as the National Institute of Mental Health's Research Domain Criteria (RDoC), the National Institute on Alcohol Abuse and Alcoholism's Addictions Neuroclinical Assessment, and the National Institute on Drug Abuse's Phenotyping Assessment Battery. Although HiTOP takes an atheoretical stance on aetiology, these latter approaches were specifically designed to organize research around biobehavioural dimensions, with the intention that these biobehavioural dimensions might be closer to potentially aetiologic biological substrates such as brain circuits and genes. HiTOP's focus on phenotypes (that is, signs and symptoms of mental disorder), and these systems' focus on putative biological bases of behaviour might seem incommensurate. However, the different dimensions included in each of these four approaches have been linked to one another, and represent similar constructs to some extent. These relationships usually do not reflect one-to-one relationships (such as one single HiTOP domain linking to one single RDoC domain) but rather multiple areas of overlap (such as one HiTOP domain linking to two RDoC domains). For instance, the HiTOP internalizing spectrum shows positive associations with RDoC's negative valence domain and both negative and positive associations with different constructs subsumed under RDoC's arousal and regulatory domain. Such associations have allowed the development of a crosswalk between the HiTOP, RDoC, Addictions Neuroclinical Assessment and Phenotyping Assessment Battery constructs, and using these systems togther produces a coherent description of psychopathology[244].

this model has been formally instantiated in the Personality Inventory for the DSM-5 (ref. 44) and similar assessment instruments.

In a separate line of inquiry, analyses of common mental disorders and their symptoms consistently revealed six major dimensions: internalizing, detachment, thought disorder, antagonistic externalizing, disinhibited externalizing and somatoform[30,45]. These dimensions have been observed across hundreds of phenotypic studies and provide a useful framework for investigating risk factors, biomarkers, prognosis and patterns of treatment response common among psychopathology features within a spectrum[45–47]. Over a hundred narrow symptom components (for example, 'insomnia') have been observed within these spectra[48].

The Hierarchical Taxonomy of Psychopathology[30] (HiTOP; Fig. 1c, Supplementary Fig. 1) was developed by a consortium of quantitative nosologists to synthesize the parallel literatures on the dimensional structures of maladaptive personality and traditional mental disorder diagnoses into a single overarching hierarchical model. The HiTOP framework organizes dimensions based on empirical patterns of covariation into a hierarchy, with the six core spectra described above at the centre. Individual symptoms, signs and traits cohere into higher-level syndromes, then broader subfactors, then the spectra and ultimately super-spectra. Current super-spectra include an externalizing dimension as well as a general factor of psychopathology (the *p*-factor) — an overarching dimension that encompasses features common to all forms of psychopathology. Thus, the *p*-factor is conceptually similar to the broad *g*-factor, which is conceptualized as general intelligence and represents the relationships among multiple subtests of intelligence (such as subtests measuring the abilities to answer factual questions, define word meanings and assemble blocks to reproduce a given pattern)[27,49–53]. The HiTOP dimensions also bear strong conceptual and structural similarities to other independently developed models of psychopathology, such as the Achenbach System of Empirically Based Assessment[54] and the PSY-5 (ref. 55) (Box 1).

Extensive evidence indicates that the general dimensions of the Five-Factor Model, Alternative Model for Personality Disorders and HiTOP are closely aligned (see Fig. 1). In particular, there is direct correspondence between the Alternative Model for Personality Disorders domains and the HiTOP spectra[56]. Compared to well established HiTOP spectra such as internalizing and externalizing, relatively less information is available about the HiTOP somatoform spectrum, which does not include traits explicitly, but nevertheless shows clear links to negative affectivity[57]. Normal-range personality domains also show expected links to HiTOP spectra[57–61]. Overall, a large body of evidence supports a consistent structure that unifies these models, with additional unique variance accounted for by openness and somatoform constructs in the Five-Factor Model and HiTOP frameworks, respectively. The models differ primarily in what aspects of this structure they emphasize: the Five-Factor Model focuses on the normal range, the Alternative Model for Personality Disorders focuses on the maladaptive range, and HiTOP includes transient symptoms as well as maladaptive personality traits.

The utility of transdiagnostic dimensions can be assessed by head-to-head comparisons to traditional diagnoses. Transdiagnostic dimensions account for longitudinal links between disorders[25] and the sequential unfolding of psychopathology over time[62] much better than do traditional diagnoses. Numerous studies have demonstrated superior prediction by dimensions for a wide variety of important variables[30]. For example, dimensions outperform diagnoses in predicting impairment[63,64], suicidality[25,65,66], and even mortality over 20 years[67]. The breadth of these sorts of comparison is reviewed elsewhere[45,63]. Investigation of additional outcomes, such as treatment-related course and outcome as well as relationship functioning, is needed to fully adjudicate the predictive utility of transdiagnostic dimensional approaches[68].

Factor meanings and causality

Although the hierarchical approach provides some clear benefits, there is debate on how to interpret transdiagnostic dimensions. One issue is the substantive interpretation of factors. For instance, there are many interpretations of the *p*-factor, including as a representation of general liability for psychopathology or of overall psychopathology severity[27,51,53]. Another possibility is that the *p*-factor is a general consequence of psychopathology (for example, impairment or distress) rather than its cause. Moreover, notable criticism has been levied against interpretation of what the statistical *p*-factor actually represents, owing to its conceptual instability as demonstrated by the varied meanings ascribed to the general factor across studies[69], samples[70], subsets of variables[71], and factor analytic methods (such as exploratory factor analysis versus confirmatory factor analysis).

This issue of interpretation extends to other transdiagnostic dimensions. Dedicated research is needed to test whether the dimensions represent risk for specific domains of psychopathology (that is, a predisposition towards experiencing the indicators of the dimension[27,51]), or a descriptive summary of the severity of presenting symptoms in that domain[45,52]. For example, the internalizing dimension might capture a propensity towards negative affect that causes experiences such as depressed mood, worry and panic; or it might only describe these experiences. Both possibilities are useful for assessment and diagnosis, but they have different implications for application in practice. However, it is important to remember that, statistically, latent variables estimated to model the structure of psychopathology simply summarize the patterns of comorbidity or covariation among the indicators in the model. Theory building and testing are required to move beyond the assumptions and limitations of relying on latent variables and to understand better the substantive nature of the dimensions.

Network psychometric approaches

Transdiagnostic dimensional approaches summarize psychopathology at the between-subjects level, and each domain is conceptualized as dimensional at the population level[26]. Network approaches to psychopathology offer an alternative point of view, where mental health and disorder are seen as complex, dynamic biopsychosocial systems. The core idea is that problems, such as psychopathology symptoms, influence each other, and mental disorders emerge from the relations among these problems[17,72–74]. Further, mental disorders are conceptualized as within-person systems that unfold over time. From this perspective, mental health conditions can be thought of as systems that have categorically distinct healthy and disordered states, similar to other complex systems in science. For instance, lakes can have clean (fresh and blue) or turbid (green and full of algae) states. Transitions between such states might be abrupt for some individuals (or lakes) but gradual for others, which is not consistent with a purely dimensional model[17,75,76].

Network approaches have become more prominent owing to the development and translation of statistical network models into psychology over the past decade and the availability of accessible tutorial papers (Box 2). The network approach is particularly useful for estimating and visualizing interrelations of variables (such as symptoms) at the group level (Fig. 2a) or at the individual level (Fig. 2b).

Compared to official nosologies of mental disorders, research on network approaches has thus far not aimed to identify or define clear-cut categories; rather, it emphasizes that comorbidity is a natural result of causal associations among problems, irrespective of diagnostic boundaries[77]. Viewed from a network perspective, existing categories such as major depressive disorder or schizophrenia are (more or less) useful simplifications of complex underlying processes, and high observed rates of comorbidity among categories reflect causal relations among psychopathology symptoms. Network theorists have not yet provided an empirically derived alternative framework to replace the DSM, but several steps forward have been suggested. One of them is to estimate psychopathology systems at the idiographic level and use data-driven, bottom-up approaches to investigate to what degree these processes can be clustered in meaningful ways across individuals[78–81].

Key classification findings

Three key findings and ongoing research efforts from network approaches are worth noting. First, the perspective of mental disorder as a dynamical system aligns with many other scientific disciplines, such as ecology or meteorology, which have developed statistical tools for forecasting system transitions to different states (such as a healthy to a turbid lake or sunny weather to tropical storm). These tools have been applied to forecast transitions into mental disorders such as depression, and there is some preliminary evidence that both variable-specific and system-level early warning signals might forecast transitions from healthy to disordered states[82–86]. Much remains to be done, and some work raises questions as to the value of early warning systems as a personalized prediction method[87,88].

Second, network approaches have shown promise in bridging the gap between theoretical and statistical models via formal theories. To build a formal network theory, researchers first embed all of the evidence about the target system that they want to capture into a coherent theoretical structure (for example, the components of panic disorder, and the exact network relations among components of panic disorder), and then translate these relations into mathematical terms (usually difference equations) that specify the theory formally[89,90]. Such formal theories facilitate theory formation by – among other factors – sidestepping ambiguities of language by requiring mathematical notation (all variables and relations among variables must be spelled out exactly) and allowing researchers to generate data from a given theory to investigate what theory-implied data would actually look like (which is not possible for verbal theories). The generated data can then be compared to observed data of the phenomenon under investigation, leading to iterative theory building and testing[89,91]. For example, a formal theory for panic disorder[73] found that the generated data were consistent with many known phenomena about panic attacks (such as key phenomenological characteristics,

Box 2

Real-world statistical implementation of dimensional and network approaches

Transdiagnostic dimensional approaches and network approaches to understanding mental disorders are grounded in particular statistical methodologies and models. Factor analytic methods that are used in transdiagnostic dimensional approaches are widely available in common software packages, including SPSS, SAS, Stata, Mplus and R. Psychometric network models are usually estimated in R, where various R packages (such as *qgraph, bootnet, gimme*) have been developed. The application of both methodologies requires a familiarity with their statistical underpinnings as well as their implementation in software. Fortunately, numerous resources are available for researchers interested in using these tools, many of which include syntax. Several books provide straightforward conceptual and applied factor analytic coverage[245,246]. We recommend approachable tutorials on transdiagnostic dimensional[247] and network models[112,119,248–252]. There is also a wealth of instructional material on network models on YouTube, produced by many of the approach's key developers (see Sacha Epskamp's YouTube channel).

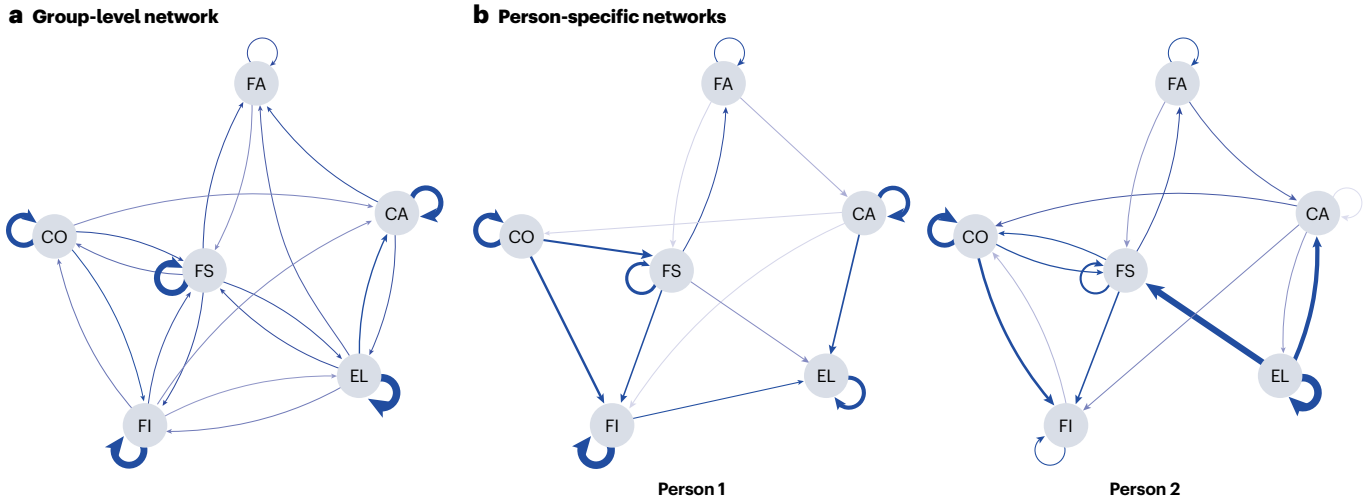

Fig. 2 | Group-level and person-specific network models. a, A directed network fit to simulated data from 25 individuals, consisting of six depression symptom variables from the Inventory for Depressive Symptomatology[243]. **b**, Networks using time-series data from two different individuals from the sample of 25. Nodes are depicted as circles and edges as arrows connecting nodes. Nodes represent items from the Inventory for Depressive Symptomatology: EL, energy level; FS, feeling sad; FI, feeling irritable; CO, concentration; FA, falling asleep; and CA, changes in appetite. Blue edges represent positive associations. The thickness and saturation of arrows indicate the strength of conditional dependence associations among nodes.

panic disorder onset and efficacy of established treatments), but it also identified gaps that future iterations of the theory need to tackle (such as the fact that there are people with panic attacks who never develop panic disorder).

Third, many tools of social network analysis have been used to investigate the predictive utility of network approaches[73,92,93]. For example, network characteristics such as node centrality (structural importance) and density (the overall degree to which all nodes are connected in a network) have been associated with depression[94] and psychosis[95]. Density has been related to psychopathology in cross-sectional data[96], dynamic networks[94,95], and dynamic networks that change over time within a person[84,85]. However, some studies did not replicate these results[97,98]. Similarly, studies have tested whether symptom centrality predicts the onset of psychopathology or treatment dropout in cross-sectional or longitudinal networks, with mixed results[99–103]. Overall, the question of whether centrality measures are useful predictive tools requires further study[93,104,105]. For example, centrality measures such as betweenness centrality were not intended to be used for networks with negative relations, and they have been shown to be conceptually questionable when applied to psychological networks[93]. Betweenness centrality was made for distance measures and meant for network structures in which there is a flow process in the network (for instance, gossip in a friendship network). However, psychological networks are not based on distance, and it is an open question whether statistical relations of psychological networks should really be conceptualized as flow, given that they differ substantially from social networks.

Causal and network inference

An important assumption of network theory is the causal influence of symptoms and other variables on each other. However, cross-sectional networks (the most published form of psychological networks[73]) do not lend themselves to causal inference[91,106]. Network models have therefore been increasingly applied to intensive longitudinal data, where temporal associations can be investigated. Although temporal associations (such as where symptom X precedes symptom Y, controlling for symptom Z) do not necessarily indicate causal relations[107], they facilitate understanding of the antecedents, concomitants and consequences of psychopathology by showing which symptoms temporally precede others[108].

Similar to transdiagnostic dimensional approaches, there are important debates on what inferences can be drawn from statistical network models — that is, how best to interpret their model output[92,93,109,110]. As such, it is an open question how the emerging field of network approaches can contribute to psychopathology classification research, and there are some important challenges that must be addressed. First, it remains unclear how useful common network models (such as the Gaussian Graphical Model) are for bringing data to bear on (often causal) network theories, given that models impose assumptions on data (such as linear relations) that are inconsistent with underlying theoretical accounts. Network theories often presuppose feedback loops, systems with multiple states, abrupt phase transitions and asymmetric relations among nodes, and some of these phenomena can arise out of only non-linear relations[91,111]. Second, it is easy to over-interpret network graphs because they rarely provide information about the accuracy of parameter estimates[112]. Bootstrapping routines can help to guide appropriate inferences (for example, whether one edge is significantly stronger than another, or one node significantly more central than another). Finally, there is disagreement about the empirical replicability of network models, which relates to network inference because it is not clear which model features are suited to assess replicability[109,110,112–118]. Importantly, accurate parameter estimation is necessary for statistical models such as network models to replicate, but some parameter estimates in the extant literature are likely to be inaccurate because they tend to be based on samples smaller than recommended[112,119]. Much work remains to be done on the accuracy and replicability of network models, particularly in time-series data[120].

Clinical staging approaches

Drawing on staging systems successfully utilized in medicine, the clinical staging of mental disorders proposes a blended categorical and dimensional approach to classification that aims to strengthen diagnostic precision and utility. The clinical staging approach identifies where an individual is situated along the continuum of illness, which is divided into stages, and facilitates the selection of preventive or pre-emptive treatment and the prediction of prognosis. In psychiatry, these stages have been defined as asymptomatic but at-risk (Stage 0), help-seeking with distress (Stage 1a), attenuated syndromes (Stage 1b), full-threshold disorder (Stage 2), recurrence or persistence (Stage 3), and treatment resistance (Stage 4)[21,121] (Fig. 3). Clinical staging can be applied to any disorder that tends to or might progress[21]. The boundaries between stages might be defined by therapeutic needs and biomarkers[121,122]. The use of a hybrid dimensional–categorical approach captures the dynamic, longitudinal and dimensional aspects of psychopathology, which are not accounted for in traditional static and cross-sectional models, while recognizing that clinical decision-making is routinely grounded in categories. Clinical staging represents a matrix of stage and syndromal formation and evolution, which is essentially transdiagnostic. There is a key distinction between a stage-based model of care and stepped care. The latter responds belatedly to a relapse or worsening of a condition, whereas staged care – like cancer treatment – aims to pre-empt onset, progression and relapse.

Key classification findings

In clinical cohorts of young people attending low-entry-threshold youth mental health services, most individuals at initial presentation are classified at Stages 1a (30–60%) and 1b (31–61%), with few presenting at Stages 2 (4–9%) and 3 or 4 (3–5%)[123–125], who often require more specialized and intensive care. Inter-rater reliability of clinical stage allocation has been shown to be acceptable ($\kappa = 0.71$)[126]. Individuals assigned to Stage 1 generally have mild impairment or non-specific symptoms, while those with attenuated syndromes (Stage 1b) present with increased symptom severity and functional impairment[123,126,127]. Individuals at Stage 1b might meet the criteria for particular DSM-5 or ICD diagnoses such as anxiety or depression; however, in comparison to Stage 2, symptoms have not reached the threshold required to prompt a change in the type or intensity of treatment (for example, the commencement of antipsychotic medication or mood stabilizers)[126]. At Stage 2, individuals present with stable, intense and sustained features of major disorders (for example, psychotic, mood or borderline personality disorders, or alcohol- and substance-use disorders). The distinction between Stages 1a and 1b is supported by their contrasting treatment needs and outcomes (for instance, simpler and less intensive treatments for Stage 1a versus Stage 1b)[128], risk of progression to Stage 2 (ref. 123), and neurobiological profiles (for example, greater sleep dysfunction and more systemic changes within the limbic system for Stage 1b)[129–132]. Similarly, early research suggests that the cut-off between Stages 1b and 2 can be validated from a neurobiological or biomarker perspective[122,133]. Compared to attenuated syndromes, individuals with full-threshold disorders show differential patterns of impairment on measures of neuropsychological function[134,135], brain imaging[134,136–138], and sleep–wake behaviours and circadian rhythms[130,139].

The transition from earlier to later stages of illness corresponds to a stepwise increase in severity, symptom specificity and functional impairment[123,125]. Longitudinal data indicate that threshold caseness (Stage 2) is reached by approximately 13–18% of young people with attenuated syndromes (Stage 1b); approximately half of these transitions occur within 12 months of baseline[123,126]. Transition from Stage 1a (non-specific symptoms) to Stage 2 is less common (3%)[123,126]. The staging model recognizes that the emergence, progression and persistence of mental illness is heightened by a range of risk factors, including prenatal environment, childhood trauma, and alcohol or substance misuse[140]. Multistate models, which can characterize how an individual occupies one state (of multiple possible states) at a given time, have been used to examine variables at baseline that are associated with transition from Stages 1b to 2 and Stages 1a to 1b[123]. Modifiable predictors of progression to any Stage 2 disorder (such as a major anxiety, mood or psychotic disorder) include not being in education, employment or training, negative symptoms, psychotic-like experiences and circadian disturbance[123,141].

Approximately a third of individuals assigned to Stage 1a transition to Stage 1b[123]. This progression is associated with lower social functioning, not being in education, employment or training, manic-like experiences, psychotic-like experiences and self-harm[123]. These additional criteria capture the concept of 'extension', which defines progression across stages. Progression to Stages 3 and 4 is estimated to occur in a third of those assigned to Stage 2 (mood and psychotic disorders)[126] and largely reflects recurrence or persistence of illness[121,142]. Individuals assigned to Stage 3 have experienced Stage 2 syndromes with persistence or incomplete remission at 12 months after mental health service entry or recurrence of illness following 3 months of complete

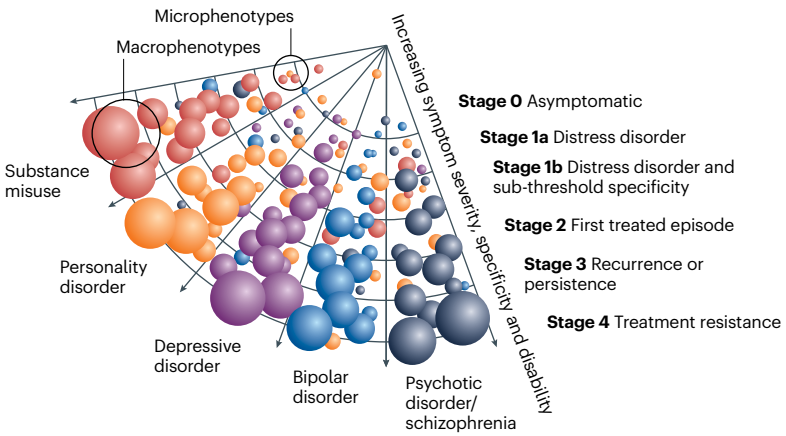

Fig. 3 | A depiction of clinical staging approaches. Symptom severity, specificity and disability begins at the vertex at the upper right and proceeds in increasing stages (represented by sphere size) outwards toward the left and bottom. Spheres and colours represent phenotypes. Stage 2 denotes the boundary between non-specific symptoms/attenuated syndromes and full-threshold disorders. Clinical staging can be applied to any disorder that tends to or may progress[21], including those not represented in the figure (for example, anxiety and eating disorders). Adapted with permission from ref. 133, Annual Reviews.

Glossary

Assessment reliability
The extent to which observed scores on a test are precise and error-free and the degree to which observed scores represent true scores of the construct being assessed.

Betweenness centrality
Assesses the relative number of shortest paths between any two nodes in the network passing through a specific node (for example, if A and B are connected to C but not to each other, the node C lies on the shortest path between A and B).

Confirmatory factor analysis
A largely theory-driven latent variable modelling approach in which the researcher decides the number of latent variables as well as which items or scales load, and do not load, on each factor.

Exploratory factor analysis
A largely atheoretical latent variable modelling approach that generally estimates the number of latent factors underlying the observed items or scales, in which each item or scale is permitted to load on all estimated latent factors.

Inference validity
The extent to which observed scores on a test reflect the construct or constructs that the test is intended to measure, and justifiably supports inferences drawn about the observed test scores' relations with other variables.

Macrophenotype
Late stage of syndrome development that consists of stable, intense and sustained, or severe syndromes (for example, psychosis, mania, depression, anxiety, alcohol- and substance-use disorders, and borderline personality disorder).

Microphenotype
Early stage of syndrome development that consists of overlapping and fluctuating symptoms.

Model fit
How well a statistical model is congruent with observed data, such as discrepancy between values in an observed correlation matrix and those in a model-implied (estimated) correlation matrix.

Structural validity
The degree to which observed scores (such as those from a measure) adequately reflect the underlying dimensionality of the construct or constructs being assessed.

recovery[126,142]. Stage 4 includes individuals with unremitting illness who have received relevant services for at least 2 years.

The clinical staging approach is currently being used to broaden criteria for identifying individuals at ultrahigh risk of developing psychosis to encompass a range of syndromes rather than solely psychosis[143]. Preliminary findings suggest that various at-risk mental states (bipolar, depression, psychosis and borderline personality disorder; that is, Stage 1b), show substantial overlap and progress to a full-threshold disorder in both homotypic and heterotypic ways, supporting the theoretical basis of transdiagnostic staging[144].

Relation to dimensional and network approaches

The clinical staging model is grounded in epidemiological evidence in terms of how mental disorders emerge and progress; that is, non-specific symptoms and a need for care exist prior to meeting conventional artificial syndromal thresholds[143], and trajectories often defy traditional diagnostic boundaries with high rates of comorbidity[145]. Clinical staging for mental disorders might be transdiagnostic[140,146] in accordance with frequently shifting trajectories across diagnostic boundaries, reflecting the pluripotent and heterotypic nature of psychopathology[144,145,147–149]. Transdiagnostic clinical staging is consistent with the fact that the early stages of major adult-type mental disorders (such as psychosis, bipolar disorder, depression and borderline personality disorder) are not sufficiently dissimilar to support a disorder-specific approach[150,151]. Early clinical stages of these disorders are characterized by non-specific and overlapping symptoms (microphenotypes) that might potentially evolve and intensify, and follow various pathways to develop into relatively stable, although typically comorbid, syndromes (macrophenotypes)[152]. Classic syndromes can be understood as relatively late macrophenotypes, which are recognizable during later stages of illness (Fig. 3).

This reality of illness progression is well captured by network analysis, in which symptom networks are more densely connected with increasing severity or persistence[73,96]. It is also compatible with dimensional approaches in which psychopathology is organized from broad to narrow dimensions. However, clinical staging adds a categorical overlay, which may increase clinical utility. Clinical decision-making is closely intertwined with categories, which clinicians rely on for treatment planning (for example, to treat or not to treat)[153], and these sorts of approaches seem to necessitate that dimensional approaches have identified cut-points to guide clinical care, with these thresholds reflecting the risks and benefits of available treatments[154]. Such cut-points create categories, enabling dimensional approaches to be clinically relevant in psychiatry (and across general medicine)[155]. The categories imposed by clinical staging also provide a heuristic research strategy to clarify neurobiological markers by stage of illness and to develop stage-specific interventions[122]. A more agnostic approach to traditional diagnoses, which have limited construct validity[156], and the dynamic and fluid nature of onset and progression provide the opportunity for dimensional and network methods to help guide and populate staging models.

Time and development

Transdiagnostic dimensional approaches and network approaches have been largely based on cross-sectional data. Although there is certainly value in cross-sectional approaches, longitudinal approaches provide promising pathways towards understanding and classifying psychopathology, because they enable the study of within-person change. Thus far, however, most existing approaches mainly focus on between-person differences instead of within-person change over time[157–160]. By contrast, clinical staging approaches have taken a more explicit longitudinal approach, and have been used to monitor and predict transitions between disorder stages[73].

As theorists, clinicians and statisticians have pointed out, studying within-person change in addition to between-person differences can reveal further insights into the nature of psychopathology[161–163]. The study of such longitudinal within-person processes has two key advantages. First, they might provide insights about how symptoms cluster over time, and therefore how comorbidity develops, potentially informing diagnostic and psychotherapeutic processes[158,159,164,165]. Second, the study of within-person processes can characterize how individuals differ from their own average instead of from the between-person average, which might help clinicians to identify dynamic psychological patterns in their patients[78,157,160,166]. Thus, some researchers argue that changes in within-person symptom dynamics can inform why individuals at risk for psychopathology transition into pathological states[74]. Investigating these dynamics over time might therefore reveal crucial insights into the prevention and treatment of mental disorders.

Within-person psychopathology

In experience sampling method (ESM) studies, participants are asked to respond to short surveys repeatedly within their daily lives. Thus, ESMs are a strong tool with which to study the dynamics of individuals' emotions, cognitions and behaviours in a natural environment, and this methodology has been applied to the study of real-life experiences underlying psychopathology and mental disorders[167,168]. For example, ESMs have been used to study how one emotion predicts itself and how this relates to constructs such as depression[169–171].

So far, studies that focus on within-person processes have mostly examined the dynamics of ESM items in relation to psychopathology with regards to affective[172–176], social[177,178] and cognitive[179–181] domains of an individual's life.

Regarding affect, individuals whose dynamic network of emotion items took longer to return to baseline values after an external shock or negative event (simulated statistically) had more negative trajectories of depression symptomatology[176]. In addition, within-person processes of affect instability and affect reactivity to interpersonal perceptions have been found to be related to borderline personality disorder[182,183]. However, the extent to which these dynamic indices (such as the instability in affect level over the course of the study) predict general psychopathology measures beyond the mean (mean level of negative affect over the course of the study) remains inconclusive[184].

Regarding the social domain, temporal dynamics of social interactions rather than the number of interactions is predictive of change in depressive symptoms, such as solitude inertia (prolonged states of being alone)[177]. Moreover, individuals with borderline personality disorder who displayed more fluctuations in mood also expressed more dominance in social interactions[185].

Finally, in the cognitive domain, an ongoing study is investigating how cognitive function is longitudinally associated with various transdiagnostic symptoms. This study aims to identify clusters of biological markers, cognitive dysfunctions and symptoms that predict psychopathology[181].

In general, deficits in these domains (affective, social and cognitive) have been associated with psychosocial dysfunction in a variety of disorders[74,186]. These findings all suggest that temporal dynamics, studied for example with ESM, are important for understanding how psychopathology manifests and develops within a person.

In transdiagnostic classification systems, the temporal ordering of structures or symptoms have been under-investigated, and HiTOP does not currently include constructs that reflect individual differences in within-person processes because few studies have investigated relations between these constructs and psychopathology dimensions[45]. Nevertheless, time remains of critical theoretical importance in dimensional transdiagnostic approaches. For instance, in the HiTOP model the distinction between symptoms and traits is thought to reflect the degree of functioning within short time frames (such as the past week) versus general functioning (such as over multiple years)[45,79]. In this framework, symptoms vary around a relatively stable trait level of functioning[45]. Increased focus on how psychopathology evolves within a person over time — and the degree to which people differ in these trajectories — will be beneficial for capturing within-person processes in classification approaches.

Classification over the lifespan

Whereas more and more research using the network approach is studying short-term changes in symptom dynamics (such as over a few weeks and months), other transdiagnostic research has examined psychopathological symptoms across the lifespan. Descriptively, predispositions towards general psychopathology are already present in early childhood[187–190] and there is substantial interest in studying maladaptive dispositions in adolescence as well[191–193]. Mirroring this observation, broad dimensions such as internalizing and externalizing tend to be used more in childhood-related research and practice, whereas there is a focus on more differentiated domains in older adolescents and adults[50,190,194].

Relatively limited research has empirically examined the extent to which dimensions of psychopathology have developmental continuity. The largest body of work to this end is captured by the Achenbach System of Empirically Based Assessment. In this framework, there is substantial consistency in the nature of the domains of psychopathology that are identified from childhood through to late middle age (ages 6–59 years). For example, the internalizing, externalizing and thought problems dimensions comprise similar symptoms and syndromes over time[195]. The internalizing and externalizing domains are also identified in children as young as 1.5 to 5 years, but not always in older adults (ages 60+)[195]. Notably, the Achenbach System of Empirically Based Assessment inventories were derived cross-sectionally within each age group, rather than based on individuals' development over time. Beyond work using these inventories, there is some evidence for substantial developmental continuity of transdiagnostic dimensions within individuals as they age[145,190,196–199] and these are useful for understanding successful ageing[200]. Studies in child, adolescent and adult samples also suggest that more differentiated dimensions, such as distress versus fear, and oppositional/antisocial behaviour versus substance use, might emerge from broader dimensions (such as internalizing) over time, but more longitudinal research is needed to corroborate these findings[201].

Translation to clinical practice

Evidence-based approaches and models of psychopathology are poised to transform how case conceptualizations and diagnostic assessments are performed. This revolution, in turn, has the potential to affect mental health treatment profoundly.

Transdiagnostic dimensional approaches

Transdiagnostic dimensional approaches propose to forfeit categorical diagnoses, and instead to delineate patients' problems dimensionally at varying levels of specificity, from general propensities to individual symptom manifestations[202,203]. Accordingly, the assessment proceeds systematically, focusing first on the broad dimensions to identify major problem areas, then examining specific features and behavioural manifestations within corresponding lower-order dimensions. Clinicians can visualize a summary of patients' problems on a profile spanning severity dimensions and specificity levels to comprehensively guide individualized treatment planning and outcome tracking. For example, a clinician might observe that a patient has elevated scores on the internalizing spectrum, driven mainly by high scores on anhedonia, fatigue and sleep problems. The clinician can consider treatment targets at a higher level, where approaches such as an antidepressant or cognitive–behavioural therapy can improve multiple internalizing symptoms simultaneously[204], and at lower levels, when a problem requires a specialized intervention (for example, hypnotic drugs for insomnia). Furthermore, strengths evident in the patient's profile might inform treatment planning. For example, a low score on the antagonistic externalizing spectrum might indicate that the patient could develop a good therapeutic alliance with the provider and therefore respond well to psychotherapy.

Dimensional transdiagnostic approaches have the potential to inform efforts to assess and treat psychopathology. With regard to assessment, previous research has indicated that these models improve assessment reliability and inference validity relative to traditional diagnoses[203]. The psychometric properties of reliability and validity are necessary for results of psychological assessment to be meaningful and interpretable, and to support clinical application (such as identifying the problems a patient is experiencing and selecting an appropriate intervention)[205–207]. Clinical case conceptualization (including the clinician's overall understanding of a patient's problems and the processes that cause and maintain these problems) are also more congruent with dimensional approaches than categorical approaches[202,208] because clinicians consider the varying severity of multiple symptoms and impairments constituting a client's multifaceted clinical presentation. Indeed, clinicians often find dimensional approaches more informative for treatment planning[209,210]. Further, patients' transdiagnostic dimension levels predict which individuals are likely to actually pursue specific forms of treatment[211]. Finally, transdiagnostic treatments, such as the Unified Protocol[212], target the common cores of multiple forms of psychopathology (for example, internalizing) in effective and efficient ways relative to treating specific disorders individually[213–215]. There are several reviews on the clinical utility of transdiagnostic dimensional approaches[202,203,216,217]. More research is needed to demarcate ranges or thresholds on psychopathology dimensions to facilitate assessment and intervention decisions[203]. More research is also needed to determine the extent to which dimensions derived from group-level analyses will be informative for individual patients.

To enhance the accessibility of transdiagnostic dimensional approaches for clinicians, a free electronic instrument, the HiTOP Digital Assessment and Tracker, that automatically generates a patient's profile and compares it to normative community ranges was developed. Clinicians can also refer to recommended actionable ranges to guide their decision-making. These ranges are being empirically tailored to specific purposes (such as severity levels recommended for initiating psychotherapy) and can be cross-walked to the ICD-11 codes for billing and administrative purposes. This multi-level depiction of a patient's problems aims to help clinicians to focus their assessment and intervention strategy. Consequently, treatments might be selected to alleviate broad psychopathology dimensions, often employing transdiagnostic approaches such as the Unified Protocol, or to target narrow symptoms. A compendium of potentially useful therapeutic techniques for each spectrum is available to clinicians[204].

Network approaches

One aim of studying networks is to reveal the interrelations among variables, such as symptoms, in order to provide guidance for clinicians. Although many networks are fitted to group-level data of multiple participants simultaneously (Fig. 2a), person-specific networks (Fig. 2b), based on intensive within-person longitudinal data, might indicate potential treatment targets (that is, which specific symptoms should be targeted in interventions)[218]. Such person-specific networks of within-person longitudinal data have been used to provide automated feedback to healthy participants[219–221] and in clinical practice, for example, by discussing individual affect or symptom networks in psychotherapy sessions[222]. However, to date, only feasibility studies on the integration of person-specific networks in clinical settings exists[99,223–228]. One randomized controlled trial evaluating the effectiveness of personalized network modules for the reduction of depressive symptoms is currently ongoing[224]. Larger samples, randomized controlled trials, and studies on the reliability and validity of person-specific networks are still needed to clarify the utility of psychological symptom networks for psychotherapy[120,229].

The advances to clinical practice proposed by network approaches are focused on the specific patient presentation, regardless of diagnostic status. Within network approaches, there is a strong emphasis on the mechanisms underpinning etiology, maintenance and the psychotherapy process[218,230]. Idiographic (person-specific) network analysis of symptom dynamics can be used in a clinical context to inform case conceptualization. Furthermore, the network of interactions between risk, maintenance and protective factors, symptoms, functioning and other clinically relevant features, can be formalized mathematically as a testable, patient-specific model. Translating case conceptualizations into mathematical language enables specific relationships included in the conceptualization to be tested or simulated. For example, clinicians could apply computational models to estimate whether an intervention targeting a suspected risk factor might be effective in preventing symptom elevation or long-term functional impairment in an individual patient. Specific idiographic network model components could be added or removed as appropriate and in collaboration with a patient. In the course of therapy, models can be updated with real-life information (such as an actual outcome of the implemented treatment) to allow model personalization and learning. Although promising, the above will require numerous observations per patient as well as training to develop the necessary mathematical competencies in a given clinic. Web-based tools are being constructed to overcome barriers to clinical implementation, with the goal of enabling clinicians to estimate network models, to use their own observations to complement data-driven estimation, and to help generate intuitive feedback[231].

In sum, idiographic modelling, including but not limited to network approaches, is becoming increasingly important in psychopathology research, especially as an approach for personalized classification and intervention design (for a review see ref. 81).

Clinical staging approaches

Clinical staging approaches are increasingly visible and utilized in clinical practice. One application is linking particular stages to specific interventions based on severity. For instance, Stage 1 might suggest application of transdiagnostic psychosocial interventions. Later stages, which are associated with greater risk, require more specific and intensive intervention that might have adverse effects. For example, Stage 2 might support the use of antipsychotic or antidepressant medication, whereas Stage 4 might indicate the need for drugs such as clozapine, which is associated with an increased risk for developing agranulocytosis (a life-threatening blood disorder)[232].

Clinical staging attempts to address a fundamental challenge in psychiatry: how to link diagnosis to treatment, prognosis and underlying biology. In doing so, clinical staging seeks to transcend simpler matrix models such as the Research Domain Criteria matrix. The staging model is particularly relevant to the mental healthcare of young people because the majority of mental disorders begin to emerge prior to young adulthood[145]. Traditional diagnostic systems largely capture adult-type and late-stage disorders. By contrast, clinical staging supports early intervention and prevention that alleviate distressing symptoms and functional impairment, irrespective of diagnostic labels or reaching threshold-level criteria, and reduce the risk of illness progression and extension through stage-specific

interventions based on risk–benefit principles[121,133,233]. Sequential clinical trials, particularly involving transdiagnostic samples, are needed to strengthen the selection of safe and proportional stage-matched interventions[234].

Transition across stages is not inevitable and the clinical staging model highlights the potential for timely and quality treatment to avert transition or progression. However, it is assumed that there is a higher risk of illness progression, persistence or recurrence at later stages. Hence, treatment delivered early in the course of illness should be more effective and safer than treatment delivered later when symptoms and functional impairment have become entrenched and neurobiological damage has occurred. The aspirational goal for researchers and clinicians alike is to move from a purely clinical staging model to establish a clinicopathological staging model, akin to the maturation of such models in oncology, in which clinical and prognostic utility and the personalization of care are strengthened by the addition of pathophysiological biomarkers (assuming that such markers can be validated and are malleable). This sort of broader staging model framework could also potentially refine the boundaries of individual stages and reduce focus on traditional diagnostic categories for later stages in instances where syndromal diagnosis alone offers limited specificity for treatment selection[152].

Summary and future directions

Transdiagnostic dimensional, network and clinical staging approaches all attempt to overcome limitations of official classification systems. Each has demonstrated promising characteristics to support subsequent research and clinical endeavours. Despite their limitations, these three approaches represent a major shift towards truly evidence-based classification, assessment and intervention.

Transdiagnostic dimensional approaches focus on overcoming the limitations of traditional nosologies in accounting for high rates of comorbidity, arbitrary thresholds for diagnosis, overlapping criteria, and their failure to describe within-diagnosis heterogeneity. Over time, official nosologies have delineated more and more putatively distinct diagnoses. Transdiagnostic dimensional approaches take the opposite approach, wherein broad sets of symptoms or diagnoses are modelled simultaneously to identify their common sources of covariation, which act as the building blocks of psychopathology. The resulting dimensions are organized into hierarchies (such as HiTOP) from fine-grained to very specific. Findings from different studies, samples, measures and constructs (such as those from studies of normal-range personality, personality psychopathology and mental disorders) converge on a consensus structure that links variation in both normative and pathological variables to relatively few core factors. These dimensions outperform traditional diagnoses in prospective prediction of important outcomes, clinical utility and the ability to account for symptom patterns that are not included as diagnoses in official nosologies. The usefulness of these models ranges from assessing a single patient to understanding broad population mental health disparities[215,217,235–237]. Transdiagnostic dimensions represent empirically derived constructs, whereas traditional nosologies to a large extent emerged from subjective expert opinion. Perhaps most importantly, extensively replicated findings suggest that transdiagnostic dimensions (the model) map closely onto the lived experiences of patients (the data)[24]. Consequently, it is possible to fully characterize an individual's symptoms and problems rather than attempt to fit the individual into a predetermined category (diagnosis).

The network approach focuses mainly on the (temporal) interrelations between elements of a system of symptoms. As such, the network approach does not primarily aim to provide a classification of mental disorders but rather provides a theoretical and statistical framework for investigating symptom clusters and transitions. To date, the network approach has not been used for classification research itself, and future research will determine how much the network approach can contribute to new nosologies. Although the network approach has gained notable traction within clinical psychology, some conceptual issues remain that need to be addressed. These include which statistical models are best suited for which purposes; what nodes to include in network models and how edges ought to be estimated (for instance, as linear or nonlinear); what measurements are best suited for network analysis; how to interpret estimated network structures; and the use and predictive utility of graph theoretical measures such as centrality and density. The explicit conceptual focus on temporal issues of network approaches (such as the sequential unfolding of psychopathology over time), the increasing empirical focus on temporal issues, and idiographic analysis all bring with them great potential to move beyond the current state of largely cross-sectional and between-person classification research paradigms.

Clinical staging approaches aim to improve the utility of mental disorder diagnosis and classification. This framework has clear implications for clinical practice, particularly in facilitating prevention, early intervention, prediction and the selection of stage-matched interventions. From the earliest stages of illness, the clinical staging model supports the deployment of proportional and pre-emptive interventions based on risk–benefit considerations as well as patient choice. Active research is refining the boundaries between stages, particularly from a biomarker perspective[140]. Like network approaches, clinical staging approaches might help to guide the development and selection of more personalized interventions.

Although there is much research to be done within the three approaches, a particularly promising future direction is a move towards their integration, given that they have developed relatively independently[238]. Fundamentally, the putative incompatibility between the three approaches is a misperception. For instance, some statistical factor models applied in transdiagnostic dimensional approaches can be thought of as a class of network models[239,240]. Indeed, there are ongoing attempts to merge statistical network models with factor models[241] as well as efforts to potentially enhance network theories by incorporating notions about common causes that are a major focus of transdiagnostic dimensional approaches[91,92]. Thus, the symptoms and disorders investigated in network approaches could be refined by developments in transdiagnostic classification[242], and network approaches could be applied to factor analytic approaches to link transdiagnostic dimensions to one another temporally and to model associations among symptoms and syndromes that are not captured fully by the dimensions. Clinical staging approaches can incorporate diagnostic constructs emerging from transdiagnostic dimensional approaches directly into their framework of disorder development and severity, and network approaches might help to link different stages of disorder to various risk or resilience factors and outcomes as well as to link patient staging levels longitudinally. Although overcoming current levels of fragmentation across approaches will require theoretical and methodological advances, such integration might hold the key to major advances in the conceptualization and classification of mental disorders.

Published online: 07 August 2023

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Author contributions

All authors contributed to the writing and editing of this article. N.R.E. was additionally responsible for article structure and integration.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s44159-023-00218-4.

Peer review information *Nature Reviews Psychology* thanks the anonymous reviewers for their contribution to the peer review of this work.

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