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Article

The Illness Management and Recovery (IMR) Scale: A Network Analysis of User and Professional Perspectives

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ABSTRACT

Background: Recovery is a multidimensional, subjective process that emphasizes personal strategies and empowerment beyond symptom remission. The *Illness Management and Recovery* (IMR) scale incorporates the perspectives of both users and professionals, although its internal structure has had only limited examination through advanced psychometric methods. Network analysis was applied to the IMR scale with the aims of (1) exploring interrelationships among items, (2) assessing network stability, and (3) analyzing measurement invariance between users and professionals. **Method:** Data were collected from 172 users and 49 mental health professionals using the IMR scale. Network analysis used the *Triangulated Maximally Filtered Graph* (TMFG) method and the *walktrap* algorithm, with stability assessed through *bootstrapping*. **Results:** The analysis indicated 39 significant connections among 15 items, highlighting coping strategies as the central node, along with symptom distress, functional difficulties, and symptom recovery. *Exploratory Graph Analysis* identified three factors: (1) Personal Growth and Planning, (2) Social and Health Behavior Management, and (3) Symptom Management and Resilience. **Conclusions:** Network analysis underscores the importance of coping strategies, suggesting that interventions should focus on strengthening these skills to support recovery.

La Escala de Gestión de la Enfermedad y Recuperación: un Análisis de Redes Desde las Perspectivas de Usuarios y Profesionales

Palabras clave:
Análisis de redes
Escala IMR
Recuperación en salud mental
Psicometría
Invariancia de medida

RESUMEN

Antecedentes: La recuperación es un proceso multidimensional y subjetivo que enfatiza las estrategias personales y el empoderamiento más allá de la remisión sintomática. La escala *Illness Management and Recovery* (IMR) integra las perspectivas de usuarios y profesionales, aunque su estructura interna ha sido escasamente examinada mediante métodos psicométricos avanzados. Se aplicó análisis de redes a la escala IMR con el objetivo de: (1) explorar las interrelaciones entre los ítems, (2) evaluar la estabilidad de la red y (3) analizar la invariancia de medida entre usuarios y profesionales. **Método**: Se recopilaron datos de 172 usuarios y 49 profesionales de salud mental aplicando la escala IMR. El análisis de redes empleó el método *Triangulated Maximally Filtered Graph* (TMFG) y el algoritmo *walktrap*, evaluándose la estabilidad mediante *bootstrapping*. **Resultados**: El análisis reveló 39 conexiones significativas entre 15 ítems, destacando las estrategias de afrontamiento como nodo central, junto con malestar sintomático, dificultades funcionales y recuperación sintomática. El *Exploratory Graph Analysis* identificó tres factores: (1) Crecimiento personal y planificación, (2) Gestión social y de conductas de salud, y (3) Manejo de síntomas y resiliencia. **Conclusiones**: El análisis de redes resalta la importancia de las estrategias de afrontamiento, sugiriendo orientar las intervenciones hacia su fortalecimiento.

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Individuals diagnosed with severe mental disorders, such as schizophrenia, schizoaffective disorder, bipolar disorder or major depressive disorder with psychotic features, have often been grouped together due to overlapping symptom profiles and treatment needs (WHO, 2022). Historically, mental health classifications, such as those found in the ICD-11, have adopted a categorical approach based on symptom clusters and diagnostic thresholds. While clinically useful, these approaches may inadequately reflect the heterogeneity and complexity of individual experiences (Marder & Galderisi, 2017). A related issue here is that dominant conceptualizations of mental illness have long been framed within biomedical models, emphasizing neurobiological and genetic determinants of behavior (Insel & Quirion, 2005), although some authors have critically questioned the limitations of purely diagnostic or categorical frameworks (Johnstone & Boyle, 2023). By contrast, contemporary frameworks increasingly recognize the role of psychosocial factors, trauma histories, and environmental stressors in the development and course of mental health conditions (Read et al., 2005). Moreover, recent work highlights the importance of integrative and transdiagnostic models that combine genetic, psychological, and environmental factors, moving beyond purely biomedical approaches to better capture the complexity of mental health and psychopathology (Eaton et al., 2023). From a network perspective, some authors propose that dynamically interacting symptoms and elements constitute the disorder itself, forming personalized, transdiagnostic systems that may improve diagnosis and intervention (Roefs et al., 2022). Furthermore, network models challenge reductionist explanations by showing that mental disorders emerge from symptom interactions rather than a single biological cause, underscoring the need for holistic research strategies (Borsboom et al., 2018). This broader understanding has facilitated the emergence of more person-centered, holistic approaches in research and practice (Davidson & Roe, 2009; Slade, 2009).

One of the most significant conceptual advances was the emergence of the recovery model (Anthony, 1993), although it is only in the last decade or so that this model began to be adopted in national policies, translated into practical instruments, and subjected to scientific evaluation (Ahmed et al., 2012; Frost et al., 2017; Canacott et al., 2019). Unlike traditional perspectives that primarily focused on symptom remission and functional restoration, the recovery model emphasizes the possibility of living a meaningful and fulfilling life despite ongoing symptoms. Recovery is thus understood as a multidimensional and deeply subjective process (Slade, 2009), encompassing not only clinical stability but also hope, empowerment, subjective well-being, and personal agency. More recently, a consensus definition of the recovery process has been sought, with researchers recognizing the need to incorporate the perspectives of health professionals, users of mental health services, family members, and other significant individuals (Sampietro et al., 2022; Guerrero et al., 2024, 2025).

Being able to quantitatively assess the recovery process is also essential for establishing appropriate interventions for each user. To operationalize this construct, several measurement instruments have been developed, including the Recovery Assessment Scale (Giffort et al., 1995), the Mental Health Recovery Measure (Young et al., 2003), and the Recovery Self-Assessment (O´Connell et al., 2005), among other more recent ones such as the Self-Identify Stage of Recovery (SIRS) scale (Sampietro et al., 2024), the Individual Recovery Outcomes Counter (I.ROC) (Garrido-Cervera et al., 2025) and the MARS-12 (Balluerka et al., 2024). However, many of these tools primarily capture the perspective of users, while failing to incorporate the clinical insights of professionals (Felix et al., 2024). Furthermore, low use of assessment scales has been observed in clinical and intervention settings due to a lack of time and interest on the part of professionals (Gilbody et al., 2002).

Although recent research acknowledges the importance of collaboration between users, professionals, and family members in the recovery process (Burger et al., 2024), this is rarely reflected in existing scales. A notable exception is the Illness Management and Recovery (IMR) scale (Mueser et al., 2005), a unique instrument in that it captures both user and professional perspectives, thus providing a more comprehensive view of the recovery process. Importantly, the IMR is designed to measure multiple interrelated domains that are central to personal recovery, including goal setting, symptom management, coping strategies, knowledge about mental illness, social support, and functional outcomes, reflecting the core components of recovery-oriented practice and aligning with theoretical frameworks that emphasize empowerment, hope, and self-directed recovery (Hasson-Ohayon et al., 2008). A recent systematic review further supports that the IMR demonstrates relationships with recovery-relevant constructs such as hope, control over life, identity, symptom management, and adaptive coping, highlighting its utility not only as a clinical outcome measure but as an instrument capturing domains that actively contribute to the recovery process (Martín-Ordiales et al., 2024).

Previous studies have validated the psychometric properties of the IMR scale in diverse populations (Hasson-Ohayon et al., 2008; Sklar et al., 2012; Jensen et al., 2019). However, no study to date has analysed the internal structure of the scale using more advanced psychometric techniques such as network analysis. Beyond its methodological novelty, network analysis is particularly well suited for the study of complex and multidimensional constructs such as mental health recovery, as assessed by the IMR. Network analysis represents a paradigm shift in how psychological phenomena are conceptualized (Borsboom, 2017), insofar as it treats psychological elements as interconnected nodes within a complex system rather than as simple manifestations of an underlying latent cause. This perspective is especially relevant for recovery-oriented constructs, in which processes such as hope, empowerment, symptom management, and social functioning are theorized to be functionally interdependent rather than hierarchically organized. This approach allows for the identification of the most central items, bridge elements, and key domains within the network, offering insights that may not be fully captured by traditional latent variable models such as Structural Equation Models (SEM) or Item Response Models (IRT). Moreover, it paves the way for more personalized and collaborative mental health care, enabling professionals and users to jointly explore which network elements may maintain distress or support recovery, and thus design more targeted interventions (Epskamp et al., 2018). However, most current applications of this approach have focused primarily on symptom networks related to psychopathology (Buchwald et al., 2024), with limited exploration of positive processes or recovery in mental health (Fried et al., 2016).

Based on the conceptual framework of recovery-oriented processes, IMR items are expected to form distinct clusters corresponding to key recovery domains, including hope and empowerment, symptom management, and social functioning (Mueser et al., 2005; Hasson-Ohayon et al., 2008). From a network perspective, items related to self-management and coping are anticipated to occupy central positions, reflecting their influence across multiple recovery processes. These expected clusters and central items provide a network-based theoretical rationale for examining the internal structure of the IMR, linking broad domains to potential item communities and guiding the interpretation of central and bridging nodes within the scale. Accordingly, we formulate the following hypotheses: (1) IMR items will cluster into communities corresponding to the theorized recovery domains, and (2) self-management and coping items will emerge as central nodes in the network.

To address these expectations, the present study applies network analysis to the IMR scale with the aim of identifying the central aspects of recovery from the perspectives of both users and professionals. The specific aims were as follows: (1) to examine the interrelationships among IMR items from a network perspective, (2) to assess the stability and structure of the estimated network, and (3) to analyze measurement invariance across the client (user self-report) and clinician versions of the scale.

Method

Participants

Users of mental health services: A total of 172 people completed the IMR client scale. Of these, 123 were men (71.5 %) and 45 were women (26.2 %), ranging in age from 19 to 68 years (M = 47.2, SD = 9.4). The majority of participants were single (75.6 %). The primary diagnosis in the sample was schizophrenia (61 %). A slight majority (56.4 %) had a recognized work disability.

Mental health professionals: A total of 49 mental health professionals completed the IMR clinician scale, a process that yielded 166 individual assessments, as each professional could report on multiple service users. Professionals were required to have detailed knowledge of the users they were providing information about, consistent with their being a lead professional in the patient's care and recovery process. The sample comprised 35 women (71.4 %) and 14 men (28.6 %), with the majority being either psychologists (53.1 %) or social workers (18.4 %). They reported an average of 11.1 years of clinical experience (SD = 7.9), including an average of 8.9 years (SD = 6.7) experience working specifically with individuals diagnosed with severe mental disorders (Supplementary material 1).

Instruments

The IMR scale (Mueser et al., 2005) is a 15-item scale derived from the IMR program that assesses key domains including progress toward personal goals, functional difficulties, relapse prevention, coping strategies, and use of medication (see Table 1). There are both client and clinician versions of the scale, with higher scores reflecting better recovery and illness management. Items are rated on a 5-point Likert-type response scale. In the current study, mental health professionals and service users completed their corresponding version of the scale. The Spanish translation of the IMR-client and IMR-professional scales (Martin-Ordiales et al., 2026) followed the International Test Commission's 2017 guidelines (Hernández et al., 2020). Participants completed the IMR with a trained professional present to provide standardized instructions and ensure understanding without altering item content.

Previous research has reported varying reliability coefficients for the test scores for the two versions: from .49 (Fortuna et al., 2020) to .85 (Tan et al., 2017) for the client version, and from .69 (Dalum et al., 2016) to .85 (Tan et al., 2017) for the clinician version.

Table 1
Key Domains of the IMR Scale

ITEM	DOMAIN
IMR1	Progress towards personal goals
IMR2	Knowledge about symptoms, treatment, etc.
IMR3	Involvement of family and friends in treatment
IMR4	Relationship with non-family members
IMR5	Time spent on work, volunteering, etc.
IMR6	Symptom distress
IMR7	Functional difficulties
IMR8	Relapse prevention plan
IMR9	Symptom recovery
IMR10	Psychiatric hospitalization
IMR11	Coping
IMR12	Participation in self-help groups
IMR13	Proper use of medication
IMR14	Impact of alcohol consumption
IMR15	Impact of drug use

Procedure

The study followed the ethical guidelines outlined in the Declaration of Helsinki and received approval from the Bioethics Committee of the University of Barcelona (CBUB; IRB No.: IRB00003099).

Participants were recruited through email and telephone outreach from mental health associations and private centers across Spain, using a convenience sampling method. Professionals were informed of the study aims and were asked to contact users who met the inclusion criteria. All participants were subsequently informed individually about the study, provided written informed consent, and completed the data collection protocol confidentially. Data collection took place between December 2022 and October 2023.

Inclusion criteria comprised adults (≥18 years) with a confirmed diagnosis of a severe mental disorder according to ICD-10 or DSM criteria (e.g., schizophrenia spectrum disorders, bipolar disorder, or severe depressive disorder with psychotic features), established at least two years prior to inclusion. All participants were fully informed about the study and provided written informed consent. Exclusion criteria comprised individuals with primary diagnoses other than severe mental illness (e.g., anxiety or substance use disorders), acute psychiatric episodes, significant cognitive impairment, major medical or neurological conditions, or insufficient language proficiency.

Data Analysis

Network Model

We estimated a network model by applying the Triangulated Maximally Filtered Graph (TMFG) method to the 15 items of the IMR scale in a sample of people with severe mental disorder. The TMFG is a network-filtering method designed to maximize the retention of relevant information while minimizing noise, iteratively adding nodes based on their correlations (Previde Massara et al., 2017). To assess the stability of the network structure, we performed bootstrap resampling to examine variability in edge strength, applying a case-drop bootstrap procedure to evaluate sample dependence. These techniques ensured the robustness and reliability of the estimated network structure. We conducted a set of sensitivity analyses comparing the TMFG approach with an alternative regularized estimator (EBICglasso). All network estimations (both TMFG and GLASSO) were based on polychoric correlation matrices (Supplementary Material 2).

To further evaluate the reliability of the network, a correlation stability analysis was conducted for the centrality measures of the IMR network (Epskamp et al., 2018). This analysis involved repeatedly estimating the network while systematically dropping a proportion of cases from the original sample. The correlation stability coefficient (CS-coefficient) was computed for each centrality index, representing the maximum proportion of cases that can be dropped while maintaining a correlation of at least 0.7 with the original centrality values in 95% of the resamples. According to established guidelines (Epskamp et al., 2018), CS-coefficients below 0.25 indicate unstable estimates, values between 0.25 and 0.5 reflect moderate stability, and values above 0.5 indicate stable estimates.

Exploratory Graph Analysis

Next, we conducted an exploratory graph analysis (EGA) using the *EGAnet* package (Golino et al., 2024). The TMFG method and walktrap algorithm were applied within a bootstrap framework to identify the most stable and representative latent structure underlying the data. The walktrap algorithm, a community detection method based on random walks, identifies densely connected subgraphs by merging communities that random walkers are more likely to traverse together. This method enabled the detection of communities (or factors) among IMR items.

Configural Invariance Analysis

Finally, configural and metric invariance analyses were performed to evaluate whether the factor structure was consistent across the samples of users and professionals. The invariance function of the *EGAnet* package estimates configural invariance by comparing the factor structures of the two groups without imposing parameter constraints. Separate EGA models were estimated for each group to determine whether they shared the same number of factors and a similar pattern of relationships among the 15 IMR items. This procedure provided evidence of concordance between the responses of users and professionals and enabled a nuanced interpretation of the factor structure by highlighting items with stable versus variable associations with specific factors. To account for multiple comparisons and control the false discovery rate (FDR), *p*-values were adjusted using the Benjamini-Hochberg (BH) procedure.

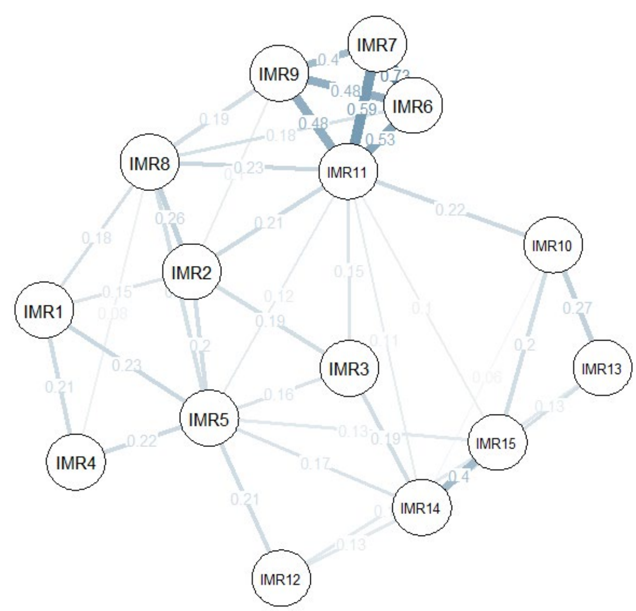
All analyses were conducted using R, with the following packages: *qgraph* (Epskamp et al., 2012), *ggplot2* (Wickham, 2016), *NetworkToolbox* (Christensen, 2018), *bootnet* (Epskamp et al., 2018), and *EGAnet* (Golino et al., 2024).

Results

Network Model

The network analysis offers a comprehensive view of the intricate relationships (edges) between various factors influencing mental health recovery. Figure 1 displays the sample network solution when considering user responses to the IMR items. There are 39 non-zero edges from a total of 105. Coping strategies (IMR11) emerge as a central hub, underscoring their pivotal role in managing symptoms and promoting well-being; note also the close community formed with IMR6, IMR7, and IMR9. The clustering of items related to social support (IMR3, IMR4, and IMR5) and substance use (IMR14, IMR15) reveals potential distinct and interpretable subgroups within the network. Items such as knowledge about symptoms and treatment (IMR2) and participation in self-help groups (IMR12) appear less interconnected, suggesting that while they may be important factors in recovery, their influence may be more specific to individual experiences. The strong connection between coping strategies (IMR11), symptom distress (IMR6), functional difficulties (IMR7), and symptom recovery (IMR9) emphasizes the importance of equipping users with robust coping mechanisms to prevent relapse.

Figure 1
Network Model With Strength Values Between the 15 IMR Items for Users



The centrality statistics (strength, closeness, betweenness, and expected influence) for user responses to the IMR scale are shown in Figure 2.

The item with the highest expected influence in the network is IMR11 (Coping), followed by IMR6 (Symptom distress), IMR7 (Functional difficulties), IMR5 (Time spent on work, volunteering, etc.), and IMR9 (Symptom recovery). The items with the least central role in the model are, in descending order, IMR4 (Relationships with non-family members), IMR12 (Participation in self-help groups), IMR13 (Proper use of medication), and IMR3 (Involvement of family and friends in treatment). Regarding betweenness, items IMR11 (Coping) and IMR5 (Time spent on work, volunteering, etc.) yield the highest values, meaning that they have a greater number of edges in relation to their nearby nodes, as well as in relation to global closeness. Table 2 shows the values for the network statistics. Strength and expected and expected influence values are the same because the network is undirected and all edges are positive, reflecting the predominantly positive zero-order correlations among IMR items, which assess related aspects of recovery being consistent with the clinical content of the items.

Figure 2
Centrality Plot of the IMR Network for User Responses

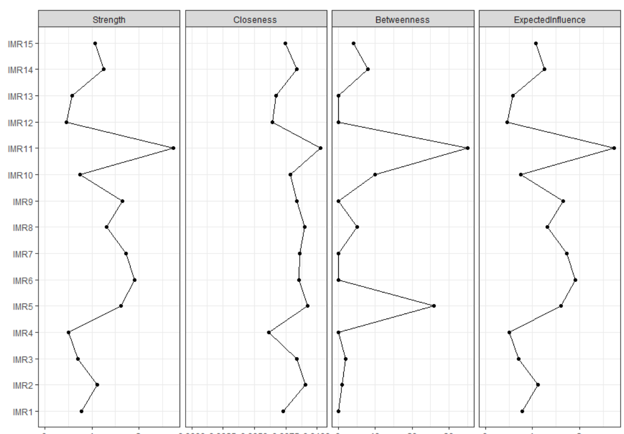


Table 2
Strength, Betweenness, and Closeness Values of the IMR Network Nodes

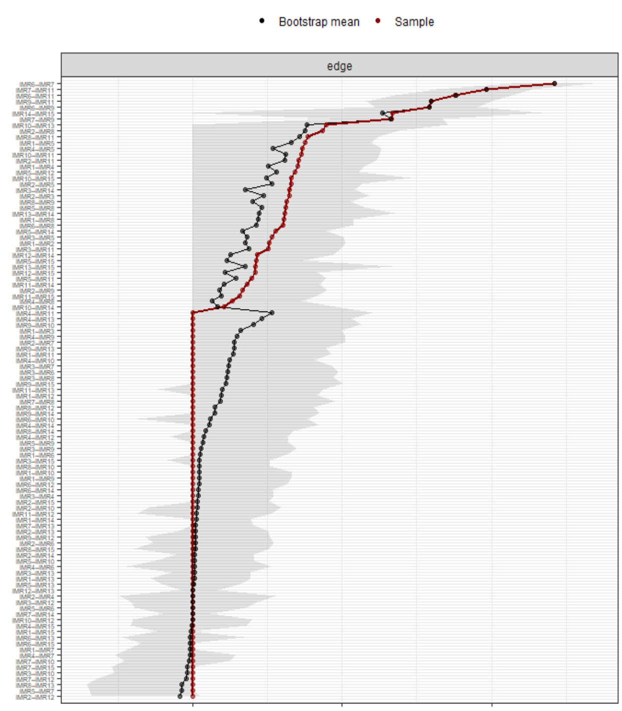
NODES	STRENGTH	BETWEENNESS	CLOSENESS
IMR11	2.73	70	0.010
IMR6	1.91	0	0.009
IMR7	1.72	0	0.009
IMR9	1.64	0	0.008
IMR5	1.61	52	0.009
IMR8	1.31	10	0.009
IMR14	1.25	16	0.008
IMR2	1.11	2	0.009
IMR15	1.07	8	0.007
IMR1	0.77	0	0.007
IMR10	0.75	20	0.008
IMR3	0.70	4	0.008
IMR13	0.58	0	0.007
IMR4	0.51	0	0.006
IMR12	0.46	0	0.006

Note: Expected influence values are omitted because they are identical to strength values in an undirected network with exclusively positive edges.

A bootstrap analysis of all edges in the network provides crucial insights into the stability and reliability of the network structure. Figure 3 illustrates the variability in edge weights across 1000 resampled networks, offering a visual representation of the confidence intervals for each connection. The black line represents the average values of the bootstrap samples, offering a smoothed representation of the underlying distribution, while the red line depicts the observed values of the sample data. The gray shaded area represents the 95% confidence intervals for the bootstrap samples. Edges that appear consistently across bootstrap samples, indicated by narrow confidence intervals, suggest robust and reliable relationships between nodes.

Overall, the discrepancies between the bootstrap values and the sample values for the network edges are minimal and generally not significant. Most of the network structure observed in the original sample is consistent with the bootstrap results. While there are a few instances where the bootstrap solution yields non-zero values for edges that were initially zero in the sample network, these differences are characterized by very low strength values. This suggests that even where discrepancies exist, they represent weak connections that likely have little practical impact on the overall network structure. The consistency between the bootstrap and sample results largely supports the reliability of the observed network, indicating that the relationships between IMR scale items are stable across resamples. This pattern of stability is particularly observed for the edges connecting IMR6 ↔ IMR7, IMR7 ↔ IMR11, IMR6 ↔ IMR11, IMR9 ↔ IMR11, IMR6 ↔ IMR9, and IMR7 ↔ IMR9, suggesting that these associations are robust and reliable within the current sample.

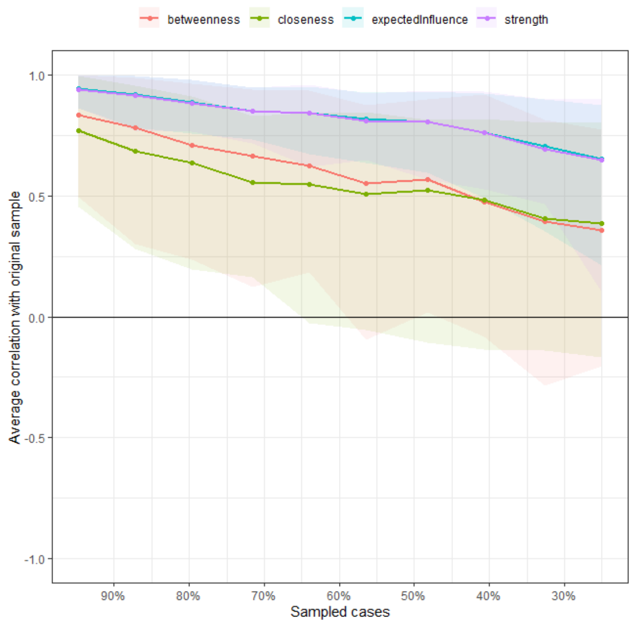
Figure 3
Bootstrap Edge Stability Analysis: Confidence Intervals and Network Connection Reliability



Results revealed varying levels of stability across centrality measures. Betweenness and closeness centrality demonstrated CS-coefficients of 0, indicating extremely poor stability. By contrast, expected influence and strength centrality exhibited moderate stability, with CS-coefficients of .36. This suggests that up to 36 % of the sample can be dropped while maintaining a 95 % probability of a correlation of at least .70 with the original centrality values.

Consequently, only expected influence and strength centrality measures can be cautiously interpreted in the current network structure. Figure 4 displays a plot with the results of a case-dropping bootstrap analysis for centrality measures in the IMR network. This plot illustrates the stability of centrality indices as cases are progressively removed from the sample. The plot shows four lines, each representing a different centrality measure (strength, expected influence, betweenness, and closeness). Lines that remain high and stable as the proportion of dropped cases increases indicate more stable centrality measures. Conversely, lines that drop quickly or show high variability suggest fewer stable measures. Generally, correlations above .70 are considered to indicate good stability.

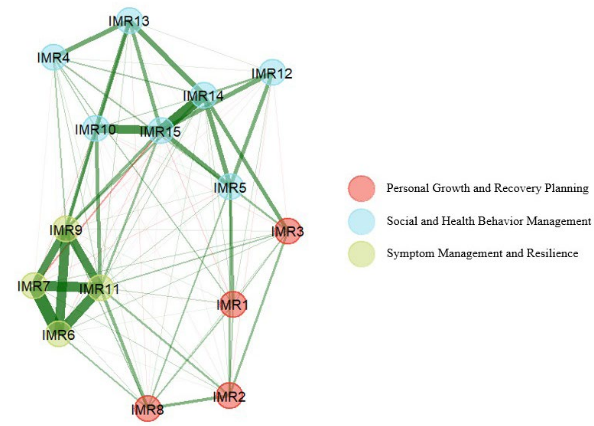
Figure 4
Centrality Stability in IMR Network: Case-dropping Bootstrap Analysis



Exploratory Graph Analysis

We estimated the EGA network using the 15 items of the IMR scale with a bootstrap approach involving 1,000 resamples. The most prevalent latent structure identified was a 3-factor model (59.5 %), followed by a 2-factor model (31.3 %), a 4-factor model (8.9 %), and an almost residual 5-factor model (0.3 %). Figure 5 displays the EGA network representing the 3-factor latent structure derived from the bootstrap analysis.

Figure 5
EGA Network for IMR Items After Bootstrap Analysis (n = 1000)



The model reveals three communities or factors: *Personal Growth and Recovery Planning*, which highlights personal goals, knowledge acquisition, social support, and relapse prevention, all essential elements for long-term recovery and personal empowerment; *Social and Health Behavior Management*, encompassing the influence of social relationships, activities, and health-related behaviors, such as medication adherence and the impact of substance use, including alcohol and drugs; and *Symptom Management and Resilience*, reflecting the focus on coping strategies, symptom recovery, and the challenges related to functioning and the distress caused by symptoms.

The Personal Growth and Recovery Planning factor is composed of items IMR1 (Progress toward personal goals), IMR2 (Knowledge about symptoms, treatments, etc.), IMR3 (Involvement of family and friends), and IMR8 (Relapse prevention plan). The Social and Health Behavior Management factor comprises items IMR4 (Relationship with non-family members), IMR5 (Time spent on work, volunteering, etc.), IMR10 (Psychiatric hospitalization), IMR12 (Participation in self-help groups), IMR13 (Proper use of medication), IMR14 (Impact of alcohol consumption), and IMR15 (Impact of drug use). Of these, the items with the strongest interrelationship are IMR10 (Psychiatric hospitalization), IMR14 (Impact of alcohol consumption), and IMR15 (Impact of drug use). Finally, the Symptom Management and Resilience factor is particularly notable for its consistency. This community comprises items IMR11 (Coping), IMR9 (Symptom recovery), IMR7 (Functional difficulties), and IMR6 (Symptom distress).

However, the robustness of this 3-factor structure may be compromised by volatility in the assignment of certain items. Table 3 shows the percentage of assignment of each item to the five potential factors identified through the 1,000 bootstrap resamples. This helps to provide a clearer understanding of the stability and consistency of item-factor associations across resamples.

The table reveals that some items exhibit less stable factor assignments, with notable overlaps across multiple factors. Specifically, IMR1, IMR2, and IMR3 show significant distributions across different factors. IMR1 is assigned to factor 2 (36.4 %) and factor 3 (50.1%), IMR2 is mainly assigned to factor 3 (50.6 %) but also has a considerable overlap with factor 1 (33.8 %), while IMR3 is distributed across factor 2 (36.9 %) and factor 3 (39.3 %). IMR8, which is predominantly associated with factor 2 (51 %), also shows some overlap with factor 3 (39.6 %). These overlapping assignments indicate that these items have ambiguous associations, contributing to a less stable factor composition.

By contrast, the items in factor 1 (IMR6, IMR7, IMR9, and IMR11) show very high stability, with all assignments exceeding 90 %. Specifically, IMR6 and IMR7 are almost exclusively assigned to factor 1 (99.8 % each), while IMR9 (93.8 %) and IMR11 (98.7 %) are also predominantly assigned to this factor. This strong and consistent assignment of items to factor 1 indicates that it is the most stable and clearly defined factor in the analysis. Similarly, factor 2 shows strong and stable associations with IMR4, IMR10, IMR12, IMR13, IMR14, and IMR15, with the latter two items (IMR14 and IMR15) demonstrating particularly high assignments (88.8 % and 88.3 %, respectively). However, item IMR5, initially related to factor 2 (.584), also shows some overlap with factor 3 (.402). These stable assignments suggest that factors 1 and 2 have clearer and more consistent structures in comparison with factor 3

Table 3
Percentage of Assignment of Each Item to the Four Latent Structures with 2, 3, 4 and 5 Factors

	1	2	3	4	5
IMR6	**.998**	.000	.001	.001	.000
IMR7	**.998**	.000	.001	.001	.000
IMR11	**.987**	.006	.006	.001	.000
IMR9	**.938**	.020	.039	.003	.000
IMR8	*.510*	.047	*.396*	.047	.000
IMR14	.008	**.888**	.096	.007	.000
IMR15	.019	**.883**	.092	.005	.000
IMR13	.045	**.801**	.134	.018	.002
IMR12	.014	**.792**	.184	.009	.001
IMR10	.197	**.679**	.116	.008	.000
IMR4	.084	**.635**	.262	.017	.002
IMR5	.002	*.584*	*.402*	.011	.001
IMR2	*.338*	.099	*.506*	.057	.000
IMR1	.110	*.364*	*.501*	.025	.000
IMR3	.194	*.369*	*.393*	.043	.000

Note: Factors identified across 1,000 bootstrap resamples (high % in bold and overlaps in italics)

Configural Invariance

Configural invariance was only achieved with 13 items forming a 3-factor solution, as IMR4 and IMR5 showed different factor adscription. For the interpretation of metric invariance, only p-values adjusted using the Benjamini–Hochberg procedure were considered as the primary inferential criterion, while uncorrected p-values are reported for descriptive purposes.

Once the items with consistent factor adscription were identified, we proceeded to analyze metric invariance, that is, the equality of the factor loadings of the items across both groups: users and professionals. Table 4 presents the results of the analysis, including the 13 configurally invariant items, their factor loadings in the two groups.

Table 4
Factor Loadings of EGA Configural Solutions for Users and Professionals

	FACTOR 1		FACTOR 2		FACTOR 3	
ITEMS	USERS	PROF.	USERS	PROF.	USERS	PROF.
IMR1	.73	.79	.00	.00	.00	.09
IMR2	.80	.99	.08	.32	.00	.10
IMR3	.75	.65	.05	.10	.00	.00
IMR6	.08	.04	1.07	.92	.00	.00
IMR7	.00	.15	1.05	1.00	-.11	.17
IMR8	.77	.91	.19	.10	.00	.10
IMR9	.11	.00	.96	.55	.24	.28
IMR10	.00	.00	.13	.22	.83	.85
IMR11	.23	.34	1.01	1.00	.10	.20
IMR12	.00	.00	.00	.00	.62	.73
IMR13	.00	.06	.00	.05	.84	.57
IMR14	.00	.23	.06	.19	.97	1.16
IMR15	.00	.00	.01	.16	1.12	1.01

The results of the metric invariance analysis, as shown in Table 5, suggest that the metric invariance assumption holds for almost all items, with the exception of IMR6 and IMR9. After adjustment for multiple comparisons using the Benjamini–Hochberg procedure, only IMR9 showed statistically significant differences in factor loadings between users and professionals. Although IMR6 yielded a significant uncorrected p-value, this effect did not remain significant after correction and was therefore not interpreted as evidence of non-invariance. For all other items (IMR1, IMR2, IMR3, IMR8, IMR7, IMR11, IMR10, IMR12, IMR13, IMR14, and IMR15), no significant differences in factor loadings were found between the two groups, as both their p and p_BH values exceed .05.

Table 5
Metric Invariance Analysis Across Users and Professionals

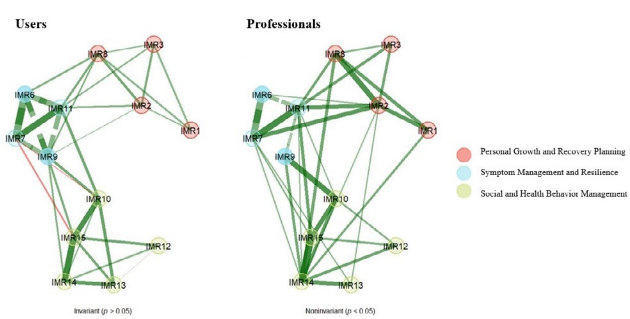
ITEMS	FACTOR	DIFFERENCE IN LOADINGS	*p*	*p*_BH	SIG	DIRECTION
IMR1	1	-.059	.603	.713	ns	
IMR2	1	-.198	.067	.290	ns	
IMR3	1	.102	.601	.713	ns	
IMR8	1	-.141	.204	.580	ns	
IMR6	2	.153	.008	.052	**, ns	
IMR7	2	.054	.223	.580	ns	
IMR9	2	.409	.002	.026	**,*	1 > 2
IMR11	2	.004	.943	.946	ns	
IMR10	3	-.015	.946	.946	ns	
IMR12	3	-.109	.441	.657	ns	
IMR13	3	.267	.393	.657	ns	
IMR14	3	-.192	.314	.657	ns	
IMR15	3	.111	.455	.657	ns	

Note: Comparison: 1. Users vs. 2. Professionals
* $p < .05$, ** $p < .01$, ns = non-significant

In summary, the metric invariance assumption appears generally supported for most items, although IMR9 shows some variation in factor loadings between groups. Due to the limited sample size, confirmatory factor analysis (CFA/SEM) could not be conducted; therefore, the findings should be interpreted as preliminary rather than definitive. Specifically, the factor loading for IMR9 is higher in the users' group compared with the professionals' group, suggesting that the relationship between this item and the latent factors differs. For IMR6, the factor loadings are equivalent after adjusting for multiple comparisons, while the factor loadings for the remaining items are also consistent. Figure 6 shows the two 3-factor EGA configural models (13 IMR items) for users and professionals, and also indicates metric invariant and non-invariant items (IMR6 and IMR9 according to the uncorrected p-value).

The metric invariance analysis of the IMR scale across the two groups provided preliminary exploratory evidence that 12 of the 15 items may exhibit equivalent factor loadings. These findings suggest that the IMR instrument captures similar constructs in both groups, but they should be interpreted cautiously due to the exploratory nature of the analysis and the limited sample size.

Figure 6
EGA 3-Factor Configural Models and Metric Invariant and Non-Invariant Items Across the Two Groups



Discussion

The present study represents the first application of network analysis to the IMR scale, offering a novel approach to understanding the interconnectedness of recovery-related dimensions in individuals with severe mental disorders. Through the use of the TMFG method, EGA, and measurement invariance techniques, we were able to identify key nodes, stable factor structures, and the extent to which the IMR scale functions equivalently across users and health professionals.

In a first step, we developed a network model based on the service user version of the IMR scale. Coping (IMR11) appears to be a central aspect of the recovery concept, and accordingly the estimated network shows high values in strength, betweenness, closeness, and expected influence. This reinforces the idea that having personal coping strategies is key to recovery. Coping strategies such as problem-solving and search for social support have been shown to play a fundamental role in managing mental health challenges, particularly among individuals diagnosed with schizophrenia (Mitikhin et al., 2024). By applying their own coping techniques, people can gain control over their thoughts, emotions, and behaviors, which often leads to improved mental well-being and even personal growth (Gautam et al., 2024). Mental health interventions should therefore prioritize the development and reinforcement of adaptive coping tools, rather than focusing predominantly on symptom management. Coping strategies such as underestimation (i.e., minimizing perceived threats), diversion (i.e., redirecting attention), compensatory satisfaction (i.e., seeking fulfillment in alternative domains), reaction control (i.e., regulating emotional expression), and positive self-instruction (i.e., engaging in constructive internal dialogue) represent valuable techniques that can support individuals in dealing with psychological stressors more effectively (Holubova et al., 2015). By understanding these relationships, professionals can tailor interventions to address specific needs and improve treatment outcomes.

Another item with a high value for betweenness was IMR5, which refers to time spent in structured roles. This indicates that engagement in meaningful activities can improve the recovery process, as has been observed in recent studies (Guerrero et al., 2024; Bjørkedal et al., 2023; Chai et al., 2024). It is likewise consistent with the view that having a purpose in life and being able to focus attention on aspects of the person unrelated to mental illness may improve prospects for recovery (Johansson et al., 2025). Nevertheless, the lack of configural invariance for IMR4 and IMR5 suggests that social contact outside the family and engagement in structured roles may be conceptualized differently by users and professionals, highlighting domains where recovery-related meanings may diverge between experiential and clinical perspectives.

We also conducted an exploratory graph analysis, identifying a 3-factor solution as a plausible model. However, the presence of multiple alternative solutions across bootstrap samples indicates a degree of structural variability, therefore this 3-factor solution should be considered exploratory. The factor structures identified through EGA should be interpreted as tentative and hypothesis-generating, rather than as definitive representations of the underlying construct, particularly in light of the limited stability of some centrality measures and the absence of clustering control. Based on their composition, we labeled these factors: *Personal Growth and Recovery Planning*, *Social and Health Behavior Management*, and *Symptom Management and Resilience.* The items included in the first of these factors underscore the importance of setting and achieving personal goals, acquiring knowledge about one's mental health condition, engaging support from family and friends, and planning to prevent relapses. Together, these components form a model grounded in empowerment and strategic self-management. This approach emphasizes the active role of the individual in building resilience and maintaining long-term mental stability through informed, goal-directed actions. This interpretation is supported by existing literature: for example, Guerrero et al. (2024) found that participants reported progress in their recovery when they felt empowered and able to make autonomous decisions.

The composition of the second factor reflects a domain focused on social functioning and health-related behaviors. Here, the inclusion of items related to social relationships, structured activities, and community involvement suggests an emphasis on external interactions and lifestyle organization. By contrast, the presence of items addressing medication adherence and substance use highlights the importance of health maintenance and its impact on psychosocial well-being. This factor may represent a dimension encompassing both social integration and health management. Empirical studies have shown that participation in standardized intervention programs targeting these goals, such as the IMR program, leads to improvements in social functioning and reductions in substance use among individuals with severe mental illness (McGuire et al., 2014; Salyers et al., 2014). Similarly, recent studies support the importance of having meaningful support networks and engaging in personally meaningful social activities to enhance the recovery process (Guerrero et al., 2024; Høgh Egmose et al., 2023; Lee & Yu, 2024).

Although it is a less relevant aspect for users' perception of recovery (Guerrero et al., 2024), adherence to pharmacological treatment has been shown to enhance important dimensions of personal recovery in individuals with schizophrenia, particularly by fostering greater engagement in help-seeking behaviors and active participation in the recovery process (Tapia et al., 2021).

Finally, the structure of the third factor relates to an individual's ability to manage and recover from mental health problems. Specifically, it encompasses the practical and emotional aspects of coping, the process of symptom recovery, difficulties in daily functioning, and symptom distress, reflecting a cohesive domain of personal resilience and symptom management. Coping strategies refer to voluntary acts aimed at reducing stress, such as seeking help, talking about feelings, establishing self-care activities, and taking time for oneself (Gautam et al., 2024). In recovery-focused studies, individuals who employ positive coping strategies—such as planning and acceptance—tend to demonstrate higher levels of resilience (Holubova et al., 2015). This, in turn, results in lower levels of psychological distress and a stronger recovery orientation.

This 3-factor structure aligns with findings from previous psychometric studies that utilized factor analysis of responses to the IMR scale (Hasson-Ohayon et al., 2008; Sklar et al., 2012; Jensen et al., 2019). However, the novel contribution of the present study lies in elucidating the relationships and the strength of association among the constituent items, with the aim of informing and optimizing intervention strategies. From an applied perspective, such exploratory patterns can still offer valuable insights for understanding recovery-related processes in individuals with severe mental health disorders, while underscoring the need for replication in larger, independent samples.

Lastly, the analysis was completed by studying the concordance between the networks obtained from the responses of service users and professionals. In general, the networks obtained appear to be similar, although one significant difference should be highlighted. IMR9 (relating to symptom recovery/relapse) emerged as the node with the highest loading in the users' network, and its value was significantly higher than the corresponding value in the professionals' network, which suggests that this item may hold more significance or be more strongly associated with the latent construct of recovery for users than for professionals. This could indicate that users perceive symptom relapse more directly in relation to their therapeutic progress, while professionals may conceptualize it differently. This item (IMR9) is part of the Symptom Management and Resilience factor. These results are consistent with the idea that users perceive changes in symptoms and their impact on functioning in a way that is distinct from the perception of professionals (Polat et al., 2020). Previous studies have shown that people with mental health problems focus their perception of the recovery process more on issues such as empowerment, creating a life project, having a satisfactory social network, and hope. The stronger loading of IMR9 in the user group should also be interpreted in light of the marked imbalance between user and professional samples, as well as the non-independence of professional ratings, which may have contributed to the observed group difference. Accordingly, this difference in perception must be taken into account so as to offer interventions that address all connected nodes, avoiding focusing efforts on controlling positive and negative symptoms of the disease. This finding highlights the robustness of the IMR scale and confirms that it can provide a consistent assessment of user and professional perceptions of the therapeutic process and recovery.

This study has several limitations that should be acknowledged. First, the sample size is relatively small, which may limit the statistical power, the estimation of predictability values and the stability of network estimations across the diverse recovery-related indicators. Although bootstrap procedures were used to examine the precision of edge weights and the stability of centrality indices, these methods provide only indirect evidence of power and do not replace a formal simulation-based assessment. Thus, these findings should be interpreted as exploratory, and future research should employ larger samples in order to evaluate the robustness of the observed networks. However, it is important to note that the study successfully recruited a clinical sample of 172 individuals with severe mental disorders, predominantly schizophrenia—a population for which recruitment is well-documented to be methodologically challenging due to cognitive impairments, symptom severity, engagement barriers, and other practical difficulties in clinical research settings (Bucci et al., 2015; Deckler et al., 2022). Beyond sample size considerations, the clinical relevance of the sample and the paired responses obtained from the participants' reference professionals provide a rich, multi-perspective dataset that enhances the interpretability and ecological validity of the findings.

Furthermore, the inclusion criteria focused exclusively on individuals with severe mental disorders, which means that other clinical populations, such as those with substance use disorders or less severe mental health conditions, were not represented. This selective sampling may limit the generalizability of the network findings to broader mental health populations. Nevertheless, the detailed insights gathered from both service users and their professionals offer valuable information about recovery processes in severe mental illness that goes beyond the limitations imposed by sample size alone.

Finally, while configural invariance was achieved for most items, two items—IMR4 (Contact with people outside of the family) and IMR5 (Time in structured roles)—did not meet this criterion, indicating potential differences in how these items are interpreted or evaluated by service users and professionals. Future research particularly longitudinal studies, should further explore these items to better understand their behavior, strengthen the relationships between recovery domains, and improve measurement equivalence across respondent types.

Despite these limitations, network analysis has proven to be a useful approach for understanding the structure of the IMR scale and for identifying the most relevant concepts for recovery from both user and professional perspectives. The results provide further support for a 3-factor structure for this scale, although the current study provides additional insight into the central concept of each factor. Importantly, the findings may inform therapeutic interventions in real-world settings by highlighting specific targets for clinical practice. For instance, the identification of *Coping* (IMR11) and *Functional difficulties* (IMR7) as central nodes suggests that clinical teams should prioritize personalized interventions aimed at enhancing coping strategies and functional skills. This could be effectively achieved through psychosocial rehabilitation programs or social skills training, which address these core areas of recovery. The prominence of nodes such as *Relapse prevention plan* (IMR8) and *Progress towards personal goals* (IMR1) indicates that clinical training programs should integrate content focused on relapse planning and patient empowerment. These elements are essential for supporting sustained recovery and should be emphasized in professional development curricula. Additionally, the observed differences in centrality between service users and professionals—such as the higher centrality of *Symptom recovery* (IMR9) among users—underscore the importance of fostering shared decision-making. Addressing these divergences could help to strengthen the therapeutic alliance by aligning treatment expectations and enhancing collaborative care. In conclusion, based on the findings presented, identifying the recovery aspects that are most relevant to service users, as well as the similarities and differences between users' and professionals' perspectives, may help inform more personalized and person-centered approaches to mental health care. These approaches align with recovery-oriented models that emphasize respect, collaboration, and individual recovery goals (Boardman & Dave, 2020).

In summary, this study adds to the literature on mental health recovery and highlights the utility of the IMR scale in shaping a line of research aligned with the needs of individuals with severe mental disorders.

Author Contributions

Nuria Martín-Ordiales: Conceptualization, Data Curation, Investigation, Resources, Visualization, Writing – Original Draft, Writing – Review and Editing. **Albert Sesé**: Conceptualization, Data Curation, Formal Analysis, Methodology, Writing – Original Draft, Writing – Review and Editing. **Mª Pilar Martín-Chaparro**: Conceptualization, Investigation, Resources, Supervision, Visualization, Writing – Original Draft, Writing – Review and Editing. **Maite Barrios**: Conceptualization, Data Curation, Formal Analysis, Funding Acquisition, Investigation, Methodology, Project Administration, Supervision, Validation, Visualization, Writing – Original Draft, Writing – Review and Editing. **Mª Dolores Hidalgo**: Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Project Administration, Resources, Supervision, Validation, Visualization, Writing – Original Draft, Writing – Review and Editing.

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Conflict of Interests

The authors declare that there are no conflicts of interest.

Data Availability Statement

R code availability statement: available from the corresponding author on reasonable request.

The datasets during and/or analysed during the current study available from the corresponding author on reasonable request.

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