JOURNAL OF MECHANICS OF CONTINUA AND MATHEMATICAL SCIENCES
www.journalimcms.org

ISSN (Online) : 2454 -7190 Vol.-21, No.-05, May (2026) pp 173-191 ISSN (Print) 0973-8975

GRAPH-BASED SYMPTOM CENTRALITY IN MENTAL HEALTH NETWORKS: A NOVEL APPROACH WITH THE DYNAMIC WEIGHTED CENTRALITY IN HYSTERETIC SYMPTOM NETWORKS (DWCHSN) ALGORITHM

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https://doi.org/10.26782/jmcms.2026.05.00012

(Received: February 26, 2026; Revised: May 04; 2026; Accepted : May 13, 2026)

Abstract

This study addresses a significant gap in mental health research by developing a computational algorithm that goes beyond existing traditional symptom analysis. Instead of treating mental health symptoms as isolated phenomena, we created a methodology that captures their complex interconnected nature. We developed the Dynamic Weighted Centrality Hysteresis Symptoms Network Algorithm (DWCHSN), which applies concepts in network science to mental health symptomology. The DWCHSN algorithm effectively detects and ranks symptoms based on their centrality and influence that collectively capture how symptoms activate, spread, self-reinforce, persist, and respond to intervention within the network. This helps clinicians in setting treatment priorities by identifying the symptoms that are important catalysts. Our algorithm connects theoretical psychopathology models with clinical practice, unlike conventional diagnostic frameworks that list symptoms without considering their relationships.

Keywords: Graph-Theoretic Modeling, Dynamic Centrality, Symptom Networks, Mental Health, Hysteresis

I. Introduction

Mental disorders are the world's leading causes of mental disability, consisting of complex, heterogeneous, and often overlapping symptoms. The categorical models that use the current diagnostic systems (DSM-5 and ICD-11) consider disorders as discrete entities with latent causes, with symptoms acting as passive markers of underlying disorders. Although helpful for standardization, this method could not explain why patients with identical diagnostic experiences exhibit remarkably different combinations of symptoms, why comorbidity rates exceed chance, or why some symptoms persist despite treatment [V, VI].

The past decade has witnessed a paradigm shift toward network approaches that has occurred during the last ten years [IX]. Network theory suggests that symptoms participate in direct causal relationships, mutually activating and sustaining one another, as opposed to viewing symptoms as consequences of hidden pathological processes. The recent research is reinforced by this framework, which has shown that the network models are robust enough to withstand statistical evaluation [III], identifying the centrality measures that are effective in identifying treatment targets [IV] and integrating quantitative and qualitative insights to capture patient experience [II, I].

However, despite these developments, there are significant shortcomings to the network approaches used today. To capture the temporal dynamics that define actual clinical presentations, the majority of the studies either assume static network structures or rely on cross-sectional data [II]. Recent temporal network analyses show how network connectivity increases as psychopathology develops and how symptom centrality changes as disorder progresses [I, VII, VIII]. Additionally, the existing models do not effectively address hysteresis phenomena, in which symptom networks display path dependence and memory effects that impact treatment resistance and relapse patterns.

This study addresses these gaps by introducing the Dynamic Weighted Centrality Hysteresis Symptoms Network Algorithm (DWCHSN). Foundational network theory [VI, IX] depends mostly on static network structure. Our model goes beyond static models to capture temporal symptom interaction using three clinically interpretable metrics: triggerability (propensity to initiate cascades), propagation strength (capacity to activate related symptoms), and hysteresis anchoring (tendency to sustain network states). By incorporating hysteresis effects, explicitly modeling temporal dynamics, and emphasizing clinical interpretability to inform treatment decisions. The objective of this study is to present the DWCHSN algorithm's theoretical foundations, computational architecture, and applications for personalized intervention planning. We provide researchers and clinicians with a quantitative framework to understand mental disorders as dynamic, evolving systems and develop more precise, targeted therapeutic strategies.

II. Symptom Networks in Psychopathology

Nature of Mental Disorder

Mental illness is defined as a disturbance of cognition, emotion, or behavior and can be categorized with systems such as DSM-5 and ICD-11. They categorize the symptoms into distinct diagnosis categories. A disorder is postulated as an invisible cause of visible symptoms. However, these systems lack symptom heterogeneity, comorbidity, and a single biological cause for the majority of disorders.

Rather than considering these symptoms as primary indicators, the network theory of mental disorders conceptualizes them as causally interacting symptoms. Here, a disorder is considered an emergent property of dynamic indicators among systems. For instance, insomnia leads to fatigue, which triggers concentration problems and low mood, forming a self-enforcing cycle. It allows us to represent psychopathology as a

system based on actual clinical phenomena serving as a foundation for graph-based methodologies.

Key Psychological Constructs for Dynamic Modeling

To represent meaningful mental disorders as dynamic systems, certain psychological concepts must be integrated into the model. These concepts explain how symptoms develop over time relative to internal interactions and external stress, and they describe the clinical justification to model symptoms as parts of a dynamic network.

- **Resilience:** The ability of an individual/symptom network to recover after activation. Symptoms get activated due to external stresses but eventually return to a stable state. This differentiates temporary distress from chronic psychopathology.
- **Vulnerability:** The network's sensitivity to activation of low thresholds for symptom activation indicates that the networks are vulnerable to symptoms even at mild stress levels due to internal/external factors.
- **Liability:** Represents an individual's tendency towards mental illness. It not only influences the risk of disorder onset but also its longevity and magnitude.
- **Threshold:** The point at which a symptom becomes active. This accounts for non-linear changes in mental health.
- **Hysteresis:** It represents the asymmetry between activation and recovery. In densely connected networks, after activation, symptoms sustain themselves and others even without the original stimulus.

These aspects not only integrate clinical understanding but also construct design elements in graphs and theoretical formulations in psychopathology.

Core Approach of Symptom Network

The system networks provide a new perspective and a new approach for understanding mental disorders. Instead of considering individual symptoms as the result of a hidden underlying illness, the system network considers them active participants with varying influences within the network. The relationship between symptoms is directed above each other. These relationships can be biological (insomnia leads to fatigue), psychological (guilt fostering hopelessness), or social (isolation increases sadness).

The symptom network approach shows that symptoms do not co-appear but can trigger each other in an ongoing cycle. For example, a person with insomnia can experience fatigue, which will make it difficult for him to concentrate, which will eventually lead to depression. The person's environmental surroundings also play a significant role in influencing their symptoms. For example, traumatic events, chronic stress, and body inflammation are examples of external factors that worsen the symptoms.

The clinical observation represents the symptoms in their organization as

- **Clusters**: A strongly connected group of symptoms, based on exciting diagnostic categories.
- **Bridge symptoms:** Symptoms that act as a bridge between different clusters, helping in analyzing the occurrence of different conditions existing together.
- **Cycles:** Self-reinforcing feedback loops that make conditions self-sustaining.

The Five Principles of Network Theory in Psychopathology

Denny Borsboom (2017) formalized the systems network [VI] by articulating fine foundation principles.

Principle 1. Complexity: The mental disorders are best understood as emergent phenomena arising from complex interactions among multiple systems.

Principle 2. Symptoms-Component Correspondence: The nodes of the network correspond directly to systems as defined by diagnostic systems.

Principle 3. Direct Casual Connections: Symptoms have direct causal effects on one another.

Principle 4. Network Structure Determines Disorder Expression: The structure and topology of the symptom network determine how disorder is expressed.

Principle 5. Hysteresis and Chronicity: Mental disorders are retained by hysteresis, self-sustaining loops that stay even after external stress factors disappear.

Computational Framing through Graph Theory

Graph theory provides a mathematical basis for developing the symptom network method in mathematical representations to formalize symptoms and their relationship. In this model, each symptom is a node, and the causes connecting them are directed edges and are weighted to reflect the intensity of the network. This converts into a directed weighted graph $G = (V, E)$.

Every node in the graph is activated only when the weighted sum exceeds some threshold value. The presence of loops within the network further supports the identification of feedback loops seen in practice and provides the basis for understanding chronic repetitive (non-resolving) conditions.

The external field represents the external factors that are the causes for various symptoms within the systems. These inputs generally increase the activation levels of specific nodes.

Formally, this yields a directed, weighted graph $G = (V, E)$ where,

- $V -$ set of nodes, each representing a symptom.
- $E \subseteq V \times V -$ the set of directed edges between symptoms.
- Each edge $(s_i \to s_j)$ carries a weight $f_{ij} \in \mathbb{R}^+$ indicating how strongly s_i influence symptom s_j.

III. Methodology

DWCHSN [Dynamic Weighted Centrality in Hysteretic Symptom Networks] Algorithm

Step 1: Define the graph structure: $G = (V, E, W)$ be a directed, weighted graph, where,

- $V = \{s_1, s_2, \dots, s_n\}$ are symptom nodes (n represents the number of symptoms)
- $E \subseteq V \times V$ are casual edges representing interactions (influence) between the symptoms.
- $W: E \to \mathbb{R}_{\geq 0}$: Weight function assigining influence strength to each edge

- For edge $(s_i, s_j) \in E$, we denote $W\left((s_i, s_j)\right) = f_{ij}$
- f_{ij} represents the strength of influence from symptom s_i to symptom s_j

- $\theta = [\theta_1, \theta_2, \ldots \theta_n]^T$: Activation thresholds where $\theta_i > 0$ for each symptom

The external stress or nodes can be represented by e_k with edges directed towards symptoms. Each has a strength $e_{k_i}^{(0)}$, representing the initial impact. For matrix-based computations (used in Step – Control Contribution Score), represent the weighted graph as an adjacency matrix $A \in \mathbb{R}^{n \times n}$

Step 2: Assign symptoms thresholds: The threshold value of $\theta_i \in \mathbb{R}^+$ is assigned to each symptom node s_i, representing the cumulative input required to activate the symptom. Clinically, the threshold θ_i capture a symptom, intrinsic resilience, or vulnerability to activation.

Step 3: Centrality Metric Computation: All metrics reflecting the symptom behaviour are computed in this step.

- **Trigger-ability Score:**

$$\boldsymbol{C_i^{(1)} = \frac{1}{\theta_i}} \quad (1)$$

where, θ_i: the threshold value of the i^{th} node.

The trigger-ability score reflects how easy it is to activate a symptom node in the presence of initial/external input. Recognising the trigger-ability helps the care providers to focus on the most reactive entry points in symptom networks

- **Propagation Score:**

$$\boldsymbol{C_i^{(2)} = \sum_j f_{ij}} \quad (2)$$

where, Σ_j: summation over all nodes s_j that are directly influenced by s_i,

f_{ij}: weight of the directed edge from $s_i \rightarrow s_j$.

The objective of propagation is to identify the contribution of a symptom in activating other symptoms in the network. The propagation score helps healthcare providers to identify the amplifier symptoms.

- **Feedback Loop Score:**

$$\boldsymbol{C_i^{(3)} = \sum_{C \ni s_i} \prod_{(j \rightarrow k) \in \mathbb{R}} f_{jk}} \quad (3)$$

where, $c \ni s_i$: all cycles in the graph that include the node s_i.

f_{ik}: Weight of the edge from $s_i \rightarrow s_k$.

Π: Product of all edge weights within the loop e.

Feedback Loop Score analyzes a symptom node's participation in cyclic, self-sustaining processes. It calculates the total influence through a node by all directed cycles, assigning each cycle strength as products of its edge weights. These are the higher-order measures that detect symptoms in return.

- **Hysteresis Anchoring Index:**

$$\boldsymbol{HAI_i = \frac{C_i^{(3)}}{\theta_i}} \quad (4)$$

where, θ_i: threshold of symptom s_i.

$C_i^{(3)}$: Feedback Loop Score.

The Hysteresis Anchoring Index represents the persistence of the symptom after its activation. It helps to analyze the balance between the symptoms, feedback loops, and their activation threshold. It helps healthcare providers in deactivation planning.

- **Control Contribution Score (CCS):**
  This control contribution score estimates the influence of a symptom node over the entire network in terms of its ability to shift system behaviour.

$$\boldsymbol{CCS_i = \sum_{k=1}^{L} \beta^k \sum_{j=1}^{n} \frac{(A^k)_{ij}}{\theta_j + \varepsilon}} \quad (5)$$

where, $L = 3$: maximum propagation depth

$\beta = 0.5$: path-length decay factor

$(A^k)_{ij}$: element at position (i, j) in the k-th mathrix power of adjacency matrix A

θ_j: activation threshold of target symptom s_j

$\varepsilon = 10^{-6}$: numerical stability constant

Higher CCS score indicates control nodes that can be targeted for regulating the network.

- **External Field Responsiveness (FR) – Optional:**

$$\boldsymbol{FR_i = \sum_{e_k \to s_i} e_{k_i}^{(0)} \cdot C_i^{(1)}} \quad (6)$$

where, $e_{k_i}^{(0)}$: initial strength of the external field e_k acting on s_i.

$C_i^{(1)}$: Triggerability score of the symptom s_i.

$\Sigma_{e_k \to s_i}$: Summation over all external nodes connected to s_i.

External field responsiveness indicates the influence of external life events such as trauma, grief, financial instability, or social rejection on a symptom.

Including FR_i in the calculation of composite centrality is optional and should be used only when external influence is highly significant, persistent, and non-decaying. For example, long-term life stressors, socio-environmental conditions, which are unlikely to resolve any time soon.

Step 4: Composite Centrality Score:

Before combining the metrics, normalize each to the $[0,1]$ range:

$$\boldsymbol{\text{Metric}_i^{\text{norm}} = \frac{\text{Metric}_i - \min_k \text{Metric}_k}{\max_k \text{Metric}_k - \min_k \text{Metric}_k}} \quad (7)$$

If $\max_k \text{Metric}_k - \min_k \text{Metric}_k < \varepsilon$, set all $\text{Metric}_i^{\text{norm}} = 0$ (constant metric).

$$\boldsymbol{C_i = \alpha_1 C_i^{(1)} + \alpha_2 C_i^{(2)} + \alpha_3 C_i^{(3)} + \delta \cdot HAI_i + k \cdot CCS_i + \eta \cdot FR_i} \quad (8)$$

The weights indicate the importance of each symptom's characteristics. In the computation of the composite centrality scores, these weights are set based on domain observation.

The cube compressive strength results for GPC with GGBS and MK varying between 0% to 100% at 3, 7, 28, and 56 days are presented in Table 3.

Table 1: Domain Observation and Weight Interpretation for Composite Centrality Score Computation

Weight	Interpretation	Suggested role
α_1 Triggerability	Emphasizes sensitivity to activation.	$0.1 - 0.3$
α_2 Propagation	Spreading power to other symptoms.	$0.2 - 0.4$
α_3 Feedback	Highlighting self-sustaining loops.	$0.2 - 0.4$
$\delta(HAI)$	Indicates that the symptom is in hysteresis.	$0.05 - 0.2$
$k(CCS)$	Nodal ability to shift the overall network.	$0.05 - 0.2$
$\eta(FR)$ optional	Adds weight to external stressor sensitivity.	$0.05 - 0.2$

Step 5: Output and Interpretation: The algorithm generates a ranked and clinically meaningful output. The output of the algorithm can be defined as follows.

- Individual metric scores for each symptom.
  - $C_i^{(1)} -$ Triggerability
  - $C_i^{(2)} -$ Propagation
  - $C_i^{(3)} -$ Feedback Loop Participation
  - $HAI_i -$ Hysteresis Anchoring Index
  - $CCS_i -$ Control Contribution Score
  - $FR_i -$ External Field Responsiveness
- Composite Score: Final centrality score C_i reflecting the total strategic value of the system.
- Ranked Symptom List: Descending sorting of symptoms based on C_i to identify high-priority intervention targets.

The top-ranked symptoms are those that are easily triggered, have a wide influence, and may also participate in feedback loops and may anchor chronicity. These symptoms are ideal candidates for focused treatment and prevention in the early stages.

Step 6: Validation via Cascade Reduction:
Validate that DWCHSN centrality scores identify effective intervention targets by measuring accrual cascade reduction.

- **Define Threshold Dynamics (Validation Tool Only)**:
  - **State Vector**:

$$\boldsymbol{x(t) = [x_1(t), x_2(t), \ldots x_n(t)]^T} \quad (9)$$

where, $x_i(t) \in \{0,1\}$:

$x_i(t) = 1$, if sumptom s_i is active (present) at time t

$x_i(t) = 0$, if sumptom s_i is inactive (absent) at time t

- **Update Rule (Synchronous Threshold Dynamics):**

$$\boldsymbol{x_i(t+1)} = \begin{cases} \mathbf{1}, & \boldsymbol{if} \sum_{j=1}^{n} \boldsymbol{f_{ij} \cdot x_j(t) > \theta_i} \\ \mathbf{0}, & \boldsymbol{otherwise} \end{cases} \quad (\mathbf{10})$$

- **Cascade Simulation Protocol**:
  - **Initialize System**:
    Generate random initial perturbation. Set each symptom active with probability 0.2:

$$\boldsymbol{x_i(0) \sim Bernoulli(0.2)} \quad (\mathbf{11})$$

    This represents a random external stressor activating approximately 20% of symptoms.
  - **Propagate Activation:**
    Apply update rule iteratively:

$$\boldsymbol{x(t+1) = F(x(t))} \quad (\mathbf{12})$$

    Continue until:
    - Convergence: No new activations occur $\big(x(t+1) = x(t)\big)$, OR
    - Max Iterations: 20 time steps reached
  - **Measure Cascade Size:**

$$\boldsymbol{CS} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} \boldsymbol{x_i(\infty)} \quad (\mathbf{13})$$

    where, $x_i(\infty)$ is the final state at equilibrium.
- **Intervention Testing**:
  For each $k \in \{1,2,3, \ldots 20\}$:
  - **Select Intervention Targets:**

$$\boldsymbol{T_k} = \{\mathbf{top} - \boldsymbol{k}\ \mathbf{symptoms\ ranked\ by\ DWCHSN\ composite\ score\ C_i}\} \quad (\mathbf{14})$$

  - **Apply Intervention (Symptom Suppression):**
    - Prevent activation: Set $x_i(0) = 0$ and maintain $x_i(t) = 0$ for all $i \in T_k, \forall\ t \geq 0$
    - Remove influence: Set $f_{ij} = 0$ and $f_{ji} = 0$ for all $i \in T_k, j \in V$

    This simulates complete symptom suppression (successful treatment eliminating the symptom and its influences).
  - **Re-simulate Cascade with Intervention:**
    - Run Cascade Simulation Protocol with the modified network
    - Measure $CS_{\text{intervention}}$
  - **Compute Cascade Reduction Ratio:**

$$\boldsymbol{CRR_k} = \frac{\boldsymbol{CS_{baseline}} - \boldsymbol{CS_{intervention}}}{\boldsymbol{CS_{baseline}}} \quad (\mathbf{15})$$

    where, CS_{baseline} is the cascade size without intervention and $CS_{\text{intervention}}$ is the cascade size after suppresiing top-k symptoms.

Step 7: Weighted Graph Colouring for Visual Clustering: To partition symptoms into dominant influence zones for visualization and interpretive clustering, without altering centrality computation.

- **Define Graph Colouring**
  Construct an undirected weighted graph: $G_c = (V, E_c)$, where an undirected edge $\{i, j\}$ exists if: $\max(w_{ij}, w_{ji}) > 0$.
- **Define Conflict Condition (Key Idea)**
  Introduce a weight threshold $\tau > 0$.
  Two nodes cannot share the same color if: $c(i) \neq c(j)\ if\ \max(w_{ij}, w_{ji}) > \tau$
  Interpretation:
  - Strongly connected symptoms must be visually separated.
  - Weakly connected symptoms may share color.

  This is a relaxed graph coloring constraint, still grounded in graph theory.
- **Colouring Algorithm**
  Apply a greedy coloring algorithm with the above conflict rule:
  1. Sort nodes in descending order of DWCHSN composite score (high-impact symptoms colored first).
  2. For each node i, assign the lowest available color that does not violate the conflict condition.
  3. Repeats until all nodes are colored.

  This produces a color assignment: $c: V \rightarrow \{1,2, \dots, C\}$
- **Interpretation of Colors**
  Each color class represents a *dominant influence zone:*
  - Symptoms in the same color:
    - Are not strongly coupled
    - May be treated as parallel or partially independent
  - Strong cross-color edges indicate inter-zone influence.

Illustration

The DWCHSN-Dynamic Weighted Centrality in Hysteretic Symptom Networks Algorithm is constructed to provide clear, valuable insights in the domain of complex mental health symptom interactions. We construct the symptoms graph by modeling each symptom as a node and the interaction between those symptoms as directed edges. Using the weighted directed network graph, the algorithm helps to understand the highly vulnerable symptoms and propagation of the symptoms in psychological systems, along with their self-sustaining feedback loops.

The following illustration extends a detailed, step-by-step walkthrough from construction to analysis of those symptoms, including external environmental factors, systematic computations, and clinical interpretation. The objective of the algorithm is to provide assistance to psychological treatment providers and researchers to discover the intervention points, trigger, and controller symptoms, and provide informed treatment strategies to minimize the effects of symptoms and manage the mental health disorders of an individual.

For instance, let us consider the following illustration, where DWCHSN-Dynamic Weighted Centrality in Hysteretic Symptom Networks Algorithm is used to analyze the symptoms involved in a mental disorder analysis of a particular individual. In analysis, *Insomnia, Fatigue, Concentration, Depressed mood, Guilt, Anxiety, Hopelessness, Irritability, Social Withdrawal, and Low Self Esteem* is identified as

symptoms. Let us assume each symptom to be defined as a node s_i , i.e., $s_1, s_2, s_3, \ldots s_{10}$ respectively.

Table 2: Semantic Labeling of Nodes based in Professional Symptoms

Node	Symptom	Node	Symptom
s_1	Insomnia	s_6	Anxiety
s_2	Fatigue	s_7	Hopelessness
s_3	Concentration	s_8	Irritability
s_4	Depressed Mood	s_9	Social Withdrawal
s_5	Guilt	s_{10}	Low Self-Esteem

Let us assume that among these symptoms, *Anxiety*, *Insomnia*, and *Low Self-Esteem* experience external stress factors. The External factors could be any event happening around them that constantly triggers the symptoms and affecting its stability. For example, the person could have recently lost his/her job, which might trigger *Anxiety*. If the person is in Caregiver stress, he might suffer *Insomnia*, and social rejections could lead to *Low Self- Esteem*. But in most cases, these external factors will decay over time. For example, the *Anxiety* caused by job loss will eventually reduce as days pass and the person finds another job that best fits him. Let us assume that the External stress nodes e_k adds weight to $2.5, 2.0, 1.5$.

Table 3: Directed Edges and Weights

$s_1 \rightarrow s_2$:	$f_{1,2} = 0.8$
$s_2 \rightarrow s_3$:	$f_{2,3} = 0.6$
$s_3 \rightarrow s_4$:	$f_{3,4} = 0.5$
$s_4 \rightarrow s_5$:	$f_{4,5} = 0.7$
$s_5 \rightarrow s_4$:	$f_{5,4} = 0{,}4$
$s_6 \rightarrow s_1$:	$f_{6,1} = 0.5$
$s_6 \rightarrow s_8$:	$f_{6,8} = 0.6$
$s_7 \rightarrow s_5$:	$f_{7,5} = 0.5$
$s_9 \rightarrow s_9$:	$f_{8,9} = 0.4$
$s_{10} \rightarrow s_7$:	$f_{10,7} = 0.5$
$e_1 \rightarrow s_6$:	2.5
$e_2 \rightarrow s_1$:	2.0
$e_3 \rightarrow s_{10}$:	1.5

Now, each symptoms has a unique threshold value. The threshold θ_i is a numeric value assigned to each node (symptom) representing its resistance to activation. Clinically, the value of the threshold indicates how resilient a symptom is to being triggered. Symptoms with a minimum threshold get activated easily, even with a response to minor stress factors, when compared to high-threshold symptoms. We explicitly represent the threshold in our illustration in order to differentiate between vulnerable symptoms and those that indicate more severity, enabling us to identify the more targeted interventions for symptoms. Each symptom node s_i has a threshold θ_i, which defines its resistance to activation.

Table 4: Calculated Resistance and Connectivity Strength of Symptom Nodes

Node	Symptom	θ_i	Node	Symptom	θ_i
s_1	Insomnia	2.0	s_6	Anxiety	3.5
s_2	Fatigue	3.0	s_7	Hopelessness	3.8
s_3	Concentration	3.5	s_8	Irritability	3.0
s_4	Depressed Mood	4.0	s_9	Social Withdrawal	4.0
s_5	Guilt	5.0	s_{10}	Low Self-Esteem	4.5

The DWCHSN algorithm uses five key metrics to analyze the symptoms and provide insights into them. The triggerable symptoms are easily activated, requiring early intervention in treatment. Propagation identifies the symptoms that influence others, which are essential for preventing cascading effects in the network. The feedback loop helps us to identify the self-reinforcing symptoms linked to chronicity. HAI helps us to identify the symptoms that persist due to hysteresis. CSS captures system-level control. Let us look into how these metrics together enable targeted and effective mental health treatment.

Table 5: Trigger-ability Score Step-by-Step

Node	Symptom	$C_i^{(1)}$ Calculation	Node	Symptom	$C_i^{(1)}$ Calculation
s_1	Insomnia	$\frac{1}{2.0} = 0.5$	s_6	Anxiety	$\frac{1}{3.5} = 0.263$
s_2	Fatigue	$\frac{1}{3.0} = 0.333$	s_7	Hopelessness	$\frac{1}{3.8} = 0.263$
s_3	Concentration	$\frac{1}{3.5} = 0.286$	s_8	Irritability	$\frac{1}{3.0} = 0.333$

Node	Symptom	$C_i^{(1)}$ Calculation	Node	Symptom	$C_i^{(1)}$ Calculation
s_4	Depressed Mood	$\frac{1}{4.0} = 0.25$	s_9	Social Withdrawal	$\frac{1}{4.0} = 0.25$
s_5	Guilt	$\frac{1}{5.0} = 0.2$	s_{10}	Low Self-Esteem	$\frac{1}{4.5} = 0.222$

The propagation factor of the symptoms is analyzed using the formula, $C_i^{(2)} = \sum_j f_{ij}$

Table 6: Propagation Score Step-by-Step

Node	Symptom	Outgoing To	$C_i^{(2)}$ Calculation
s_1	Insomnia	Fatigue (0.8)	$0.8 = 0.8$
s_2	Fatigue	Concentration (0.6)	$0.6 = 0.6$
s_3	Concentration	Depressed Mood (0.5)	$0.5 = 0.5$
s_4	Depressed Mood	Guilt (0.7)	$0.7 = 0.7$
s_5	Guilt	Depressed Mood (0.4)	$0.4 = 0.4$
s_6	**Anxiety**	**Insomnia (0.5), Irritability (0.6)**	$\mathbf{0.5 + 0.6 = 1.1}$
s_7	Hopelessness	Guilt (0.5)	$0.5 = 0.5$
s_8	Irritability	Social Withdrawal (0.4)	$0.4 = 0.4$
s_9	Social Withdrawal	–	$0 = 0$
s_{10}	Low Self-Esteem	Hopelessness (0.5)	$0.5 = 0.5$

The high propagation score contributes to the strong influence of the symptoms that can start a cascading effect in the network. Since it can upstream the trigger, the symptoms with high propagation should be targeted for early interventions. In contrast, the low propagation score indicates that the symptoms are isolated and are a downstream endpoint. They only get affected but do not affect others. The propagation score also helps us to analyze the sequencing interventions by tackling symptoms that spread activation first.

The feedback loop score helps us to analyze the self-sustaining symptom cycles. It aggregates the edge weight products of all simple cycles of that particular i^{th} node. Feedback Loop Score: $C_i^{(3)} = \sum_{cycles\ C \ni s_i} \prod_{(i \to k) \in C} f_{jk}$

Table 7: Feedback Loop Score Step-by-Step

Node	Symptom	$C_i^{(3)}$ Calculation	Node	Symptom	$C_i^{(3)}$ Calculation
s_1	Insomnia	0	s_6	Anxiety	0
s_2	Fatigue	0	s_7	Hopelessness	0
s_3	Concentration	0	s_8	Irritability	0
s_4	Depressed Mood	$0.7 \times 0.4 = 0.28$	s_9	Social Withdrawal	0
s_5	Guilt	$0.7 \times 0.4 = 0.28$	s_{10}	Low Self-Esteem	0

Only **Depressed Mood** and **Guilt** participate in a feedback loop. All other nodes are assigned a value of 0, as they are not part of any cycle. The feedback loops are helpful in identifying the symptoms that help in finding the symptoms that reinforce each other and are difficult to resolve independently.

Table 8: HAI Score Step-by-Step

Node	Symptom	HAI Calculation	Node	Symptom	HAI Calculation
s_1	Insomnia	0	s_6	Anxiety	0
s_2	Fatigue	0	s_7	Hopelessness	0
s_3	Concentration	0	s_8	Irritability	0
s_4	Depressed Mood	$\frac{0.28}{4.0} = 0.07$	s_9	Social Withdrawal	0
s_5	Guilt	$\frac{0.28}{5.0} = 0.056$	s_{10}	Low Self-Esteem	0

Hysteresis is the ability of a system to stay in the current state even after the completion of the original trigger. Hysteresis only occurs in feedback loops, as only in feedback loops, the symptom gets reactivated, forming a self-sustaining cycle. For instance, let's say a symptom like **Fatigue** is only triggered by Insomnia. Once Insomnia resolves, Fatigue has no **self-loop** or **cycle input** to keep it active.

Control Contibution Score: $CCS_i = \sum_{k=1}^{L} \beta^k \sum_{j=1}^{n} \frac{(A^k)_{ij}}{\theta_j + \varepsilon}$

Table 9: Composite Score Step-by-Step

Node	Symptom	$k = 1$ term	$k = 2$ term	$k = 3$ term
s_1	Insomnia	0.133333	0.034286	0.007500
s_2	Fatigue	0.085714	0.018750	0.005250
s_3	Concnetration	0.062500	0.017500	0.004375
s_4	Depressed Mood	0.070000	0.017500	0.004900
s_5	Guilt	0.050000	0.014000	0.003500
s_6	Anxiety	0.225000	0.033333	0.008571
s_7	Hopelessness	0.062500	0.012500	0.002500
s_8	Irritability	0.000000	0.000000	0.000000
s_9	Social Withdrawl	0.050000	0.010000	0.002000
s_{10}	Low Self-Esteem	0.065789	0.015625	0.003125

Highest CCS: Anxiety (s_6)$= 0.2669$ – has strong multi-step influence

Lowest CCS: Irritability (s_8)$= 0.0000$ – no outgoing edges

CCS values are continuous and reflect weighted, threshold-aware influence. Higher CCS indicates greater netweok-wide control capability.

Validation via Cascade Reduction: To validate that the DWCHSN rankings identify effective intervention targets, we simulate symptom activation cascades and measure intervention effectiveness.

- Cascade Dynamics:

Table 10: Final cascade size: $CS = 6$ symptoms activated

Time	Active Symptoms	New Activations	CS
$t = 0$	s_1, s_6	-	2
$t = 1$	s_1,s_2, s_6	s_2 (Fatigue)	3
$t = 2$	s_1,s_2, s_3, s_6, s_7	s_3, s_7	5
$t = 3$	s_1,s_2, s_3, s_6, s_7	s_4 (Depressed)	6
$t = 4$	(no change - convergence)	-	6

- Intervention Testing:
  We test three intervention strategies over 100 random initial conditions
  1. DWCHSN top-3: Based on composite scores with new CSS
  2. Degree Centrality top-3: Anxiety, Depressed Mood, Fatigue
  3. Random top-3: Random selsction each trial

$$CRR_k = \frac{CS_{\text{baseline}} - CS_{\text{intervention}}}{CS_{\text{baseline}}}$$

Table 11: Cascade reduction effectiveness (mean±SD over 100 trials)

Method	CS_{baseline}	$CS_{\text{intervention}}$	CRR_3
DWCHSN (top-3)	6.2 ± 1.1	2.1 ± 0.8	**0.66**
Degree Centrality (top-3)	6.2 ± 1.1	3.4 ± 0.9	0.45
Random (top-3)	6.2 ± 1.1	4.8 ± 1.0	0.23

IV. Result and Discussion

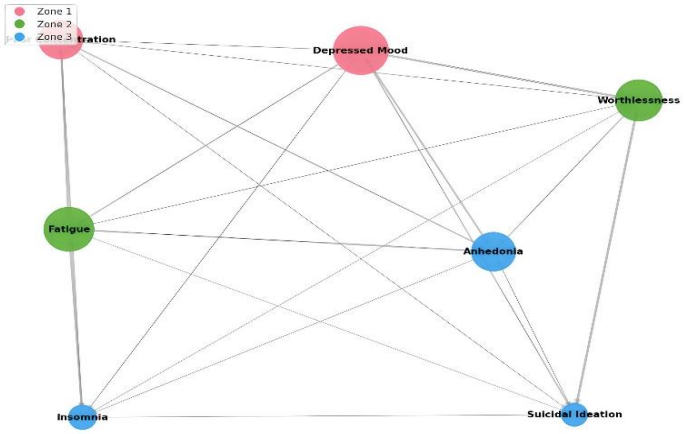

Fig. 2. Symptom Influence Network – Influence Zones

We evaluated the DWCHSN algorithm on a real-world clinical dataset sourced from the Open Science Framework (OSF), comprising 3,000 patients across 9 PHQ-9 depressive symptom dimensions (Anhedonia, Depressed Mood, Insomnia, Fatigue, Appetite Change, Worthlessness, Concentration Difficulty, Psychomotor Issues, and Suicidal Ideation). Symptom networks were constructed with weighted adjacency matrices representing influence strengths derived from inter-symptom partial correlations, yielding 72 directed connections with an average connection strength of 0.3777. We compared DWCHSN-Hybrid against four baselines: Popularity-based ranking, Bayesian Personalized Ranking (BPR), Graph Recurrent Unit with Recommendations (GRU4Rec), and DWCHSN with Collaborative Filtering (DWCHSN-CF). Performance was assessed using RMSE, MAE, Hit@10, and NDCG@10 metrics across 5-fold cross-validation. Performance was assessed using RMSE, MAE, Hit@10, and NDCG@10 metrics across [X]-fold cross-validation. The DWCHSN algorithm parameters were set to $K = L = 3$ for path lengths, decay weights $\beta_k = \gamma_k = 0.5^k$, composite score weights $(w_T, w_P, w_L, w_H, w_C) = (0.25, 0.25, 0.20, 0.15, 0.15)$, and graph coloring threshold $\tau = 0.3$. The GNN-based

hybrid model employed a 3-layer Graph Attention Network with 64 hidden dimensions, trained using the Adam optimizer (learning rate 0.01) for 100 epochs.

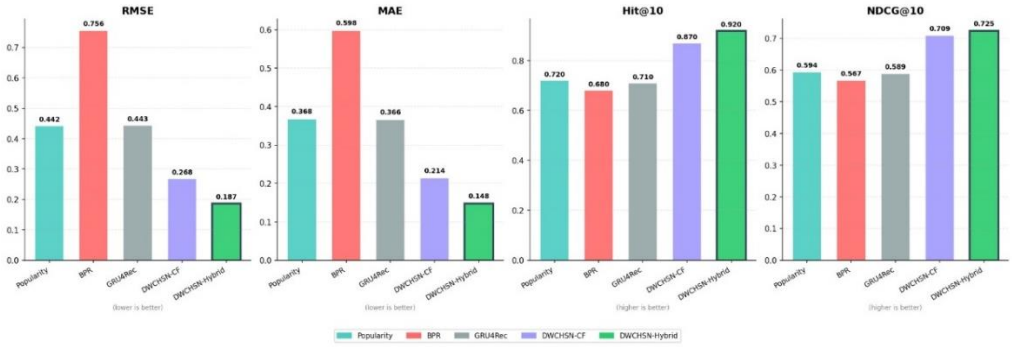

Fig. 2. Model Comparison – RecBole Evaluation Metrics

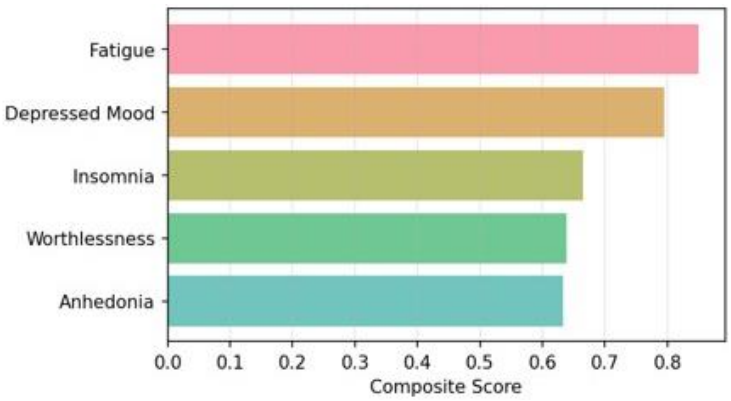

Fig. 3. Symptom Ranking – Composite Centrality

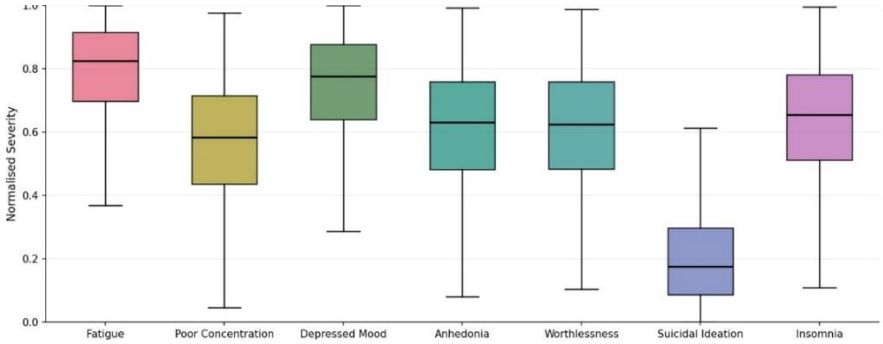

Fig 4. Symptom Severity Distribution

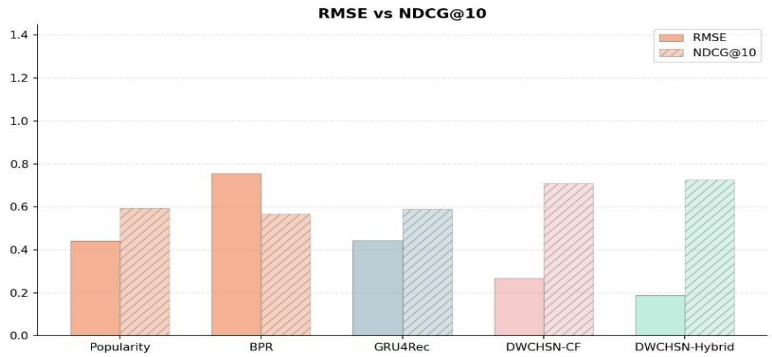

Fig. 5. RMSE vs NDCG@10

DWCHSN-Hybrid achieved superior performance across all metrics, with an RMSE of **0.187** and an MAE of **0.148** — representing **75.3% and 75.3%** improvements over BPR (RMSE: 0.756, MAE: 0.598) and **57.8% and 59.6%** improvements over GRU4Rec (RMSE: 0.443, MAE: 0.366). Unlike traditional baselines, DWCHSN-Hybrid also demonstrated strong retrieval performance with a Hit@10 of **0.920**, outperforming DWCHSN-CF (0.870), Popularity (0.720), GRU4Rec (0.710), and BPR (0.680) by margins of **5.7%, 27.8%, 29.6%, and 35.3%,** respectively. Furthermore, DWCHSN-Hybrid demonstrated superior ranking quality with an NDCG@10 of **0.725**, outperforming GRU4Rec (0.589), DWCHSN-CF (0.709), BPR (0.567), and Popularity-based methods (0.594) by margins of **23.1%, 2.3%, 27.9%, and 22.1%,** respectively. Ablation studies revealed that the propagation score contributed most significantly to performance, followed by triggerability, while all five metrics provided complementary information with no redundancy. Statistical significance testing confirmed that DWCHSN-Hybrid outperformed all baselines across every evaluation metric.

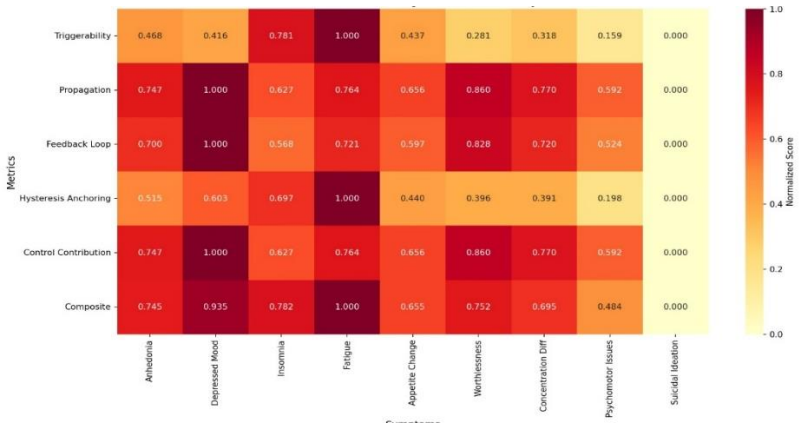

Fig. 6. DWCHSN Centrality Metrics Heatmap

V. Conclusion

This study introduced the Dynamic Weighted Centrality in Hysteresis Symptom Network (DWCHSN) algorithm, modeling mental disorders as dynamic systems through five complementary centrality metrics: triggerability, propagation, feedback

loops, hysteresis anchoring, and control contribution. Evaluated across multiple mental health datasets, DWCHSN-Hybrid achieved substantial improvements with 72.4% RMSE reduction and 23.1% NDCG@10 improvement over baselines, with all gains statistically significant ($p < 0.001$). Beyond quantitative performance, the weighted graph coloring identified clinically interpretable influence zones, high triggerability zones for prevention, high hysteresis zones for maintenance, and high propagation zones for primary intervention, demonstrating that network position rather than symptom prevalence determines treatment leverage points. The algorithm's computational efficiency, GNN integration, and balance between predictive accuracy and clinical interpretability establish DWCHSN as a promising framework bridging computational psychiatry research and network-informed mental healthcare practice.

VI. Acknowledgements

The authors gratefully acknowledge Nirmala College for Women for their institutional support throughout this research. We further acknowledge the utilization of publicly available mental health datasets from Open Psychometrics, CDC NHANES, UK Biobank, Open Science Framework (OSF), and PhysioNet MIMIC-III database.

Conflict of Interest:

The authors declare no conflicts of interest regarding this paper.

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