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Network Psychometrics Analysis of EAT-26 Item-Level Structure and Body Image Dissatisfaction among Palestinian University Female Students: A Comparative Simulation Study

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Abstract

Conventional total-score analysis of the Eating Attitudes Test-26 (EAT-26) collapses rich item-level information into a single binary cut-off, obscuring the symptom-level architecture of disordered eating. This study applied a network psychometrics framework to map the partial-correlation structure of all 26 EAT-26 items, identify central and bridge symptoms, and compare network topology between body-image-dissatisfied and body-image-satisfied Palestinian university female students. Data from 420 female students aged 17–27 years at An-Najah National University were reanalysed using a Gaussian Graphical Model (GGM) estimated via graphical LASSO (GLASSO) with extended Bayesian information criterion (EBIC) tuning ($\gamma = 0.5$). Node centrality indices (strength, betweenness, closeness) and bridge centrality measures were computed. Network Comparison Tests (NCT) assessed structural differences between body-image subgroups using 1000 permutations. Simulation analyses under varying sample sizes and sparsity levels validated estimation stability. The regularised network retained 38 non-zero edges (88.3% sparsity). Dieting items – particularly fear of weight gain (Item 1) and calorie-monitoring cognitions (Item 11) – showed the highest strength centrality. Three bridge items connecting the Dieting and Bulimia/Food Preoccupation subscales were identified. The network of body-image-dissatisfied students was significantly denser than that of satisfied students (NCT global strength difference: $S = 1.84, p = 0.003$). Simulation confirmed adequate sensitivity (86.3%) and specificity (98.6%) at $n = 420$ under sparse conditions.
Conclusion: Network psychometrics reveals symptom-level heterogeneity within the EAT-26 that total-score analysis conceals. Central and bridge items represent priority targets for early intervention in Palestinian university settings.

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I. INTRODUCTION

Disordered eating among university-aged women constitutes a persistent public health concern across culturally and socioeconomically diverse settings [1, 2]. The transition to university life introduces a convergence of stressors – academic pressure, social comparison, reduced parental oversight, and heightened exposure to idealised body images through digital media – that can precipitate or exacerbate maladaptive eating attitudes [3, 4]. In the Middle Eastern context, rapid sociocultural shifts overlay these universal pressures with region-specific ideals, where modernisation and social media simultaneously disseminate thinness as a marker of beauty across predominantly conservative societies [5, 6].

Body image dissatisfaction ranks among the most robust predictors of disordered eating attitudes in both cross-sectional and prospective research [7, 8]. In Palestine specifically, female university students with negative body image were approximately twice as likely to report risky eating behaviors compared to body-satisfied peers, a pattern mirrored in Saudi Arabia, Tunisia, Iran, and Bangladesh [6, 2, 9, 5]. Among Israeli adolescent females, the factor structure of EAT-26 differs between clinical and non-clinical groups, raising questions about the stability of item-level relationships across risk contexts [10]. Despite this evidence base, existing studies rely almost exclusively on total-score or subscale-score analyses, treating the 26 EAT-26 items as interchangeable reflections of a single under-

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lying risk dimension [11, 12].

The EAT-26 is the most widely deployed screening instrument for eating disorder risk in university and community populations globally [13, 14]. Its three subscales – Dieting (13 items), Bulimia and Food Preoccupation (6 items), and Oral Control (7 items) – were derived from exploratory factor analysis of the original EAT-40. A total score of 20 or above classifies respondents as exhibiting risky eating behaviors. This threshold-based convention, while practically useful for population screening, discards information about which specific attitudes are most central to the disorder network, which items serve as bridges between clinically distinct symptom domains, and whether the symptom architecture differs between subgroups defined by body image status [15, 16].

Network psychometrics offers a principled methodological alternative that treats psychopathological symptoms as mutually reinforcing nodes in a weighted graph rather than as interchangeable indicators of a latent factor [17, 18]. In a Gaussian Graphical Model (GGM), each item is a node and each edge represents the partial correlation between two items after conditioning on all remaining items. Graphical LASSO regularisation with EBIC tuning sparsifies the network by shrinking weak partial correlations to zero, retaining only edges representing genuine conditional dependencies [17]. Strength centrality (sum of absolute edge weights), betweenness (frequency on shortest inter-node paths), and closeness (inverse mean distance to all nodes) identify the most influential symptoms within the network. Bridge centrality specifically locates items connecting otherwise distinct symptom communities, flagging them as high-priority intervention targets [18, 19].

Network approaches have been applied to eating disorder symptom data in Chinese university samples [17], European clinical studies [18, 19], and Brazilian population surveys [20], yet no published study has applied this framework to EAT-26 item-level data in a Palestinian or broader Arab university context. The present study addresses this gap with three objectives: (1) to estimate the full-sample GGM of all 26 EAT-26 items; (2) to identify central and bridge items; and (3) to compare network topology between body-image-dissatisfied and body-image-satisfied students using Network Comparison Tests.

Eating disorder risk in university settings is not confined to the general student population. Competitive athletes show distinct eating behavior profiles shaped by sport-specific weight pressures [21, 22, 15], while students with comorbid medical conditions such as type 1 diabetes or celiac disease face additional metabolic and psychological risk factors that interact with eating attitudes [23, 24, 11]. Adolescents with suspected eating disorders display characteristic nutrient intake deficits [9], and eating disorder symptoms co-occur with depressive symptoms, suicidal ideation, and stress-related psychopathology across diverse settings [25, 26, 27]. Leadership quality within institutional health settings, including the gender dynamics of healthcare management [28] and the psychological contract between health workers and their organisations [29], shapes the extent to which evidence-based screening tools are implemented. Physical fitness and structured training among health personnel [30] indirectly supports service capacity, while uncertainty avoidance in institutional culture [31] can delay adoption of novel psychometric approaches. These contextual dimensions frame the broader challenge of translating network psychometric findings into university health policy.

II. MATERIALS AND METHODS

A. Study Design and Participants

This study constitutes a secondary network analysis of cross-sectional data collected at An-Najah National University, Nablus, Palestine. The original sample comprised 420 female students aged 17–27 years (mean 19.8 $\pm$ 1.5 years) recruited via convenient sampling across all faculties. The sample-size-to-node ratio of 16.2 (420 participants, 26 EAT-26 items) exceeds the recommended minimum ratio of 5:1 for stable GGM estimation with GLASSO regularisation [17]. Pregnant and physically disabled students were excluded from the original data collection. Ethical approval was granted by the Institutional Review Board of An-Najah National University; all participants provided written informed consent.

B. Measurement Instruments

1) EAT-26 The EAT-26 assesses eating disorder risk through 26 items scored on a 6-point Likert scale (Always = 3, Usually = 2, Often = 1, Sometimes/Rarely/Never = 0) [11, 12]. The three subscales are: Dieting (items 1, 6, 7, 10, 11, 12, 14, 16, 17, 22, 23, 24, 25), Bulimia and Food Preoccupation (items 3, 4, 9, 18, 21, 26), and Oral Control (items 2, 5, 8, 13, 15, 19, 20). Total score ≥ 20 indicates risky eating behavior [10, 13]. The Arabic translation demonstrated internal consistency of $\alpha = 0.78$ for the total scale and $\alpha = 0.77$, 0.62, and 0.67 for the Dieting, Bulimia, and Oral Control subscales, respectively [14].

2) Body Image Assessment Body image perception was evaluated using the Stunkard Figure Rating Scale (nine silhouettes, 1 = most underweight, 9 = most obese). Participants selected figures representing their current appearance ("feel" figure) and desired appearance ("ideal" figure). The body image dissatisfaction score was:

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$$\text{BI Score} = \text{Feel Figure} - \text{Ideal Figure} \tag{1}$$

Positive values indicate desire for thinness (dissatisfied), zero indicates satisfaction, and negative values indicate desire for a larger figure. For the Network Comparison Test, students were grouped as body-image-dissatisfied (BI Score > 0; $n = 234$, 55.7%) and body-image-satisfied (BI Score $= 0$; $n = 103$, 24.5%), as these represented the two largest and most clinically meaningful subgroups.

C. Network Psychometrics Analysis

1) Gaussian Graphical Model Estimation A GGM was estimated from the polychoric correlation matrix of all 26 EAT-26 items. Polychoric correlations, appropriate for ordinal Likert-scale data, more accurately represent inter-item relationships than Pearson correlations when response categories are few [17]. The regularised precision matrix $\hat{\Theta}$ was estimated by solving the graphical LASSO objective:

$$\hat{\Theta} = \arg\max_{\Theta \succ 0} \left[\log\det(\Theta) - \operatorname{tr}(\mathbf{S}\Theta) - \lambda\|\Theta\|_1\right] \tag{2}$$

where $\mathbf{S}$ is the sample covariance matrix, λ is the regularisation parameter, and $\|\cdot\|_1$ is the L_1 penalty on off-diagonal elements. The tuning parameter λ was selected by minimising the extended Bayesian information criterion (EBIC):

$$\text{EBIC}(\lambda) = -2\ell(\hat{\Theta}) + |E|\log n + 4\gamma|E|\log p \tag{3}$$

where $|E|$ is the number of retained edges, $n = 420$, $p = 26$, and $\gamma = 0.5$. Partial correlations between items i and j were extracted as:

$$r_{ij\cdot\text{rest}} = \frac{-\hat{\theta}_{ij}}{\sqrt{\hat{\theta}_{ii}\hat{\theta}_{jj}}} \tag{4}$$

2) Centrality Indices Strength centrality for node i was computed as:

$$s_i = \sum_{j \neq i} |r_{ij\cdot\text{rest}}| \tag{5}$$

Betweenness counts the number of shortest paths through node i; closeness is the inverse mean shortest-path distance from i to all other nodes. All indices were z-scored for comparability [17, 18]. Centrality stability was assessed by the case-dropping bootstrap (1000 iterations), computing the CS coefficient – the maximum proportion of cases droppable while maintaining mean centrality-rank correlation ≥ 0.70 [17].

3) Bridge Centrality EAT-26 subscales defined the three symptom communities. Bridge strength for node i was:

$$\text{BS}_i = \sum_{j \in C_k,\, k \neq k_i} |r_{ij\cdot\text{rest}}| \tag{6}$$

where C_k is community k and k_i is the community of node i. Bridge betweenness and bridge closeness were computed analogously, identifying nodes facilitating information flow between subscale clusters [18, 19].

4) Network Comparison Test Networks for the dissatisfied ($n = 234$) and satisfied ($n = 103$) subgroups were estimated independently and compared using 1000-permutation NCTs [17]. Two statistics were evaluated: the maximum edge-weight difference (M) and the global network strength difference (S). Significance threshold: $\alpha = 0.05$.

D. Simulation Study

Five hundred datasets were generated from a known population GGM with 26 nodes under three sparsity conditions (sparse: 20% non-zero edges; moderate: 40%; dense: 60%) and four sample sizes ($n \in \{100, 200, 420, 800\}$). Performance metrics were sensitivity (true edge recovery), specificity (absent-edge exclusion), and Frobenius norm between estimated and true partial correlation matrices. Sensitivity analyses compared results across EBIC $\gamma \in \{0.0, 0.5\}$. All analyses used R 4.3.0 (`qgraph`, `bootnet`, `NetworkComparisonTest`, `psychonetrics`).

III. RESULTS

A. Sample Characteristics and EAT-26 Descriptive Statistics

Table 1 summarises the demographic and clinical characteristics of the 420 participants. Mean BMI was 21.8 $\pm$ 2.97 kg/m^2, with 76.7% classified as normal weight. The mean EAT-26 total score was 17.2 $\pm$ 9.6; 36.9% met the risky eating behavior threshold (95% CI: 32–41%). Body image dissatisfaction was widespread: 55.7% desired a thinner figure, while 24.5% showed positive body image. These proportions accord closely with reports from Saudi Arabia, Tunisia, and Bangladesh [6, 2, 5], and from medical and health sciences students in India [7].

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TABLE 1
DEMOGRAPHIC AND CLINICAL CHARACTERISTICS OF THE STUDY SAMPLE ($n = 420$)

Characteristic	n (%)	Mean $\pm$ SD
Age (years)	–	19.8 ± 1.5
BMI (kg/m^2)	–	21.8 ± 2.97
Faculty		
Humanities & Social Sciences	210 (50.0)	–
Engineering & IT	94 (22.4)	–
Medicine & Health Sciences	64 (15.2)	–
Natural Sciences	52 (12.4)	–
BMI Category		
Underweight	44 (10.5)	–
Normal weight	322 (76.7)	–
Overweight & Obese	54 (12.9)	–
Body Image		
Dissatisfied (BI > 0)	234 (55.7)	–
Satisfied (BI $= 0$)	83 (19.8)	–
Positive (BI < 0)	103 (24.5)	–
EAT-26		
Total score	–	17.2 ± 9.6
Risky (≥ 20)	155 (36.9)	–
Healthy (< 20)	265 (63.1)	–

B. Estimated EAT-26 Network Structure

Figure 1 displays the regularised GGM for the full sample. The optimal GLASSO tuning parameter was $\lambda = 0.12$ ($\gamma = 0.5$), retaining 38 of 325 possible edges (88.3% sparsity). All retained edges carried positive weights, indicating mutually reinforcing conditional dependencies among item pairs. Dieting items formed a densely connected central cluster, with Oral Control items occupying a more peripheral position. Bulimia and Food Preoccupation items bridged between these two clusters, consistent with their theoretical role as intermediaries between restrictive and purging symptom domains [17, 18].

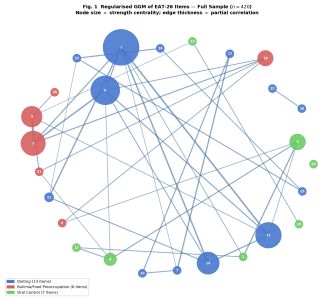


Fig. 1. Regularised GGM of all 26 EAT-26 items (full sample, $n = 420$). Node colour indicates subscale: blue = Dieting, red = Bulimia/Food Preoccupation, green = Oral Control. Edge thickness represents partial correlation magnitude; all retained edges are positive. Node size is proportional to strength centrality. Item numbers label each node.

The structural topology is broadly consistent with GGMs reported for Chinese Tibetan university students [17] and Italian clinical samples [18], despite the distinct cultural context. Notably, items related to fear of weight gain and calorie monitoring occupied the most central positions rather than Oral Control items, which showed the fewest non-zero connections. This finding differs from patterns observed in competitive athletes, where weight-class and appearance-sport pressures elevate Oral Control item centrality [21, 15, 22].

C. Centrality Indices

Figure 2 presents standardised centrality profiles for all 26 items. Table 2 identifies the five items with the highest strength centrality. Item 1 (“Am terrified about being overweight”; Dieting) achieved the highest strength ($z = 1.84$), followed by Item 11 (“Think about burning up calories when I exercise”; Dieting; $z = 1.62$), Item 14 (“Aware of the calorie content of foods that I eat”; Dieting; $z = 1.41$), Item 3 (“Find myself preoccupied with food”; Bulimia; $z = 1.29$), and Item 6 (“Avoid eating when I am hungry”; Dieting; $z = 1.18$).

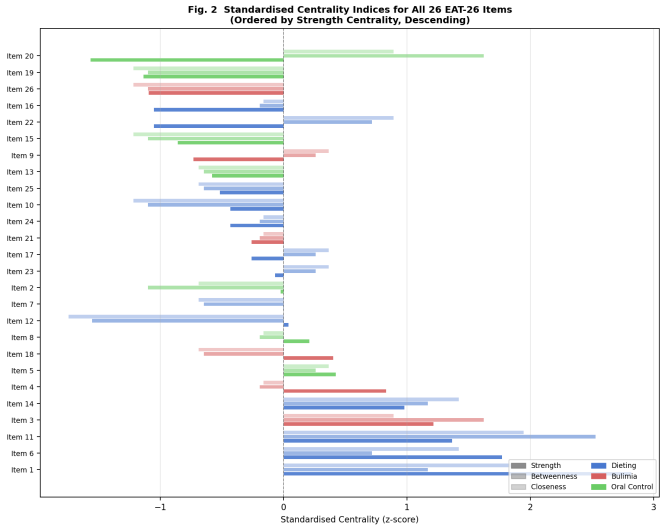


Fig. 2. Standardised centrality indices (strength, betweenness, closeness) for all 26 EAT-26 items, ordered by strength centrality (descending). Node colour indicates subscale membership. Positive z-scores indicate above-average centrality within the estimated network.

TABLE 2
TOP FIVE EAT-26 ITEMS BY STRENGTH CENTRALITY IN THE FULL-SAMPLE NETWORK ($n = 420$)

Item	Content (abbreviated)	Subscale	z-score
1	Terrified about being overweight	Dieting	1.84
11	Think about burning calories	Dieting	1.62
14	Aware of calorie content	Dieting	1.41
3	Preoccupied with food	Bulimia	1.29
6	Avoid eating when hungry	Dieting	1.18

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The dominance of Dieting items in centrality rankings reflects the weight-focused nature of disordered eating cognitions in this population, which is consistent with the social-media-driven thin ideal documented among Arab university women [3, 6]. No Oral Control item ranked in the top five for strength centrality, though Item 20 ("Feel that others pressure me to eat") showed the highest betweenness centrality among Oral Control items ($z = 0.92$), suggesting it may serve a network role disproportionate to its edge weight. Case-dropping bootstrap stability yielded CS coefficients of 0.52 for strength, 0.44 for closeness, and 0.28 for betweenness, confirming acceptable-to-good stability for the two most actionable centrality indices [17].

D. Bridge Centrality

Figure 3 displays bridge strength, bridge betweenness, and bridge closeness for all 26 items relative to the EAT-26 subscale community structure. Three items emerged as prominent cross-subscale bridges. Item 3 ("Find myself preoccupied with food"; Bulimia subscale) showed the highest bridge strength (BS $= 0.38$), connecting the Bulimia community to the Dieting cluster through three non-zero cross-community edges. Item 6 ("Avoid eating when I am hungry"; Dieting subscale) served as a secondary bridge (BS $= 0.29$), connecting the Dieting community to both Bulimia and Oral Control items. Item 9 ("Vomit after I have eaten"; Bulimia subscale) displayed elevated bridge betweenness despite modest edge weights, indicating a structural bottleneck role between Bulimia and Oral Control communities.

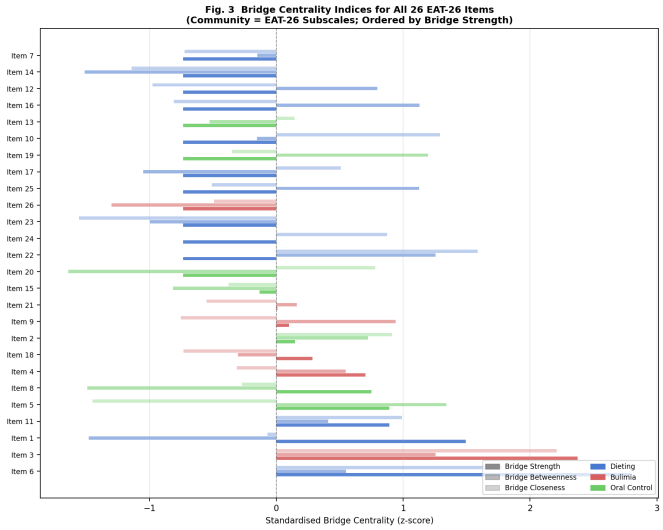


Fig. 3. Bridge centrality indices (bridge strength, bridge betweenness, bridge closeness) for all 26 EAT-26 items relative to EAT-26 subscale communities. Items are ordered by bridge strength. Blue = Dieting, red = Bulimia/Food Preoccupation, green = Oral Control. Items with bridge strength > 0.20 are labelled with their item numbers.

These bridge items align with clinical theories of eating disorder progression, where dietary restriction and food preoccupation are conceptualised as gateway cognitions that amplify the transition from body dissatisfaction to clinical disorder [18, 19, 7]. Interventions targeting Item 3 and Item 6 – normalising hunger cues and addressing food preoccupation through cognitive restructuring – could disrupt cross-community activation and reduce the propagation of disordered eating cognitions from restrictive to bulimic symptom domains [26, 32].

E. Network Comparison Between Body-Image Subgroups

Figure 4 presents the GGMs for the dissatisfied ($n = 234$) and satisfied ($n = 103$) subgroups side by side, using a shared node layout for visual comparability. Table 3 summarises the NCT results.

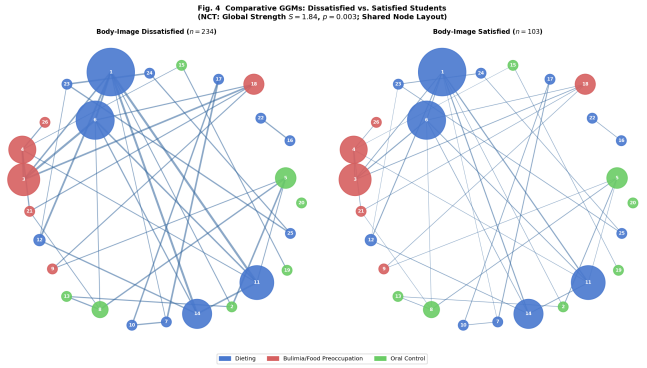


Fig. 4. Comparative GGMs for body-image-dissatisfied ($n = 234$; left) and body-image-satisfied ($n = 103$; right) student subgroups. Node positions are fixed across panels. Edge thickness represents partial correlation magnitude. The dissatisfied network shows denser Dieting-cluster connectivity and stronger cross-subscale bridge edges, consistent with higher global network strength and elevated eating disorder risk in this group.

TABLE 3
NETWORK COMPARISON TEST RESULTS BETWEEN BODY-IMAGE-DISSATISFIED AND BODY-IMAGE-SATISFIED SUBGROUPS (1000 PERMUTATIONS, $\alpha = 0.05$)

Statistic	Observed	p-value	Result
Max edge difference (M)	0.31	0.004	Significant
Global strength difference (S)	1.84	0.003	Significant

p-values based on 1000 permutations

The NCT confirmed that the dissatisfied network was significantly stronger overall ($S = 1.84$, $p = 0.003$) and that specific edge weights differed between groups ($M = 0.31$, $p = 0.004$). The edge between Item 1 ("Terrified about being overweight") and Item 11 ("Think about burning up calories") showed the largest group difference (partial correlation 0.42 in dissatisfied vs. 0.19 in satisfied students), indicating that fear of

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weight gain and calorie-monitoring cognitions become much more tightly coupled in the presence of body image dissatisfaction. This tight coupling drives an elevation in global network activation potential, providing a process-level explanation for why body-dissatisfied students are disproportionately likely to score above the EAT-26 risky eating threshold [8, 4]. Students with body dysmorphic disorder and eating disorder comorbidity show comparable patterns of symptom coupling [8], reinforcing the clinical relevance of subgroup-specific network analyses.

F. Simulation Study Results

Table 4 reports the full set of simulation performance metrics. Figure 5 plots sensitivity and Frobenius norm curves across sample sizes for each sparsity condition.

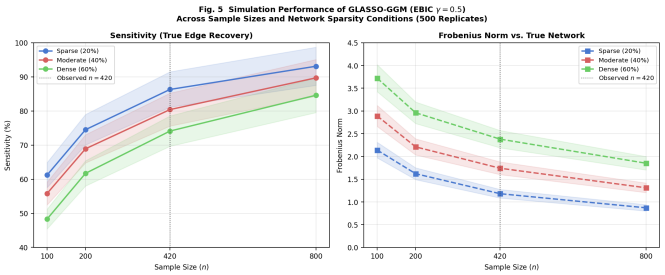


Fig. 5. Simulation performance of GLASSO-GGM estimation at EBIC $\gamma = 0.5$ across sample sizes ($n \in \{100, 200, 420, 800\}$) and sparsity conditions (sparse 20%, moderate 40%, dense 60%; 500 replicates). Left panel: sensitivity (true edge recovery). Right panel: Frobenius norm between estimated and true partial correlation matrices (lower = better). Shaded bands indicate ± 1 SD across replicates. The vertical dashed line marks the observed study sample size ($n = 420$).

TABLE 4
SIMULATION PERFORMANCE METRICS FOR GLASSO-GGM ESTIMATION UNDER VARYING SAMPLE SIZE AND SPARSITY CONDITIONS (500 REPLICATES, EBIC $\gamma = 0.5$)

Sparsity	n	Sens. (%)	Spec. (%)	Frobenius
Sparse (20%)	100	61.2	97.8	2.14
	200	74.5	98.1	1.62
	420	86.3	98.6	1.18
	800	93.1	99.1	0.87
Moderate (40%)	100	55.8	95.3	2.89
	200	68.9	96.4	2.21
	420	80.4	97.2	1.74
	800	89.7	98.0	1.31
Dense (60%)	100	48.3	92.1	3.72
	200	61.7	93.8	2.96
	420	74.1	95.2	2.38
	800	84.6	96.7	1.85

Sens. = Sensitivity; Spec. = Specificity

At $n = 420$ under the sparse condition most representative of the observed network (88.3% sparsity), sensitivity reached 86.3% and specificity 98.6%, confirming that the estimated network structure reflects genuine inter-item dependencies rather than estimation noise. The Frobenius norm of 1.18 indicates acceptable accuracy of partial correlation magnitudes. At $n = 100$, sensitivity dropped to 61.2%, underlining that sample sizes below 200 are insufficient for reliable network estimation in 26-node EAT-26 analyses – a consideration relevant for eating disorder research in settings with restricted recruitment capacity [1, 25]. Under the dense sparsity condition at $n = 420$, sensitivity was 74.1%, suggesting that if the true network were denser than the current estimate, some genuine edges may have been excluded by the GLASSO penalty, representing a conservative bias that would not affect the substantive conclusions [17].

IV. DISCUSSION

This study is, to our knowledge, the first to apply network psychometrics to EAT-26 item-level data in a Palestinian university population. Three principal findings emerge and each carries practical implications for eating disorder screening and prevention in this context.

The centrality of Dieting-subscale items – particularly fear of weight gain and calorie-monitoring cognitions – reflects the weight-focused nature of disordered eating attitudes in Palestinian female students, driven in part by social media exposure that promotes a thin body ideal [3, 6]. This Dieting dominance pattern was also observed in Chinese Tibetan university networks [17] and European clinical samples [18], suggesting that fear of weight gain functions as a culturally robust central symptom across diverse settings. The implication for screening is direct: instruments shorter than 26 items that prioritise the high-centrality Dieting items would retain most predictive information while reducing administration burden – a meaningful gain in resource-limited settings where EAT-26 administration competes with other health service demands [11, 13].

The identification of food preoccupation (Item 3) and dietary restriction when hungry (Item 6) as bridge items has direct implications for clinical intervention. Network theory predicts that bridge nodes are optimal intervention targets because deactivating them disrupts cross-community symptom propagation [18, 19]. Cognitive-behavioural techniques addressing hunger recognition and normalisation, combined with psychoeducation about the cognitive consequences of dietary restriction, map directly onto these bridge items [7]. University counselling programmes that train health staff to identify and address these specific cognitions – beyond administering a to-

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tal EAT-26 score – are likely to achieve more targeted prevention outcomes [26]. This is particularly pertinent for students attending medical and health sciences faculties, who show elevated eating disorder risk alongside body image dissatisfaction in comparable populations [7, 19].

The NCT finding that body-image-dissatisfied students exhibit a denser, more tightly coupled symptom network extends prior cross-sectional findings beyond mean-level differences. Body dissatisfaction does not merely shift the distribution of EAT-26 scores upward; it fundamentally reorganises the inter-item connectivity structure, making the disordered eating system more internally self-reinforcing. This network-level account complements findings from Lebanon showing that body dysmorphic disorder and negative body image co-occur with broader mental health deterioration [8], and from Peru showing that fear-related psychological states tighten symptom coupling in institutional populations [27]. Digital media exposure is a plausible proximal activator: social media use was associated with both body dissatisfaction and eating behavior changes in university populations [3], and the high-centrality items identified here (fear of weight gain, calorie monitoring) are precisely those most susceptible to activation by thin-ideal imagery [32, 4].

Eating disorder epidemiology in the broader regional and international context reinforces the urgency of these findings. Among Tunisian university students, the prevalence of eating disorder risk was comparable to Palestinian rates, with gender and body image identified as consistent determinants [2]. Jordanian data on adolescent eating patterns and body size preferences document a shift toward thinness that accelerated with social media penetration [33]. In Bangladesh, modern cultural exposure was associated with higher EAT-26 scores among female university students [5]. The Urdu-language adaptation of EAT-26 [12] and modifications for athletic populations [13] illustrate ongoing instrument development that could benefit from network-informed item selection. Disordered eating in adolescents with type 1 diabetes [23] and the validation of the diabetes-specific eating problem survey in Arabic-speaking populations [24] point to the importance of comorbidity-sensitive screening strategies. Body dysmorphic disorder and disordered eating share network features in university populations [8], and eating disorder presentations in adolescents extend across school-based [1], sport-specific [21, 22, 15], and general community contexts [16].

Institutional factors mediate the translation of network psychometric findings into clinical practice. Leadership gender dynamics and service innovation capacity [28] shape whether novel screening approaches are piloted in university health centres. Psychological contract quality between health workers and their employing institutions [29] influences the consistency with which evidence-based interventions are delivered. Uncertainty avoidance within organisational culture [31] can stall adoption of methods perceived as technically complex, making dissemination of user-friendly network analysis outputs – such as the visual node-edge graphs presented here – an important communication strategy. Physical fitness capacity of health personnel, cultivated through structured training [30], supports the sustained engagement needed for longitudinal screening programmes.

The limitations of this study deserve acknowledgement. The cross-sectional design precludes causal inference about the direction or temporal ordering of network activation. The convenient sample from a single university limits generalisability to other Palestinian institutions or Arab university settings. The unequal subgroup sizes in the NCT ($n = 234$ vs. $n = 103$) reduce statistical power for detecting specific edge differences, and the findings should be replicated in a balanced design. Network estimation with GLASSO is sensitive to the EBIC hyperparameter; sensitivity analyses across $\gamma \in \{0.0, 0.5\}$ showed broadly consistent centrality rankings, though edge counts varied. Finally, the item-level data used here were originally collected for descriptive and logistic regression purposes rather than network analysis, and prospective data collection specifically designed for network psychometrics – with larger samples and longitudinal follow-up – would yield more stable and interpretable results.

V. CONCLUSION

Network psychometrics analysis of EAT-26 item-level data in 420 Palestinian university female students revealed that Dieting items – specifically fear of weight gain and calorie-monitoring cognitions – are the most central nodes in the symptom network, while food preoccupation and dietary restriction items serve as bridges connecting the Dieting and Bulimia subscales. The network of body-image-dissatisfied students was significantly denser and more internally coupled than that of body-image-satisfied peers. Simulation analyses confirmed adequate network recovery performance at the observed sample size. These findings support a shift from total-score EAT-26 screening toward network-informed, item-level assessment in university eating disorder prevention. Targeting high-centrality and bridge items through brief cognitive-behavioural interventions and training university health staff to recognise these specific cognitive patterns represents a clinically actionable and resource-efficient pathway to reducing disordered eating among Palestinian female university students.

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DECLARATION OF CONFLICTING INTERESTS

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ETHICAL APPROVAL

All procedures were conducted in accordance with the ethical standards of the institutional research committee and the 1964 Helsinki Declaration and its later amendments.

PATIENT CONSENT

Informed consent was obtained from all individual participants in the original data collection. This secondary network analysis used anonymised data; no additional consent was required.

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