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Exploring Relationships between Common Healthy Behaviors in Adolescents Using Innovative Social Network Analysis

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ABSTRACT

Data on the interrelationship between common healthy behaviors is not available for adolescents. **Objective:** To explore the relationships among common healthy behaviors in a population sample using network analysis. **Methods:** A random sample of 250 adolescents (34% female) was selected from a population of adolescents, who visited the Nutrition, Education, Awareness and Training (NEAT) Clinics during January-March, 2024. Data was collected on a validated questionnaire. This study applied network centrality analysis to investigate six health related behaviors non-smoking, fruit intake, vegetable intake, proper sleep, eating breakfast, and walking. Centrality measures (betweenness, closeness, strength, and expected influence) were used to assess the role and influence of each behavior within health behavior networks. **Results:** The overall network density was high (0.80; 12 edges out of total 15 possible edges), suggesting that the healthy behaviors in the sample population were tightly interconnected. Such a dense network indicates that changes in one behavior may potentially influence others, supporting the need for multi-behavior interventions. With mean scores grouped between 2.3 and 2.6, moderate variability, symmetric distributions, and full-scale utilization, descriptive analysis showed that teenagers modestly engaged in six fundamental health behaviors. This suggests that while these behaviors are present, they are not widely adopted in the population. **Conclusion:** Walking and eating breakfast were identified as key lifestyle habits in adolescent health networks, suggesting that they may be targeted strategically for treatments aimed at preventing obesity.

INTRODUCTION

Obesity is an ongoing, worldwide public health issue [1, 2], with substantial contributions to the load of non-communicable chronic diseases like diabetes, cardiovascular disease and some cancers [3-5]. It is well accepted that obesity is determined not solely by individual influences, but by intricate interactions between several lifestyle factors [6]. Notwithstanding rigorous health promotion campaigns, obesity prevalence continues to escalate, particularly in middle- and low-income nations, necessitating a more subtle insight into behavioral determinants. Healthy behaviors like routine physical activity, adequate sleep, breakfast consumption [7-9], the intake of fruits and vegetables, and not smoking have been shown to protect against obesity [11]. These behaviors, however, are not isolated; they tend to co-occur and interact in ways that will either promote health or add to risk. Recognizing these patterns is necessary for creating comprehensive and effective interventions. Network analysis provides a new and compelling structure for analyzing inter-behavioral relationships [12]. In contrast to classical statistical approaches that emphasize single effects, network analysis views behaviors as interlinked nodes in a system. This enables researchers to find central behaviors with potential to dominate others, identify clusters of co-occurring habits, and reveal structural properties of behavioral networks that might be used to guide interventions. The current study will apply network analysis to examine the associations between prevalent

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healthy behaviors in a population sample. In particular, it was aimed to characterize key behaviors as central nodes in the behavior network, determine the modular organization of behavior clusters, and gain insights that will inform more focused, system-level obesity prevention efforts. Recognizing how health behavior is connected can provide useful insight for constructing effective public health interventions. Instead of considering behaviors such as diet, physical activity, or sleep separately, network analysis enables us to look at how these habits group and affect each other within practical behavioral systems. This research explores the centrality and impact of six typical health behavior categories non-smoking, fruit eating, vegetable eating, good sleeping, breakfast eating, and walking. Through the application of network centrality metrics like betweenness, closeness, strength, and expected influence, we determine what behaviors are most embedded within an individual's lifestyle networks and are more on the periphery. This method tells us not only what habits are most effective in advancing healthy living, but also how behavioral patterns vary along demographic and geographic lines.

Such information is vital to where health promotion efforts are most likely to build upon larger positive lifestyle change.

METHODS

The cross-sectional analytical study sought to examine the interrelations of prevalent healthy lifestyle behaviors that are likely to play a role in preventing obesity, employing a network analysis strategy. The aim was to map behavioral co-occurrence patterns and detect important behaviors that could be points of leverage for intervention. Male and female adolescents aged 16-20 years were recruited from the population of those who had visited the NEAT (Nutrition, Education, Awareness, and Training) Clinics for nutrition and health counselling in January-March. 2024. NEAT registered with cooperative society Pakistan, has been actively assisting studies related to health and nutrition [13-16]. The sample size for this cross-sectional study was estimated using the standard formula for calculating a single population proportion: n=Z2·p·(1−p)/d2; Where: n = required sample size; Z = Z-score for 90% confidence level (1.645); p = assumed prevalence of the outcome (in this case, 70% prevalence of healthy BMI among adolescents based on previous NEAT Clinic records); d = margin of error (5% or 0.05). Putting the values into the formula. Thus, the required minimum sample size was rounded to 227 participants [17]. This ensures adequate power to estimate the proportion of adolescents with healthy BMI within a 5% margin of error at a 90% confidence level. As a precaution against non-response, the target sample size was a 10% increase, and the final sample size was about 250 adolescents. Participants were selected using a consecutive sampling technique. All eligible adolescents who visited the NEAT Clinic during the study period (January to March 2024) and met the inclusion criteria were invited to participate. This approach ensured that every individual meeting the criteria during the specified timeframe had an equal opportunity to be included, thereby reducing selection bias while maintaining feasibility in a clinical setting. Questionnaire data were gathered from a sample of 250 respondents aged 16years and older. The questionnaire items were modified and modeled against tested instruments utilized in public health and behavioral nutrition studies (Table 1). Every item represents essential concepts of lifestyle behavior and conforms to WHO and national health guidelines for daily habits that impact non-communicable disease (NCD) risk. Content Validity was maintained by incorporating central lifestyle behaviors (physical activity, diet, sleep, smoking) proven to influence health outcomes, aligned with the WHO STEPwise Approach to NCD Risk Factor Surveillance exported elsewhere [18]. Construct Validity is informed by the Health-Promoting Lifestyle Profile-II (HPLP-II) and the Global School-based Student Health Survey (GSHS), both of which have been shown to possess acceptable psychometric properties across different populations [19]. Public health and nutrition experts' (n = 3) expert review was employed to verify the appropriateness and understandability of each question. The scoring scheme (0–4 scale) was developed from behavioral nutrition literature's practices (e.g., frequency and dietary diversity scoring), providing interval-level data for statistical analysis [20]. The respondents self-reported their practice of the following health-related behaviors: 1) Regular walking; 2) Consumption of fruit; 3) Intake of vegetables; 4) Adequate sleep; 5) Consumption of breakfast; 6) Non-smoking status. Responses were coded between 0-4; where 0=no consumption; 4=high consumption (for variables fruits and vegetables consumption) and for other variables, for instance for appropriate sleep (0=poor sleep; 4=highly appropriate sleep); for breakfast consumption (0=rarely consuming; 4=daily consuming); for walking (0=no walking; 4=daily walking). For network building, a binary co-occurrence matrix was built from the co-occurrence of behavior across participants [21]. Each behavior as a node was represented, and edges (links) between nodes represented the frequency of co-occurrence between two behaviors. The edges were weighted with pairwise Phi coefficients, representing the strength of association between the behaviors. The weighted, undirected network obtained was plotted using the igraph and qgraph packages in R. We calculated centrality measures for every node: 1) Strength

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centrality to find most connected behaviors; 2) Closeness centrality to identify nodes with shortest average paths to other nodes; 3) Between centrality to find behaviors that play bridge roles. Edges were visually scaled by weight, and node sizes were scaled by strength centrality. Colors and positions were optimized using the Fruchterman-Reingold algorithm for readability. In order to determine the clusters of behavior, community detection was carried out with the walk trap algorithm. Networks were created for the total sample, and also for male and female as well as rural and urban dwellers separately. All network analyses were conducted in R using relevant packages including igraph, qgraph, and bootnet. Responses were coded between 0-4; where (for walking) 0 = Never 1 = Once a week; 2 = 2-3 times/week; 3 = 4-6 times/week; 4=Daily. Similarly, (for variables fruits and vegetables consumption) 0 = None; 1 = Less than once/day; 2=Once/day; 3 = Twice/ day; 4=More than twice/day; for appropriate sleep (0 = Very poor; 1=Poor; 2=Average; 3=Good; 4=Excellent); for breakfast consumption (0 = Never/rarely; 1 =1-2 days/week; 2=3-4 days/ week; 3=5-6 days/week; 4=Daily); for non-smoking status (0=Regular smoker; 1=Occasionally; 2=Recently quit; 3=Non- smoker, but exposed; 4=Never smoked or exposed). The table 1 outlined the six key health behaviors assessed in adolescents along with their respective response categories(Table 1).

Table 1: Description of Health Behavior Items and Response Options Used in the Adolescent Health Network Analysis

S. No.	Behavior	Description	Response Options
1	Regular Walking	How often do you engage in walking for at least 30 minutes a day?	0 = Never1 = Once a week2 = 2-3 times/week3 = 4-6 times/ week4 = Daily
2	Fruit Consumption	How often do you consume fresh fruits in a day?	0 = None1 = Less than once/day2 = Once/day3 = Twice/ day4 = More than twice/day
3	Vegetable Consumption	How often do you eat vegetables (cooked or raw)?	0 = None1 = Less than once/day2 = Once/day3 = Twice/ day4 = More than twice/day
4	Adequate Sleep	How would you rate your sleep in terms of adequacy (7-9 hrs)?	0 = Very poor1 = Poor2 = Average3 = Good4 = Excellent
5	Breakfast Consumption	How often do you eat breakfast in a typical week?	0 = Never/rarely1 = 1-2 days/week2 = 3-4 days/ week3 = 5-6 days/week4 = Daily
6	Non-Smoking Status	Are you currently smoking?	0 = Regular smoker1 = Occasionally2 = Recently quit3 = Non-smoker, but exposed4 = Never smoked or exposed

RESULTS

Utilizing measures of central tendency, dispersion, and shape of distribution, distribution of six key healthy behaviors among adolescents was examined (Table 2). On a 0 to 4 scale, the average scores for all the behaviors walking (M = 2.61), breakfast eating (M = 2.63), sleep (M = 2.47), fruit consumption (M = 2.36), nonsmoking (M = 2.43), and vegetable consumption (M = 2.41) were bunched at 2.3 to 2.6, indicating that the sample had accepted these behaviors on a moderate level. Standard deviations indicated moderate behavior adoption diversity ranging from 1.67 to 1.73. All the values of items' skewness ranging from -0.117 to 0.087 were close to zero, indicating that the distributions were relatively symmetric. Light-tailed relative to normal was suggested by repeatedly negative kurtosis values ranging from -1.21 to -1.31. The full range of the scale was used, indicated by the minimum observed score of 0 across all behaviors and the maximum score of 4. Descriptive data overall indicate that the healthy behaviors are indeed in the population but are not yet highly practiced and differ moderately from person to person.

Table 2: Mean Scores of Healthy Behaviors

Variables	Frequency (%)	Skewness	Standard Error of Skewness	Kurtosis	Standard Error of Kurtosis	Minimum	Maximum
Non-smoking	2.43 (1.71)	0.037	0.086	-1.31	0.172	0	4
Veg-Intake	2.41 (1.69)	0.079	0.086	-1.207	0.172	0	4
Proper-Sleep	2.47 (1.73)	0.068	0.086	-1.311	0.172	0	4
Fruit-Intake	2.3 (1.69)	0.087	0.086	-1.226	0.172	0	4
Eating-Breakfast	2.62 (1.67)	-0.117	0.086	-1.21	0.172	0	4
Walking	2.61 (1.71)	-0.1	0.086	-1.261	0.172	0	4

Network Structure

The behavioral network comprised seven nodes, each representing a healthy lifestyle behavior: Walking, Proper Sleep, Eating Breakfast, Vegetable Intake, Fruit Intake, and Non-Smoking. All nodes were interconnected with varying edge weights, indicating positive associations between behaviors. The edge thickness reflected the strength of co-occurrence or correlation; for example, strong ties were observed between Eating Breakfast and Non-Smoking, and between Fruit Intake and Vegetable Intake, suggesting these behaviors often co-exist in individuals.

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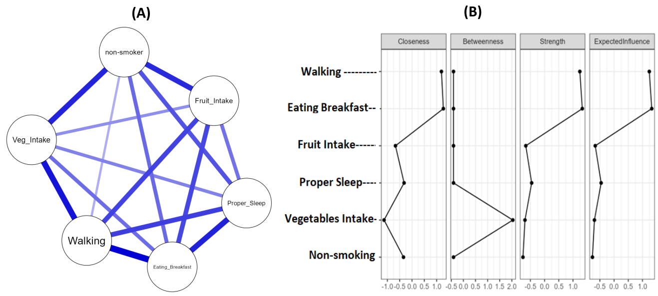

Figure 1: Network plot. The overall network consists of seven nodes connected through edges (A). the centrality plot defects centrality measures: closeness, betweenness, strength, and expected influence(B).

Centrality Measures

To determine the most central behaviors in the network, centrality measures were calculated: Degree Centrality: Fruit Consumption, Adequate Sleep, and Walking had the highest degree centrality, meaning that they were most often linked to other behaviors. Betweenness Centrality: Breakfast Consumption showed high betweenness, functioning as a bridge among clusters of physical activity/sleep and eating habits. Closeness Centrality: Walking and Non-Smoking had high closeness scores, indicating that they were able to effectively reach or influence other nodes in the network.

Modularity and Community Detection

With modularity optimization, the network divided into two major clusters: Cluster 1 (Lifestyle + Physical Activity): Walking, Proper Sleep, and Non-Smoking. Cluster 2 (Dietary Behaviors): Eating Breakfast, Fruit Intake, and Vegetable Intake. This suggests a modular distinction between lifestyle and dietary behaviors, albeit with bridging nodes such as Eating Breakfast that link the two clusters.

Cohesion and Network Density

The network density was high overall (0.80; 12 edges out of total 15 possible edges), which implies that the healthy behaviors in the sample population were densely connected. Such a dense network implies that changes in one behavior can potentially have an influence on others, which supports the necessity of multi-behavior interventions.

DISCUSSION

Applying network centrality measures such as degree, closeness, and betweenness, the current research analyzed the centrality of six health behaviors: not smoking, having breakfast, walking, sleeping enough, and eating fruits and vegetables. These measures can be applied to enable researchers to identify critical leverage points for intervention programs by determining how central a behavior is in a network of co-occurring lifestyle habits [22, 23]. The findings indicate that walking and eating breakfast across all subgroups consistently demonstrate the highest values of centrality, indicating they are most likely to influence and drive other positive behaviors. Walking is a low-intensity physical activity that improves cardiovascular health and mental well-being and eating breakfast, in specific, has been consistently associated with enhanced cognitive function, metabolic control, and reduced BMI in teenagers [24-26]. Non-smoking was also identified as a bridging behavior for men, which connects otherwise weakly related behaviors. This indicates that its effects transcend its direct health benefits and can also assist individuals in adopting other positive habits [27]. Eating fruits, vegetables, and obtaining sufficient rest all have low centrality scores and are seemingly peripheral in every network. This means that adolescents' schemas of health behavior do not consider such activities as interdependent or that they are practiced less often with other behaviors. Peripheral activities might have a lesser effect on overall lifestyle patterns and require more specific, stand-alone interventions, as stated by [28, 29]. In creating integrated interventions that increasingly link nutrition quality and sleep hygiene to leading lifestyle pathways, these results underscore the importance of strengthening core, high-centrality behaviors such as eating breakfast and walking. This approach is consistent with systems-based models of public health that emphasize equal attention to behavioral clustering and scalability of interventions.

CONCLUSIONS

Walking and eating breakfast were identified as key lifestyle habits in adolescent health networks, suggesting that they may be targeted strategically for treatments aimed at preventing obesity.

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Authors Contribution

Conceptualization: IA
Methodology: IA
Formal analysis: IA
Writing, review and editing: IA

All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

All the authors declare no conflict of interest.

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