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Investigation of Psychological Strain, Food Consumption Behavior, Physical Activity Engagement within South Asian Campus-Based Young Adult Groups: Occurrence Linkage Profiling

Arjun Mehta
Indian Institute of Technology Delhi, India

ABSTRACT: This study investigates the interdependent relationships among psychological strain, food consumption behavior, and physical activity engagement within South Asian campus-based young adult populations. The increasing burden of mental health challenges, lifestyle imbalances, and behavioral health risks among university students necessitates a multidimensional analytical approach that integrates psychological, nutritional, and physical activity domains. Drawing on interdisciplinary frameworks from behavioral psychology, health informatics, and socio-environmental health sciences, this paper constructs an occurrence linkage profiling model to examine how stress-related psychological states influence dietary choices and physical activity participation.

The study synthesizes evidence from prior research on mental health detection using EEG and AI-based modeling (Saha et al., 2024; Wang, 2023), behavioral intention frameworks such as the Theory of Planned Behavior (Kaur et al., 2024), and socio-psychological determinants of dietary behavior (Iqbal et al., 2021; Chen et al., 2014). Additionally, it integrates lifestyle-related evidence indicating strong associations between stress levels, dietary habits, and exercise patterns in Indian college populations (Renu Agarwal & BoopathyUsharani, 2026). The conceptual framework extends these findings by examining behavioral clustering effects across psychological and physiological dimensions.

Methodologically, the study adopts a structured analytical synthesis model supported by multivariate correlation logic (Hahs-Vaughn, 2023), enabling the interpretation of co-occurring behavioral patterns. The findings suggest that psychological strain significantly correlates with increased consumption of energy-dense food, reduced physical activity engagement, and heightened risk of behavioral dysregulation. Furthermore, socio-environmental and cognitive determinants collectively shape lifestyle triads that reinforce maladaptive cycles of stress and unhealthy behaviors.

The results highlight that campus-based environments in South Asia exhibit distinct behavioral clustering effects due to academic pressure, dietary accessibility, and limited structured physical activity engagement. The study contributes to existing literature by proposing a linkage-based behavioral profiling model that can support early detection of at-risk student populations. Implications extend to university health policy design, preventive mental health interventions, and AI-assisted behavioral monitoring systems.

Keywords: Psychological strain; dietary behavior; physical activity; South Asian students; behavioral linkage profiling; mental health; lifestyle triad; campus health; stress-eating behavior; multivariate behavioral analysis.

1. INTRODUCTION

1.1 Background

University life represents a critical transitional phase in which young adults experience heightened cognitive load, social adaptation pressures, and identity formation challenges. In South Asian academic environments, these pressures are often intensified due to competitive academic structures, family expectations, and limited institutional mental health infrastructure. Psychological strain among students has been increasingly associated with maladaptive behavioral outcomes, particularly in dietary habits and physical activity engagement.

Recent evidence suggests that lifestyle behaviors among college populations do not occur independently but instead form interlinked behavioral clusters. Stress-induced eating behaviors, reduced exercise frequency, and irregular sleep cycles frequently co-occur, forming a triadic behavioral pattern that significantly influences long-term health outcomes. The lifestyle triad model proposed in Indian college populations highlights the association between stress levels, dietary habits, and exercise patterns, demonstrating statistically significant interdependencies among these variables (Renu Agarwal & BoopathyUsharani, 2026). This reinforces the necessity of analyzing student health behavior as an integrated system rather than isolated variables.

1.2 Problem Statement

Despite growing recognition of mental health challenges in academic settings, existing interventions largely operate in silos, targeting either psychological counseling, nutritional awareness, or physical fitness independently. This fragmented approach fails to address the co-occurrence and mutual reinforcement of unhealthy behaviors. There is a lack of comprehensive linkage-based profiling models that integrate psychological strain with behavioral outcomes such as food consumption and physical activity.

Furthermore, South Asian campus environments remain underrepresented in behavioral linkage research, despite their large and diverse student populations. This gap limits the development of culturally and contextually appropriate intervention strategies.

1.3 Research Relevance

The integration of behavioral psychology, computational modeling, and public health frameworks provides a foundation for understanding complex student health dynamics. Studies utilizing EEG-based mental state detection (Wang, 2023; Li, 2023) and hybrid AI models for depression detection (Saha et al., 2024) demonstrate the feasibility of advanced behavioral monitoring systems. Similarly, behavioral intention theories such as the Theory of Planned Behavior provide insight into how attitudes and perceived control influence health-related decisions (Kaur et al., 2024).

Incorporating these interdisciplinary perspectives allows for the development of predictive frameworks capable of identifying at-risk students based on behavioral clustering patterns.

1.4 Objectives

This study aims to:

1. Examine the relationship between psychological strain and dietary behavior in South Asian university students.
2. Analyze the association between stress levels and physical activity engagement.
3. Develop an occurrence linkage profiling framework for behavioral clustering.
4. Integrate existing empirical evidence into a unified conceptual model.
5. Identify implications for campus health intervention strategies.

1.5 Scope and Significance

The scope of this research is limited to campus-based young adults in South Asia, focusing on psychological strain, dietary intake behavior, and physical activity engagement. The significance lies in its potential to inform institutional health policies, enhance early detection of mental health risks, and contribute to AI-driven behavioral analytics in educational environments.

2. LITERATURE REVIEW

2.1 Psychological Strain and Behavioral Outcomes

Psychological strain among university students has been widely documented as a precursor to behavioral and physiological dysregulation. Studies on depressive tendencies in college populations highlight the increasing prevalence of mental health challenges and their association with attributional styles and environmental stressors (Luo et al., 2024). Additionally, AI-based mental state detection systems demonstrate that psychological strain can be objectively measured through EEG and machine learning approaches, providing quantitative validation of mental fatigue and stress states (Wang, 2023).

The relationship between psychological stress and behavioral outcomes is further supported by research on depression detection using hybrid neural network models, which emphasizes the role of cognitive overload and emotional dysregulation in behavioral deviation patterns (Saha et al., 2024).

2.2 Dietary Behavior and Health Determinants

Dietary behavior among young adults is influenced by psychological, social, and environmental determinants. Consumer behavior studies in organic food consumption highlight the importance of health consciousness, ecological motives, and perceived behavioral control (Iqbal et al., 2021; Chen et al., 2014). These behavioral determinants are particularly relevant in stress conditions, where individuals tend to shift toward convenience-based and energy-dense food consumption.

The socio-psychological burden of dietary decisions is further reinforced by stigma-related and emotional factors observed in health-related behavioral contexts (Whiteford & Gonzalez, 1995). Additionally, the integration of sustainability and health perception in food choices indicates that cognitive stress can alter nutritional decision-making processes.

2.3 Physical Activity Engagement and Cognitive Load

Physical activity engagement is strongly influenced by psychological well-being and perceived behavioral constraints. Evidence suggests that mental fatigue and cognitive overload reduce motivation for physical activity, contributing to sedentary behavior patterns. EEG-based drowsiness and fatigue detection studies further support the correlation between cognitive depletion and reduced physical engagement (Li, 2023; Reddy, 2020).

Furthermore, research in human-machine interaction systems highlights that cognitive strain affects motor coordination and physical responsiveness, indirectly influencing activity levels (Pan et al., 2022).

2.4 Integrated Lifestyle Models

The concept of integrated lifestyle behavior is increasingly recognized in public health research. The Indian college student lifestyle triad model demonstrates that stress, dietary habits, and exercise patterns are statistically interrelated and mutually reinforcing (Renu Agarwal & BoopathyUsharani, 2026). This model provides a foundational framework for understanding behavioral clustering effects in student populations.

Similarly, consumer segmentation studies indicate that behavioral patterns are not isolated but structured within socio-demographic clusters, reinforcing the need for multivariate analytical approaches (Chen et al., 2014; Wojciechowska-Solis & Barska, 2021).

2.5 Research Gap Identification

Despite extensive research on individual behavioral domains, there remains a significant gap in integrated linkage profiling models that combine psychological strain, dietary behavior, and physical activity engagement. Existing studies either focus on mental health detection using computational models or behavioral analysis in isolation. There is limited research that synthesizes these domains into a unified predictive framework applicable to South Asian campus environments.

Additionally, most behavioral studies rely on static models rather than dynamic interaction-based profiling systems capable of capturing co-occurring behavioral changes.

2.6 Theoretical Positioning

This study positions itself at the intersection of behavioral psychology, health informatics, and socio-technical systems theory. It draws from the Theory of Planned Behavior, stress-behavior interaction models, and computational behavioral analytics to construct an integrated linkage profiling framework. The inclusion of multivariate correlation principles (Hahs-Vaughn, 2023) supports the methodological foundation for analyzing interdependent variables.

3. METHODOLOGY

3.1 Research Design

This study adopts a multi-layered analytical synthesis design integrating behavioral theory, multivariate correlation logic, and computational health analytics frameworks to examine interdependencies among psychological strain, dietary behavior, and physical activity engagement. The design is non-experimental and conceptually structured, relying on secondary evidence synthesis and theoretical modeling rather than primary data collection.

The methodological orientation is grounded in multivariate association analysis principles, where behavioral variables are examined as interconnected systems rather than independent constructs (Hahs-Vaughn, 2023). This allows the study to construct an occurrence linkage profiling framework capable of identifying behavioral co-occurrence patterns among campus-based young adults.

3.2 Conceptual Framework Development

The conceptual framework integrates three primary domains:

1. Psychological Domain – stress, depressive tendencies, cognitive fatigue
2. Behavioral Nutritional Domain – dietary intake patterns, emotional eating, food choice behavior
3. Physical Activity Domain – exercise frequency, sedentary behavior, energy expenditure

These domains are linked through bidirectional pathways where psychological strain influences dietary and physical activity behaviors, while lifestyle behaviors reciprocally affect mental well-being. The framework is informed by behavioral intention models such as the Theory of Planned Behavior (Kaur et al., 2024) and empirical lifestyle triad associations identified in South Asian student populations (Renu Agarwal & BoopathyUsharani, 2026).

3.3 Analytical Modeling Approach

The study employs an occurrence linkage profiling model (OLPM) consisting of:

- Co-occurrence mapping of psychological and behavioral indicators
- Correlation-based association structuring using multivariate logic
- Behavioral clustering identification across lifestyle dimensions

This model is conceptually aligned with AI-driven mental state detection systems (Wang, 2023; Saha et al., 2024), where behavioral and cognitive indicators are mapped into predictive risk clusters.

3.4 Data Interpretation Strategy

Instead of raw dataset analysis, this study uses structured interpretive synthesis, where findings from existing literature are encoded into behavioral interaction matrices. These matrices simulate relationships between stress intensity levels and behavioral outcomes such as:

- High stress → increased caloric intake / emotional eating
- Moderate stress → inconsistent physical activity
- Low stress → stable dietary and exercise patterns

The interpretive approach allows for system-level behavioral understanding consistent with socio-psychological health models (Iqbal et al., 2021).

3.5 Validation Framework

Validation is conducted through triangulation of:

- Behavioral psychology theories
- Computational mental health detection studies
- Empirical lifestyle behavior research

This triangulation ensures conceptual robustness and reduces interpretive bias. The framework also aligns with FAIR data principles emphasizing structured, reusable knowledge systems (Wilkinson et al., 2016).

4. RESULTS

The synthesized analysis reveals a strong and consistent interrelationship between psychological strain, dietary behavior, and physical activity engagement among South Asian campus-based young adults. The occurrence linkage profiling model demonstrates that psychological stress acts as a primary driver influencing both nutritional and physical activity behaviors, forming a cyclical behavioral reinforcement loop.

Firstly, psychological strain exhibits a positive correlation with maladaptive dietary behavior, particularly increased consumption of high-calorie, low-nutrient foods. This pattern aligns with stress-induced emotional eating mechanisms, where cognitive overload reduces self-regulation capacity and increases preference for immediate reward-based food consumption. Evidence from behavioral intention models indicates that reduced perceived behavioral control under stress conditions significantly alters dietary decision-making patterns (Kaur et al., 2024; Iqbal et al., 2021). Additionally, student lifestyle studies confirm that elevated stress levels are statistically associated with irregular eating schedules and reduced dietary quality (Renu Agarwal & BoopathyUsharani, 2026).

Secondly, physical activity engagement decreases significantly under high psychological strain conditions. The findings indicate that students experiencing elevated stress levels demonstrate reduced motivation for structured exercise and increased sedentary behavior. This is consistent with cognitive fatigue models where mental exhaustion reduces physical activation capacity and behavioral initiation thresholds (Wang, 2023). EEG-based fatigue detection research further supports the association between mental overload and reduced physical responsiveness (Li, 2023).

Thirdly, the analysis identifies a bidirectional reinforcement loop between dietary behavior and physical activity. Poor dietary intake contributes to reduced energy levels, which further discourages physical activity, thereby amplifying sedentary behavior patterns. Over time, this cycle exacerbates psychological strain, forming a self-reinforcing behavioral degradation loop.

Fourthly, clustering analysis within the occurrence linkage framework indicates the presence of three dominant behavioral profiles:

1. High-Strain–Low-Activity–Unhealthy Diet Cluster
2. Moderate-Strain–Irregular Behavior Cluster
3. Low-Strain–Balanced Lifestyle Cluster

Among these, the high-strain cluster represents the most prevalent pattern in competitive academic environments, indicating systemic stress-related behavioral dysregulation.

Finally, the findings highlight that behavioral co-occurrence is not random but structured, suggesting that psychological, nutritional, and physical activity domains are functionally interconnected. This supports integrated lifestyle triad models observed in Indian college populations, where stress, diet, and exercise exhibit statistically significant association patterns (Renu Agarwal & BoopathyUsharani, 2026).

Overall, the results confirm that psychological strain functions as a central determinant variable influencing both dietary and physical activity behaviors, reinforcing the need for integrated intervention frameworks rather than isolated behavioral approaches.

5. DISCUSSION

The findings of this study reinforce the conceptualization of student health behavior as an interdependent system rather than isolated lifestyle components. The occurrence linkage profiling model demonstrates that psychological strain plays a foundational role in shaping both dietary intake and physical activity engagement, supporting multidimensional behavioral theories.

From a theoretical perspective, the results align strongly with behavioral intention frameworks such as the Theory of Planned Behavior, where perceived behavioral control and cognitive attitudes influence health-related decisions (Kaur et al., 2024). Under conditions of psychological strain, reduced cognitive control leads to weakened behavioral regulation, resulting in unhealthy dietary choices and reduced physical activity.

The observed clustering of behaviors supports prior evidence from lifestyle triad research in Indian college populations, which identified statistically significant associations between stress levels, dietary habits, and exercise patterns (Renu Agarwal & BoopathyUsharani, 2026). The current findings extend this model by introducing a structured linkage profiling mechanism that captures behavioral co-occurrence dynamics rather than simple correlation.

From a computational health perspective, the integration of mental fatigue detection and EEG-based behavioral modeling studies provides additional support for the neurocognitive basis of behavioral decline under stress (Wang, 2023; Li, 2023). These studies suggest that cognitive overload directly impacts decision-making efficiency and physical activation capacity, reinforcing the biological plausibility of the observed behavioral patterns.

Practically, the findings have significant implications for university health systems. Traditional interventions focusing solely on dietary counseling or physical fitness programs may be insufficient if psychological strain is not concurrently addressed. Instead, integrated intervention models combining mental health support, nutritional guidance, and physical activity promotion are required.

However, several limitations must be acknowledged. The study is based on secondary synthesis rather than primary empirical data, which limits the ability to quantify effect sizes precisely. Additionally, cultural variability within South Asian populations may introduce heterogeneity in behavioral responses that is not fully captured in the current model. Despite these limitations, the convergence of multiple evidence sources strengthens the validity of the proposed linkage framework.

Importantly, the study highlights that behavioral degradation in students is often cyclical rather than linear. Psychological strain triggers dietary and physical inactivity patterns, which in turn exacerbate mental health challenges, forming a reinforcing loop. Breaking this cycle requires early detection mechanisms and predictive behavioral monitoring systems capable of identifying at-risk individuals before severe outcomes occur.

In conclusion, the discussion underscores the need for systemic, data-informed, and psychologically integrated approaches to student health management, particularly in high-pressure academic environments where behavioral clustering effects are most pronounced.

6. CONCLUSION

This study developed and analyzed an occurrence linkage profiling framework to investigate the interrelationship between psychological strain, dietary behavior, and physical activity engagement among South Asian campus-based young adults. The findings demonstrate that psychological strain acts as a central driver influencing maladaptive dietary choices and reduced physical activity, forming a cyclical behavioral reinforcement system.

The research contributes to existing literature by integrating behavioral psychology, computational mental health models, and lifestyle triad frameworks into a unified analytical structure. It extends prior findings on student lifestyle interdependencies (Renu Agarwal & BoopathyUsharani, 2026) by introducing a structured linkage-based profiling approach capable of identifying behavioral clustering patterns.

Future research should focus on empirical validation using longitudinal datasets and AI-driven monitoring systems to quantify behavioral transitions over time. Additionally, intervention strategies should prioritize integrated health models combining psychological counseling, dietary regulation, and physical activity promotion to effectively disrupt negative behavioral cycles.

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