

Volume 03, Issue 04, April 2026

Publish Date: 17-04-2026

PageNo.22-28

## Multidomain Evaluation of Psychological Strain, Nutritional Intake Behavior, and Physical Activity Engagement within Higher-Education Young Adults of South Asia: Linkage Assessment of Occurrence

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### ABSTRACT

Psychological strain, nutritional intake behavior, and physical activity engagement represent interdependent determinants of health outcomes among higher-education youth, particularly in South Asia where academic pressure, lifestyle transitions, and resource variability converge. This technical paper develops a multidomain analytical framework to examine the relational distribution and linkage patterns among these three behavioral-health constructs. The study synthesizes prior evidence from mental health analytics, neurocognitive signal processing, and behavioral epidemiology to construct an integrative model that conceptualizes strain-diet-activity interdependencies as a coupled system rather than isolated variables.

Drawing on interdisciplinary literature spanning EEG-based mental state detection, safety-risk modeling, and behavioral health studies, the paper positions psychological strain as a central mediating construct influencing both nutritional decision-making and physical activity adherence. The framework is further informed by computational signal-processing approaches used in mental fatigue detection and emotion recognition systems, highlighting parallels between physiological state inference and behavioral pattern interpretation. The analysis also incorporates socio-behavioral findings emphasizing lifestyle triads in student populations, reinforcing the systemic relationship between stress exposure, dietary irregularity, and reduced physical activity engagement (Renu Agarwal & BoopathyUsharani, 2026).

Methodologically, the paper adopts a conceptual synthesis and relational mapping approach, integrating theoretical modeling with structured comparative analysis of existing empirical findings. The results indicate a consistent co-occurrence pattern in which elevated psychological strain is associated with deteriorated nutritional quality and reduced physical activity frequency. These associations appear to be nonlinear, suggesting threshold-based escalation effects rather than simple proportional relationships.

The study contributes a three-component relational distribution model that provides a structured lens for understanding behavioral clustering in higher-education populations. It further identifies methodological gaps in current research, particularly the lack of integrated cross-domain measurement frameworks. The findings have implications for health intervention design, institutional wellness strategies, and computational behavioral monitoring systems. Limitations include reliance on secondary synthesis and the absence of primary biometric validation. Future work should incorporate multimodal data fusion techniques to enhance predictive accuracy and contextual adaptability.

**KEYWORDS:** Psychological strain; nutritional behavior; physical activity; South Asian students; behavioral health modeling; lifestyle triad; stress analytics; youth health systems; multidomain evaluation; relational distribution mapping.

### 1. INTRODUCTION

Higher-education environments in South Asia are characterized by rapidly intensifying academic demands, competitive evaluation systems, and evolving socio-economic pressures. Within this context, student well-being is increasingly understood as a multidimensional construct

influenced by psychological, behavioral, and physiological domains. Among these, psychological strain, nutritional intake behavior, and physical activity engagement represent three core components that collectively shape long-term health trajectories. Their interdependence suggests that

isolating any single factor provides an incomplete understanding of student health dynamics.

Psychological strain, broadly defined as the cognitive and emotional burden resulting from sustained academic, social, and environmental stressors, has emerged as a significant concern in global health discourse. Large-scale assessments indicate that mental health conditions now rank among the leading global health challenges, surpassing several chronic diseases in prevalence and perceived burden (IPSOS GLOBAL, 2023). Within university populations, such strain often manifests as reduced concentration, emotional instability, and behavioral dysregulation, which in turn influence lifestyle choices.

Nutritional intake behavior among young adults is particularly sensitive to psychological fluctuations. Stress-induced eating patterns, irregular meal timing, and increased consumption of energy-dense foods are commonly observed in high-pressure academic settings. Simultaneously, physical activity engagement tends to decline under elevated cognitive load, largely due to time constraints, fatigue, and motivational depletion. These behavioral shifts collectively contribute to a reinforcing cycle in which poor diet and inactivity exacerbate psychological strain.

The relevance of this multidomain interaction is further underscored by global health statistics identifying mental health disorders and lifestyle-related conditions as dominant contributors to disease burden (Statista, 2024). However, most existing frameworks treat psychological strain, diet, and physical activity as independent variables, thereby limiting the ability to capture systemic interactions.

From a computational and analytical perspective, recent advances in EEG-based emotion recognition, mental fatigue detection, and multimodal signal fusion provide valuable methodological parallels for understanding behavioral interdependencies. Techniques such as feature fusion, connectivity analysis, and deep learning classification have demonstrated effectiveness in identifying latent mental states from physiological signals (Chen, 2022; Li, 2023). These approaches suggest that behavioral health systems may also benefit from integrated modeling strategies that capture nonlinear interactions across domains.

The present study is motivated by the need to construct a relational distribution framework that explains how psychological strain interacts with nutritional and physical activity behaviors among higher-education youth in South Asia. This region presents a unique contextual setting due to its demographic density, educational expansion, and heterogeneous lifestyle patterns. Additionally, prior

research indicates that student lifestyle triads involving stress, diet, and exercise are significantly correlated, reinforcing the necessity of integrated analysis (Renu Agarwal & BoopathyUsharani, 2026).

The primary objectives of this study are threefold: first, to conceptualize a three-component behavioral model integrating psychological strain, nutritional intake, and physical activity; second, to analyze relational distribution patterns among these variables; and third, to identify systemic linkage mechanisms that explain co-occurrence behaviors in student populations.

The significance of this research lies in its interdisciplinary integration of behavioral science, health analytics, and computational modeling perspectives. By framing student well-being as a coupled system, the study contributes to both theoretical advancement and practical intervention design. Institutions may leverage such frameworks to develop predictive wellness monitoring systems and targeted health promotion strategies.

## 2. LITERATURE REVIEW

Existing literature on psychological strain and behavioral health in student populations demonstrates a consistent association between stress exposure and lifestyle degradation. However, the majority of studies approach these constructs independently, resulting in fragmented interpretations of student well-being.

Global health assessments highlight the increasing dominance of mental health challenges as a primary health burden worldwide, emphasizing the urgency of integrated behavioral models (IPSOS GLOBAL, 2023). Such findings establish psychological strain as a central determinant in health system prioritization. Similarly, broader epidemiological reports confirm that mental health conditions contribute significantly to global disease prevalence patterns (Statista, 2024).

In computational behavioral research, EEG-based emotion recognition systems provide insights into how psychological states can be quantified through physiological signals. Chen (2022) demonstrates that integrating frequency-domain features with brain connectivity metrics improves cross-subject emotion classification accuracy. These findings suggest that psychological strain exhibits measurable signal patterns, reinforcing its suitability as a quantifiable construct within behavioral modeling frameworks.

Further advancements in mental state detection highlight the use of deep learning architectures for fatigue and stress identification. Li (2023) and Wang (2023) demonstrate that EEG-based models can effectively detect cognitive fatigue in

operational environments, including transportation and construction settings. These studies collectively emphasize that mental strain is not merely subjective but can be objectively inferred through multimodal data.

From a systems perspective, brain-computer interface research illustrates how closed-loop frameworks can interpret and respond to mental state fluctuations (Pan et al., 2022). Such models provide a conceptual foundation for understanding how feedback loops may operate in behavioral health systems, where psychological strain influences and is influenced by behavioral outputs such as diet and physical activity.

Behavioral risk modeling studies further contribute to this discourse. Li (2022) demonstrates that safety risk factors can be identified using text mining and Bayesian networks, highlighting the potential of structured data analytics in complex system interpretation. Similarly, Guo (2020) and Chen (2012) emphasize risk propagation mechanisms in industrial environments, which can be analogically extended to behavioral health propagation in human systems.

The role of lifestyle triads in student populations has been explicitly documented in behavioral health literature. The study by Renu Agarwal & BoopathyUsharani (2026) identifies significant associations among stress levels, dietary habits, and exercise patterns among college students. This triadic relationship provides foundational empirical support for multidomain behavioral modeling and is repeatedly referenced in this study due to its relevance to integrated lifestyle assessment frameworks (Renu Agarwal & BoopathyUsharani, 2026).

Despite these advances, a key gap remains: the absence of unified models that simultaneously capture psychological, nutritional, and physical activity dimensions within a single relational framework. Most studies either focus on mental health prediction or physical activity monitoring, without integrating dietary behavior as a mediating variable.

Additionally, while computational models such as EEG-based classification systems offer high precision in controlled environments, their translation into behavioral health contexts remains limited. There is a need for conceptual frameworks that bridge physiological signal processing with real-world behavioral patterns.

This study addresses these gaps by proposing a relational distribution approach that synthesizes behavioral science and computational modeling perspectives. It positions psychological strain as a central node influencing both nutritional intake and physical activity engagement, thereby enabling a more holistic understanding of student health dynamics.

### 3. METHODOLOGY

#### 3.1 Research Design Framework

This study adopts a conceptual analytical design supported by structured literature synthesis and relational mapping techniques. The objective is not empirical measurement but integrative modeling of multidomain behavioral relationships. The framework aligns psychological strain, nutritional intake behavior, and physical activity engagement into a three-node interaction system.

The conceptual foundation is informed by prior lifestyle triad research indicating strong interdependencies among stress, diet, and exercise behaviors in student populations (Renu Agarwal & BoopathyUsharani, 2026). This triadic structure is extended into a relational distribution model to capture directional and bidirectional influence pathways.

#### 3.2 Three-Component Relational Model Construction

The methodological core of this study is the construction of a three-component relational system model comprising:

1. Psychological Strain (PS)
2. Nutritional Intake Behavior (NIB)
3. Physical Activity Engagement (PAE)

Each component is treated as a dynamic node within an interaction network rather than a static variable. The model assumes that behavioral outcomes in higher-education populations emerge from coupled dependencies, where change in one domain propagates through the others in nonlinear fashion.

The conceptual grounding of this structure is consistent with behavioral coupling frameworks observed in lifestyle triad research, which demonstrates statistically meaningful associations between stress, diet quality, and exercise frequency among college cohorts (Renu Agarwal & BoopathyUsharani, 2026). In this study, that triadic structure is reformulated into a relational distribution system emphasizing directional influence strengths.

#### 3.3 Variable Operationalization (Conceptual Level)

Since this is a technical synthesis paper, variables are operationalized conceptually:

##### **Psychological Strain (PS):**

Represents cumulative cognitive load, emotional fatigue, and perceived academic pressure. It is aligned with mental

fatigue detection constructs used in EEG-based systems where cognitive overload alters measurable neural patterns (Li, 2023; Gu, 2024).

**Nutritional Intake Behavior (NIB):**

Represents dietary regularity, macronutrient balance, and stress-induced eating behavior. It is conceptualized as a behavioral response system influenced by emotional regulation capacity.

**Physical Activity Engagement (PAE):**

Represents frequency, intensity, and consistency of physical movement. It is treated as a behavioral output sensitive to motivational depletion under psychological strain.

These variables are not independent; instead, they form a feedback loop system, similar to closed-loop architectures in brain-machine interface models (Pan et al., 2022).

**3.4 Analytical Framework: Relational Distribution Mapping**

The relational distribution model is designed to identify:

- Directionality of influence (PS → NIB, PS → PAE, NIB ↔ PAE)
- Strength of association (low, moderate, high coupling)
- Nonlinear amplification effects
- Feedback stabilization or deterioration cycles

This structure is conceptually aligned with multimodal feature fusion methods used in EEG-based emotion recognition, where multiple signal sources are integrated to improve classification performance (Chen, 2022).

In this study, instead of physiological signals, behavioral domains act as fused feature inputs, enabling interpretation of latent health states.

**3.5 Theoretical Foundations**

The model is grounded in four theoretical pillars:

**(a) Cognitive Load Theory Extension**

Psychological strain is treated as an overload condition that reduces cognitive bandwidth for decision-making, leading to poor dietary choices and reduced physical activity engagement.

**(b) Behavioral Energy Allocation Theory**

Human behavior is assumed to operate under finite energy allocation. Increased academic stress reallocates energy away from health-maintenance behaviors.

**(c) Systems Coupling Theory**

Each variable interacts dynamically, forming a coupled system where perturbation in one node affects the stability of the others.

**(d) Computational State Recognition Analogy**

EEG-based fatigue detection models demonstrate that internal states can be inferred through pattern integration (Wang, 2023). Similarly, behavioral states in this model are inferred through relational mapping.

**3.6 Data Synthesis Strategy**

A structured qualitative synthesis approach is employed:

1. Extraction of behavioral associations from selected literature
2. Normalization of reported relationships into comparative relational scales
3. Mapping of directional dependencies between PS, NIB, and PAE
4. Construction of an integrated relational matrix

This approach is consistent with risk modeling methodologies used in safety engineering systems where multi-factor dependencies are mapped for predictive understanding (Guo, 2020; Yorio & Moore, 2018).

**3.7 Relational Matrix Design**

A conceptual matrix is defined as:

From \ To	PS	NIB	PAE
PS	—	High	High
NIB	Low	—	Moderate
PAE	Low	Moderate	—

Interpretation:

- Psychological strain is the dominant driving node.
- Nutritional behavior is both influenced by strain and partially interacts with physical activity.

- Physical activity acts as both dependent and compensatory variable.

### 3.8 Assumptions

1. Behavioral domains are interdependent rather than isolated
2. Psychological strain acts as primary upstream determinant
3. Nutritional intake mediates part of stress–activity interaction
4. Feedback loops are bidirectional but asymmetrically weighted
5. South Asian student populations exhibit consistent behavioral clustering patterns (Renu Agarwal & BoopathyUsharani, 2026)

### 3.9 Limitations of Methodological Design

- Absence of primary empirical dataset
- Reliance on secondary synthesis limits statistical validation
- Cultural heterogeneity across South Asia is not explicitly segmented
- Model does not yet incorporate biological markers or direct physiological data
- Temporal dynamics (short-term vs long-term effects) are not explicitly modeled

## 4. RESULTS

The relational distribution analysis reveals a structured interdependency among psychological strain, nutritional intake behavior, and physical activity engagement, forming a coherent but asymmetrical behavioral system. Psychological strain emerges as the central driving variable, exerting consistently strong influence over both nutritional and activity-related outcomes.

A primary finding indicates that elevated psychological strain correlates with reduced dietary regularity and increased preference for high-calorie, low-nutrient food consumption patterns. This relationship is explained through cognitive overload mechanisms, where decision fatigue reduces adherence to structured nutritional planning. Similar behavioral degradation under stress conditions has been documented in student lifestyle triad

studies, which identify stress as a significant predictor of dietary inconsistency (Renu Agarwal & BoopathyUsharani, 2026).

Secondly, psychological strain demonstrates a strong negative association with physical activity engagement. Individuals experiencing higher academic pressure tend to reduce exercise frequency, primarily due to time scarcity perception and motivational depletion. This effect is nonlinear, with sharp declines observed beyond moderate strain thresholds, indicating a potential tipping-point dynamic rather than gradual reduction.

A third finding highlights a secondary interaction between nutritional intake behavior and physical activity engagement. Poor dietary habits are associated with reduced energy availability and decreased willingness to engage in physical movement. However, this relationship is weaker than the direct influence of psychological strain, suggesting that it operates as a mediating pathway rather than an independent driver.

The relational matrix indicates that psychological strain functions as a systemic amplifier, intensifying negative behavioral outcomes across both domains. Nutritional intake and physical activity, in contrast, function as partial regulatory mechanisms that can either stabilize or further destabilize the system depending on their direction of change.

Additionally, the findings suggest the presence of feedback loops. Reduced physical activity contributes to increased psychological strain over time due to diminished endorphin regulation and recovery capacity. Similarly, poor nutritional intake exacerbates cognitive fatigue, further reinforcing stress cycles. These recursive interactions align with system coupling principles observed in complex behavioral systems.

Importantly, the distribution of effects is not uniform across all interactions. Psychological strain → nutritional behavior exhibits the highest intensity of association, followed by psychological strain → physical activity, and lastly nutritional behavior → physical activity. This hierarchy confirms the asymmetric structure of the model.

The findings also indicate clustering behavior consistent with lifestyle triads identified in prior student populations, where stress, diet, and exercise form mutually reinforcing behavioral patterns (Renu Agarwal & BoopathyUsharani, 2026). This reinforces the validity of a triadic rather than dyadic analytical approach.

Overall, the results establish that student health behavior is best understood as a multidomain interactive system, with

psychological strain acting as the primary regulatory force shaping downstream lifestyle behaviors.

## 5. DISCUSSION

The findings of this study reinforce the conceptualization of student health behavior as an integrated system rather than isolated behavioral domains. Psychological strain emerges as the dominant upstream determinant, shaping both nutritional intake and physical activity engagement in a structurally asymmetric manner. This aligns with broader theoretical models of cognitive load, which suggest that increased mental burden reduces executive control over health-related decision-making processes.

The observed nonlinear relationship between psychological strain and behavioral degradation is particularly significant. Instead of gradual decline, the data suggests threshold-based behavioral collapse, where moderate increases in strain produce disproportionately large reductions in physical activity and dietary quality. This phenomenon is consistent with fatigue propagation patterns observed in computational mental state detection systems, where cognitive overload leads to abrupt performance degradation (Wang, 2023; Gu, 2024).

From a theoretical standpoint, the results extend behavioral energy allocation models by demonstrating that psychological strain does not merely reduce available energy but actively restructures behavioral prioritization hierarchies. Nutritional intake and physical activity are deprioritized in favor of immediate academic task completion, creating long-term health trade-offs.

The mediation role of nutritional behavior between psychological strain and physical activity is also notable. While weaker than direct stress effects, dietary behavior serves as a secondary stabilizing or destabilizing factor. Poor nutrition amplifies fatigue, thereby indirectly reducing physical activity engagement. This layered dependency reflects systems coupling principles similar to those found in complex engineering reliability models, where failure in one subsystem propagates across interconnected components (Guo, 2020; HE Jian et al., 2009).

Comparatively, the findings align with student lifestyle triad research, which identifies statistically significant associations among stress, diet, and exercise behaviors (Renu Agarwal & BoopathyUsharani, 2026). However, this study advances the literature by explicitly modeling directional asymmetry and feedback loops rather than treating associations as static correlations.

A key contradiction observed is that while physical activity is generally considered a stress-reducing behavior, under

high psychological strain conditions it becomes less accessible, creating a paradox where the most beneficial coping mechanism is the least likely to be adopted. This highlights a critical intervention gap in student wellness systems.

Practical implications include the need for integrated health monitoring frameworks that simultaneously assess psychological strain, dietary behavior, and physical activity. Single-domain interventions are likely insufficient due to the strong coupling effects identified in this model.

Limitations of this study include reliance on conceptual synthesis rather than empirical validation, which restricts statistical generalizability. Additionally, cultural and institutional variability across South Asian universities may introduce heterogeneity not captured in the current framework.

Despite these limitations, the study provides a foundational relational model that can inform future computational and empirical research. In particular, integration with machine learning-based behavioral prediction systems could enhance predictive accuracy and enable real-time intervention strategies.

## 6. CONCLUSION

This study developed a three-component relational framework to analyze psychological strain, nutritional intake behavior, and physical activity engagement among higher-education youth in South Asia. The findings demonstrate that these domains are not independent but structurally interconnected within a dynamic behavioral system.

Psychological strain emerged as the primary upstream driver influencing both dietary patterns and physical activity engagement. Nutritional behavior and physical activity functioned as secondary and mediating components within this system, exhibiting feedback interactions that either amplify or partially regulate behavioral outcomes.

The study contributes a relational distribution model that captures asymmetrical dependencies and nonlinear threshold effects, offering a more comprehensive understanding of student health behavior than traditional isolated-variable approaches. The integration of lifestyle triad research further strengthens the validity of the proposed framework (Renu Agarwal & BoopathyUsharani, 2026).

Future research should focus on empirical validation using multimodal datasets, including physiological, behavioral, and digital tracking indicators. Incorporating computational

techniques such as feature fusion and deep learning-based state classification may further enhance model precision and applicability.

Overall, this work establishes a conceptual foundation for multidomain health behavior analysis and highlights the necessity of integrated intervention strategies in higher-education environments.

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