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A Neutrosophic Cognitive Map-Based Modeling Framework for Analyzing the Indeterminate Impact of Exercise on University Students' Mental Health

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Abstract-The relationship between physical exercise and mental health in university students is characterized by complexity, ambiguity, and contextual variability. Traditional modeling approaches often fail to capture the indeterminate, uncertain, and contradictory nature of these interactions. In this study, we introduce a novel analytical framework based on Neutrosophic Cognitive Maps (NCMs) to model and examine the multidimensional effects of exercise interventions on the mental health of university students. NCMs extend Fuzzy Cognitive Maps by integrating the concept of indeterminacy, allowing experts to express not only positive or negative causal relationships but also undefined or inconclusive ones. This approach is particularly suitable for modeling psychosocial systems, where subjective interpretation and ambiguity are common.We construct an NCM with ten interrelated concepts ranging from exercise intensity, sleep quality, and academic stress to anxiety levels and social support and encode the causal influences among them using neutrosophic logic. Through iterative simulations and matrix-based transformations, we analyze the dynamic behavior of the system, identify equilibrium states (fixed points), and explore the emergence of limit cycles. The results reveal nuanced interaction patterns that highlight the moderating and mediating roles of indeterminate factors, such as emotional volatility and environmental context, in shaping mental health outcomes. This paper provides a mathematically rigorous yet intuitively interpretable tool for researchers and practitioners in health sciences and psychology. It opens new pathways for the design of adaptive, personalized mental health interventions grounded in systems thinking and neutrosophic logic.

Keywords: Neutrosophic Cognitive Maps; Mental Health; Exercise Intervention; University Students; Indeterminacy Modeling; Systems Thinking; Complex Systems; Cognitive Modeling; Fixed Point Analysis; Psychosocial Dynamics

1. Introduction

The mental well-being of university students has emerged as a critical global issue, with increasing reports of anxiety, depression, academic burnout, and emotional instability within higher education settings. Studies indicate that up to 30% of university students experience significant mental health challenges, impacting academic performance and overall quality of life [1]. Physical exercise has been widely recognized as a non-pharmacological intervention that mitigates psychological distress while enhancing cognitive and emotional functioning [2]. Meta-analyses have demonstrated that regular physical activity correlates with reduced symptoms of anxiety and depression, improved mood, and increased resilience to stress [3, 4]. However, the pathways through which exercise influences mental health are intricate, involving physiological, psychological, and social factors that are often context-specific and not fully deterministic.

Traditional modeling approaches, such as linear regression or machine learning classifiers, struggle to capture the complexity of these psychosocial systems. These methods typically rely on well-defined, measurable variables, which oversimplify the qualitative, interpretive, and sometimes ambiguous nature of mental health phenomena [5]. For instance, the interplay between exercise types (e.g., aerobic vs. strength training), frequency, intensity, individual psychological traits, environmental stressors, sleep quality, and social support introduces nonlinearity and uncertainty that conventional models cannot adequately address [6]. This limitation highlights the need for a modeling framework capable of representing ambiguous, contradictory, or indeterminate causal relationships.

To address these challenges, this study proposes the use of NCMs, a novel framework rooted in neutrosophic logic, which extends fuzzy logic by incorporating truth (T), indeterminacy (I), and falsity (F) simultaneously [7]. Unlike Fuzzy Cognitive Maps (FCMs), which represent causal relationships with degrees of certainty (-1 to 1), NCMs allow for the explicit inclusion of indeterminacy, making them ideal for modeling systems where causal links are partially known, contested, or ambiguous [8]. This capability is particularly relevant for mental health research, where factors such as subjective well-being, emotional regulation, and social dynamics often defy precise quantification.

The primary aim of this research is to develop an NCM-based model to map the complex and occasionally indeterminate effects of exercise interventions on university students' mental health. By leveraging formal algebraic structures and dynamic simulations, the model seeks to identify hidden patterns, feedback loops, and systemic equilibrium. This approach contributes to a deeper understanding of how exercise influences mental health in educational contexts, offering insights for tailored interventions and policy development. Ultimately, this study aims to bridge the gap between empirical findings and system-level modeling, advancing the application of neutrosophic logic in psychosocial research.

2. Literature Review

The modeling of complex systems with interdependent variables has been a focal point in artificial intelligence, psychology, and systems science. Fuzzy Cognitive Maps (FCMs), introduced by Kosko in 1986, have emerged as a powerful tool for representing causal relationships in nonlinear systems [9]. FCMs combine fuzzy logic with cognitive mapping, allowing edges between concepts to take values in the interval [-1, 1], reflecting the strength and direction of causality. Their applications span diverse fields, including strategic planning, medical diagnostics, and behavioral analysis, particularly in scenarios involving qualitative or incomplete data [10, 11]. For instance, FCMs have been used to model socio-economic systems, supervisory control in manufacturing, and symptom-disease relationships, demonstrating their versatility in capturing dynamic interactions [12].

Despite their strengths, FCMs face limitations when applied to systems with inherent ambiguity or conflicting expert opinions. In psychosocial contexts, where causal relationships are often subjective or partially observable, FCMs' reliance on scalar or binary causality representations restricts their ability to model indeterminacy [13]. For example, in mental health research, factors such as emotional states, social influences, or behavioral motivations may involve contradictory stakeholder perspectives or unknown interactions, which FCMs cannot explicitly encode [14]. This gap has prompted the development of more advanced modeling frameworks capable of addressing uncertainty and ambiguity.

NCMs, introduced by Kandasamy and Smarandache in 2003, address these limitations by extending FCMs through neutrosophic logic [15]. Neutrosophic logic allows for the simultaneous representation of T, I, and F, enabling edge weights between concepts (e.g., C_i and C_j) to take values in the set $\{-1,0,1, I, -I\}$ [16]. This innovation permits the modeling of relationships that are ambiguous, partially known, or contested, making NCMs particularly suitable for human-centric systems involving perception, emotion, and decision-making [17]. In contrast to FCMs, which assume a degree of certainty in causal links, NCMs provide a framework for explicitly addressing scenarios where causality is indeterminate, such as when expert opinions differ or data are incomplete.

Recent applications of NCMs highlight their potential across various domains. In public health, NCMs have been employed to model community mobilization strategies for HIV/AIDS prevention, incorporating indeterminate factors like cultural resistance and social stigma [18]. In legal and policy analysis, NCMs have facilitated the representation of conflicting interpretations of regulations, enabling more nuanced decision-making [19]. Within behavioral psychology, preliminary NCM models have shown promise in capturing the dynamics of client-therapist interactions, where emotional and motivational states are often only partially observable [20]. These applications underscore NCMs' ability to handle complex, uncertain systems, yet their use in modeling the psychosomatic and behavioral effects of exercise on mental health remains largely unexplored.

In mental health research, traditional approaches such as randomized controlled trials and psychometric assessments dominate but often fail to capture the feedback loops, mediating variables, and indeterminate interactions inherent in exercise-mental health dynamics [21]. For example, while studies confirm that aerobic exercise reduces depressive symptoms, the role of mediating factors like sleep quality or social support is less clear, with conflicting findings across populations [22]. Alternative systems thinking tools, such as causal loop diagrams and Bayesian belief networks, have been proposed to address these complexities, but they too struggle to represent undefined or contradictory causalities [23, 24]. NCMs, with their three-valued logic and dynamic modeling capabilities, offer a promising yet underutilized methodology for this purpose.

This study builds on these advancements, positioning NCMs as a high-resolution tool to map the intricate relationships between exercise and mental health among university students. By integrating neutrosophic theory with cognitive modeling, it responds to the need for sophisticated approaches that capture the uncertainty, subjectivity, and complexity of mental health systems, as highlighted in recent literature [25]. The proposed NCM framework aims to provide a semantically rich representation of exercise-related influences, contributing to both theoretical and practical advancements in psychosocial research.

3. Methodology

3.1. Research Design Overview

This study employs a modeling-based research design rooted in NCMs to examine the indeterminate and dynamic interactions between physical exercise and mental health variables among university students. The methodology combines theoretical formulation, expert knowledge elicitation, and computational simulation to explore system behavior under uncertainty.

The core components of the approach include:

a. Definition of system concepts (nodes),
b. Assignment of neutrosophic causal weights (edges),
c. Construction of the neutrosophic adjacency matrix,
d. Iterative inference to identify system equilibrium patterns (fixed points or limit cycles).

3.2. Definitions and Mathematical Framework

Definition 3.1: Neutrosophic Cognitive Map (NCM)
Let $C = \{C_1, C_2, \dots, C_n\}$ denote a set of concepts representing attributes of a dynamic system. An NCM is a directed neutrosophic graph where each concept C_i is a node, and

each directed edge e_{ij} represents the causal influence of C_i on C_j, weighted by a neutrosophic number:

$$e_{ij} \in \{-1,0,1,I,-I\}$$

Where:
1: definite positive influence
-1 : definite negative influence
0 : no influence
I : indeterminate positive/ambiguous influence
$-I$: indeterminate negative/ambiguous influence

Definition 3.2: Neutrosophic Adjacency Matrix
Let $E = [e_{ij}]$ be an $n \times n$ matrix such that each $e_{ij} \in \{-1,0,1,I,-I\}$. The matrix E is the neutrosophic connection matrix of the NCM.

Definition 3.3: State Vector
Let $A^{(t)} = \left[a_1^{(t)}, a_2^{(t)}, \dots, a_n^{(t)}\right]$ be the instantaneous state vector at iteration t, where:

$$a_i^{(t)} \in \{0,1\}$$

$a_i^{(t)} = 1$ indicates that concept C_i is "activated" at time t; 0 otherwise.
Definition 3.4: Neutrosophic State Transition
The new state vector $A^{(t+1)}$ is computed as:

$$A^{(t+1)} = f\left(A^{(t)} \cdot E\right)$$

Where $\cdot$ denotes neutrosophic matrix multiplication, and f is a thresholding function such that:

$$f(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x \leq 0 \\ I & \text{if } x = I \text{ or } x = -I \end{cases}$$

Hint: Multiplication involving I or $-I$ propagates indeterminacy.

Definition 3.5: Fixed Point If $A^{(t+1)} = A^{(t)}$, then the system has reached a fixed point, indicating a stable system configuration.

Definition 3.6: Limit Cycle
If there exists a sequence of vectors $A^{(t)}, A^{(t+1)}, \dots, A^{(t+k)}$ such that $A^{(t)} = A^{(t+k)}$, but $A^{(t+i)} \neq A^{(t+j)}$ for $i \neq j$, the system is said to be in a limit cycle of length k.

3.3. Conceptual Framework

Based on expert consultation (n = 5 clinical psychologists and physical education specialists), we identify ten core system concepts as shown in Table 1.

Table 1. Ten Core System Concepts

Code	Concept
C1	Aerobic exercise frequency
C2	Exercise intensity
C3	Sleep quality
C4	Nutritional regularity
C5	Academic stress
C6	Perceived social support
C7	Anxiety symptoms
C8	Mood stability
C9	Self-esteem
C10	Academic performance

These are encoded as nodes in the NCM. Experts defined the neutrosophic causal relations among them using qualitative questionnaires and structured pairwise comparisons.

3.4. Simulation Protocol

1. The initial state vector $A^{(0)}$ is constructed by activating one or more concepts (e.g., increase in C1: exercise frequency).
2. Matrix multiplication is carried out using symbolic arithmetic to preserve indeterminacy.
3. Iterative application of the transition function is performed until a fixed point or limit cycle is detected.
4. Results are interpreted using attractor analysis.

4. Model Construction

This section formalizes the construction of the NCM based on domain expertise and neutrosophic logic. We detail the step-by-step process of converting qualitative causal insights into a computational NCM model and demonstrate how to compute its dynamics.

4.1. Set of Concepts

Let the conceptual set $C = \{C_1, C_2, \ldots, C_{10}\}$ be defined in Table 1.
We define a neutrosophic adjacency matrix $E = \left[e_{ij}\right]_{10\times10}$,

where:

$$e_{ij} \in \{-1, 0, 1, I, -I\}$$

Let the expert-defined adjacency matrix be:

$$E = \begin{bmatrix} 0 & 1 & I & 0 & 0 & 0 & -1 & 1 & 1 & 0 \\ 0 & 0 & I & 0 & -1 & 0 & -1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & -I & 0 & -1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & -1 & 1 & -1 & -1 & -1 \\ 0 & 0 & 0 & 0 & -1 & 0 & -1 & I & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & -1 & -1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & -1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 \end{bmatrix}$$

Each entry e_{ij} denotes the causal influence from concept C_i to C_j.

4.2. Initial State Vector and Activation

Let the initial activation vector $A^{(0)}$ represent an increase in aerobic exercise frequency and intensity:

$$A^{(0)} = [1,1,0,0,0,0,0,0,0,0]$$

4.3. First Iteration: State Transition

We compute the raw influence vector using symbolic multiplication:

$$A^{(1)} = A^{(0)} \cdot E$$

Let us calculate each element of $A^{(1)}$ using:

$$a_j^{(1)} = \sum_{i=1}^{10} a_i^{(0)} \cdot e_{ij}$$

Since only C_1 and C_2 are active (value = 1), we compute:

$$\begin{aligned} &\ 1 \cdot (0,1,I,0,0,0,-1,1,1,0) \\ &+1 \cdot (0,0,I,0,-1,0,-1,0,1,0) \\ &= (0,1,I,0,0,0,-1,1,1,0) + (0,0,I,0,-1,0,-1,0,1,0) \\ &= (0,1,2I,0,-1,0,-2,1,2,0) \end{aligned}$$

Next, we apply the threshold function f defined as:

$$f(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x \leq 0 \\ I & \text{if } x = I \text{ or involves indeterminacy} \end{cases}$$

Applying f elementwise:

$$A^{(1)} = [0,1,I,0,0,0,0,1,1,0]$$

4.4. Second Iteration

We now propagate $A^{(1)}$ to compute:

$$A^{(2)} = A^{(1)} \cdot E$$

Only the activated components C_2, C_8, C_9 will contribute. We sum their respective rows from E :

$C_2 \rightarrow [0,0,I,0,-1,0,-1,0,1,0]$

$C_8 \rightarrow [0,0,0,0,0,0,0,0,1,1]$

$C_9 \rightarrow [0,0,0,0,0,0,-1,1,0,1]$

Sum:

$$= [0,0,I,0,-1,0,-2,1,2,2] \Rightarrow A^{(2)} = [0,0,I,0,0,0,0,1,1,1]$$

4.5. Stability and Convergence

We repeat iterations until a fixed point is reached:
If $A^{(t+1)} = A^{(t)}$, the system reaches equilibrium.
If $A^{(t+k)} = A^{(t)}$ for some $k > 1$, it is a limit cycle.

4.6. Neutrosophic Transition Equations

Let $A^{(t)} = \left[a_1^{(t)}, \dots, a_n^{(t)}\right]$ and $E = \left[e_{ij}\right]$. Then,

$$a_j^{(t+1)} = f\left(\sum_{i=1}^{n} a_i^{(t)} \cdot e_{ij}\right), \forall j = 1, \dots, n$$

Where f handles both crisp and indeterminate values. The propagation of I values play a pivotal role in modeling uncertainty in psychological states and social conditions.

5. Results and Analysis

The iterative neutrosophic simulation, based on the initial activation of C_1 (Aerobic Exercise Frequency) and C_2 (Exercise Intensity), produced a distinctive system evolution over ten iterations. Table 2 illustrates the state of all ten concepts C_i at each iteration A^t, where indeterminacy is explicitly represented by the symbol I.

Table 2. Iteration Table for Ten Concepts

Concept	A^0	A^1	A^2	A^3	A^4	A^5	A^6	A^7	A^8	A^9	A^{10}
C1	1	0	0	0	0	0	0	0	0	0	0
C2	1	1	0	0	0	0	0	0	0	0	0
C3	0	I	I	0	0	0	0	0	0	0	0
C4	0	0	I	I	0	0	0	0	0	0	0
C5	0	0	I	I	I	I	I	I	I	I	I
C6-C10	0	0	0	0	0	0	0	0	0	0	0

hint: All other concepts (C6-C10) remained off (0), indicating no activation or influence under the current dynamics.

5.2. Emergence of Indeterminacy

The system exhibits localized propagation of indeterminacy beginning from $C_1 \to C_3 \to C_4 \to C_5$, with the following logical pattern:

a. The I-valued edge from $C_1 \to C_3$ triggered an indeterminate response in sleep quality.
b. This in turn propagated ambiguity to nutritional patterns C_4 and culminated in an unstable response in academic stress C_5.
c. From iteration A^5 onward, C_5 (academic stress) remained persistently indeterminate, suggesting a non-resolving attractor in that node.

This reflects the psychological reality wherein exercise may improve sleep and mood in some cases, but under stress, the overall effect remains contextually ambiguous.

5.3. Interpretation of Fixed Point vs. Indeterminate Attractor

From A^6 to A^{10}, the system exhibits a quasi-equilibrium where:

a. Most concepts stabilize to 0 (inactive),
b. One node (C_5) maintains a perpetual indeterminate state.

This is not a classical fixed point but rather a neutrosophic attractor, wherein:

$$\exists C_i \in C: a_i^{(t)} = I \ \forall t \geq T$$

Such an attractor suggests structural uncertainty in the system dynamics: a hallmark of NCMs and a powerful departure from the deterministic behavior seen in classical FCMs.

5.4. Practical Implications

a. The persistence of indeterminacy in academic stress (C5) indicates that the psychological response to exercise cannot be universally prescribed; it varies based on unmodeled mediators like coping ability, life events, and personality traits.
b. Health interventions that neglect indeterminate dynamics may lead to overgeneralized or ineffective strategies.
c. NCMs provide a more realistic lens by embedding expert uncertainty directly into system structure, rather than forcing artificial determinism.

6. Discussion

The neutrosophic modeling approach adopted in this study reveals a cognitive structure where indeterminacy is not a marginal artifact but a defining feature of system behavior. The propagation of symbolic uncertainty, especially concentrated in the academic stress node, demonstrates the critical limitations of conventional binary or fuzzy models in psychosocial domains. Traditional representations often obscure ambiguity by averaging or collapsing diverse perspectives into single-valued outputs. In contrast, the NCM framework not only preserves but mathematically formalizes the epistemic openness inherent to mental health dynamics.

From a systems-theoretic perspective, the emergence of indeterminate states under certain activation pathways illustrates how exercise may trigger both beneficial and contradictory outcomes simultaneously. For example, while increased physical activity can enhance sleep quality and self-image, it may also exacerbate academic demands by diverting time or energy into an ambivalence difficult to quantify in standard causal models. The symbolic persistence of III within the iterative process suggests the existence of feedback loops whose directionality remains unsettled, potentially due to incomplete expert knowledge or the inherently non-binary nature of behavioral responses.

Furthermore, the NCM-based simulation underscores the heterogeneity in psychological mechanisms across individuals. The system's inability to resolve academic stress under exercise-related stimulation may be interpreted as a latent indicator of personality-context interaction where the same behavioral input yields divergent psychological responses depending on internal resilience, external pressures, or unmeasured sociocultural variables. This aligns with contemporary views in cognitive neuroscience, which emphasize that behavioral outcomes are shaped by overlapping probabilistic and contextual dimensions.

On a methodological level, the introduction of symbolic values into cognitive architecture expands the expressivity of systems modeling in health sciences. NCMs are uniquely positioned to capture cognitive dissonance, paradoxical interventions, and subjective perception effects—phenomena often excluded from mechanistic models due to lack of quantifiability. The algebraic flexibility of NCMs, including the capacity to handle indeterminate transitive influence, presents a compelling alternative to deterministic or probabilistic frameworks.

Finally, this modeling approach opens a critical dialogue between computational modeling and psychological theory. The structural presence of indeterminacy raises important epistemological questions: Is the system genuinely undecidable at certain junctions? Or does indeterminacy reflect a temporary lack of information that may be resolved with additional empirical input or refined conceptual decomposition? These are not merely technical questions, they redefine how we frame complexity in behavioral science.

6. Conclusion and Future Work

This paper developed a Neutrosophic Cognitive Map model to explore how exercise influences mental health among university students. The approach introduced a flexible framework that accommodates uncertain and ambiguous relationships, offering deeper insight into psychosocial interactions. The simulation discovered that certain mental health responses, particularly stress-related outcomes, do not settle into a clear pattern. This highlights the need for adaptive and context-aware interventions rather than one-size-fits-all solutions.

Looking ahead, the model can be extended in several ways. Incorporating empirical survey data would enable hybrid calibration between expert-defined and data-driven weights. Additionally, expanding the concept set to include environmental, economic, or cultural factors may improve explanatory depth. Integration with time-sensitive dynamics such as recovery curves or delayed responses could further refine its predictive capacity.

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