Bol. Soc. Paran. Mat.
©SPM – E-ISSN-2175-1188
SPM: www.spm.uem.br/bspm

(3s.) **v. 2025 (43) 3** : 1–9.
ISSN-0037-8712
doi:10.5269/bspm.78406

# Intelligent Fuzzy Distributed Computing Approach to Analyse the Social Media's Impact on Graduate Student's Mental Health

Anju Khandelwal

ABSTRACT: This study explores the application of fuzzy numbers in ranking Likert-scale responses, focusing on improving the accuracy and reliability of rankings in different research areas. By utilizing Cronbach's alpha, we assess the internal consistency and reliability of the Likert-scale data collected from graduate students. The research applies a novel fuzzy ranking method which is multi-criteria decision-making (MCDM) to transform subjective ordinal data into a more robust, measurable format, addressing the limitations of traditional ranking methods. Through this approach, the paper aims to provide a more nuanced and reliable ranking system for surveys and questionnaires, ultimately enhancing the interpretation of Likert-scale data in various fields such as marketing, psychology, and education. The results highlighted the potential of fuzzy logic in refining data analysis and the importance of reliability measures and Cronbach's alpha ensures data consistency. Also, resultant clustering effectively segments students based on patterns in their mental and physical health indicators.

**Background.** The rapid rise of social media has transformed the way university students interact, communicate, and view the world around them. While these platforms offer benefits such as increased connectivity, academic collaboration, and access to information, they are also associated with adverse psychological effects including anxiety, depression, low self-esteem, and disrupted sleep patterns. Traditional analytical models struggle to capture the complexity and ambiguity inherent in human emotions and behaviours influenced by social media use. Fuzzy logic, a mathematical approach that handles uncertainty and ambiguous data, presents a powerful alternative for studying such subjective experiences. Unlike binary logic, fuzzy logic allows for degrees of truth, making it particularly suitable for modelling human psychological responses. By applying fuzzy logic, researchers have been able to better study the subtle effects of social media exposure on university students — such as emotional well-being, perceived social pressure, and digital fatigue. This approach enables more realistic assessments and supports the development of targeted interventions. Integrating fuzzy logic into psychological research provides a novel, adaptive framework for insight into the mental health challenges facing students in the digital age.

Key Words: Fuzzy logic, psychological assessment, social media, mental health, measurement accuracy, education, Multi-Criteria Decision Making (MCDM).

## Contents



## 1. Introduction

In today's modern and digital age, social network plays a pretty big role in shaping the mental health of its users, impacting various aspects of their well-being. The psychological, physiological, and cognitive constructs of individuals are increasingly influenced by their online interactions, creating both positive

2010 *Mathematics Subject Classification:* 90B99, 90C70, 68T07.
Submitted August 14, 2025. Published October 16, 2025



Typeset by $\mathcal{B}^{S}\mathcal{P}_{\mathcal{M}}$ style.
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and negative outcomes. Research shows that excessive social networking use can result to psychological issues such as anxiety, depression, and stress, particularly among adolescents and young adults [1, 7]. These psychological impacts are further exacerbated by the physiological effects of prolonged screen time, which can contribute to poor sleep quality and increased levels of physical stress [3, 14]. Moreover, cognitive functions, such as attention and memory, are increasingly being influenced by the constant flow of information on social platforms, leading to issues with focus and mental fatigue [6].

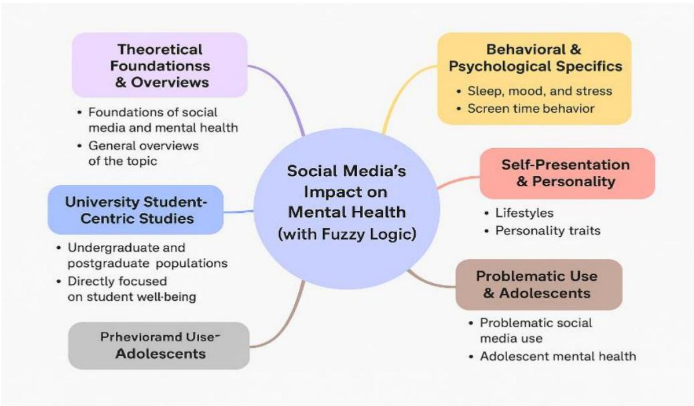


Figure 1: Social Media Impact Factors

Social network and mental health have a complicated and intricate relationship [Fig. 1], as it involves an intricate interplay between psychological, physiological, and cognitive aspects. Psychological well-being is often undermined by the pressure of self-presentation and social comparison on platforms like Instagram and Facebook, which can heighten feelings of inadequacy and low self-esteem [2, 11]. Physiologically, the impact of social media use is evidenced by changes in sleep patterns, with higher screen time associated with poorer sleep quality and increased risk for sleep disturbances, which, in turn, affect overall health [4, 9]. Cognitively, the regular exposure to information overload on social network has been linked to reduced attention span, multitasking issues, and difficulties in deep concentration [13, 9].

**Health Factors**

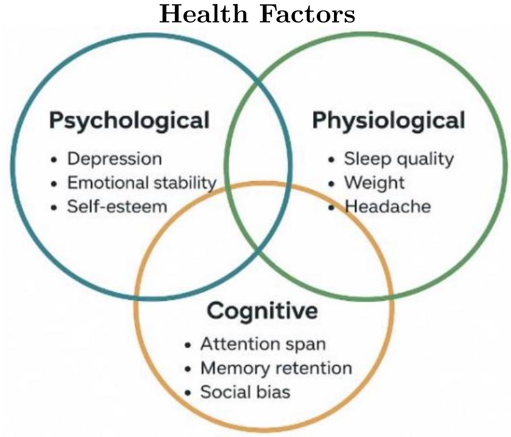


Figure 2: Health Impact Factors

By examining these three constructs-psychological, physiological, and cognitive-and consulting [Fig. 2] the body of existing literature, this study aims to investigate the complex linkages between social network use and mental wellbeing to gain a better understanding of the multifaceted effects of digital engagement on wellbeing. By concentrating [23] on these constructs, the study seeks to present a thorough examination of the way in which digital platforms affect all facets of human functioning, providing insightful information about how to minimize their detrimental effects while optimizing their potential for beneficial ones.

## 2. Literature Review

Social media has become an essential tool for everyday life, with individuals needing real-time information and communication. While it has greatly improved accessibility to information and facilitated connections across the globe, it has also expressed worries regarding its effects on psychological and physiological health.

Social network has significantly influenced the mental health of individuals, particularly among students, where research has explored both the negative and positive impacts of its use. Studies suggest that prolonged Use of social network can induce mental wellbeing conditions like sadness, anxiety, and low self-esteem, especially when usage surpasses a certain threshold [1, 13]. However, other research highlights the potential benefits of social media, including enhanced social support, networking opportunities, and maintaining connections with peers [9, 24].

The sophisticated technique of fuzzy logic, which deals with ambiguous and unclear data, has shown to be a useful instrument in investigating the complex connection between social networking use and mental health. In order to captures the complexity of how social networking affects users' mental health, traditional study methodologies frequently rely on precise, binary categorization. Fuzzy logic, on the other hand, accommodates various degrees of effects, allowing for a more flexible and detailed analysis of this relationship [17, 18]. This approach is particularly useful for modelling subjective experiences, such as the varying emotional responses users might have to social media.

Applying fuzzy logic to social media research allows for more precise categorization of usage patterns and their effects on mental health. By considering the intensity and type of social media engagement, such as passive scrolling versus active interaction, fuzzy models provide deeper insights into how these behaviours influence psychological well-being. This more tailored approach offers a clearer understanding of when social media can either support or harm users' mental health, providing a more nuanced and personalized assessment of its effects [19,20]. A study conducted in Bangalore, Karnataka, found a significant correlation between the time spent on social media and mental well-being. It showed that individuals with lower mental well-being tended to spend more time on social media. This study, involving 311 students, used the Pearson chi-square test through SPSS software to analyse the data [13, 16].

Similarly, a study in Japan during the COVID-19 pandemic used logistic regression and other statistical analyses to examine the impact of screen time, body weight, and other variables on 959 children. The study revealed that over 50% of the children exhibited behavioural issues, highlighting the negative effect of excessive screen time on both psychological and physical well-being [14]. In Wuhan, China, research explored both the sides of the coin i.e., positive and negative aspect of social media on various aspects of life, including relationships, work, and self-esteem [10, 15]. The study also examined the benefits of networking, increased social interaction, and information sharing among peers. To mitigate the negative effects, the study recommended strategies like filtering negative feedback, seeking support, and setting usage limits [9].

A factor analysis study identified three key factors-"Subjective Overuse," "Social Obligation," and "Social Concern"-which were positively associated with mental health issues. This study also used multiple linear regression analysis, adjusted for gender, to see the relationship between social network usage and factors like anxiety, depression, and overall well-being [5].

In Bergen, Norway, a study involving 2023 senior high school students explored how selfpresentation on social media correlated with various personality traits and behaviours. The study found that self-presentation was particularly prevalent among women and was linked to higher extraversion, lower emotional stability, alcohol consumption, and tobacco use [6]. Fuzzy logic provides a more reliable and nuanced approach than traditional scoring methods, enhancing the accuracy and relevance of psychological assessments. Its integration with advanced technologies offers promising potential for more precise and inclusive future evaluations [21]. In another study [22] developed a fuzzy decision support system to assess pre-schoolers' mental health using the Preschool Pediatric Symptom Checklist. It achieved high accuracy and specificity by addressing data uncertainty. Despite promising results, limitations include data diversity, suggesting future work should involve real-time, dynamic data from wearable or mobile technologies.

## 3. Methodology

This study utilizes a descriptive methodology to analyse the impact of social media network on graduate students' mental health. The Hungarian method will be applied to match the preferences of respondents with specific social media-related factors.

Fuzzy Ranking is a technique used to rank alternatives when the evaluation criteria are uncertain, imprecise, or linguistically expressed. It is grounded in fuzzy set theory, which allows partial membership instead of a binary true/false classification. It helps decision-makers to Evaluate alternatives based on subjective and incomplete data, capture human thinking more naturally through linguistic variables and make better decisions in complex scenarios. There are different ranking methods for defuzzification like Centroid method (Centre of Gravity), Mean of Maximum (MoM), $\alpha$-cut method and Signed Distance Method. Here, a ranking method is used to evaluate the psychological, physiological, and cognitive aspects of health that is based on fuzzy distributed computing logic. This approach allows to get in-depth comprehension of how social network usage affects different dimensions of students' mental health. Here 258 responses are used for analysing the impact of social media network with psychological, physiological, and cognitive constructs of individuals.

### 3.1. Objective

The objective of the problem is to find the effective role of fuzzy distributed computing, clustering techniques and Hungarian Technique for assigning cluster for analysing psychological, physiological, and cognitive constructs of students. Here $k$-means clustering technique on respondents (students) is applied to find which cluster of students has most impact of mental construct i.e. psychological, physiological, and cognitive constructs. The structural model [Fig. 3] representing the objective of the problem.

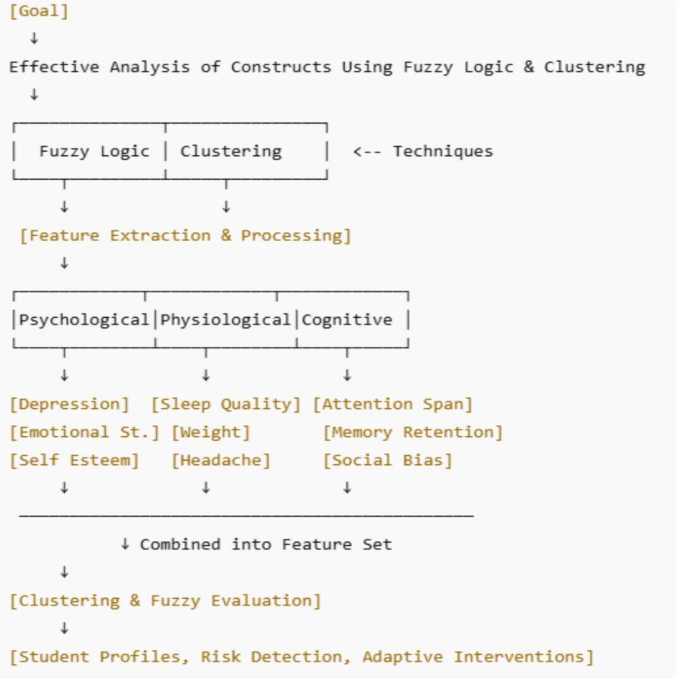


Figure 3: Structural Model for Analysing Effective role of Different Construct

### 3.2. Analysis

#### a. Cronbach Alpha Value

```
import pandas as pd
sheet_name = 'Sheet1'
df = pd.read_excel(r"F:\DT\research solution.xlsx", sheet_name=sheet_name)
# Number of items (columns/questions)
num_items = df.shape[1]
# Variance for each item
item_variance = df.var(axis=0, ddof=1)  # variances of each column/item
# Total variance across items for each respondent, then variance of
these sums total_score_variances = df.sum(axis=1).var(ddof=1)
# Calculate Cronbach's alpha
alpha = num_item / (num_item - 1) * (1 - item_variance.sum() /
total_score_variances)
# Output of result
print("Cronbach's alpha:", alpha)
Result:
Cronbach's alpha: 0.7354304973212205
```

**Interpretation:** With a Cronbach's alpha value of 0.735 , the data appear to have a reasonable level of internal consistency, meaning they consistently measure the same underlying construct. According to standards, an alpha value above 0.7 is generally considered acceptable [16].

#### b. Constructs

```
# Construct groups
constructs = {
 "Construct1": ["Q4. Do you have trouble sleeping?", "Do you have headaches?",
 "What is your Weight?"],
 "Construct2": ["How do you feel about your mood?", "How do you perceive your
 emotional stability?", "How would you rate your overall self-esteem?"],
 "Construct3": ["How would you describe your ability to maintain focus on
 tasks or activities?",
 "How would you rate your ability to remember information over time?",
 "How often do you feel that social bias affects your interactions with others?"]
}
def calculate_fuzzy_centroid(scores):
# Calculate the centroid of a fuzzy triangular number
lower = min(scores)  # Min score as lower
upper = max(scores)  # Max score as upper
center = np.mean(scores)  # Mean score as center
return (lower + center + upper) / 3  # Centroid formula for
triangular fuzzy numbers
# Calculate ranks for each construct
rankings = pd.DataFrame(index=df.index)
for construct_name, columns in constructs.items():
# Calculate centroid score for each row (individual) for the construct
rankings[construct_name] = df[columns].apply(calculate_fuzzy_centroid, axis=1)
# Rank individuals within each construct
for construct_name in constructs.keys():
rankings[f"{construct_name}_Rank"] =
rankings[construct_name].rank(method="min", ascending=False)
# Display the final ranks
```

```
print(rankings)
```

**Interpretation:** The developed code calculates fuzzy centroid scores for each individual based on the three constructs (psychological, physiological, and cognitive) defined by groups of questions. The centroid represents a fuzzy number derived from the minimum, mean, and maximum scores within given set of responses, which is commonly used in fuzzy logic to capture uncertainty in data. After calculating the centroids for each construct, individuals are ranked based on their scores, with the highest centroid score receiving the top rank.

### c. Clustering

```
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
import pandas as pd
# Assuming your DataFrame with ranks is 'rankings' with columns:
'Construct1_Rank', 'Construct2_Rank', 'Construct3_Rank'
# Step 1: Standardize the data
scaler = StandardScaler()
rankings_scaled = scaler.fit_transform(rankings[['Construct1_Rank',
'Construct2_Rank', 'Construct3_Rank']])
# Step 2: Applying K-Means Clustering
kmeans = KMeans(n_clusters=3, random_state=42)
rankings['cluster'] = kmeans.fit_predict(rankings_scaled)
# View clustered data
print(rankings[['Construct1_Rank', 'Construct2_Rank', 'Construct3_Rank'
'Cluster']])
```

**Interpretation:** This process helps in segmenting individuals into meaningful clusters based on their responses, which can be useful for identifying patterns and differentiating groups in your analysis. By clustering, you can find subgroups of individuals that exhibit more or less similar behavior across the constructs measured.

### d. Hungarian Method

```
import numpy as np
from scipy.optimize import linear_sum_assignment
# Step 1: Calculate the average rank for each construct within
each cluster
# Using 'Cluster' column instead of 'Hungarian_Cluster'
cluster_averages = rankings.groupby('Cluster')[['Construct1_Rank',
'Construct2_Rank', 'Construct3_Rank']].mean()
# Step 2: Create a cost matrix based on the difference between the
average ranks of each construct and each cluster
# The cost matrix will have rows as clusters and columns as constructs
cost_matrix = np.zeros((3, 3))  # 3 clusters and 3 constructs
for i, cluster in enumerate(cluster_averages.index):
for j, construct in enumerate(['Construct1_Rank', 'Construct2_Rank',
'Construct3_Rank']):
# Calculate the absolute difference between the cluster's average
rank for the construct
cost_matrix[i, j] = cluster_averages.loc[cluster, construct]
# Step 3: Applying the hungarian algorithm to the cost matrix
row_ind, col_ind = linear_sum_assignment(cost_matrix)
# Step 4: Assign the constructs to clusters
construct_to_cluster = dict(zip(col_ind, ['Construct1',
```

```
'Construct2', 'Construct3']))
print ("Cluster to Construct Mapping (Hungarian Method):")
for cluster_idx, construct_name in construct_to_cluster.items():
print (f"Cluster {cluster_idx+1} matches with {construct_name}")
```

**Interpretation:** The results of applying the Hungarian method for clustering psychological, physiological, and cognitive constructs shows a distinct pattern of cluster-construct alignment.

Cluster 1 corresponds to the psychological construct, Cluster 2 matches with the cognitive construct, and Cluster 3 aligns with the physiological construct [Fig. 4].

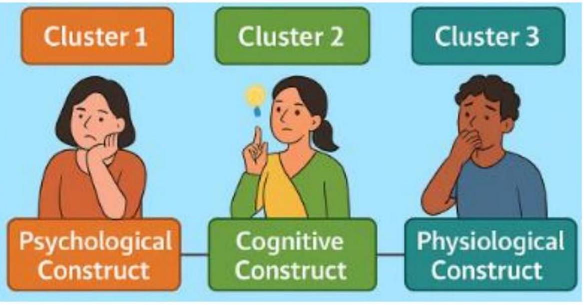


Figure 4: Cluster Distribution on three Construct

To get insight by optimizing the assignment of constructs to clusters, helps uncover relationships among variables that may not be immediately apparent, providing deeper insights into how individuals respond across different domains. The Outcomes as obtained support the relevance of using clustering techniques and optimization algorithms to better understand complex constructs in psychological and behavioral sciences. These results contribute to refining psychological and physiological models by identifying patterns that can inform interventions or targeted assessments in various fields like mental health and behavioral science.

## 4. Result Discussion

This study highlights the effective role of fuzzy logic and clustering techniques to analyse psychological, physiological, and cognitive constructs. The use of Cronbach's alpha confirmed the reliability of the measurement scales, while the ranking method helped in categorizing responses based on fuzzy centroids. The K-means clustering identified distinct patterns in how an individual responded across different constructs. Along with the Hungarian method providing an optimized way to align clusters with specific constructs.

The heatmap [Fig. 5] shows the mean scores of 258 students clustered into 3 distinct groups using K-means clustering based on psychological, physiological, and cognitive features. Here we got cluster 0 , cluster 1 , and cluster 2 . The labels assigned to each cluster by the KMeans algorithm because we have 3 construct i.e. psychological, physiological, and cognitive (k = 3) with each having three indicators. These are arbitrary labels assigned to each cluster with respect to each construct. They do not carry any meaning by themselves. They are just identifiers for the groups the algorithm formed and each clusters having indicators from all three construct. Here's the results suggest:

- Cluster 0: Higher Self Esteem, Sleep Quality, and Memory Retention, but lower Headache.
- Cluster 1: Lowest Depression and highest Weight scores.
- Cluster 2: Most balanced across Emotional Stability and Attention Span, but lower Social Bias.

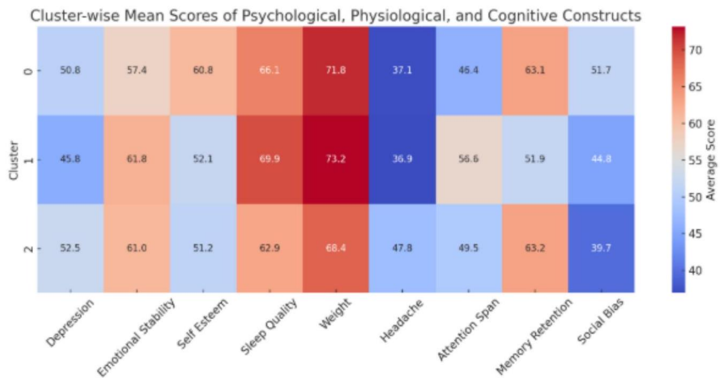


Figure 5: Cluster Distribution on three Construct

This clustering effectively segments students based on patterns in their mental and physical health indicators. These findings emphasize the value of advanced statistical techniques in behavioural science research, offering insights into the complex relationships between mental, physical, and cognitive areas. The discussed approach contributes to a deeper insight as well understanding of individual responses, which can guide targeted interventions in psychological and health-related fields.

## 5. Recommendations

**Application of Fuzzy Ranking in Diverse Fields:** Extend the fuzzy ranking approach to other domains such as healthcare, customer satisfaction surveys, and employee performance evaluation to validate its effectiveness across different contexts.
**Advanced Statistical Techniques:** Combine fuzzy ranking with advanced statistical or machine learning models to enhance predictive analytics for decision-making in areas such as marketing and policy analysis.
**Cross-Cultural Studies:** Test the fuzzy ranking method in cross-cultural studies to account for cultural variations in Likert-scale interpretations and enhance its global applicability.

## 6. Limitations

**Subjectivity in Fuzzy Number Assignment:** The process of converting Likert-scale responses into fuzzy numbers involves subjective judgment, which could introduce bias and affect the accuracy of the rankings.
**Sample Size Constraints:** The reliability and generalizability of the findings may be limited by the sample size used in the study. Larger and more diverse samples are needed for robust validation.
**Lack of Comparative Analysis:** The study may not have compared the fuzzy ranking method with other advanced ranking or reliability measurement techniques, leaving room for further investigation.

**Acknowledgement-** We thank the organizers of the "International Conference on Mathematical Sciences and Computing Innovations and Applications (ICMSC-2025)" jointly organized by Department of Mathematics, North-Eastern Regional Institute of Science and Technology (NERIST) and Department of Mathematics, National Institute of Technology (NIT), Uttarakhand held over June 26-28, 2025.

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*Anju Khandelwal (Corresponding author),*

*School of Actuarial Science,*

*Sri Balaji University, Pune, India.*

*E-mail address:* `dranju20khandelwal@gmail.com`