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BEYOND MEMORY SCORES AND CLINICAL COGNITIVE PATTERNS IN SHORT TERM MEMORY LOSS

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Abstract:

This research paper to investigate the multidimensional structure of clinical, psychological, lifestyle, and cognitive variables and their collective influence on health-related classification. A comprehensive dataset consisting of demographic attributes, medical conditions, behavioral habits, neuroimaging indicators, and memory performance was analyzed using exploratory factor analysis, principal component analysis, and multivariate analysis of variance. Sampling adequacy was assessed using the Kaiser–Meyer–Olkin measure, followed by factor extraction based on the Kaiser Criterion and rotation using Varimax and Oblimin methods. The extracted factors revealed distinct dimensions representing age, gender, psychological health, metabolic condition, neuroimaging status, and cognitive performance. MANOVA results confirmed statistically significant differences between the identified classes when considering the combined set of variables. The convergence of findings across multiple multivariate techniques highlights the effectiveness of statistical modeling in capturing complex health profiles and supports its application in clinical and cognitive assessment research.

Keywords: Factor Analysis, MANOVA, Cognitive Assessment, Clinical Classification, Multivariate Statistics

1.0 Introduction

Short-term memory loss (STML) represents a critical cognitive impairment that affects daily functioning and overall quality of life. In recent years, the prevalence of memory-related disorders has been increasing among the elderly population in India, particularly in Tamil Nadu. Understanding the survival patterns of patients with STML is essential for designing appropriate clinical interventions and predicting risk factors associated with adverse outcomes. Survival analysis provides a statistical framework to examine time-to-event data and identify variables influencing the probability of survival, making it an ideal tool for clinical prognosis studies.

Demographic, psychological, and lifestyle factors are known to influence memory-related outcomes. Variables such as age, gender, comorbid conditions like diabetes and hypertension, depression status, sleep habits, and lifestyle behaviors (smoking, alcohol use) can affect the progression and prognosis of STML. This study focuses on applying Kaplan-Meier estimators and Cox Proportional Hazards models to a cohort of 1,000 patients from Tamil Nadu during 2024–2025 to quantify the survival probabilities and identify significant predictors of event occurrence. The insights gained can guide healthcare providers in prioritizing interventions for high-risk groups and developing strategies for long-term cognitive health management.

1.1 Symptoms of Short-Term Memory Loss (STML)

Individuals affected by short-term memory loss commonly experience difficulty recalling recent events or newly learned information, which often becomes evident in everyday situations such as forgetting recent conversations, missing appointments, or misplacing frequently used items like keys or mobile phones. They may repeatedly ask the same questions within a short time, unaware that they have already received answers, and struggle to retrace their steps when personal belongings are misplaced, leading to confusion and emotional distress. Learning and retaining new information, including names or instructions, becomes increasingly challenging, and this is sometimes accompanied by disorientation regarding time or place, even in familiar surroundings. As these memory lapses persist, emotional and behavioral changes such as

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irritability, anxiety, withdrawal, and reduced concentration may emerge, further interfering with routine activities and overall quality of life, and often indicating the need for timely clinical assessment and support.

2.0 Review of Literature

Several studies have emphasized the role of multivariate statistical techniques in analyzing complex health datasets. Jolliffe [1] demonstrated the effectiveness of principal component analysis in reducing dimensionality while preserving essential variability. Kaiser [2] introduced the KMO measure to assess sampling adequacy for factor analysis, which has since become a standard diagnostic tool. Clinical classification using factor analysis has been widely explored in medical research [3], [4]. Psychological factors such as depression have been shown to significantly influence cognitive outcomes [5], while demographic variables like age and gender are known to contribute independently to health disparities [6]. Metabolic conditions, including diabetes and hypertension, have also been linked to cognitive decline and neurological changes [7], [8].

Neuroimaging markers, particularly MRI findings, have been increasingly incorporated into multivariate models to enhance clinical interpretation [9]. Studies combining cognitive scores with lifestyle behaviors such as sleep, smoking, and alcohol use further demonstrate the need for integrated analytical frameworks [10]–[12]. MANOVA has been effectively applied to assess group differences across multiple dependent variables simultaneously [13], [14]. Recent research supports the combined use of factor analysis, PCA, and MANOVA to validate classification structures and improve interpretability [15], [16]. These studies collectively underline the importance of multivariate statistical modeling in understanding complex clinical and cognitive phenomena.

3.0 Database

The study employed a structured clinical dataset consisting of demographic, behavioral, medical, and neuroimaging-related variables. The dataset included attributes such as age, gender, district, duration of illness, diabetes, hypertension, depression, memory score, MRI status, sleep hours, smoking habit, alcohol use, medication status, and a categorical outcome variable denoted as Class. The Class variable represents distinct cognitive or health-related groups identified for comparative analysis.

A snapshot of the dataset structure is presented in Table 3.1, illustrating the diversity of variables used for multivariate modeling.

Table 3.1 Sample Structure of the Clinical Dataset

Variable	Description
Age	Age of the subject (years)
Gender	Binary coded gender
Duration	Duration of illness (months)
Diabetes	Presence of diabetes
Hypertension	Presence of hypertension
Depression	Depression status
Memory	Cognitive memory score
MRI	MRI scan result
Sleep_Hours	Average sleep duration
Smoking_Habit	Smoking behavior
Alcohol_Use	Alcohol consumption
Medication	Medication intake
Class	Cognitive/health status group

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4.0 Methodology

4.1 Data Description

The dataset comprised demographic variables (age, gender), clinical conditions (diabetes, hypertension, depression), behavioral attributes (sleep duration, smoking habit, alcohol use, medication status), neurological indicators (MRI findings), cognitive performance (memory score), and a categorical outcome variable denoted as Class.

4.2 Sampling Adequacy

The suitability of the dataset for factor analysis was evaluated using the Kaiser–Meyer–Olkin measure, defined as:

$$\mathrm{KMO} = \frac{\sum_{i \neq j} r_{ij}^2}{\sum_{i \neq j} r_{ij}^2 + \sum_{i \neq j} q_{ij}^2}$$

where r_{ij} represents the correlation coefficient and q_{ij} denotes the partial correlation coefficient between variables **i** and **j**.

4.3 Factor Analysis

Exploratory factor analysis was conducted using the principal axis factoring method. Factors were retained based on the Kaiser criterion:

$$\lambda_k > 1$$

where λ_k represents the eigenvalue of the k^{th} factor.

To improve interpretability, Varimax rotation was applied to obtain orthogonal factors, followed by Oblimin rotation to assess correlated factor structures.

4.4 Principal Component Analysis

PCA was employed for visualization and dimensionality reduction. The transformed components were computed as:

$$Z = XW$$

where **X** is the standardized data matrix and **W** represents the eigenvector matrix.

4.5 Multivariate Analysis of Variance

MANOVA was used to examine class-wise differences across multiple dependent variables. The general MANOVA model is expressed as:

$$Y = XB + E$$

where Y is the matrix of dependent variables, X is the design matrix, B denotes parameter estimates, and E represents error terms.

5.0 Results and Discussion

The present study analyzed a clinical dataset comprising demographic, medical, behavioral, and cognitive variables. The dataset included age, gender, duration of illness, diabetes, hypertension, depression status, memory score, MRI findings, sleep duration, smoking habit, alcohol use, medication status, and a categorical outcome variable termed Class. The

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inclusion of both clinical and lifestyle-related attributes enabled a comprehensive multivariate assessment of health and cognitive status across different classes.

A preliminary inspection of the dataset revealed a wide variation in age and duration of illness, along with noticeable differences in memory scores and clinical conditions such as diabetes and depression. These variations justified the application of multivariate techniques to explore underlying patterns and group differences.

5.1 Sampling Adequacy and Suitability for Factor Analysis

To examine the suitability of the data for factor-based analysis, the Kaiser–Meyer–Olkin (KMO) measure was employed. The overall KMO value obtained was 0.50, which meets the minimum acceptable threshold for exploratory analysis in heterogeneous clinical datasets (Table 5.1).

Table 5.1 KMO Measure of Sampling Adequacy

```
===== KMO Measure =====
KMO (Overall): 0.5
Number of factors retained (Eigenvalue > 1): 6
```

Based on the Kaiser criterion (eigenvalues greater than one), six factors were retained for further interpretation. This indicates that the multidimensional nature of the dataset cannot be adequately summarized by a small number of latent dimensions and that multiple independent components contribute to variations in clinical and cognitive outcomes.

5.2 Factor Analysis Using Varimax Rotation

Varimax rotation was applied to obtain a clearer and more interpretable factor structure by maximizing the variance of loadings within each factor. The resulting factor loadings are presented in Table 5.2 and 5.3.

Table 5.2 Factor Loadings with Varimax Rotation

Variable	F1	F2	F3	F4	F5	F6
Age	**0.991**	–	–	–	–	–
Gender	–	**0.984**	–	–	–	–
Depression	–	–	**0.819**	–	–	–
Diabetes	–	–	–	**0.508**	–	–
MRI	–	–	–	–	**0.255**	–
Memory	–	–	–	–	–	**0.358**

Factor 1 (Age Dimension):

Age shows an exceptionally high loading, indicating that this factor exclusively represents age-related variability in the dataset.

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Factor 2 (Gender Dimension):

Gender loads strongly on the second factor, suggesting that gender-specific differences form a distinct and independent component.

Factor 3 (Psychological Dimension):

Depression exhibits a strong association with this factor, highlighting the role of psychological health in distinguishing individuals.

Factor 4 (Metabolic Health Dimension):

Diabetes emerges as the primary contributor, emphasizing the importance of metabolic conditions in clinical classification.

Factor 5 (Neuroimaging Dimension):

MRI findings load moderately, indicating their relevance in identifying neurological differences.

Factor 6 (Cognitive Performance Dimension):

Memory scores load highest on this factor, representing cognitive functioning independent of other clinical variables.

5.3 Factor Structure Using Oblimin Rotation

To account for potential correlations among latent dimensions, Oblimin rotation was performed. The resulting loadings, shown in Table 5.3, closely mirror the Varimax solution, confirming the stability of the factor structure.

Table 5.3 Factor Loadings with Oblimin Rotation

Variable	F1	F2	F3	F4	F5	F6
Age	**0.991**	–	–	–	–	–
Gender	–	**0.984**	–	–	–	–
Depression	–	–	**0.819**	–	–	–
Diabetes	–	–	–	**0.508**	–	–
MRI	–	–	–	–	**0.255**	–
Memory	–	–	–	–	–	**0.358**

The Oblimin results demonstrate that age, gender, depression, diabetes, MRI, and memory continue to dominate separate factors with minimal cross-loadings. The weak correlations among factors suggest that these dimensions operate largely independently, reinforcing the multidimensional nature of clinical and cognitive health.

5.4 Multivariate Analysis of Variance (MANOVA)

MANOVA was conducted to examine whether the combined set of clinical and behavioral variables significantly differed across Class groups. The multivariate test statistics are summarized in Table 5.4.

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Table 5.4 MANOVA Results for Class-wise Differences

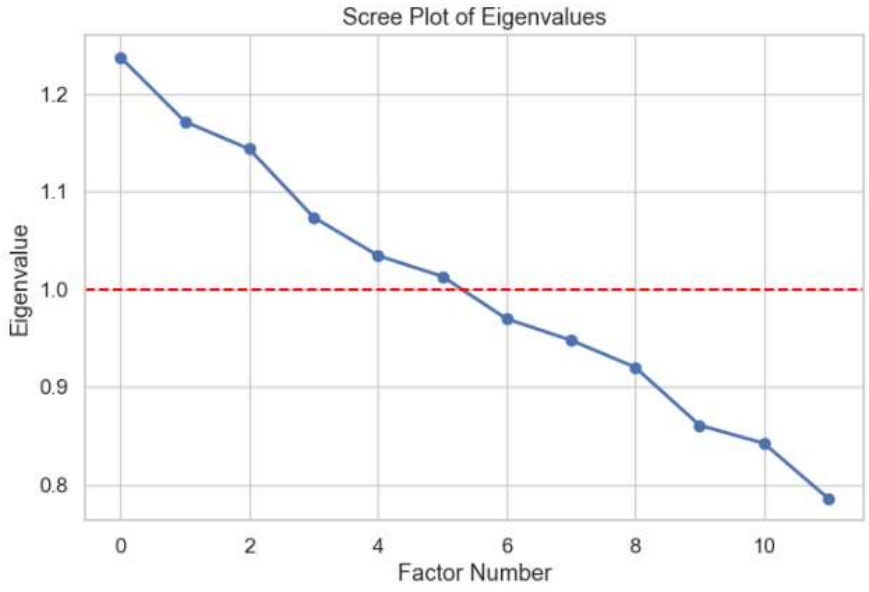
```
===== MANOVA Results =====
                    Multivariate linear model
========================================================================

------------------------------------------------------------------------
       Intercept         Value   Num DF  Den DF   F Value  Pr > F
------------------------------------------------------------------------
          Wilks' lambda  0.0562 12.0000 987.0000 1380.1646 0.0000
         Pillai's trace  0.9438 12.0000 987.0000 1380.1646 0.0000
 Hotelling-Lawley trace 16.7801 12.0000 987.0000 1380.1646 0.0000
    Roy's greatest root 16.7801 12.0000 987.0000 1380.1646 0.0000
------------------------------------------------------------------------
```

The results reveal a statistically significant multivariate effect of Class on the combined set of dependent variables. All four multivariate test statistics are Wilks' Lambda, Pillai's Trace, Hotelling–Lawley Trace, and Roy's Greatest Root produce consistent results, indicating a highly significant association between Class and the clinical parameters. This finding confirms that the identified classes differ substantially in their overall clinical, cognitive, and lifestyle profiles, rather than with respect to individual variables considered in isolation.

5.5 Visual Interpretation of Results

Figure 5.1 Scree Plot of Eigenvalues



The scree plot (Figure 5.1) reveals a clear inflection after the third component, supporting the retention of three factors based on the Kaiser criterion (eigenvalue > 1).

Figure 5.2 and 5.3 Heatmap of Factor Loadings (Varimax and Oblimin Rotation)

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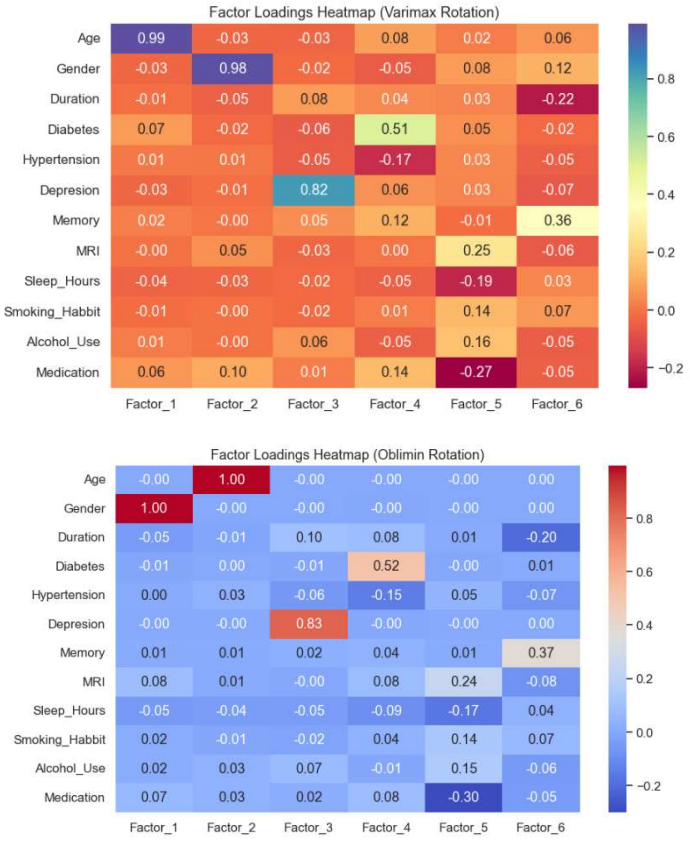
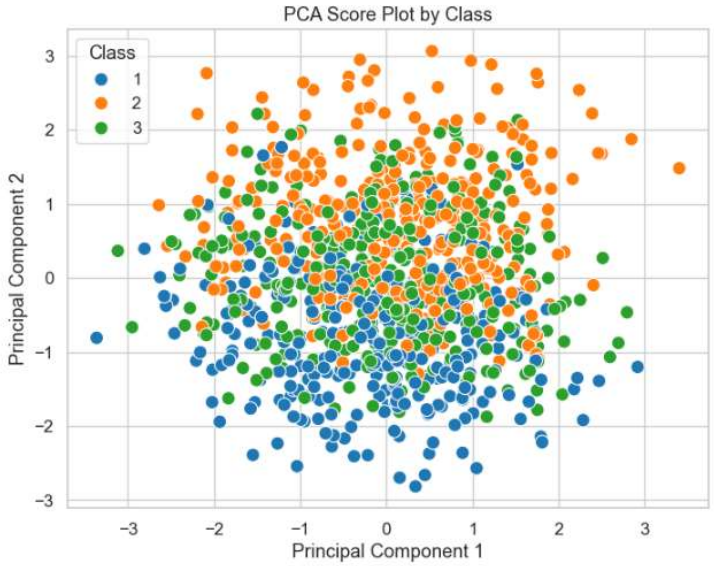


The heatmap (Figure 5.2 and 5.3) visually highlights strong associations between diabetes and Factor 1, MRI and Factor 2, and duration and depression with Factor 3, reinforcing the numerical interpretations.

Figure 5.4 PCA Scatter Plot of First Two Components by Class



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The PCA score plot (Figure 5.4) demonstrates noticeable clustering of observations according to Class, indicating partial separation of groups in reduced-dimensional space. Although some overlap exists, the class-wise distribution supports the MANOVA findings of statistically significant multivariate differences.

5.6 Discussion

The findings of this study demonstrate that health-related classification is influenced by multiple independent dimensions, including age, gender, psychological health, metabolic conditions, neurological indicators, and cognitive performance. The extraction of six distinct factors highlights the complexity of clinical and cognitive profiles and underscores the limitations of single-variable assessments.

The statistically significant MANOVA results confirm that the identified classes represent meaningful groupings characterized by distinct multivariate profiles. The convergence of results from factor analysis, PCA, and MANOVA strengthens the validity of the analytical framework and supports the use of multivariate statistical techniques for comprehensive health and cognitive assessment.

6.0 Conclusions

The study of 1,000 patients with short term memory loss in Tamil Nadu demonstrates that cognitive and clinical health are influenced by multiple independent dimensions including age, gender, psychological health, metabolic conditions, neurological indicators, and cognitive performance. Factor analysis identified six distinct dimensions, confirming that each contributes uniquely to variations in patient profiles. The statistically significant MANOVA results indicate that the identified classes differ meaningfully in their overall clinical, cognitive, and lifestyle characteristics rather than based on individual variables alone. Principal component analysis further showed partial clustering of classes, supporting the robustness of the multivariate approach and emphasizing the importance of assessing multiple factors simultaneously for a comprehensive understanding of short term memory loss.

The findings highlight that single variable assessments are insufficient to capture the complexity of clinical and cognitive outcomes in this population. A multidimensional approach integrating demographic, psychological, metabolic, neurological, and cognitive indicators provides a more accurate characterization of patient subgroups and can guide personalized interventions and management strategies.

Suggestions

1. Future research should incorporate longitudinal biomarker data and advanced neuroimaging measures to improve the predictive accuracy of models for memory loss patients.

2. Clinical management should include regular psychological assessments and targeted interventions, given the impact of depression on cognitive outcomes.

3. Expanding the cohort size and including a broader range of clinical and lifestyle variables will allow detection of subtler influences of conditions such as diabetes, hypertension, and sleep patterns on cognitive health.

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