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Original Research Article

Principal component analysis of clinical, mental health, and behavioral factors in a mixed population: insights for public health strategies

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ABSTRACT

Background: Non-communicable diseases (NCDs) such as type 2 diabetes mellitus (T2DM) and mental health disorders set forth substantial public health challenges in Tamil Nadu, India. Formulating targeted therapies requires an understanding of the behavioural, mental health, and clinical variables. Aim was to explore patterns in health outcomes among a mixed population with and without T2DM, focusing on socio-demographic, clinical, and mental health factors using principal component analysis (PCA).
Methods: A cross-sectional study was conducted during April 2020 to March 2021 with 614 participants (307 with T2DM and 307 without diabetes) in Alpha Hospital and Research Centre, a tertiary healthcare centre in Madurai, Tamil Nadu, India. Statistical analysis was done using IBM statistical package for the social sciences (SPSS) version 23.
Results: PCA discovered nine components from a set of clinical, behavioural, and socio-demographic variables, with a KMO value of 0.915 and Bartlett's Test of Sphericity showing significant Chi-square (11,932.50, $p<0.001$). 52.23% of the total variance was explained by the first five components. The clustering of stress, anxiety and depression in mental health components as well as the importance of glycaemic management and physical exercise as metabolic markers were among the key findings. Risky behaviours like smoking and alcohol consumption are exposed to have strong associations with adverse effects on health.
Conclusions: This study highlights novel insights on the interactions between clinical, mental health and behavioural aspects among the population of Tamil Nadu. Public health strategies converging on stress reduction, mental health support and chronic disease management are recommended for improved health outcomes.

Keywords: Non-communicable diseases, Type 2 diabetes mellitus, Principal component analysis, Stress, Anxiety, Depression

INTRODUCTION

Non-communicable diseases (NCDs) including type 2 diabetes mellitus (T2DM), cardiovascular disease and mental illness are causing growing concerns for global public health. Globally, NCDs account for 74% of deaths. Premature deaths or those that occur before the age of 70, account for 86% of these deaths and are primarily found in low- and middle-income nations like India.[1] As of 2021, 77 million people in India had diabetes indicating that the country is bearing an increasing burden of non-communicable diseases.[2]

In Tamil Nadu, one of India's most urbanized states, increasing trends in obesity, mental health disorders, and behavioural risks such as smoking have been documented. Nationally, around 21% of adults are obese, while in Tamil Nadu, approximately 29% of men and 17% of women use tobacco regularly.[3] These lifestyle-related factors are further exacerbated by rising alcohol consumption and the prevalence of mental health conditions, such as anxiety and depression, in urban populations.[4,5] The need for integrated public health strategies that target both behavioural risks and mental health is critical to shortening this dual burden of chronic diseases in Tamil Nadu and similar regions.[1]

There is much evidence to support the interconnectedness between mental health, physical health and socio-demographic factors.[6-9] Psychiatric disorders including depression, anxiety and stress (DAS) are examples of mental health issues that frequently coexist with chronic conditions like diabetes and hypertension, both of which can impair health outcomes.[10] Therefore, implementing effective public health interventions requires an understanding of the relationships between numerous clinical, behavioural and psychological characteristics.[11]

Principal component analysis (PCA) is a widely used technique for reducing data that aids in finding significant patterns among a large set of variables.[12] This study primarily focused on a mixed sample with and without T2DM individuals in Tamil Nadu, intends to investigate the association between clinical, behavioral, and psychological characteristics by PCA. Thus, this study aims to explore patterns in health outcomes among a mixed population with and without T2DM, focusing on socio-demographic, clinical, and mental health factors using PCA.

METHODS

Study design and population

A cross-sectional study was conducted in the diabetic and endocrinology-focused Alpha Hospital and Research Centre, a tertiary healthcare centre in Madurai, Tamil Nadu, India, from April 2020 to March 2021. Of the 614 participants, 307 were T2DM patients, while the remaining 307 were healthy individuals without DM. PCA was used to determine the primary contributing factors prevailing among these groups of participants. Inclusion criteria involved participants with at least 18 years old and willing to participate, while those with known severe mental health conditions as defined by the ICD-10 classification of mental and behavioural disorders (the): diagnostic criteria for research (ICD-10 DCR) was not allowed to participate.[13]

Sample size determination

The estimate of the patient sample size was derived from a pilot study in which 27.5% of 40 T2DM patient who were not part of the main investigation, exhibited symptoms of DAS. Using the Central Limit Theorem and the formula given below, the sample size (n) was ascertained as 307.[14]

$$N = (Z^2 \times p \times (1 - p))/d^2$$

The formula's 95% confidence interval (Z=1.96) and margin of error are both 5%. Through the use of probability sampling, participants were chosen from outpatient clinics and community health programs. As a reference group, 307 people without DM from the general community were chosen; their sociodemographic and clinical traits (FBS levels) were similar.

Ethical approval and informed consent statements

This study was approved by the Internal Research and Review Board (IRB), Ethical Clearance (EC), Biosafety and Animal Welfare Committee of Madurai Kamaraj University, Madurai (Registration ID: EC/MKU/20-21/039) on 11 December 2020. Every participant provided written informed consent before being included in the study. This study was conducted ethically in accordance with the World Medical Association's Declaration of Helsinki.

Data collection

Using validated semi-structured questionnaires, information was gathered on clinical variables such as blood pressure (BP), body mass index (BMI), fasting blood sugar (FBS), postprandial blood sugar (PPS), insomnia, physical activity, and diet, as well as socio-demographic variables such as age, gender, marital status, educational attainment, occupation, income, and socioeconomic status. Behavioural metrics included smoking, drinking, and smoking. A patient was classified as diabetic, per the guidelines set forth by the American Diabetes Association, if their fasting plasma glucose levels were 126 mg/dl or higher in two separate tests; or if their postprandial (after meal) blood sugar level was 200 mg/dl or higher two hours after eating.[15]

The Hamilton depression rating scale (HAM-D), Hamilton anxiety rating scale (HAM-A), and perceived stress scale (PSS) were three standardised questionnaires used to measure mental health indicators, including depression, anxiety, and stress. The study by Dedeken et al found that the Cronbach's alpha for the HAM-D 17 items was 0.92, indicating an appropriate level of internal consistency.[16] According to Kummer et al, the HAM-A 14 items exhibit a high level of internal consistency, with a Cronbach's alpha of 0.893.[17] On the other hand, the PSS 10 items show great internal consistency, with a Cronbach's alpha of 0.85.[18]

Statistical analysis

IBM statistical package for the social sciences (SPSS) statistics version 23 was used to do the statistical analysis. To find underlying patterns in the dataset, PCA was used. The dataset was found to be appropriate for PCA based on the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (0.915) and Bartlett's test of sphericity (χ^2=11932.499, p<0.001). A total of 67.14% of the variance was explained by nine components with eigenvalues >1, which were kept in the Scree Plot. An interpretability-enhancing technique called Varimax rotation was applied.

RESULTS

According to the sociodemographic comparison (Table 1), T2DM patients are substantially distinct from the general population in terms of age, gender, marital status, income, occupation, education, and socioeconomic status. The majority of T2DM patients are female and younger (56.3% between the ages of 18 and 40). Their unemployment rate is greater (62.9%), and they are primarily from lower-income groups, with 63.5% belonging to the lowest economic class. Due to limited access to healthcare and favourable lifestyle choices, these factors imply that early onset of type 2 diabetes may be associated with socioeconomic restrictions. T2DM prevention and management outcomes may be enhanced by addressing these disparities through customized health interventions.

Table 1: Characteristics profile of T2DM patients and general population.

Sociodemographic factors	T2DM patients (n=307)		General population (n=307)	
	Frequency (N)	Percentage (%)	Frequency (N)	Percentage (%)
Age (years)				
18-40	173	(56.3)	41	(13.3)
41-60	113	(36.8)	132	(43)
61 and above	21	(6.8)	114	(37)
Gender				
Male	107	(34.9)	113	(36.8)
Female	200	(65.1)	194	(63. 1)
Marital status				
Unmarried	54	(17.6)	55	(17.9)
Married	223	(72.6)	214	(69.7)
Others	30	(9.8)	38	(12.3)
Educational qualification				
No formal education to middle school	87	(28.3)	77	(25)
High school	82	(26.7)	85	(27.6)
Diploma and above	138	(45)	145	(47.2)
Occupation				
Unemployed	193	(62.9)	75	(24.4)
Daily wage and business	48	(15.6)	114	(37)
Others	66	(21.5)	118	(38.4)
Income (in rupees)				
Housewife/student	135	(44)	125	(40.7)
Less than 18496	72	(23.5)	141	(45.9)
18497 above	100	(32.6)	41	(13.3)
Economic status				
Upper class	34	(11.1)	22	(7.16)
Middle class	78	(25.4)	141	(45.9)
Lower class	195	(63.5)	144	(46.9)

The results of Bartlett's test of sphericity show a statistically significant chi-square value (11,932.499, $p<0.001$), confirming that correlations between variables are sufficient for factor extraction. The Kaiser-Meyer-Olkin (KMO) value of 0.915 (Table 2) indicates excellent adequacy, suggesting that the sample size is sufficient for PCA. These findings validate the use of PCA to identify underlying relationships between variables, supporting the interpretation of patterns among clinical, behavioural, and mental health factors.

The PCA findings are summarized in Table 3 above, along with the cumulative variance, eigenvalues, and percentage of variation explained for each component. More than half of the volatility in the data is likely to be explained by the first five components, which account for 53.19% of the variance.

Table 2: KMO and Bartlett's test for sampling adequacy and sphericity.

Test	Value
Kaiser-Meyer-Olkin measure of sampling adequacy	0.915
Bartlett's test of sphericity	
Approximately Chi-square	11,932.50
Degrees of freedom (df)	496
Significance (sig.)	0

In Table 4 the nine components are categorized according to their respective significant factor loadings. Every constituent clusters variable with elevated loadings, signifying their role in the fundamental pattern. These classifications highlight the multidimensional nature of health factors, showing how clinical, behavioural, and mental health aspects are interlinked. Behavioural risks such as smoking and alcohol use are grouped under a separate component, suggesting their independent contribution to health outcomes.

The scree plot (Figure 1) validates the determination of nine components based on the "elbow," or the point at which the eigenvalue drops rapidly. The slope flattens after the third component, suggesting that the explanatory value of subsequent components decreases. The most significant variation is captured while dimensionality is decreased by retaining components with eigenvalues larger than 1.

The distribution of variables among the first three principal components can be seen in three dimensions using the rotating component plot (Figure 2). Stress, anxiety, and depression are examples of variables that cluster closely together, suggesting a high association between mental health problems. Clinical measures, such as FBS and SBP, also cluster together, indicating a unique metabolic health pattern. Furthermore, sociodemographic variables such as occupation and gender show up in different clusters, indicating their independent influence.

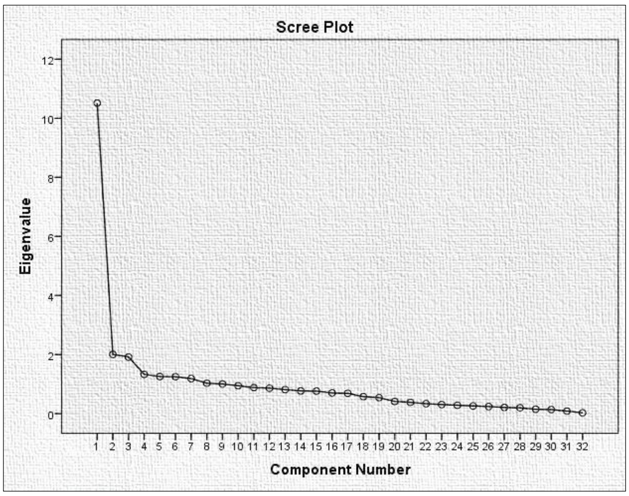

Figure 1: Scree plot for principal component analysis.

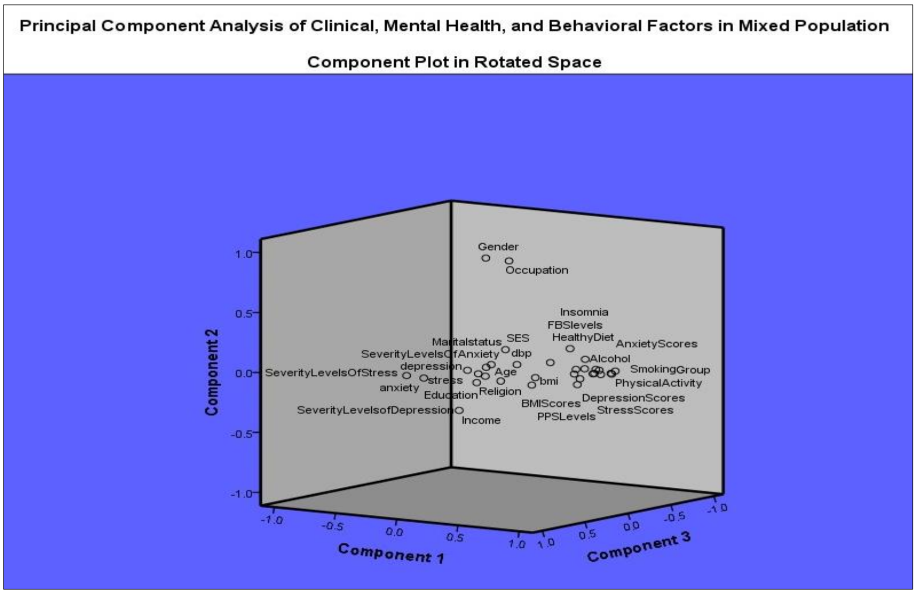

Figure 2: A rotated component plot in 3D space for clinical, behavioral, and mental health factors.

Table 3: Principal components analysis with eigenvalues and variance.

S. no.	Components	Eigenvalue	% of variance	Cumulative % of variance
1	Metabolic indicators and glucose control	10.339	32.31	32.31
2	Lifestyle and health behaviours	1.949	6.09	38.40
3	Emotional well-being and mental health	1.51	4.72	43.12
4	Blood pressure and BMI dynamics	1.486	4.64	47.76
5	Socioeconomic and mental health associations	1.43	4.47	52.23
6	Socioeconomic and cardiovascular factors	1.395	4.36	56.59
7	Psychological distress and coping	1.175	3.67	60.26
8	Social engagement and structure	1.103	3.45	63.71
9	Age-related health dynamics	1.097	3.43	67.14

Table 4: Classification of components with significant factor loadings.

S. no.	Components and variables (key findings)	Positive loadings	Negative loadings
1	**Metabolic indicators and glucose control**		
	Groups (total participants) - T2DM and healthy groups	0.973	
	FBS level	0.697	
	Postprandial sugar level	0.693	
	Adherence to physical activity	0.807	
	Blood sugar control status-controlled/uncontrolled levels	0.828	
	Postprandial sugar status- normal/abnormal levels	0.887	
	Systolic blood pressure	0.864	
	Diabetes status- normal pre-diabetes, diabetes mellitus	0.938	
	Income		-0.353
2	**Lifestyle and health behaviour**		
	Gender	0.904	
	Occupation	0.891	
	Alcohol addiction	0.834	
	Smoking addiction	0.941	
	Insomnia	0.779	
	Adherence to healthy diet	0.566	
	Income		-0.418
	Education		-0.729
3	**Emotional well-being and mental health**		
	Anxiety score	0.739	
	Depression score	0.656	
	Severity levels of depression	0.827	
	Severity levels of anxiety	0.818	
	Prevalence of stress symptoms	0.537	
	Education qualification		-0.49
	Severity levels of stress		-0.134
4	**Blood pressure and BMI dynamics**		
	Systolic blood pressure	0.864	
	Postprandial sugar level	0.693	
	Diastolic blood pressure	0.417	
	BMI levels	0.319	
	BMI status- underweight, normal, overweight, obese	0.357	
	Anxiety score		-0.221
	Religion		-0.104
5	**Socioeconomic and mental health associations**		
	Socioeconomic status	0.762	
	Depression	0.799	
	Marital status	0.909	
	Income per month		-0.127
	Religion		-0.682
6	**Socioeconomic and cardiovascular factors**		
	Socioeconomic status	0.762	
	Diastolic blood pressure	0.31	
	BMI levels	0.279	
7	**Psychological distress and coping**		
	Depression	0.799	-
	Severity levels of depression	0.827	
	Severity levels of anxiety	0.818	
	Severity levels of stress	0.804	
	Income		-0.418
8	**Social engagement and structure**		
	Marital status	0.909	

Continued.

S. no.	Components and variables (key findings)	Positive loadings	Negative loadings
	Occupation	0.891	
	Religion		-0.682
	Education		-0.729
9	**Age-related health dynamics**		
	Age	0.885	-
	Diastolic blood pressure	0.374	
	BMI status- underweight, normal, overweight, obese	0.242	

DISCUSSION

Characteristics profile of T2DM patients and general population

According to socioeconomic statistics, lower income and unemployment rates may make T2DM more common and make treatment more difficult by restricting access to healthcare and lifestyle modifications.[19] According to Perng et al, the early onset of type 2 diabetes also suggests that preventive treatments are required to target younger people from families with low incomes.[20] Addressing economic inequality, enhancing employment, and increasing healthcare education are vital for effective T2DM prevention and management (WHO, 2016) (Table 1).[21]

KMO and Bartlett's test results

The data are suitable for PCA, according to the KMO measure of sampling adequacy (0.915) and Bartlett's test of sphericity (χ^2=11932.499, df=496, p<0.001). A KMO value of more than 0.9 is deemed "excellent," signifying that the dataset is very suitable for factor analysis.[14] The results of the significant Bartlett's test indicate that there is sufficient strength in the correlations between the variables to achieve dimensionality reduction. These outcomes certify that latent components in the dataset may be found using PCA (Table 2).[22]

Principal component analysis and scree plot results

According to the results in Table 2, 67.14% of the variance in the data can be explained by the first nine components taken combined. According to the Kaiser criterion, the first nine components' eigenvalues above 1.0 attest to their significance.[14] The significance of components 1 through 5 in comprehending the dataset is demonstrated by the fact that they account for a sizable percentage of the explained variation (52.23%). To facilitate additional analysis, components having eigenvalues larger than one were retained.

An evident "elbow" appears after the ninth component in the scree plot (Figure 1), providing visual evidence for this interpretation that only these nine components include significant information. This technique aligns with established PCA practices for identifying important dimensions from complex datasets.[23]

Classification of components

The rotation of components in three dimensions (Figure 2) illustrates in the way variables are clustered among various components. Table 3 demonstrates that clinical variables such as PPS and FBS are predominantly captured by component 1, highlighting the important role that metabolic health plays in the mixed population. This is consistent with earlier research that showed how metabolic risk factors contribute to the development of T2DM.[24]

Component 2 is a reflection of behavioural factors including smoking and consuming alcohol, which have been shown to be associated with the advancement of chronic diseases.[25] According to Veter et al, the clustering of these variables emphasizes the necessity of behavioural interventions in public health programs to lower risks associated with lifestyle choices.[10]

The third component is devoted to mental health issues, such as anxiety, depression, and stress. According to earlier studies, there is a considerable correlation between chronic diseases and mental health, as indicated by the high factor loadings for these variables.[26] In addition to clinical care, interventions that target psychological well-being are essential for enhancing overall health outcomes.[11]

Socioeconomic variables like occupation, income, and level of education are discussed in components 4 and 5. Reduced socioeconomic status is associated with worse health outcomes, which is one way that these variables contribute to health disparities.[5] This result is consistent with international studies that highlights the necessity of health disparities policies in order to mitigate the burden of noncommunicable diseases.[3,25]

The residual elements (6 to 9) encompass extraneous variables such as age and gender, physical activity, and sleeplessness. These elements emphasize the lifestyle choices and demographic traits interact, highlighting the significance of tailored interventions even more.[27]

Public health implications

The clustering of metabolic, behavioural, mental health, and socioeconomic factors in this study has significant public health implications. Comprehensive health programs that address physical and mental health are essential in Tamil Nadu, where the burden of chronic diseases has risen.[5] Behavioural interventions that target alcohol consumption, smoking, and stress management can lower the risk of non-communicable diseases.[3] Furthermore, public health strategies should prioritize lowering health disparities by expanding access to economic, healthcare, and educational opportunities.[28] By treating the psychological comorbidities connected to chronic diseases, integrating mental health services into routine medical care can also improve health outcomes.[29]

Strength and limitations of the study

The current study is carried out in a tertiary healthcare centre located in Madurai, Tamil Nadu and holds significant novelty as it uses PCA to examine a heterogeneous population with and without T2DM. This study is distinct in that it integrates clinical, psychological, and behavioural components, in contrast to previous research that concentrate on specific topics like diabetes treatment or mental health. Deeper insights into public health issues are provided by this multifaceted approach, which makes the results thorough and area-specific.

The study's strengths are found in its broad sample of 614 participants and in the way PCA is used to find important behavioural, mental, and clinical patterns that offer practical public health insights. Nevertheless, there are certain drawbacks, such as the cross-sectional design, which restricts underlying inference. Longitudinal studies and sample expansion to various regions are suggested strategies to enhance future study. The significance of these results could be increased by public health initiatives supporting alleviating stress, physical exercise, and mental health assessment in the context of chronic illness treatment. Collaboration amongst communities, policymakers, and healthcare professionals can encourage sustainable lifestyle modifications, particularly in metropolitan environments.

CONCLUSION

This study breaks new ground by adopting a multi-dimensional approach to health analysis conducted in Tamil Nadu, South India, particularly Madurai. The complex interactions between clinical, behavioural, mental health, and socioeconomic factors that affect health outcomes in a diverse population are highlighted by this study. The PCA results, illustrating nine significant components accounting for 67.14% of the variance, establish a clear framework for comprehending these interdependencies. Important discoveries show that lifestyle choices, mental health, and metabolic health all influence health outcomes. The way these characteristics cluster together emphasizes the necessity of all-encompassing public health initiatives that incorporate clinical, behavioural, and mental health interventions.

Targeted interventions with an emphasis on early diagnosis and prevention are crucial for Tamil Nadu and other areas dealing with an increasing NCD burden. In order to achieve sustainable health outcomes, addressing economic and health inequities through social and economic policies will also be essential. Future studies ought to examine the effects of long-term treatments aimed at these variables on health outcomes. This study offers a data-driven framework for creating multifaceted public health initiatives that enhance people's quality of life both individually and as a community.

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