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PAPER

Predicting Markers of Cognitive Decline within Small Population Samples of Daily Life Activities

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ABSTRACT

Lifestyle markers associated with health can be used to predict decline in cognitive function among individuals. The objective of this study was to investigate how lifestyle factors assessed from data surveys impact decline in cognitive function by employing a cognitive assessment questionnaire across subpopulations in three districts in India. Lifestyle attributes and their correlations to cognitive strength were identified using machine learning methods. Our analysis suggests that modifiable lifestyle factors, including physical activity, choice of smoking, social interaction, and following a regular diet, significantly impact changes in explicit and implicit memory, emphasizing the interconnectedness between lifestyle choices and cognitive function. Neuropsychological assessment scores for visuospatial and delayed recall memory abilities between male and female participants showed significant differences, highlighting the importance of considering sex differences in cognitive research and clinical practice. Lifestyle choices can have implications across perceived states of cognitive functions that can be crucial for public health and intelligent app development.

KEYWORDS

modifiable lifestyle parameters, physical activity, smoking, social interaction, diet, memory, cognitive decline

1 INTRODUCTION

Within healthcare settings, the recognition of the value of data arising from common methods such as surveys and digital media is highlighted by worldwide governmental efforts to develop infrastructure and technology for maximizing the use of generated data [1], [2]. Lifestyle factors refer to individual lives, habits, behaviors, choices, and routines whereas modifiable lifestyle factors refer to specific elements of a person's lifestyle that can be changed or influenced to improve health. By understanding the impact of lifestyle factors on cognitive outcomes, researchers can inform policies and interventions aimed at promoting healthy behaviors and reducing the risk of cognitive

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impairment on a population level. Studies have shown that lifestyle choices for cognitive decline in people impact through the forms of hypertension, lower education, midlife obesity, smoking, alcohol consumption, lack of physical activity, nutrition, and social isolation [3], [4]. Notably, smoking has been identified as a significant factor with neurotoxic effects on the brain, potentially doubling the risk of dementia in older adults. While initial findings [5] suggested cognitive benefits and a reduced risk of dementia associated with smoking tobacco, recent research, including studies [6], [7], presents compelling evidence indicating the neurotoxic effects of active smoking on the brain in demented adults. People involved in doing more physical exercises have been reported to have lesser cognitive decline compared to those with lower physical activity levels [8]. Although accelerometers and other sensors such as health monitoring devices have long been utilized to track variations in physical activity levels [9], [10], it is only with recent technological advancements that embedding cognitive tasks within ecological momentary assessments has become popular [11]. Sensor-based technology enables the assessment of cognitive functioning in real-life contexts, providing a more comprehensive understanding of how cognitive processes unfold within the complexities of daily life [12]. Engaging in regular physical activity holds considerable importance for overall physical health, potentially modifying the risk of various chronic conditions such as coronary heart disease, stroke [13], depression [14], and diabetes [15], recognized as significant contributors to cognitive impairment [16].

Using techniques such as machine learning and deep learning for classification and identification of individuals with subjective cognitive decline (SCD) and mild cognitive impairment (MCI) may be proposed for identifying biomarkers that facilitate early detection of Alzheimer's disease [17]. Studies have shown that machine learning models have been deployed to analyze data collected from games, aiming to accurately distinguish individuals cognitive competency states as either healthy or indicative of MCI [18].

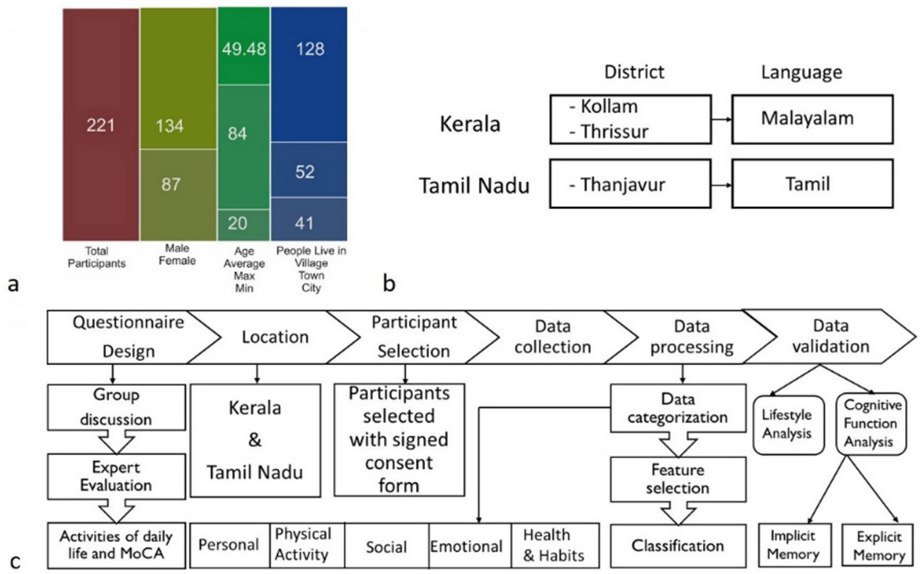

Fig. 1. Demographic parameters of the survey respondents, location and experimental design

Gaining insights into modifiable lifestyle factors associated with cognitive impairments is crucial for intervention and better treatment in the vulnerable stage of MCI, potentially leading to a delay in the progression to dementia [19]. When examining cognitive analysis tools, the Mini-Mental State Examination (MMSE) and the Montreal Cognitive Assessment (MoCA) had emerged as the predominant methods for detecting cognitive impairment in both clinical and research settings [20].

In this study, to assess the role of modifiable lifestyle risk factors on predicting cognitive decline in populations, we collected survey data from three locations in India that included activities of daily life and MoCA scores to understand the cognitive diversity across people with different ages and genders (male and female). The interactions of lifestyle factors were analyzed using different machine learning algorithms and statistical approaches to model the indirect influences of choices on memory changes. We also explored correlations between implicit and explicit memory changes among individuals influenced by modifiable lifestyle factors such as physical activity, social interaction, smoking, and diet that could be linked to working memory. We examined memory-related changes influenced by physical activity by categorizing participants who performed physical activity (including minutes of exercise, yoga, cycling, etc.) and who did not do exercise or physical activity. Through this study, we aimed to explore associations between modifiable lifestyle factors and cognitive function that can have a role in assessing and improving healthcare and to provide feasible management strategies for health conditions.

2 METHODS

2.1 Lifestyle data questionnaire and data collection

Activities of daily life questionnaire survey were modelled using standard literature, group discussions, expert evaluation, and validation to understand cognitive impairments concerning lifestyle data. This survey-based study was reviewed and approved by the institutional ethics committee at Amrita Vishwa Vidyapeetham, and subjects were explained the aim of the study before they participated in the survey. The participation of all survey respondents was voluntary. The modelled questionnaire was administered (see Figure 1) to 221 individuals aged between 20 and 80 years with a mean age of 49.48 during the period of June-July 2019 across three districts in south India, including Kollam (Kerala), Thrissur (Kerala), and Thanjavur (Tamil Nadu) (see Figure 1b). The recruited participants were of different demographic characteristics such as age, gender, and socio-economic status in terms of obtaining maximum diversity (see Figure 1a). The questionnaire was administered verbally in the local regional languages, Malayalam in Kerala and Tamil in Tamil Nadu (see Figure 1b). A signed informed consent was taken from all the participants before the test. The survey lasted approximately 20 minutes per subject, with the administrator sitting in front of the subject, usually at the subject's place of residence. The survey included questions focused on personal data, emotional status, physical health, social interactions, and health [21]–[23]. The entire dataset was statistically analyzed with all the quantitative variables expressed as mean ± standard error. Qualitative questions with a yes/no were converted to binary values, whereas categorical values were represented with a range of high to low based on the scores. The extracted data was classified using different machine learning algorithms with the feature evaluation technique to understand the best-fit attributes (see Figure 1c). The dataset is available on Mendeley Data under a CC-by-NC-SA 4.0 license [24].

2.2 Analysis of neuropsychological characteristics and cognitive functional changes across people with different age groups and genders

Montreal Cognitive Assessment is a cognitive assessment tool, and activities of daily life data were used to assess various cognitive functions [25]. The test consists of cognitive tasks designed to evaluate different cognitive domains. For the visuospatial memory task, subjects were asked to draw a clock set to a specific time. Evaluate their ability to place the numbers correctly and draw the clock hands; a correct answer was given 5 points. For the naming task, pictures of animals were shown to individuals, who were then asked to name the animals. Correct answers were assigned 3 points. In the memory recall task, 5 words were taught to the subject, which were to be recalled later, and a score of 1 was given to each correct answer with a maximum of 5 points. For the language task, the subjects were asked to repeat two sentences one after another given by the surveyor; the correct answer will be rewarded with a score of 1 point each. Also, the subjects were asked to come up with as many words starting with the letter given by the surveyor in one minute. If the subject manages to report 11 or more words starting with the given letter, they will be rewarded with 1 point. Also, to understand differential age and gender-related cognitive functional changes in terms of explicit and implicit memories, scores of the language and memory task were considered to represent the explicit memory, and the naming task was considered to represent the implicit memory across people.

2.3 Statistical analysis

Descriptive statistics, including mean and standard deviation, were computed for each of the four study groups of people who are involved in physical activity and who don't do physical activity, people who smoke vs. people who do not smoke, people who eat a regular diet vs. people who do not eat regular food, and people involved in social gatherings were summarized and analyzed. The significant differences between visuospatial memory and delayed recall memory between male and female participants were statistically analyzed using one-way ANOVA. *t*-tests were conducted separately for visuospatial memory and delayed recall memory to compare mean scores between male and female participants. Significance levels were set at $\alpha = 0.05$. The relationship between the attributes, including memory and delayed recall, attention, abstraction, and visuospatial memory, on cognitive functionality was analyzed using multiple linear regression analysis. The overall fit of the regression model was evaluated using the adjusted R-squared statistic, which indicated the model's accuracy towards cognitive function.

2.4 Machine learning models

In this study we used different machine learning algorithms and a comprehensive feature evaluation method to classify and identify the most appropriate attributes representing lifestyle patterns. The dataset was split into training and testing sets using the 10-fold cross-validation method, comprising a total of 38 features and 221 instances divided into training and testing (137 and 80) data. A combination of attribute evaluators, including the class subset evaluator, correlation attribute, gain ratio, and info gain, was used to assess the significance of various features in relation to cognitive behavior.

Four machine learning algorithms were used to build prediction models, namely, support vector machine (SVM) with radial basis function [26], decision trees (J48, random tree) [27], multilayer perceptron (MLP) [28], and a Naive Bayes classifier [29]. The models' performances were evaluated by adjusting parameters such as learning rate, hidden layers, training time, confidence factor, number of instances, and smoothing parameters. Classification accuracy was evaluated with a MoCA score of 26 as the class variable. Along with the MoCA score, demographic data, including age, sex, place of living, years of education, work style, and daily life habits, were also incorporated as independent variables.

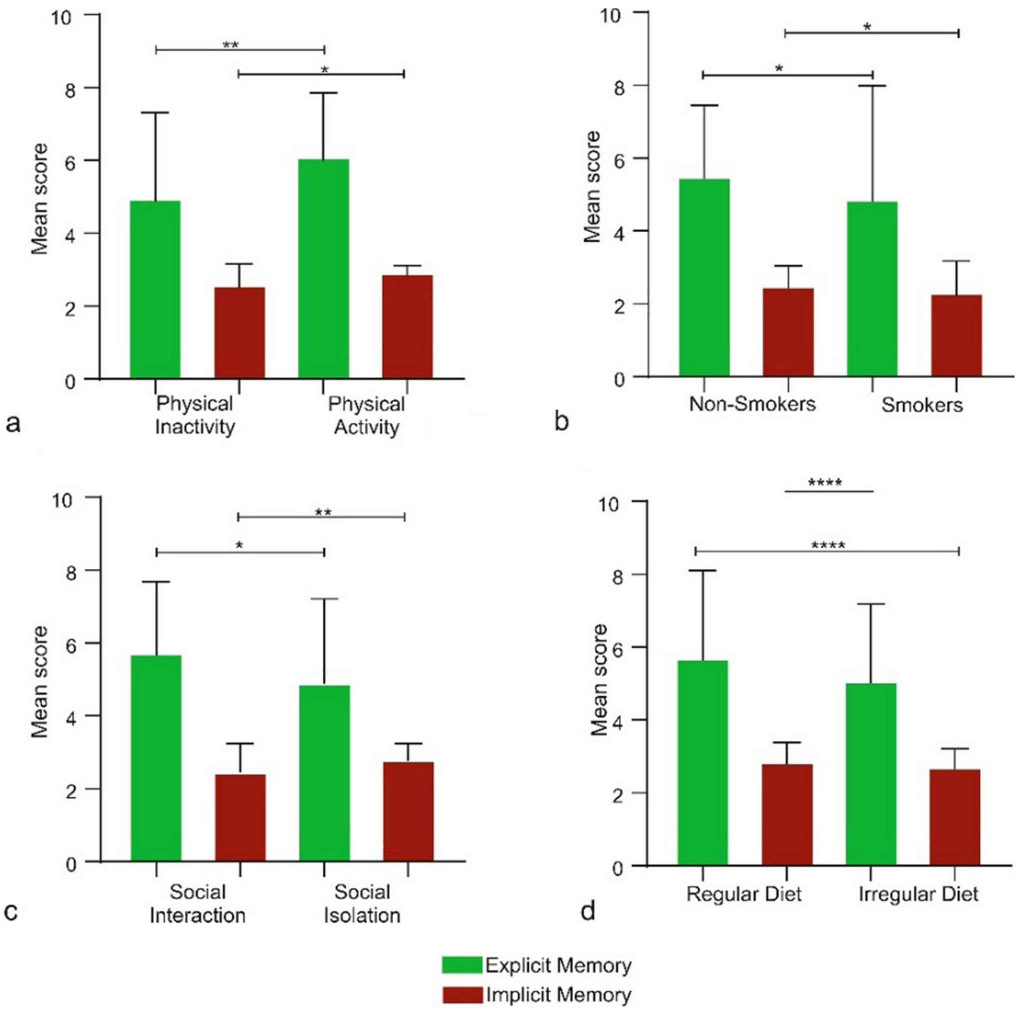

Fig. 2. Modifiable lifestyle factors and associated cognitive functional changes across people

3 RESULTS

3.1 Effects of modifiable lifestyle factors on cognitive functions: a comparative analysis of smoking, physical activity, diet, and social gatherings in a population-based study

The impact of modifiable lifestyle factors (smoking, diet, physical activity, and social gatherings) on cognitive functions in population-based samples was analyzed (see Figure 2). Mean implicit and explicit scores of people who don't smoke (see Figure 2b), do physical activity (see Figure 2a), have a regular diet (see Figure 2d), and are involved in social gatherings (see Figure 2c) were compared with people who smoke, have no physical activity, follow an irregular diet, and have no social gatherings. The decrease in both explicit and implicit memory parameters was evident in comparisons between smokers and non-smokers, with values declining from 5.5 to 4.8 and 2.5 to 2.3, respectively (see Figure 2b).

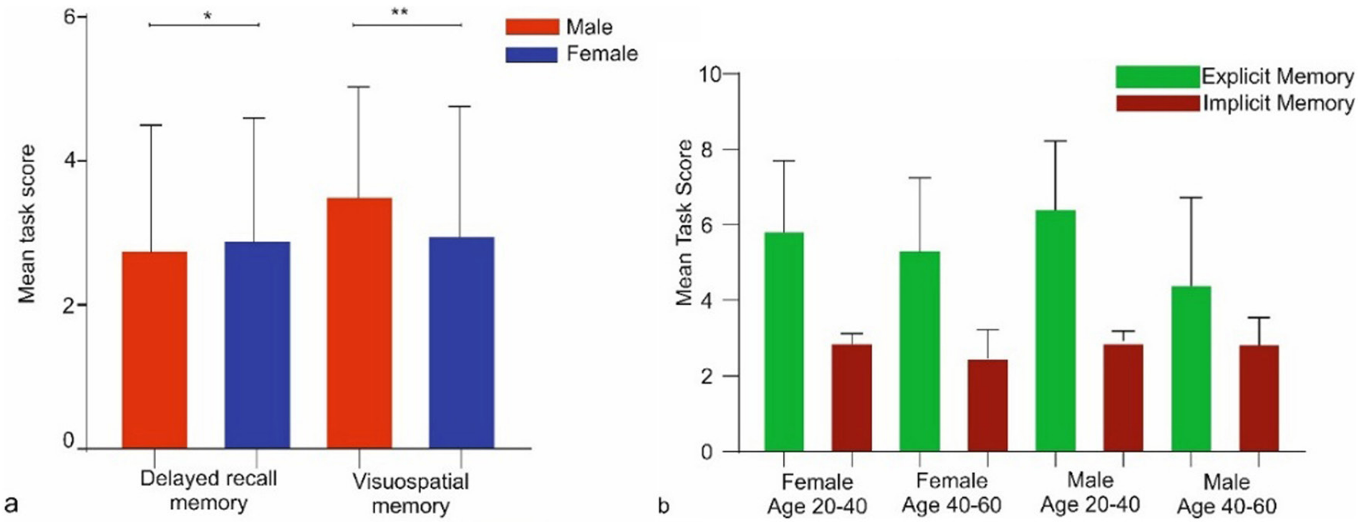

Fig. 3. Quantification of visuospatial and memory recall abilities across male and female survey respondents

3.2 Exploring gender differences neuropsychological assessment through visuospatial and recall memory

Visuospatial and delayed recall memory abilities across biological genders (male and female) were analyzed to gain insights into psychological gender differences and individual learning experiences (see Figure 3). In the analysis, women outperformed men significantly in the delayed recall memory task with an average task score of 2.98 versus 2.77 (see Figure 3a). Conversely, men excelled in the visuospatial memory task, scoring significantly higher with an average task score of 3.51 compared to 2.9 for women (see Figure 3a). These disparities were statistically significant, with a p-value of 0.0010 for delayed recall memory and 0.0020 for visuospatial memory (see Figure 3a).

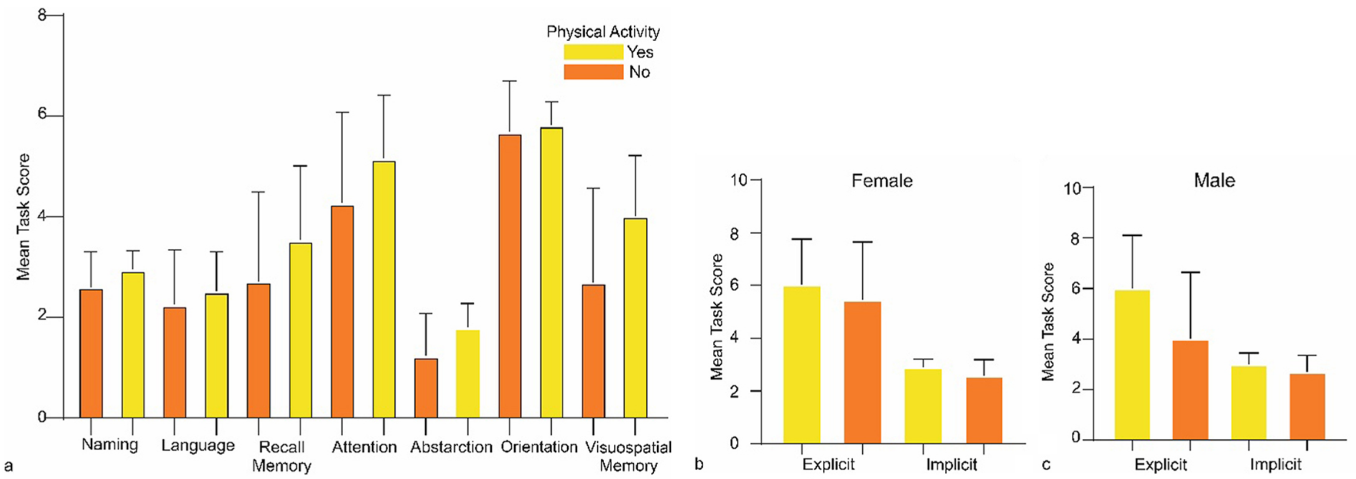

Fig. 4. Influence of regular physical activity and cognitive test scores across survey participants

The mean task scores, stratified by age and gender, clearly suggest that as individuals grow older, a decline in memory function may have been evident. Specifically, men and women exhibited superior performance in explicit tasks during the early age range of 20–40 years compared to the ages between 40 and 60 years. However, as the age band advanced between 40 and 60 years, women outperformed men in explicit tasks. Conversely, women experienced a decline in implicit memory changes as they aged, while men did not show a major difference as they aged between 40 and 60 years (see Figure 3b).

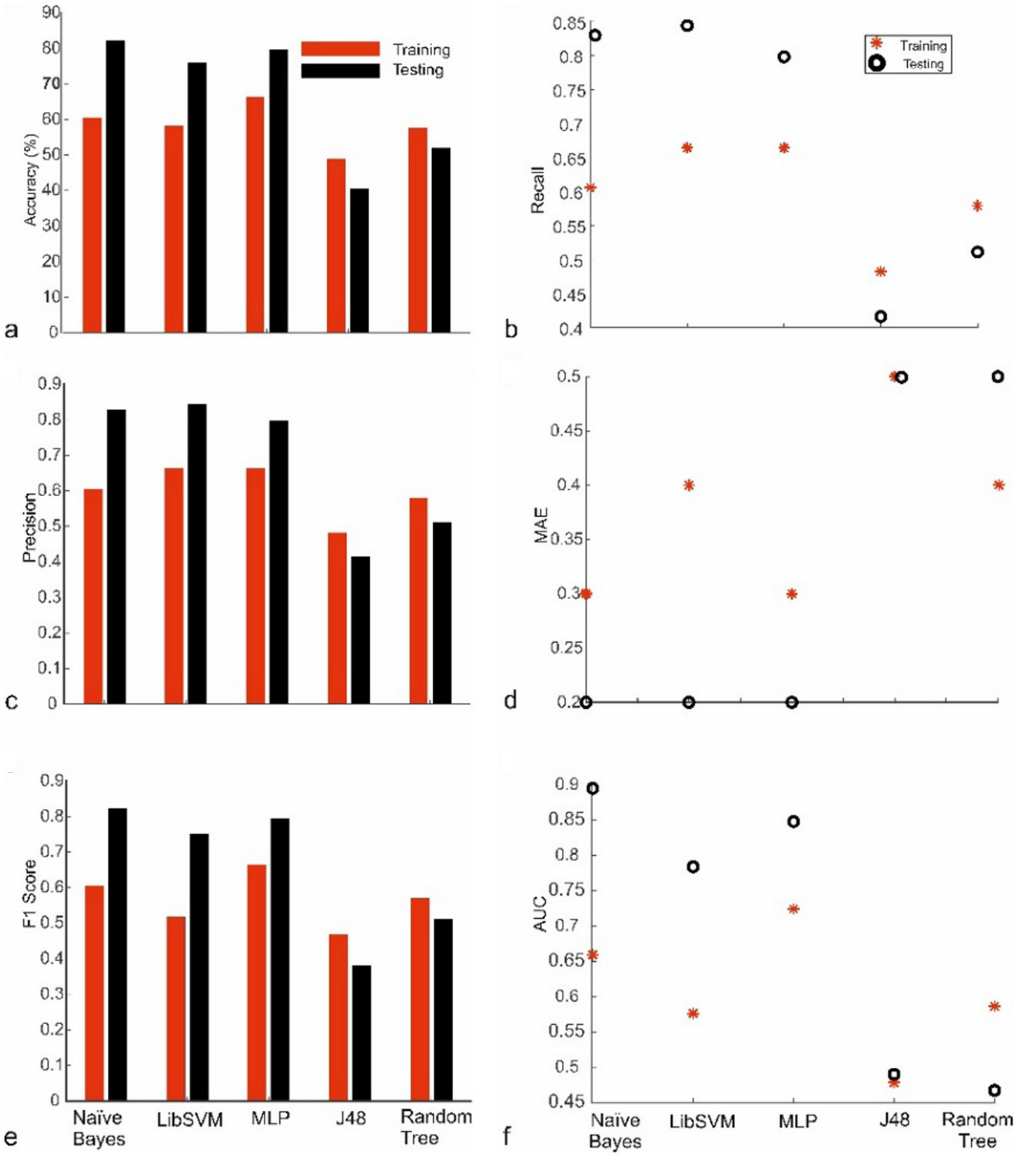

Fig. 5. Classification of lifestyle attributes using machine learning algorithms

3.3 The impact of regularly practiced physical activity on cognitive functional changes

Physical activity-dependent cognitive function across people was analyzed (see Figure 4). People who did regular physical activity showed a mean score of 2.9 for naming objects, 2.50 for language tasks, 3.50 for memory and delayed recall, and 5.14, 1.8, 5.85, and 4 for attention, abstraction, orientation, and visuospatial cognitive tasks (see Figure 4a). People who did not practice any physical activity showed reduced cognitive functionality scores of 2.6 for naming objects, 2.36 for language, 2.73 for memory delayed recall, 4.39, 1.24, 5.70, and 2.78 for attention, abstraction, orientation, and visuospatial cognitive tasks (see Figure 4a).

Physical activity-dependent neuropsychological test scores (explicit and implicit memory changes) across both male and female participants were analyzed. Individuals who performed daily physical activities demonstrated higher mean scores during explicit and implicit memory tasks compared to those who did not engage in physical activity. Specifically, female subjects who indicated that they participated in physical activities showed a mean explicit task score of 6.03 and a mean implicit task score of 2.9, while males demonstrated mean scores of 6 and 3, respectively. In contrast, females not involved in physical activity showed mean scores of 5.4 for explicit memory and 2.5 for implicit memory, while males had mean scores of 4 for explicit memory and 2.7 for implicit memory (see Figure 4b). In cross-group analysis, females consistently outperformed males in both explicit and implicit memory tasks across both experimental groups: those engaged in daily physical activities and those not involved in physical activities.

When assessing the performance of machine learning algorithms (see Figure 5), such as LibSVM (linear kernel), Naive Bayes, and MLP, we observed 58.3%, 60.58%, and 66.45% as training accuracy and 75.94%, 82.5%, and 79.7% as test accuracy (see Figure 5a). The precision during testing was 0.78, 0.89, 0.84, and 0.57, 0.65, 0.72 during training (see Figure 5c). The corresponding area under the receiver operating curve (AUROC) was 0.78, 0.89, 0.84, for testing and 0.57, 0.65, and 0.72 for training data as presented (see Figure 5f). The mean absolute error was 0.2 for testing and 0.38 for LibSVM, Naïve Bayes, and MLP during training (see Figure 5d). Along with SVM and Apriori algorithms, decision tree classifier models were used. From the training data, the root node represented the concept of "using gadgets" and branched into different sub-nodes related to physical activity, regular diet, and social interactions, showing a training accuracy of 48.9% for J48 and 57.6 for random tree and a test accuracy of 40.50% and 51.89% (see Figure 5a) with an average precision of 48% for training data and 57% for testing data (see Figure 5c). The corresponding area under the receiver operating curve (AUROC) was 0.47 and 0.58 for training data and test data (see Figure 5f), recall (Figure 5b), precision (Figure 5c), MAE metrics (see Figure 5d), and f1score (Figure 5e).

Multiple linear regression analysis was conducted to understand the influence of change in attributes, including memory and delayed recall, attention, abstraction, and visuospatial memory, on cognitive functionality. Through the analysis, a multiple correlation coefficient (R) and proportion of the variance in the dependent variable (R^2) of 0.6647 indicating that the independent variables account for 66.47% of the variability in the dependent variable cognitive score. Furthermore, the independent variables exhibited a statistically significant predictive capacity for the dependent variable, as evidenced by an F-statistic (4.216) = 107.0, with $p < 0.0001$. Subsequently, the statistical significance of each independent variable was examined, revealing coefficients with remarkably low p-values (<0.001) and corresponding *t*-values of 8.7, 4.9, 5.4, and 6.8 for memory and delayed recall, attention, abstraction, and visuospatial memory, respectively.

4 DISCUSSION

Attributing to the relationship between lifestyle factors (smoking, diet, physical activity, and social gatherings) and cognitive performance, this study focused on implicit and explicit memory changes. The findings implied a decline in both implicit and explicit memory scores among people who smoke and follow an irregular diet compared to people who do not smoke and follow a regular diet pattern. The risk exhibits a dose-dependent relationship, indicating that both the quantity and duration of smoking may contribute to an elevated risk of cognitive decline in later life. Data suggests adopting a balanced and nutrient-rich diet not only contributes to overall physical health but also plays a crucial role in promoting optimal cognitive function and potentially reducing the risk of unforeseen cognitive decline over the lifespan. Similarly, individuals who did not engage in social gatherings generated lower memory scores compared to their counterparts who participated in social gatherings. Active participation in social gatherings could lead to improved explicit memory quality across people that promotes language and recall memory, thereby not affecting implicit memory. Maintaining an active social life and participating in intellectually stimulating activities may have direct links to a lower risk of cognitive decline.

Furthermore, data suggests a positive relationship between regular physical activity and various aspects of cognitive functions including naming, attention, language, memory, abstraction, orientation, and visuospatial cognitive tasks. This relationship indicates the importance of incorporating physical activity into daily routines to support cognitive health and enhance overall well-being by reducing the risk of conditions such as hypertension, stroke, and heart disease, which are known risk factors for cognitive decline and dementia. Alongside gender-based analysis, it was revealed that women participants consistently outperformed men in both explicit and implicit memory tasks across both experimental groups: those engaged in physical activities and those not involved in physical activities. There may be potential cognitive benefits across women demonstrating a notable advantage in memory performance regardless of activity levels in some communities. Lifestyle factors have been consistently associated with cognitive outcomes and may contribute to the observed decline in memory performance among older individuals.

The analysis of visuospatial and delayed recall memory abilities across biological genders (male and female) provides valuable insights into psychological gender differences and individual learning experiences. Results indicated that the female population performed significantly higher on delayed recall, whereas men scored higher on visuospatial memory. The significant gender disparities highlight the complexity of gender-specific cognitive processes and the influence of biological and sociocultural factors on individual learning experiences. Also, findings revealed that women outperformed men in explicit memory tasks as age advanced between 40 and 60. Conversely, a distinct pattern emerged regarding implicit memory changes with advancing age. While women participants in this study experienced a decline in implicit memory performance as they aged, men did not exhibit a significant difference in implicit memory performance across the same age range. The observed gender differences in explicit and implicit memory performance with aging could highlight a complex interplay between psychological and environmental factors influencing cognitive functioning over the lifespan. The higher scores of women participants in explicit memory tasks may reflect underlying differences in neural processing or cognitive strategies, potentially influenced by sex-associated behavioral differences or sociocultural factors. Data also suggests visuospatial memory and delayed recall memory can serve as biomarkers for differentiating cognitive profiles between male and female groups. The trends observed in implicit and explicit memory across different age groups and genders, when compared with the distribution of lifestyle choices, offer valuable insights into the potential factors underlying cognitive decline. Gender-based cognitive differences are crucial for understanding educational strategies, cognitive interventions, and memory-enhancement programs to better accommodate the diverse learning needs of individuals across genders. Additionally, further research exploring the underlying mechanisms driving these cognitive disparities will be needed in order to provide accurate insights into the neurological basis of gender differences in memory processing and inform the development of targeted interventions to optimize cognitive functioning in both men and women.

Studies using machine learning algorithms indicated that factors such as alcohol consumption, tobacco usage, mobile phone usage, place of residence, occupation, physical activity, and social interactions were key features used for classifying cognitive behavior among individuals. Based on the attribute evaluation, most classifiable attributes were mood (happy), social interaction, regular diet, alcohol consumption, mobile usage, and physical activity that represent the lifestyle patterns. Using leave-one-out cross-validation, both J48 and random tree performed better than the remaining classifiers with training samples of all metrics, including precision, recall, F1score, AUC, accuracy, and MAE. For the test samples, MLP, Naive Bayes, and LibSVM showed better accuracy, AUC, F1 score, precision, recall, and MAE metrics. These models can help analyze similar and more complex datasets, aiding in the identification and categorization of biomarkers within lifestyle patterns with high accuracy and efficiency. On small population assessments, machine learning algorithms such as J48 trees can be used as explainable models to analyze individual lifestyle patterns to design and suggest interventions, such as personalized diet plans, exercise routines, or stress management strategies that help in improving cognitive functions.

5 CONCLUSION

The aim of this study was to explore the impact of lifestyle factors on cognitive function across three various subpopulations in India. Our findings indicate that modifiable lifestyle factors such as physical activity, smoking habits, social interaction, and dietary patterns significantly influence changes in both explicit and implicit memory. The differences observed in neuropsychological assessment scores, particularly in visuospatial and delayed recall memory abilities, serve as valuable biomarkers for distinguishing cognitive factors between males and females. Using machine learning and by classifying lifestyle data, personalized health recommendations can be generated, which may have several implications for hospital policy decisions. The validation of these findings will require extending this methodology to large populations across geolocations and diversities. The current study needs to be evaluated with a larger dataset that captures specific and generic trends across variations that can be relevant for public health, including a study size of over 5000 or more participants across cosmopolitan large populations, indigenous or remote communities, and varied climatic regions. With diversity, predictive models can be further developed into a clinical diagnosis support system, where healthcare professionals should be aware of associations between different lifestyle factors and health promotion strategies attributed to cognitive assessments.

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