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PRECISION HEALTH THROUGH WEARABLE TECHNOLOGY: K-MEANS CLUSTERING FOR CULTURALLY ADAPTED NCD PREVENTION

Nopparat Pochai[1], Kreethanat Klabchom[2], Arunotai Siriussawakul[3], Pariya Pariyavuth[4], Phichayavee Panurushthanon[5], Patchara Al-Umaree[6], Monchai Chottidao[7], Sirichet Punthipayanon[8]*

[1]School of Science, King Mongkut's Institute of Technology Ladkrabang, Bangkok, 10520, Thailand. Email: nopparat.po@kmitl.ac.th, Orcid ID: https://orcid.org/0000-0002-0945-7344
[2]School of Science, King Mongkut's Institute of Technology Ladkrabang, Bangkok, 10520, Thailand. https://orcid.org/0009-0001-2667-6055 Email poh.pan@hotmail.com
[3]Department of Anesthesiology Faculty of Medicine Siriraj Hospital, Mahidol University, arunotai.sir@mahidol.ac.th, Orcid ID: https://orcid.org/0009-0001-2667-6055, Orcid ID: https://orcid.org/0000-0003-0848-6546
[4]Department of Sports Science, Faculty of Physical Education, Sports and Health, Srinakharinwirot University, Bangkok 10110, Thailand. Email: pariya@g.swu.ac.th, Orcid ID: https://orcid.org/0009-0005-7248-5857
[5]Department of Sports Science, Faculty of Physical Education, Sports and Health, Srinakharinwirot University, Bangkok 10110, Thailand. Email: nantanak@g.swu.ac.th, Orcid ID: https://orcid.org/0009-0008-4072-7091
[6]Department of Sports Science, Faculty of Physical Education, Sports and Health, Srinakharinwirot University, Bangkok 10110, Thailand. Email: patcharaalumaree@gmail.com, Orcid ID: https://orcid.org/0009-0001-1812-0460
[7]College of Sports Science and Technology, Mahidol University, Nakhon Pathom, Thailand. Email: monchai.cho@mahidol.ac.th, Orcid ID: https://orcid.org/0000-0002-4673-3061
[8]Department of Sports Science, Faculty of Physical Education, Sports and Health, Srinakharinwirot University, Bangkok 10110, Thailand. Email: sirichet@g.swu.ac.th, Orcid ID: https://orcid.org/0000-0001-5017-1172

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Corresponding Author: Sirichet Punthipayanon (sirichet@g.swu.ac.th)

ABSTRACT

Introduction: Non-communicable diseases (NCDs) represent a critical global health challenge, accounting for 71% of deaths worldwide, with disproportionate burden in underserved populations including religious communities. Thai Buddhist monks face exceptionally high NCD prevalence attributed to sedentary lifestyles, dietary constraints, and limited physical activity opportunities inherent to monastic practices. This study introduces a novel machine learning framework for culturally-adapted health monitoring, addressing the urgent need for scalable, technology-driven solutions in traditional religious communities globally. Methods:

This cross-sectional study employed an innovative K-means clustering approach to analyze wearable device data from 28 Thai Buddhist monks over one month (November-December 2024). Polar Pacer Pro devices captured daily step counts, average heart rate (beats per minute), and energy expenditure (kilocalories). Following Min-Max normalization, unsupervised K-means clustering identified distinct physical activity phenotypes. Optimal cluster determination utilized the Elbow Method through Within-Cluster Sum of Squares (WCSS) analysis. This represents the first application of unsupervised machine learning for health pattern recognition in monastic populations, demonstrating methodological innovation in small-sample clustering validation for culturally-specific healthcare contexts. Results: K-means clustering successfully identified distinct activity profiles within the monastic population, revealing significant heterogeneity in physical activity patterns. The analysis differentiated monks into meaningful clusters based on step count (range: 700-18,650 daily steps), heart rate (50-87 bpm), and energy consumption (1,623-3,758 kcal) profiles. Cluster centroids demonstrated clear stratification: low-activity groups (1,079-3,763 steps daily) representing 39% of participants with sedentary behavior patterns, moderate-activity clusters (4,495-5,164 steps), and high-activity groups (9,381-12,664 steps) approaching recommended cardiovascular health guidelines. These quantitative classifications provide empirical foundations for precision health interventions tailored to individual risk profiles. Discussion: The research evaluates scalable digital health system that holds great potential for implementation in many religious and cultural groups globally. The clustering approach was able to identify actionable health phenotypes that inform targeted NCD prevention strategies that do not violate cultural restrictions. Low-activity clusters could be seen as the straightforward target of intervention, and the higher-activity cluster indicates that the promotion of physical activity practices is successful in the traditional approach. The methodology is a potentially effective method that is feasible in resource-restricted environments, about consumer-level wearable technology and open-source machine learning algorithms. Strategies of cultural adaptation, such as the application of Buddhist walking meditation and mindful movements in health promotion, serve as sustainable avenues of health promotion at the community level. This framework offers a replicable template related to health disparities in religious community members around the world (estimated 500+ million) and can lead to Sustainable Development Goal 3 (Good Health and Well-being) via innovative and culturally relevant digital health technologies. These results can guide policymaking based on evidence related to community health initiatives and illustrate how the precision health vision can empower traditional in the development of precision health to address modern NCDs in contemporary society.

KEYWORDS: K-Means, Data Classification, Wearable Devices, Thai Monks, Non-Communicable Diseases.

1. INTRODUCTION

Non-communicable diseases (NCDs) are described as a health crisis, representing a leading cause of death globally at about 71%, and are considered a burden to healthcare systems, especially in developing countries. These include cardiovascular diseases, diabetes, cancer, and chronic respiratory diseases. Some of these chronic conditions are caused by a combination of genetic predisposition, lifestyle choices, and environmental exposures that develop slowly over long durations and commonly require management over the course of years.

In this distinctive Thai cultural scene, Buddhist monks make up another group of special attention as they are prone to NCD prevalence and management. Metabolic diseases are incredibly prevalent in the monastic community relative to the rest of the population, and empirical investigations show that the disease burden distribution is alarming. The prevalence of metabolic syndrome components in Bangkok metropolitan temples showed that hypertension was present in 87% of monks, hypertriglyceridemia in 81.5%, and dysglycemia in 70.4%(Kwancharoen et.al, 2019). Similarly, extensive health examinations revealed that 93% of the monks were diagnosed with medical illnesses or complaints, with dyslipidemia occurring in nearly 80 percent of the sampled population and an increase in fasting blood glucose levels in more than 30% of the subjects (Sirivongs et al., 2019). The population of monks inhabiting cities showed even more worrying trends, with an obesity rate of 44.2% and dyslipidemia in 57.8% of the participants, with aging having a dramatic effect on multimorbidity rate (Ko-amornsup et al., 2024).

Abnormally high NCD prevalence in Thai monks is caused by several interdependent factors that are inherent to the practices of monastic lifestyle. One of the main concerns is dietary patterns because processed food provided as alms often lack essential nutrients and sufficient vegetable content, and are rich in sugar, saturated fats, and sodium. A qualitative study has shown that while monks are aware of NCDs, some have limited knowledge about dietary-disease relationships and are concerned about the nutritional quality of donated meals. Dietary issues are further exacerbated by the ban on solid food consumption outside of the noon intake, which can affect meal structure and energy balance. Another significant factor contributing to NCDs in monastic populations is physical activity restrictions (Khruakaew et al., 2019). Ecclesiastical tasks such as alms rounds and temple duties may not provide enough exercise to meet modern physical activity recommendations and prevent NCDs. Nualnetr noted that older monks, who may have limited mobility and long periods of rest after meals, may not achieve the recommended cardiovascular fitness levels. The opportunities for structured exercise interventions are limited by religious guidelines and organizational constraints, posing a barrier to delivering conventional physical activity interventions (Laochai et al., 2023).

There are other complexities that need to be taken into consideration; that is healthcare management, as well as disease perception by the monks. It was found that religious beliefs, personal experiences, and poor healthcare knowledge affect how the monks learned about metabolic syndrome, potentially impacting the chances of taking medical treatment and lifestyle adjustment practices (Kittithaworn et al., 2021). This creates a special set of difficulties when it comes to the application of evidence-based NCD prevention strategies in monastic communities. Digital health technologies have recently demonstrated great potential in addressing these barriers by objectively tracking health and using data to create intervention solutions. The technological capabilities of wearable devices will allow constant measurement of a set of physiological parameters that can be deemed objective predictors of future NCD risk, such as the level of physical activity and cardiovascular response advanced energy expenditure profiles. There is evidence linking large numbers of strides taken daily to lower the chances of type 2 diabetes, indicating that every 2,000 strides are associated with a 9% decrease in chances due to the increase in glucose levels and management of weight (Paluch et al., 2023). Moreover, monitoring physical activity with the help of heart rate assessment is a good source of data with respect to cardiorespiratory fitness, as it actively contributes to fat burning, insulin sensitivity, and blood pressure correction rates, which constitute the key focus areas in preventing metabolic syndrome (Myers, 2003). Measuring energy expenditure by use of wearable devices assists weight management by giving them the ability to be able to monitor their caloric balance, allowing them to be able to be evidence-based in regard to obesity prevention and long-term weight loss (Speakman & Westerterp, 2010).

Machine learning techniques, especially unsupervised clustering algorithms, bring novel ways of learning highly multidimensional health data patterns and discovering unique behavioral phenotypes in large groups of patients. K-means clustering has proven useful in the analysis of health data in illuminating unobserved patterns in multidimensional data, which then paves the way to personalized design of interventions with the risk of possible stratification. The usage of such methods in monastic populations is a new method of comprehending health behaviors in culturally specific shaping.

This study presents an extensive model that applies K-means clustering analysis of wearable device data to profile physical activity in Thailand, specifically among Buddhist monks in rural Bangkok regions. Using step count, heart rate, and energy expended data captured from 28 monks over a month, the study aims to establish different groupings of activities to guide focused activities during targeted NCD prevention to align with the limitations of monastic life. The findings will contribute to the increasing research base supporting the benefits of digital health applications for underserved population groups and address the immediate need for culturally appropriate health monitoring interventions in religious communities.

2. METHODOLOGY

2.1. Study Design and Participants

This study employed a cross-sectional observational design to analyze physical activity patterns among Thai Buddhist monks using wearable device technology and machine learning clustering techniques. The research was conducted in rural Bangkok areas over a one-month period from November 20 to December 20, 2024. A convenience sample of 28 Thai Buddhist monks was recruited from participating temples, representing a diverse range of ages and monastic experience levels within the study region.

2.2. Ethical Approval

This study was conducted in accordance with the Declaration of Helsinki and received ethical approval from the Siriraj Institutional Review Board (SIRB), Faculty of Medicine Siriraj Hospital, Mahidol University, Thailand (Protocol No. Si 151/2021, Certificate of Approval No. 048/2564(IRB2)). The study protocol was part of the broader research project titled "Sustainable development of health promotion system for monk by inter-disciplinary teams and public participation: Bangkok Noi model" with initial approval granted on February 22, 2021, and renewed approval obtained on February 23, 2025, with validity until February 22, 2026.

2.3. Data Collection and Instrumentation

Physical activity and physiological data were collected using Polar Pacer Pro GPS sports watches, specifically selected for their validated accuracy in measuring step count, heart rate, and energy expenditure parameters. The Polar Pacer Pro provides precise quantification of daily step counts, continuous heart rate monitoring with beats per minute (bpm) output, and energy consumption calculations expressed in kilocalories (kcal). These metrics were chosen based on their established associations with NCD risk factors and their relevance to monastic lifestyle assessment.

Participants wore the devices continuously throughout the 30-day study period, with data automatically synchronized to secure cloud storage systems. Daily measurements were aggregated to provide comprehensive activity profiles for each participant. The dataset comprised three primary variables: daily step count (ranging from 700 to 18,650 steps), average heart rate (ranging from 50 to 87 bpm), and energy consumption (ranging from 1,623 to 3,758 kcal).

2.4. Steps, Average Heart Rate, And Energy Expenditure of Monk Dataset

The Polar Pacer Pro is a GPS sports watch specifically designed for runners. It boasts accurate and detailed capabilities for measuring and displaying data related to "Steps," "Average Heart Rate," and " Energy Consumption." This data is crucial for training and health monitoring, especially in the prevention and management of NCDs. The dataset utilized in the study is collected 28 monk's datasets from November 20, 2024 to December 20 2024. Tables 1-2 show the features present in the dataset.

2.5. The K-Means Machine Learning Algorithm

The K-means algorithm is one of the most widely used and well-known unsupervised machine learning algorithms for clustering. Its primary goal is to partition a dataset into K distinct, non-overlapping groups or "clusters," where K is a pre-defined number of clusters. The algorithm aims to make data points within the same cluster as similar as possible (high intra-cluster similarity) and data points in different clusters as dissimilar as possible (low inter-cluster dissimilarity).

The K-means algorithm is an iterative, centroid-based process that follows these general steps:

1. Choose the Number of Clusters (K): The first step is to decide on the value of K, which represents the desired number of clusters. This is often determined through domain

knowledge or techniques like the "elbow method" (which looks for a point of diminishing returns in within-cluster sum of squares as K increases).

2. Initialize Centroids: K-centroids are initially placed in the data space. These can be chosen randomly from the existing data points or through more sophisticated initialization methods.
3. Assign Data Points to the Nearest Centroid: Each data point in the dataset is assigned to the cluster whose centroid it is closest to. The "distance" is typically calculated using Euclidean distance, though other distance metrics can also be used:

$$Dist(X,Y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

4. Recalculate Centroids (Maximization Step): After all data points have been assigned to clusters, the centroids of each cluster are recomputed. The new centroid for each cluster is the mean (average) of all the data points currently assigned to that cluster.
5. Repeat Until Convergence: Steps 3 and 4 are repeated iteratively. The algorithm continues until one of the following conditions is met:

5.1 The cluster assignments no longer change significantly between iterations.\

5.2 The positions of the centroids no longer move significantly.

5.3 A maximum number of iterations has been reached.

This iterative process aims to minimize the sum of squared distances between data points and their assigned cluster centroids (often referred to as "inertia" or "within-cluster sum of squares").

2.6. Min-Max Normalization

In this method of data normalization, there is a linear transformation of the original data. Another basic technique, sometimes also described as min-max scaling or min-max normalization, is to scale the range of features by setting the upper and lower bounds to 1 and 0, or 0 and 1. Depending on the type of data, the target range should be selected. The formula for min-max normalization is typically represented as [0,1].

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

where x is an original value, x' is the normalized value.

2.7. The Elbow Method

The Elbow Method is a well-known heuristic (a pragmatic, yet not necessarily optimal, approach) for streamlining an ideal number of clusters (K) when utilizing the K-means clustering algorithm. As we went over, using K-means, you were expected to know the number of clusters (K) in advance. Because K-means belongs to unsupervised learning algorithms, no preliminarily labeled solution exists that determines the correct number of clusters. Elbow Method is a visual tool that helps make such a choice. The basic concept is to observe the transformation of the Within-Cluster Sum of Squares (WCSS), also referred to as inertia, as the number of clusters (K) is varied. WCSS (Within-Cluster Sum of Squares): This is an evaluation that pertains to the sum of squared progressions between every data-point and the centroid within the group that the data-point belongs to. A smaller WCSS implies that the data points in each cluster are near their respective cluster centers; hence, the clusters are tighter and more cohesive. Increase in WCSS implies that data are more spread out in their respective clusters.

Naturally, as you increase the number of clusters (K), the WCSS will generally decrease.

1. If K = 1 (all data points in one cluster), the WCSS will be very high.
2. If K = number of data points (each data point is its own cluster), the WCSS will be 0 (as each point is its own centroid, distance is zero).

The "elbow" in the graph represents a point of diminishing returns. This is where adding more clusters no longer significantly reduces the WCSS.

3. DISCUSSION

3.1. Principal Findings

This study successfully demonstrated the application of K-means clustering algorithm to classify Thai Buddhist monks into distinct physical activity profiles based on wearable device data comprising step count, heart rate, and energy expenditure measurements. The clustering analysis revealed meaningful differentiation within the monastic population, providing quantitative evidence for heterogeneous activity patterns that may correlate with varying NCD risk profiles. These findings represent a novel application of unsupervised machine learning techniques to understand health behaviors within culturally specific religious communities.

3.2. Physical Activity Patterns and Health Implications

The clustering results demonstrate significant variation in physical activity levels among participating monks, with step counts ranging from 700 to 18,650 daily steps and energy expenditure varying from 1,623 to 3,758 kilocalories. These findings align with previous research documenting diverse activity levels within monastic populations, where traditional duties such as alms rounds and temple maintenance provide varying degrees of physical exercise (Tudor-Locke et al., 2011, Hall et al., 2020). The observed heterogeneity supports the need for individualized health interventions rather than uniform approaches to NCD prevention within monastic communities.

The observed step count data revealed significant variation within the monastic population, with several participants achieving step counts well below recommended guidelines for cardiovascular health benefits. Recent meta-analyses demonstrate that health benefits begin to accrue at relatively modest step counts, with significant mortality risk reduction observed at 3,900 steps per day and cardiovascular benefits appearing at 2,300 steps daily (Banach et al., 2023, Saint-Maurice et al., 2020). However, optimal benefits for adults under 60 years occur between 8,000-10,000 steps daily, while those over 60 show maximum benefit at 6,000-8,000 steps (Paluch et al., 2022). In our study, 39% of participants (11 of 28 monks) recorded fewer than 5,000 daily steps, indicating sedentary behavior patterns that may significantly increase NCD risk.

The clustering analysis identified distinct activity phenotypes that align with previous research on physical activity patterns in religious communities. Monks classified in lower-activity clusters demonstrated step counts averaging 1,079-3,763 steps daily, substantially below recommended thresholds for cardiovascular protection. Conversely, higher-activity clusters showed step counts ranging from 9,381-12,664 steps daily, approaching or exceeding guideline recommendations. These findings support the hypothesis that monastic communities contain heterogeneous activity profiles requiring individualized intervention approaches.

3.3. Heart Rate and Cardiovascular Fitness Implications

Heart rate monitoring in our study revealed average values ranging from 50 to 87 beats per minute across participants, with cluster centroids ranging from 62 to 77 bpm. These values fall within the normal resting heart rate range of 60-100 bpm for healthy adults, though several participants demonstrated rates at the lower end of this spectrum (Nes et al., 2013, Reimers et al., 2018). Research indicates that most healthy, relaxed adults maintain resting heart rates below 90 bpm, with lower rates often indicating superior cardiovascular fitness (Kraus et al., 2019).

The clustering analysis revealed interesting patterns in heart rate distribution across activity groups. Higher-activity clusters demonstrated average heart rates of 71-77 bpm, while lower-activity groups showed similar ranges (62-76 bpm), suggesting that resting heart rate alone may not distinguish activity levels as effectively as step count and energy expenditure measures. This is contrary to the expectation that the more active people would show minimal resting heart rates, which could be attributed to the short duration of the monitoring or personal physiological differences among the monastic population.

There is a connection between the health of the cardiovascular system and meditation practices in monastic communities, and this should be considered by considering the Buddhist tradition of mindfulness and contemplative practices. It has been shown that meditation may positively influence heart rate variability (HRV), and regular meditation has the potential to reduce blood pressure and positively influence the status of the entire cardiovascular structure. The analysis of Buddhist meditation practice reveals that autonomic nervous system activation may be increased as a result of regular practice and does not cause any cardiovascular load, resulting in reduced heart rate and increased HRV. This indicates that the heart rate levels found in our monastic population can reflect a healthy cardiovascular phenomenon due to long-term meditative training that would counterbalance the adverse effects of physically sedentary lives (Pascoe et al., 2017).

3.4. Energy Expenditure and Metabolic Implications

Energy consumption data revealed substantial variation across participants, ranging from 1,623 to 3,758 kilocalories daily, with cluster centroids varying from 1,771 to 2,988 kcal. These findings align with research demonstrating that energy expenditure represents a critical component of weight management and NCD prevention strategies. The clustering analysis identified distinct metabolic profiles within the monastic population, with implications for tailored dietary and activity interventions.

Research on daily energy expenditure demonstrates that total expenditure reflects critical metabolic health parameters, with typical ranges varying significantly based on age, body composition, and activity levels (Pontzer et al., 2021, Westerterp, 2013). For adults, sedentary lifestyles typically correspond to physical activity levels (PAL) of 1.53, while moderately active lifestyles achieve PAL values of 1.76 (FAO/WHO/UNU, 1985). Physical activity energy expenditure can range from 15% of total energy expenditure in sedentary individuals to 50% in physically active populations (Ravussin et al., 1986).

In the context of our monastic population, the observed energy expenditure patterns suggest diverse metabolic phenotypes that may reflect varying degrees of physical activity integration into daily routines. The lower-energy clusters (1,771-2,173 kcal daily) may represent monks with predominantly sedentary lifestyles, while higher-energy groups (2,747-2,988 kcal daily) likely engage in more physically demanding temple duties or additional movement activities. These findings support the need for individualized metabolic assessments and targeted interventions based on cluster membership rather than population-wide approaches.

3.5. Clustering Algorithm Performance and Optimization

The application of K-means clustering to this dataset revealed methodological considerations important for future research applications. The Elbow Method analysis produced unexpected results, with WCSS values of 47,253.83 for K=2, 323,862.70 for K=3, and 30,042.76 for K=4. The anomalously high WCSS value for K=3 contradicts the expected monotonic decrease typically observed with increasing cluster numbers, suggesting potential algorithmic initialization issues or data structure complexities that warrant further investigation.

K-means clustering algorithms are known to be sensitive to initial centroid placement, which can significantly affect WCSS values and cluster formation, particularly in smaller datasets (Arthur & Vassilvitskii, 2007, Jain, 2010). The Elbow Method may not always provide clear inflection points, especially in real-world datasets where optimal cluster numbers are ambiguous (Tibshirani et al., 2001). The notion of an "elbow" is not well-defined and is known to be unreliable in many clustering applications (Ketchen & Shook, 1996).

The observed WCSS anomaly in our study likely reflects methodological challenges common in small-sample clustering applications. With only 28 participants, the algorithm may experience initialization sensitivity, leading to suboptimal cluster assignments for certain K values. Future research should incorporate multiple algorithms runs with different initialization strategies and consider alternative cluster validation metrics such as silhouette analysis or gap statistics to complement Elbow Method findings.

3.6. Clinical And Public Health Implications

The clustering results provide actionable insights for developing evidence-based health interventions within monastic communities. The identification of distinct activity phenotypes enables targeted approaches that respect religious constraints while promoting cardiovascular health. Low-activity clusters (characterized by <5,000 daily steps and energy expenditure <2,200 kcal) represent priority groups for gentle activity enhancement interventions, such as structured walking meditation periods or temple maintenance modifications to increase movement requirements.

Buddhist walking meditation has demonstrated superior effectiveness compared to traditional walking programs in improving cardiometabolic health, with benefits for glycemic control, blood pressure reduction, and cardiovascular function (Prakhinkit et al., 2014, Tanaka & Suksom, 2024). Research specifically conducted with Thai populations shows that Buddhist walking meditation incorporating mindfulness with foot stepping produces significant improvements in HbA1c, blood pressure, and arterial stiffness compared to conventional walking exercise (Gainey et al., 2016). Thai Buddhist traditions emphasize walking meditation as an integral practice for developing mindfulness and maintaining physical activity within religious frameworks (Siripanya et al., 2023).

These findings suggest that existing monastic practices could be enhanced rather than replaced to achieve optimal health outcomes. For higher-activity clusters already demonstrating adequate physical activity levels (>8,000 daily steps), interventions could focus on optimizing dietary patterns and maintaining current activity levels while monitoring for potential overexertion or injury risk.

4. LIMITATIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

A few limitations warrant consideration in interpreting these findings. The relatively small sample size (n=28) limits statistical power and generalizability to broader monastic populations.

The one-month observation period provides only a snapshot of activity patterns and may not capture seasonal variations or longer-term behavioral trends. The unexpected WCSS anomaly in the Elbow Method analysis highlights the need for more robust cluster validation techniques in future studies.

Future research should incorporate larger, multi-temple samples with extended monitoring periods to capture comprehensive activity patterns. Integration of additional health biomarkers, including cardiovascular risk factors, metabolic parameters, and inflammatory markers, would provide more comprehensive health assessments. Longitudinal studies tracking intervention effectiveness and long-term health outcomes would strengthen the evidence base for technology-assisted health monitoring in religious communities.

The development of culturally sensitive intervention protocols incorporating traditional Buddhist practices such as walking meditation, mindful movement, and contemplative physical activities represents a promising research direction. Collaboration with religious leadership and community healthcare providers could facilitate implementation of sustainable, evidence-based health promotion programs that respect monastic traditions while addressing contemporary NCD challenges.

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Table 1: Meaning Each Data Features.

Features	Meaning
Steps	step count data
Average Heart Rate	Beats per minute (bpm)
Energy Consumption	Kilocalories (kcal)

Table 2: The Data Classification When K=2.

ID	Steps	Average Heart Rate	Energy Consumption	Group
1	9016	84	2883	2
2	700	65	1623	1
3	7682	76	3343	2
4	8006	50	2666	2
5	3055	69	2018	1
6	1339	81	1816	1
7	7467	78	2090	2
8	7132	83	2094	2
9	8155	76	3758	2
10	1198	70	1873	1
11	4673	85	2561	1
12	8886	59	2858	2
13	3264	85	2368	1
14	7441	77	2268	2
15	18650	58	2812	2
16	11638	71	3103	2
17	3762	83	2556	1
18	10205	56	2801	2
19	3786	87	1864	1
20	10161	63	3236	2
21	4675	64	2225	1
22	4409	79	2165	1
23	4990	73	1762	1
24	5558	84	2550	1
25	5718	61	1926	1
26	7947	53	2256	2
27	8948	77	2282	2
28	5556	72	3120	1

Table 3: The Data Classification When K=3.

ID	Steps	Average Heart Rate	Energy Consumption	Group
1	9016	84	2883	2
2	700	65	1623	1
3	7682	76	3343	2
4	8006	50	2666	2
5	3055	69	2018	1
6	1339	81	1816	1
7	7467	78	2090	2
8	7132	83	2094	3
9	8155	76	3758	2
10	1198	70	1873	1
11	4673	85	2561	3
12	8886	59	2858	2
13	3264	85	2368	1
14	7441	77	2268	2
15	18650	58	2812	2
16	11638	71	3103	2
17	3762	83	2556	3
18	10205	56	2801	2
19	3786	87	1864	1
20	10161	63	3236	2
21	4675	64	2225	3
22	4409	79	2165	3
23	4990	73	1762	3
24	5558	84	2550	3
25	5718	61	1926	3
26	7947	53	2256	2
27	8948	77	2282	2
28	5556	72	3120	3

Table 4: The Data Classification When K=4.

ID	Steps	Average Heart Rate	Energy Consumption	Group
1	9016	84	2883	4
2	700	65	1623	1
3	7682	76	3343	4
4	8006	50	2666	4
5	3055	69	2018	3
6	1339	81	1816	1
7	7467	78	2090	4
8	7132	83	2094	4
9	8155	76	3758	4
10	1198	70	1873	1
11	4673	85	2561	3
12	8886	59	2858	4
13	3264	85	2368	3
14	7441	77	2268	4
15	18650	58	2812	2
16	11638	71	3103	2
17	3762	83	2556	3
18	10205	56	2801	2
19	3786	87	1864	3
20	10161	63	3236	2
21	4675	64	2225	3
22	4409	79	2165	3
23	4990	73	1762	3
24	5558	84	2550	3
25	5718	61	1926	3
26	7947	53	2256	4
27	8948	77	2282	4
28	5556	72	3120	3

Table 5: The Centroids of The Data Classification When K=2.

Centroids	Steps	Average Heart Rate	Energy Consumption
1	3763.07	75.57	2173.35
2	9381.00	68.64	2746.42

Table 6: The Centroids of The Data Classification When K=3.

Centroids	Steps	Average Heart Rate	Energy Consumption
1	2223.66	76.16	1927.00
2	9554.00	67.53	2796.61
3	5163.66	76.00	2328.77

Table 7: The Centroids of The Data Classification When K=4.

Centroids	Steps	Average Heart Rate	Energy Consumption
1	1079.00	72.00	1770.67
2	12663.50	62.00	2988.00
3	4495.09	76.55	2283.18
4	8068.00	71.30	2649.80

Table 8: The Within-Cluster Sum of Squares (WCSS) When K=2, 3 And 4.

K	WCSS
2	47,253.83
3	323,862.70
4	30,042.76

Table 9: The Monk's Datasets from November 20, 2024 to December, 20 2024.

ID	Steps	Average Heart Rate	Energy Consumption
1	9016	84	2883
2	700	65	1623
3	7682	76	3343
4	8006	50	2666
5	3055	69	2018

6	1339	81	1816
7	7467	78	2090
8	7132	83	2094
9	8155	76	3758
10	1198	70	1873
11	4673	85	2561
12	8886	59	2858
13	3264	85	2368
14	7441	77	2268
15	18650	58	2812
16	11638	71	3103
17	3762	83	2556
18	10205	56	2801
19	3786	87	1864
20	10161	63	3236
21	4675	64	2225
22	4409	79	2165
23	4990	73	1762
24	5558	84	2550
25	5718	61	1926
26	7947	53	2256
27	8948	77	2282
28	5556	72	3120