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A holistic energy expenditure tracking framework: fuelling wellness with holistic energy tracking

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ABSTRACT

Effective public health management is essential for a country's social and economic development. A strong public health system reduces the strain on healthcare infrastructure by encouraging preventive measures. With significant lifestyle changes in recent years, monitoring both energy intake (EI) (diet) and energy expenditure (EE) (physical activity (PA)) has become crucial to maintaining public health. Existing methods primarily track exercise-related EE using self-assessment tools or wearable devices, often neglecting occupation-related activities. This results in an underestimation of total EE. To address this limitation, we propose the holistic energy expenditure tracking (HEET) framework, which aims to provide a comprehensive estimate of daily EE by including occupational activities. The framework was applied to data from a dietitian who collected 180 data points from working professionals across three different occupations. Exploratory data analysis revealed a 41% increase in metabolic equivalent of task (MET) values and a 27% rise in calorific values when occupational EE was considered. A categorical scoring system was developed based on the new calorific values, enabling dietitians to offer more personalized dietary recommendations. The study highlights the need for a standardized framework that captures all daily activities, offering a more accurate and holistic approach to public health monitoring and intervention.

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1. INTRODUCTION

The growing use of automated technology has led to lower levels of physical activity (PA) on a daily basis compared to previous generations, which has had a negative effect on public health. A lack of PA is a cause of obesity, which is a major risk factor for respiratory, circulatory, musculoskeletal, and metabolic diseases [1]. By issuing timely PA recommendations, the World Health Organization (WHO) wants to lead and maintain a healthy lifestyle because this rise in load has put more pressure on a healthcare system that was already overburdened [2]. Adherence to these guidelines leads to improved health outcomes in both children and adults by enhancing physical fitness, cardiometabolic and bone health, cognitive function, sleep quality, and mental well-being [3].

Obesity is mainly influenced by genetic factors, energy intake (EI), and energy expenditure (EE), where genetics pose a limited risk. Conversely, discrepancies between energy consumption and expenditure, which are influenced by physical inactivity, environment, occupation, supplements, and medications, are major factors in the development of obesity [4]. EE is the main focus in this research work. EE refers to the energy the body uses to support essential functions like breathing, digestion, blood circulation, and PA [5]. PA is linked to EE resulting from activities other than digestion and includes all the bodily movements that occur on a daily basis, such as sleeping. In order to measure an individual's level of PA, it is necessary to measure it on a daily basis and record it, either manually or automatically [6]. International physical activity questionnaire (IPAQ) is a manual questionnaire method to log the PA and identify the metabolic equivalent of task (MET) for a week [7]. The automatic method of measuring PA is by mobile APPs [8], [9], web apps [10] or wearable devices like fitness bands [11], [12].

In spite of the fact that over-informing or under-informing leads to mistakes when using manual suggestions, the method for PA tracking by IPAQ has shown remarkable reliability if the testing population has been adapted or some modifications have been made to measure EE [13], [14]. The questionnaire-based methods assess PA through three intensity levels, which include vigorous, moderate, and low-intensity activities that people perform during their work, home, and free time activities. The use of wearable devices and mobile technologies enables continuous monitoring of health data, yet people still depend on questionnaire-based frameworks because they face challenges with device accessibility and understanding technology. The existing methods for assessing weekly PA and calorie expenditure face limitations because they do not consider physical activities that workers perform in their specific jobs [15]. The development of personalized PA recommendations becomes necessary because occupational physical activity (OPA) shows distinct variations across different job roles while OPA serves as a major contributor to daily EE [16], [17]. The proposed work will create a complete system that enables accurate total energy expenditure (TEE) calculation through the integration of all movement activities.

2. LITERATURE REVIEW

The study proposed by Prince *et al.* [17] recognized the role of weight status in workers and put forward a solution adhering to U.S. legal considerations. The study also emphasized the subjective nature of the current physical load evaluations. Occupational movements were estimated with high accuracy by AI-based inertial measurement unit systems, although workplace interventions with accelerometers and counseling did not demonstrate significant improvements in PA, productivity, or health outcomes compared to controls [18].

Canadian researchers demonstrated promising outcomes through a health monitoring system, showing substantial improvement in blood pressure, sleep quality, emotional resilience, and reduced fatigue over a 12-month period [19]. The one-year walking exercise for sedentary males showed encouraging cardiovascular results, reflected in decreased heart rate and lactate," indicating improved endurance and delays in fatigue [20]. Other studies exhibited the impact of digitization on health in the workplace. Live workshops and tracking devices raised hope; the pandemic, however, called for more scalable web-based models [21].

A 21-week "10,000 Steps®" program in an academic setting enjoyed strong initial participation but with minimal behavior change in the long run. The findings suggested that future research should take into account individual baseline activity and motivators [22]. A comparison of movement activity levels between brewery workers and office staff using two kinds of activity trackers revealed major differences in EE, heart rate, and step count, emphasizing the importance of choosing a device and observing the environment of a person [23].

Meanwhile, email-based interventions among healthcare workers showed improvements in dietary habits and PA with lasting effects [24]. Similarly, the "Activate your health" program demonstrated that integrated workplace wellness initiatives focusing on stress management, nutrition, and PA positively benefited both employees and organizations [25]. The major shortcomings identified by the review are that the present PA tracking systems underestimate EE by not considering occupation, sleep, and household activities, and they fail to personalize EE by not considering individual differences. These shortcomings form the rationale for the proposed holistic energy expenditure tracking (HEET) system.

3. BIOLOGY OF ENERGY EXPENDITURE

This section will cover the biological components of EE, where TEE is made up of PA EE, the thermic effect of food (TEF) for digestion energy expenditure (DEE) and resting energy expenditure (REE) that supports essential bodily functions [26], [27]. The relationship between these components can be expressed as (1).

$$T_{EE} = R_{EE} + D_{EE} + PA_{EE} \tag{1}$$

Where, T_{EE} represents TEE, R_{EE} represents REE, D_{EE} represents DEE, and PA_{EE} represents PA EE.

REE is the energy expended by the vital organs for their basic functions. It is strongly associated with the basal metabolic rate. Diet-induced EE (DEE/TEF) is the EE that occurs after meals due to digestion. REE accounts for 60% of TEE, DEE accounts for 10%, and PA EE differs from person to person based on their lifestyle [28], [29]. Based on these proportions, TEE can be expressed as (2).

$$T_{EE} = 0.6 \times T_{EE} + 0.1 \times T_{EE} + PA_{EE} \quad (2)$$

By rearranging this expression gives (3).

$$PA_{EE} = 0.3 \times T_{EE} \quad (3)$$

In (2) can be verified by the study done in [28]. The PA EE component can also be derived as (4).

$$PA_{EE} = 0.9 \times T_{EE} - R_{EE} \quad (4)$$

Substituting the REE contribution into this expression results in (5).

$$PA_{EE} = 0.3 \times T_{EE} - 0.6 \times T_{EE} \quad (5)$$

Thus, it leads to (3).

While the equation is valid, accurately estimating PA_{EE} requires consideration of multiple contributing factors. PA EE is the total energy expended in 24 hours through exercise, work-related activities, leisure activities (which include household chores to passive behavior), and commuting, while exercise is the intentional effort to increase heart rate. Thus, PA EE can be represented as (6).

$$PA_{EE} = \sum_{n=1}^{7} \mathrm{EPA} + \mathrm{LPA} + \mathrm{TPA} + \sum_{m=1}^{6} OPA \quad (6)$$

Where EPA represents exercise-specific activity, OPA represents occupational of PA, LPA represents leisure PA, and TPA represents transportational PA. The occupational and leisure components of PA EE are defined as (7) and (8), respectively.

$$\mathrm{OPA} = \sum_{m=1}^{6} \mathrm{ST} + \mathrm{SI} + \mathrm{HL} \quad (7)$$

$$\mathrm{LPA} = \sum_{n=1}^{7} \mathrm{HW} + \mathrm{SI} \quad (8)$$

Where ST represents standing PA, SI represents sitting PA, HL represents heavy work PA, and HW represents household PA; each component is expressed in METs per week.

4. PROPOSED METHOD

Figure 1 presents a three-layer HEET framework comprising data, knowledge, and decision layers for collecting, preprocessing, analyzing, and interpreting PA data from wearables, apps, and questionnaires. The framework uses machine learning to perform classification and prediction tasks. Which help create personalized health recommendations that take into account a person's occupation.

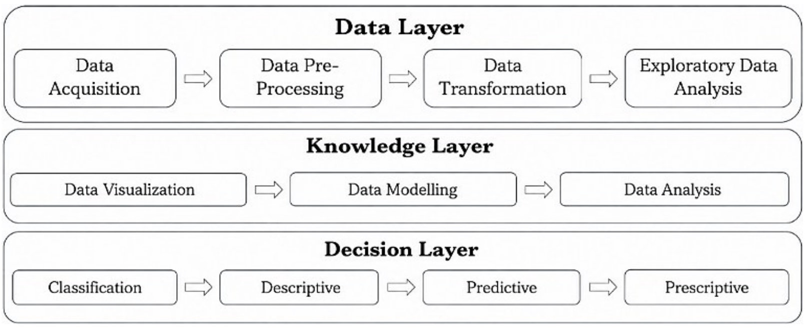

Figure 1. Holistic EE tracking framework

The study used IPAQ standards to classify occupational activities into three categories, which included sitting and standing, and heavy labor, while assigning MET values to estimate weekly EE. The study involved 180 professionals from IT, teaching, and shop-floor occupations representing different OPA levels. The expert evaluation process, together with the preprocessing validation procedure, confirmed the content validity and established acceptable reliability standards.

5. RESULTS AND DISCUSSION

The trend of PA from the experiment shows that it is necessary to include OPA and other smaller activities for MET/week calculations. The graphical representation of the results is depicted in the trends below. Figure 2 shows the difference between MET values for specific physical activities and total MET for all activities.

MET/week from PA alone, while the red line shows total OPA MET/week, that includes daily tasks, occupational activity, sleep, transportation, and leisure activities. The PA without OPA and with OPA comparison showed 41% increase in MET and 27% increase in the number of calories. The observed increase in percentage represents a substantial effect in magnitude, indicating a strong contribution of OPA to the overall EE. The differences are practically significant, particularly for occupations where work-related activity constitutes a major portion of daily movement.

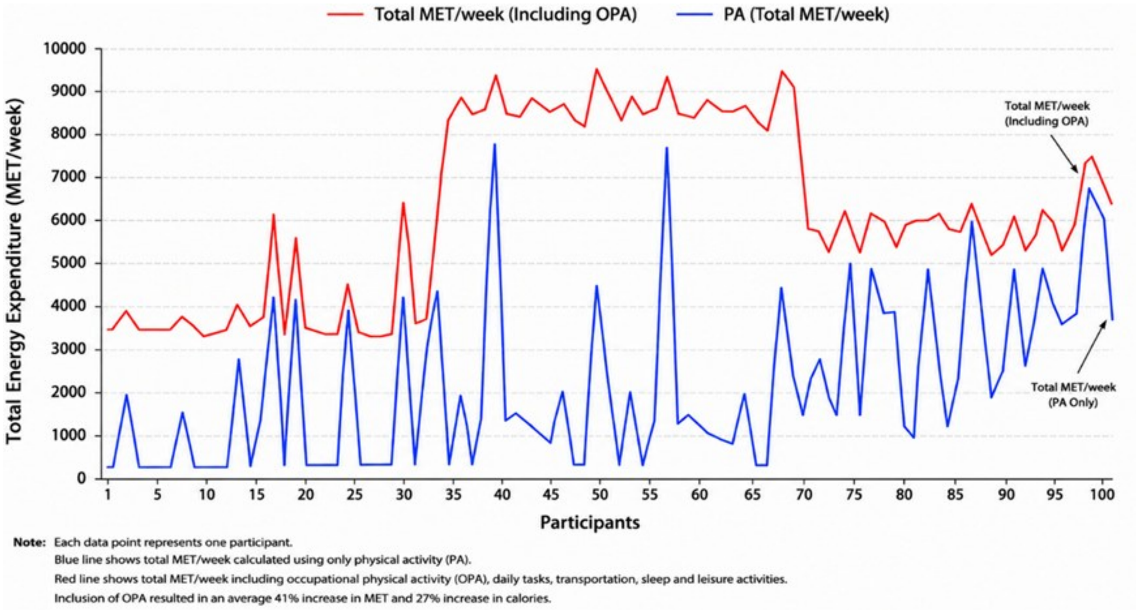

Figure 2. Comparison of PA levels including and excluding OPA

5.1. Categorical score

In the IPAQ, categorical scores are based on the specific activities. An individual performs daily or weekly. Building on this baseline, the HIPAQ MET total score is classified into three categories according to PA intensity. Category 3 represents high PA.

5.1.1. Category 3 (high)

Individuals at this level are considered highly active, regularly exceeding public health guidelines for PA and maintaining a lifestyle that supports overall well-being. Figure 3 illustrates the weekly MET trends observed among IT professionals. The results indicate consistently lower MET values, reflecting a predominantly sedentary work pattern characterized by prolonged sitting durations. Figure 4 presents the MET/week trends for teaching professionals. Compared to IT professionals, teachers demonstrate moderate to high PA levels due to a combination of standing activities during lectures and laboratory sessions, along with sedentary academic tasks such as research and grading. Here, individuals achieve more than 6,000 MET/minutes per week or burn more than 3,000 calories, indicating that teaching professionals often fall within the high PA category.

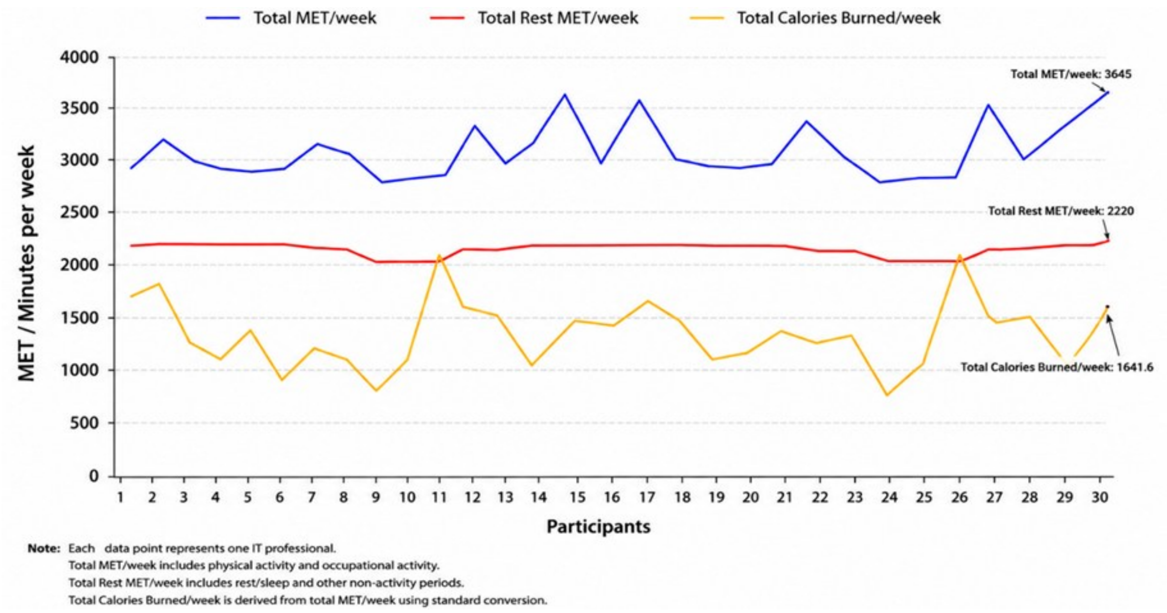

Figure 3. Trend of IT profession vs. MET/week

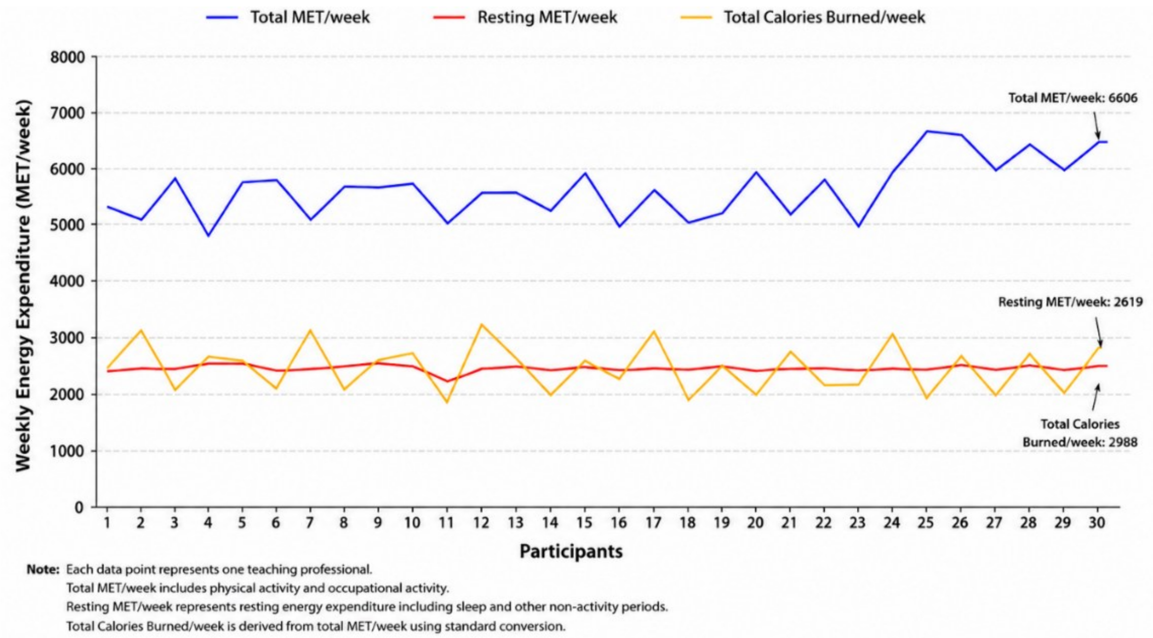

Figure 4. Trend of teaching profession vs. MET/week

5.1.2. Category 2 (medium)

To be considered 'sufficiently active,' an individual must engage in vigorous PA that aligns with the baseline criteria for minimal activity. This level is referred to as the moderate activity category. In this category, an individual’s MET/minutes per week range from 3,000 to 6,000, or the calories burned are between 1,800 and 3,000 per week. Figure 5 depicts the MET/week trends for shop-floor workers. The significantly higher MET values highlight the physically demanding nature of shop-floor occupations, which involve prolonged standing, manual handling, and operation of heavy machinery.

5.1.3. Category 1 (low)

Activities that don’t meet the criteria for Categories 2 or 3 are deliberated ‘insufficiently active’ and classified as low-intensity activity. In this category, an individual’s MET/minutes per week is less than 3,000, or the calories burned are fewer than 1800 per week. Applying the MET Total equation for every profession, the categorical score is assigned. The summary of profession-based categorical scores is shown in Table 1.

From Table 1, it can be observed that IT professionals are mostly sedentary with low MET values, teachers are moderately active due to mixed tasks, and shop-floor workers are highly active due to physically demanding and standing-intensive tasks. To further contextualize the findings, a comparison of the proposed HEET framework with conventional PA assessment approaches, along with the key findings from existing literature, is presented in Table 2. As evident from Table 2, the traditional methods of IPAQ underestimate OPA and are primarily concerned with leisure and exercise activities. The HEET framework takes into account occupation-specific physical activities, is a more realistic approach to EE, and can be used as a decision-support tool for health professionals to offer personalized interventions.

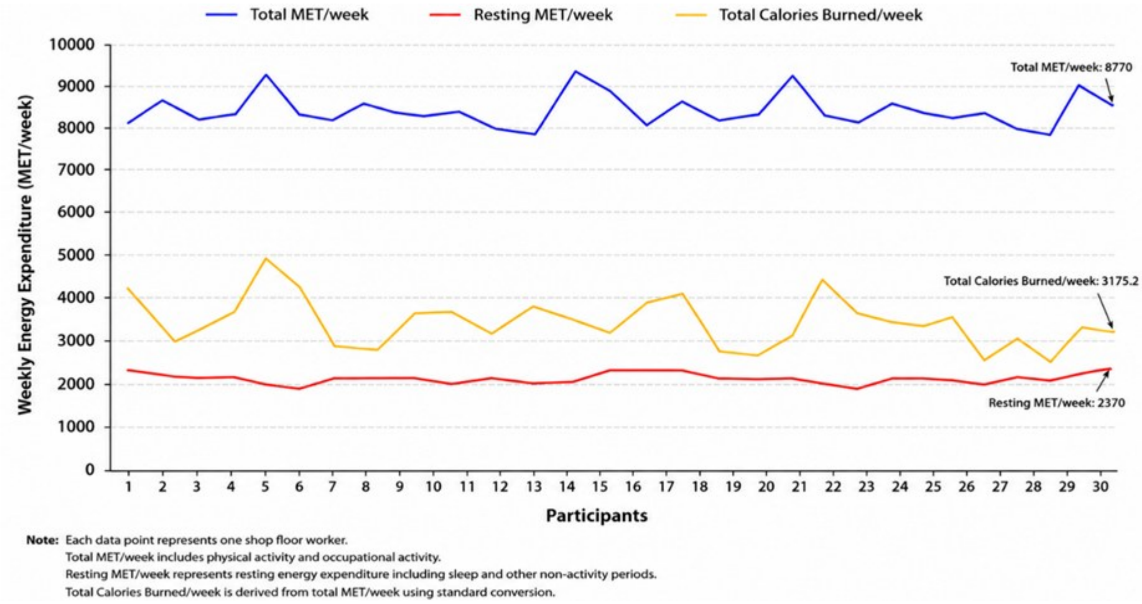

Figure 5. Trend of shop floor workers vs. MET/week

Table 1. Profession-based categorical scores

Occupation	Total MET	Total calories burned	Categorical score
IT	2,933	1,547	Low
Teachers	5,475	2,514	Moderate
Shop-floor	8,385	3,426	High

Table 2. Comparison of HEET framework with existing PA assessment approaches

Aspect	Conventional IPAQ/ existing methods	Findings from literature	Proposed HEET framework
Primary focus	Leisure-time and exercise-related PA	Emphasis on exercise and step count [7], [11], [12]	Holistic 24-hour EE
OPA	Limited or aggregated	Often underrepresented or device-dependent [15], [17]	Explicitly modelled and quantified
Activity coverage	Exercise, leisure	Partial inclusion of work or transport [23]	Occupational, leisure, household, transport, and sleep
EE estimation	Frequently underestimated	Underreporting noted in occupational studies [15], [17]	47% increase in MET and 27% increase in calories
Personalization	Minimal	Often population-level analysis	Profession-based and individualized
Data collection method	Self-reported or wearable-based	Device accuracy varies by context [11], [28]	Modified questionnaire with scope for wearable integration
Practical applicability	General health monitoring	Limited clinical translation	Clinical and occupational decision support

5.2. Clustering analysis

The trend analysis indicates that sedentary desk-based jobs have low to moderate activity scores, while physically demanding jobs with heavy labor have high activity scores. This trend was further explored using K-means clustering, which was preferred due to its capability to discover natural groupings in the normalized MET and caloric values by minimizing the within-cluster variance. Figure 6 illustrates the clustering of professions based on resting MET and occupational MET values, while Figure 7 presents the clustering results derived from total MET and total caloric expenditure.

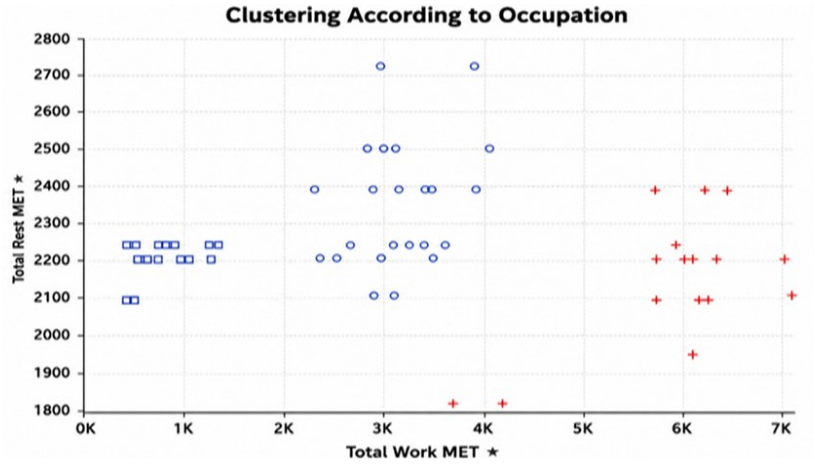

Figure 6. Cluster analysis of resting MET and occupational MET

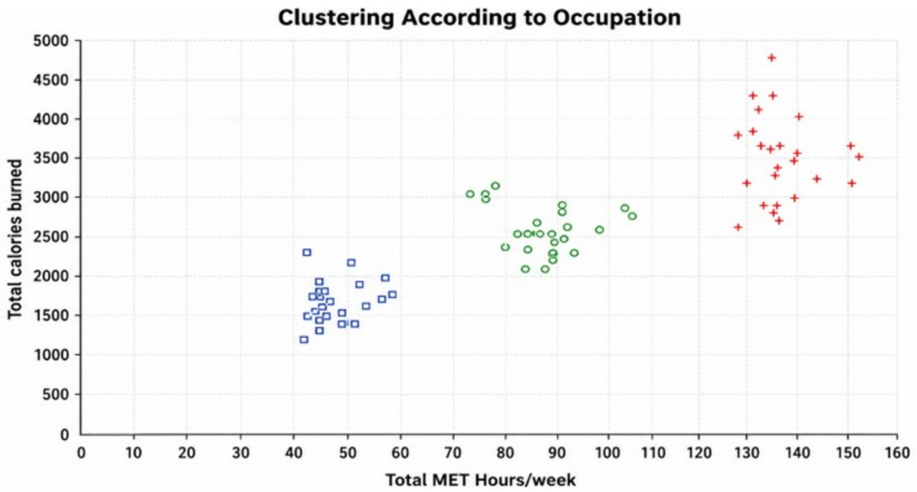

Figure 7. Cluster analysis of caloric expenditure and total MET

5.3. Logistic regression analysis

Logistic regression analysis was conducted on the data collected from IT professionals, teachers, and shop floor workers with occupation, age, and gender as predictors of weekly expenditure of calories per MET. The results indicate higher expenditure in physically demanding occupations and lower expenditure in sedentary IT jobs, suggesting the need for increased leisure-time PA among IT professionals. Additional analysis covering precision, standard error, accuracy, and coefficient values is presented in Table 3 and visualized graphically in Figure 8.

Table 3. Performance analysis

Occupation	Precision	Recall	F1-score	Accuracy	Coeff.	Std. Err.
Female	0.86	0.6	0.71	0.8	0.0179	0.0119
Male	0.68	0.93	0.79	0.76	0.0155	0.007
IT	0.85	0.78	0.82	0.93	0.0181	0.0205
Teachers	0.87	0.8	0.85	0.93	0.0717	0.0205
Workers	0.86	0.87	0.79	0.97	0.1123	0.0359

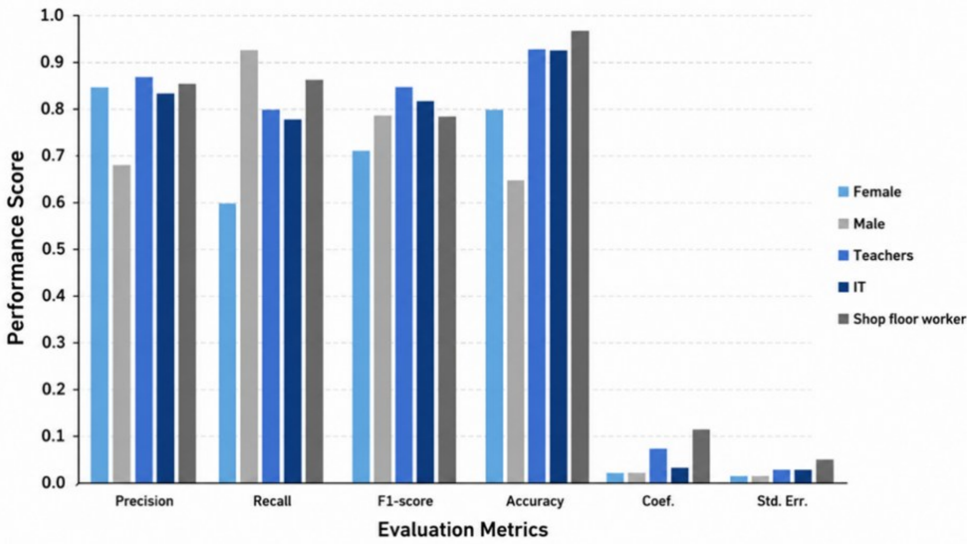

Figure 8. Performance analysis using OLS regression

6. CONCLUSION

This study highlights the significance of including OPA in estimating TEE. The inclusion of OPA led to a 47% increase in MET and a 27% rise in caloric output, highlighting its critical role in daily energy calculations. The integration of occupational, leisure, and rest-related activities in the HEET framework provides a comprehensive 24-hour energy profile and enables profession-specific categorization, achieving an accuracy of 89.354% through clustering analysis. The outputs support personalized dietary and PA recommendations in clinical and occupational health settings. However, the study is limited by its reliance on self-reported data, a modest sample size drawn from selected occupations, and its cross-sectional design, which restricts generalizability and longitudinal inference. Future work will focus on multi-center validation with larger and more diverse populations with the integration of wearable and multimodal data to reduce reporting bias, with longitudinal and intervention-based studies to evaluate the effectiveness of HEET-guided recommendations on health outcomes.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Leena Manojkumar Panchal	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓			
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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [GK], upon reasonable request.

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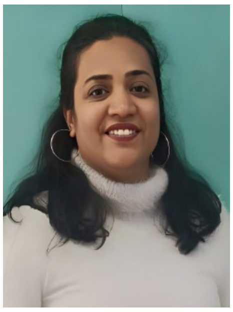
BIOGRAPHIES OF AUTHORS



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