Regular Article

Title

Development of preliminary validation of the hitoe system: A smartphone application and wearable device to monitor physical activity levels for cardiac rehabilitation

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Number of tables

4

Number of figures

21

Running title

Smartphone application for cardiac rehabilitation

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Abstract

This study aimed to develop and conduct a preliminary validation of the hitoe system, a novel smartphone application and wearable device designed to tailor exercise loads to individual exercise tolerance, with the goal of supporting personalized cardiac rehabilitation. A preliminary validation study was conducted involving 28 healthy adults (26 males, mean age 42.3 ± 11.2 years). Participants used the hitoe system to perform 13 activities, including sedentary tasks, household chores, walking, and cycle ergometer. Exercise intensity was measured in metabolic equivalents (METs) and compared with values obtained using a standard gas analyzer. Statistical analyses, including intraclass correlation coefficients (ICCs) and Bland-Altman analyses, were applied to assess the accuracy and reliability of the device. The hitoe system demonstrated satisfactory agreement with gas analyzer measurements across most activities. Bland-Altman analyses revealed that the majority of data points fell within ±2.0 METs, indicating limits of agreement. High ICCs were observed for activities such as cycle ergometer (ICC = 0.797), vacuuming the floor (ICC = 0.693), and lifting a 5 kg weight (ICC = 0.614), reflecting strong reliability. In contrast, sedentary activities such as sitting (ICC = 0.033) and desk work (ICC = 0.144) showed lower ICCs, although the absolute differences between the two methods remained within approximately 1 MET. The preliminary findings suggest that the hitoe system may be useful for assessing physical activity intensity, particularly during higher-intensity activities. The system may offer a promising tool for real-time feedback and tailored exercise prescription in cardiac rehabilitation. Further studies involving patients with cardiovascular diseases are warranted to validate these preliminary results and enhance the system's precision in clinical settings.

Keywords

Cardiovascular Disease; Exercise Therapy; Mobile Application; Telerehabilitation

日本語情報

タイトル

hitoe システムの妥当性の検証：心臓リハビリテーションにおける身体活動レベルをモニタリングするスマートフォンアプリケーションおよびウェアラブルデバイス

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抄録

目的

本研究では、個別の運動耐容能に応じて運動負荷を調整し、個別化された心臓リハビリテーションを支援することを目的に開発された新規スマートフォンアプリおよびウェアラブルデバイス「hitoe システム」の開発と予備的な妥当性の検証を行った。

方法

本予備的検証研究では、健常成人 28 名（男性 26 名、平均年齢 42.3±11.2 歳）を対象に検証を実施した。参加者は、座位作業、家事動作、歩行、自転車エルゴメータなど 13 種類の活動を hitoe システムを用いて実施し、活動強度（METs）は呼気ガス分析装置による測定値と比較された。機器の精度および信頼性を評価するため、ICC（級内相関係数）および Bland–Altman 解析を行った。

結果

hitoe システムによる測定値は多くの活動において呼気ガス分析装置と良好な一致を示した。Bland–Altman 解析では、大多数のデータ点が±2.0 METs の範囲内（limits of agreement）に収まっていた。特に、自転車エルゴメータ（ICC = 0.797）、床掃除（ICC = 0.693）、5 kg 物品の持ち上げ（ICC = 0.614）などの活動で高い ICC が示され、良好な信頼性が認められた。一方で、座位（ICC = 0.033）やデスクワーク

（ICC = 0.144）といった低強度活動では ICC が低値を示したが、2 手法間の差異は概ね±1 MET 以内であった。

結論

本予備的検証の結果、hitoe システムは特に高強度活動時における身体活動強度の評価に有用である可能性が示唆された。また、心臓リハビリテーションにおけるリアルタイムなフィードバックと個別化された運動処方の実現に向けた有望な手段となる可能性がある。今後は、心疾患患者を対象としたさらなる臨床研究を通じて、本システムの有効性および精度の検証が求められる。

Introduction

Cardiovascular diseases are increasing globally, affecting an estimated 26 million patients worldwide, making them the leading cause of death [1], [2]. Although treatments for cardiovascular diseases have evolved both in terms of pharmacological and non-pharmacological interventions, a high rate of post-discharge readmission remains [3], [4]. Cardiac rehabilitation is a comprehensive intervention that includes exercise therapy [5]. According to numerous previous studies, exercise therapy tailored to individual exercise tolerance in patients with cardiovascular diseases has been reported to effectively reduce readmission and mortality rates [6], [7], [8].

There is ample evidence regarding the effectiveness of cardiac rehabilitation; however, its implementation rate remains low in many countries. A previous study reported that when patients develop heart disease, only 33% of them undergo cardiac rehabilitation during hospitalization, and only 7% of patients participate in outpatient cardiac rehabilitation [9]. One of the reasons cited for this low implementation rate is the limited access to facilities offering cardiac rehabilitation [10]. Remote rehabilitation using smartphone applications and wearable devices has been considered a solution [10], [11]. However, to date, no device has been developed that adjusts the exercise intensity based on each patient's exercise tolerance in this remote rehabilitation approach.

We developed a smartphone application and wearable device (the hitoe system) that allows exercise intensity to be tailored to each patient’s exercise tolerance and provides feedback to the patient on whether they are achieving the set intensity and duration of exercise for cardiac rehabilitation. The present study aimed to develop the smartphone application and wearable device and conduct a preliminary validation of its accuracy in healthy adults prior to implementation in future studies and clinical practice involving patients with cardiovascular diseases.

Materials and Methods

Study setting and participants

We conducted a validation study to verify whether the developed smartphone application and wearable device could accurately measure the exercise intensity of the participants between April and December 2021. This study complied with the principles of the World Medical Association and subsequent amendments to the Declaration of Helsinki. The Yokohama City University’s Ethics Committee approved this study (approval number: B200400063). Participants in this study were healthy adults who met the following inclusion criteria: they were between 20 and 80 years of age at the time of enrollment, had no history of cardiovascular disease, and were not undergoing any treatment for cardiovascular conditions. Cardiovascular diseases were defined to include heart failure, ischemic heart disease, arrhythmias (such as atrial fibrillation or atrioventricular block), implantation of cardiac devices (e.g., pacemakers), valvular diseases, aortic dissection, aortic aneurysm, history of cardiovascular surgery, peripheral artery disease, and other related conditions. Exclusion criteria included the presence of physical or cognitive impairments that would interfere with study procedures. Additionally, individuals with a history of non-cardiovascular diseases such as diabetes or respiratory disorders were excluded if they had physician-imposed restrictions on daily activities or exercise, or if they experienced subjective symptoms such as fatigue or shortness of breath at rest or during activities relevant to the study, including walking and housework. Participants were voluntarily recruited from staff members of Yokohama City University and Nippon Telegraph and Telephone Corporation (NTT). Informed consent was obtained from all individual participants included in this study. Given that the device had not previously been tested in any population, this preliminary validation study was conducted involving healthy adult participants prior to its intended clinical application in cardiac rehabilitation.

Wearable device and smartphone application (the hitoe system)

The wearable device and smartphone application (the hitoe system) were as follows: (i) a belt-type physical activity measurement device worn on the chest, and (ii) a smartphone application that displays the measured physical activity (Fig. 1). The belt-type physical activity measurement device consisted of two main components: a band made of functional fiber material (hitoe®, Nippon Telegraph and Telephone Corporation [NTT] and Toray Industries, Inc. Japan) that allowed for continuous measurement of biometric data, such as cardiac potentials, simply by wearing it (Fig. 1A) and a transmitter that measured posture and physical activity when connected to hitoe® (Fig. 1B and 1C). The validity and reliability of heart rate (HR) measurement by these devices has been previously established [12]. This device incorporates a commercially available iNEMO 6-degree-of-freedom inertial measurement unit (LSM6DSL) for acceleration (ACC) measurement, from which ACC data are obtained [13]. The transmitter transferred the measurement results to a smartphone application via Bluetooth. In the smartphone application, the participants checked their step count, physical activity (metabolic equivalents: METs), and HR and received feedback on whether they had achieved their personalized activity goals (Fig. 1D). Medical staff can set personalized activity goals for participants, tailored to their exercise tolerance measured during cardiopulmonary exercise testing, through a specialized website. Additionally, medical staff or others who managed application users checked the participants' data and the status of their goal achievement on the same specialized website. We confirmed that no itching or redness was observed during a 48-hour continuous wearing test of the device.

Validation procedure

In this validation study, the participants wore the belt-type physical activity measurement device on their chest and a portable gas analyzer (mobile aeromonitor, AE-100i, Minato Medical Science Co., Ltd. Japan) and performed specific activities that were set in advance. The specific activities (with 13 items) were as follows: (1) quiet supine position (reference), (2) supine position, (3) sitting, (4) desk work, (5) laundry, (6) washing dishes, (7) lifting a 5 kg weight, (8) vacuuming the floor, (9) slow walking (3.3 km/h), (10) normal walking (4.2 km/h), (11) brisk walking (6.0 km/h), (12) jogging, and (13) cycle ergometer (Table 1) [14], [15]. Given the importance of enhancing habitual physical activity in cardiac rehabilitation, postural behaviors during rest and various household tasks were also incorporated into the specific activities in the assessment [5]. All tests were conducted in a well-ventilated room, with ambient temperature maintained at approximately 22–24 °C. To minimize the influence of recent food intake on metabolic measurements, all physical activities were initiated at least 60 minutes after eating. During the experimental sessions, only water consumption was permitted; intake of other food or beverages and smoking were strictly prohibited. Before each activity, the participants rested for 5 min in a quiet supine position until the METs and HR displayed on each device reached a resting state and then performed the specific activity. Between activities, they took a 5-min rest before proceeding to the next specific activity. The duration of each activity was 10 min in activities 1–3; 7 min in activity 4; 6 min in activities 5, 6, 8, 9, and 13; and 5 min in activities 7 and 10–12 [14]. The portable gas analyzer AE-100i was operated in breath-by-breath mode, measuring data for each breath and subsequently outputting calculated values at 10-second intervals. Accordingly, the estimated MET values derived from the hitoe-based algorithm were also calculated and output at 10-second intervals to allow for appropriate comparison. Physical activity was estimated using METs, which are generally correlated with both movement intensity and heart rate. Accordingly, two primary modeling approaches have been proposed: (1) a linear regression model based on accelerometer output, which provides detailed information on movement type and intensity [15], and (2) a heart rate–based model, which estimates METs as a function of the difference between the current and resting heart rate, reflecting cardiovascular load [16]. Since each modality captures only a partial aspect of physical activity, and their outputs are often complementary, our method integrates both accelerometry and heart rate data. For example, during ergometer exercise, heart rate increases significantly while body movement is minimal; conversely, in prolonged low-intensity activities, accelerometer data may indicate ongoing motion with minimal heart rate elevation. To effectively model energy expenditure across a broad range of daily activities, we employed a dynamic combination of both input signals. Specifically, a sigmoid weighting function was applied to transition smoothly between accelerometer- and heart rate–based estimates according to the dominant characteristics of the current activity. 1 MET is generally defined as a resting oxygen uptake of 3.5 mL/kg/min. In this study, the model includes a single fixed constant determined by the definition of 1 MET as resting energy expenditure. Thus, under conditions of zero acceleration and resting heart rate, the estimator is constrained to output exactly 1 MET. All other model parameters were derived through data-driven optimization using a mathematical fitting procedure. Four computational models were created to estimate METs from HR and ACC data tailored to (i) sedentary and household activities, (ii) mobility activities, (iii) jogging, and (iv) cycle ergometers. This classification framework is designed to address the interplay between the significance of changes in ACC and variations in HR. Through the development of these four computational models, we aimed to achieve precise calculation of MET values for activities categorized into four distinct groups. Model (i) targeted activities 2–8, Model (ii) targeted activities 9–11, Model (iii) targeted activity 12, and Model (iv) targeted activity 13. We collected METs measured using the belt-type physical activity measurement device and the portable gas analyzer for each participant and analyzed the data to investigate how closely the two matched. We calculated the METs for the three groups from the HR and ACC obtained from the belt-type physical activity measurement device using the following formulas:

METs were calculated as

$$MET = 1 + theta \times h \times rHR + (1 - theta) \times a \times rACC$$

$$theta = sigmoid(t1 \times (rHR - rACC \times t2 - t3)).$$

The sigmoid() is a sigmoid function represented by $sigmoid(x) = 1/(1+e^{-x})$. rHR and rACC are representative values of HR and ACC, respectively, measured using the belt-type physical activity measurement device. rHR and rACC were calculated every 10 seconds. HR was measured using the belt-type physical activity measurement device at 1 Hz. Resting HR was assumed to be the lowest during the measurement period, including the quiet supine position period. We calculate the rHR within each 10 seconds time window as an average and subtract the resting HR. ACC is measured using the belt-type physical activity measurement device at 25 Hz along the three axes. After applying a high-pass filter, we calculate the rACC as the norm of the average deviation in the previous minute for each axis. The five parameters (t1, t2, t3, h, and a) are optimized on the basis of best fit to the data. Variables t1, t2, and t3 are parameters that adjust the degree of correlation. Variables h and a are also parameters representing the proportionality coefficients of MET to HR and ACC, respectively. We strictly enforce a constraint of 1 MET during rest with resting HR, i.e., MET = 1 when rHR = 0 and rACC = 0 by this formulation with these parameters. Exercise intensity is positively correlated with both ACC and HR; however, the degree of correlation for each activity is different.

Parameter tuning was conducted using Bayesian optimization. We sought parameters that minimized the difference in MET values (mean squared error) compared with those measured using the portable gas analyzer.

For implementation, we used Python 3.7 and the following Python libraries: SciPy 1.7.3 for data preprocessing, Optuna 2.2.0 for parameter exploration, and Pingouin 0.5.1 for statistical analysis. The parameter search ranges were [0.001, 0.1], [1, 100], [0, 100], [0.01, 0.1], and [1, 100] for t1, t2, t3, h, and a, respectively. The exploration area was carefully chosen to cover all possible value ranges for METs, HR, and ACC.

We calculated the intraclass correlation coefficient (ICC) and correlation coefficient for each specific activity [17]. ICC (2, 1) was the preferred indicator because our purpose was to verify the accuracy of the estimations obtained from multiple participants for each activity. The magnitude of the ICC was interpreted according to the commonly used criteria, where values less than 0.5 indicate poor reliability, values between 0.5 and 0.75 indicate moderate reliability, values between 0.75 and 0.9 indicate good reliability, and values greater than 0.9 indicate excellent reliability [17]. Additionally, a Bland-Altman analysis was performed [18]. In this analysis, limits of agreement (LoA) were calculated to assess agreement between MET values estimated with the hitoe system and those obtained with the portable gas analyzer. LoA were defined as the mean difference of paired MET values ± 1.96 × SD of these differences, representing the interval within which 95 % of individual discrepancies between the two methods are expected to lie. Furthermore, an extension of the Bland-Altman analysis was implemented, incorporating a hypothesis regarding the probability distribution of error. This approach enabled the estimation of the probability that the estimated value deviates from the true value by no more than 1.

The sample size was estimated based on the reliability classification criteria for Cohen's kappa proposed by Landis et al. [19], in which an ICC of ≥0.80 is interpreted as indicating "almost perfect agreement." To ensure sufficient clinical applicability, the target ICC was conservatively set at 0.90. Assuming an expected ICC (r) of 0.90, a minimum acceptable ICC (r_0) of 0.80, a statistical power of 0.80, and a significance level (α) of 0.05, the required sample size was calculated to be 60 participants. However, due to considerable challenges in participant recruitment over an extended period, the final sample size was limited to 28 participants.

Results

The total number of participants included in this study was 28 (26 males, 92.9%), and their average age was 42.3 ± 11.2 years. No participants were excluded. The characteristics of the participants are shown in Table 2. Among the participants included in this study, three individuals had hypertension (10.7%) and five had dyslipidemia (17.9%). However, none of the participants had been previously diagnosed with arrhythmia or cardiovascular disease. A total of three participants had a history of Achilles tendon rupture or bronchial asthma; however, none of them had any disabilities that impaired their ability to perform physical activities.

The optimized parameters of the three computational models were as follows: for Model (i), the optimized t1, t2, t3, h, and a values were set to 0.0166, 10, 8, 0.0453, and 19, respectively; for Model (ii), the optimized t1, t2, t3, h, and a values were set to 0.0165, 21, 0, 0.0218, and 24, respectively; for Model (iii), the optimized t1, t2, t3, h, and a values were set to 0.0109, 45, 0, 0.0660, 12; for Model (iv), the optimized t1, t2, t3, h, and a values were set to 0.0043, 49, 33, 0.0671, and 71, respectively.

Table 3 presents the ICCs for the METs measured using both belt-type physical activity measurement devices and gas analyzers across specific activities. The results are presented separately for the four computational models. Table 4 displays the proportion of the absolute differences in METs measured using belt-type physical activity measurement device compared with that measured using gas analyzer falls within 1 MET. Figure 2 shows the distribution of METs measured using belt-type physical activity measurement devices and gas analyzers. Figure 3 presents the results of the Bland-Altman analysis of METs for each activity.

The ICCs between the two measurement methods for activities 2–4 were not particularly high, and their 95% confidence intervals (CI) also showed considerable variablity. However, the proportion of the differences between the two methods fell within 1 MET was 100%. Furthermore, the results of the Bland-Altman analysis indicated that most data points were within the limits of agreement, which were defined as around ±0.5 METs. For activities 5–8, the ICC showed relatively higher values for activities 5, 7, and 8. Although the proportion of the differences between the two measurement methods fell within 1 MET decreased compared to earlier activities, the Bland-Altman analysis revealed that most data points were within the limits of agreement, ±1.0 METs. For activities 9–12, the ICC showed a relatively high value only for activity 11 and 12. Nonetheless, the Bland-Altman analysis indicated that, for these activities as well, most data points fell within the limits of agreement, around ±1.0 METs. For activity 13, the ICC demonstrated a remarkably high value of 0.797 (95% CI 0.607–0.901), indicating excellent agreement. In Table 4, the relative differences were approximately 10–20% for activities 2–7, whereas they remained comparatively small for activities 8–13.

Discussion

We conducted a validation investigation of a smartphone application and device developed to measure the intensity of physical activity conducive to cardiac rehabilitation by comparing the METs measured using this smartphone application and device to those obtained using a gas analyzer. The results indicated that the developed smartphone application and device estimates METs using three computational models based on the measured HR and gravitational ACC. While the consistency between the device and the reference method appeared generally acceptable, the level of accuracy — as reflected in the LoA and other results — may still be insufficient for precise clinical decision-making. Nonetheless, the findings suggest that such technology holds promise for enabling remote and personalized cardiac rehabilitation, highlighting the need for further validation in clinical settings.

In the four calculation models set according to activities of daily living, the intensity of physical activity (METs) obtained with the smartphone application and device used in this study and the intensity of physical activity obtained with the gas analyzer achieved overall consistency. In the models for calculating METs in activities of daily living and mobility, while activities such as 2–4, 6, and 9 exhibited lower ICC values, other activities demonstrated ICC values of 0.5–0.6 or higher. Moreover, Bland-Altman analysis revealed that the majority of data points for all activities fell within the limits of agreement, around ±0.5–1.0 METs. Previous studies have reported that measurements taken with the developed device can deviate by approximately 10–20% from the accurate values obtained using respiratory gas analyzers [20], [21], [22]. Given these findings, the models for calculating METs in activities of daily living and mobility were considered to demonstrate overall consistency between the device and the gas analyzer, supporting their potential practical applicability. Systematic bias observed during low-intensity activities (Activities 2–9) may result from reduced variability in HR and acceleration signals, limiting the model's sensitivity. In addition, greater inter-individual variability in physiological responses at low intensities may further contribute to this trend. In the computational model for the cycle ergometer, the ICC indicated “good” relative reliability [17]. While this suggests that the model performs consistently across measurements, it does not necessarily imply sufficient measurement accuracy for clinical application, as a LoA of ±2 METs may not fall within a clinically acceptable range. Overall, these findings highlight the need for continued research and the development of more accurate devices to enhance clinical applicability.

The device validated for accuracy in this study can set target values according to the exercise tolerance of the wearer. Furthermore, it can provide feedback on whether set exercises are being performed, suggesting their potential applicability for implementing tailored cardiac rehabilitation programs. Integrating applications and devices for monitoring physical activity into cardiac rehabilitation programs has been demonstrated to increase physical activity levels and healthy behaviors as well as reduce hospital readmission rates, according to an umbrella review that aggregated findings from systematic reviews [23]. However, among the smartphone applications available for cardiac rehabilitation, few can accurately set exercise intensities tailored to individual patients based on the test results and provide precise feedback. Furthermore, guidelines increasingly emphasize the importance of the duration and intensity of physical activity, leading to better outcomes [5], [24]. The smartphone application and device developed in this study are capable of setting target exercise intensities tailored to the patient’s exercise tolerance and can provide feedback on whether the patient has achieved their physical activity goals in terms of both duration and intensity. This approach has the potential to maximize the effects of rehabilitation while considering the safety of individual patients.

This study had several limitations. This study focused on healthy adults with no history of cardiovascular disease. Therefore, to validate the effectiveness of this smartphone application and device, future studies should conduct prospective randomized controlled trials involving patients with cardiovascular diseases. Additionally, certain activities, such as desk work and slow walking, exhibited lower ICC values and slightly higher relative differences, which may in part be due to challenges in accurately assessing MET values under low-intensity conditions close to rest when using a breath-by-breath method, suggesting that future studies may need to reconsider or refine the measurement methodology for such conditions. These findings indicate the need for further research to enhance the accuracy of the smartphone application and device. Moreover, this study evaluated the device’s use over a relatively short period, necessitating future research to assess the risks related to device wear, such as adherence to wearing the device. In addition, the final sample size was smaller than originally planned, which may have limited the statistical power and the generalizability of the findings. Future studies with larger sample sizes are warranted to confirm and extend the present results. Another limitation is that posture was not considered in the acquisition of resting data due to the variable orientation of the wearable sensor, which precluded accurate posture estimation using accelerometry. While the potential difference in resting MET values between seated and supine positions is acknowledged, it is likely to be minimal relative to the dynamic changes observed during exercise. Nevertheless, future studies should consider incorporating reliable posture estimation techniques to further refine the accuracy of MET-based assessments. Finally, this study did not include alternative thresholds such as ±0.5 METs, which may offer a more sensitive assessment of systematic errors across varying activity intensities. Future studies should consider incorporating other thresholds to better capture intensity-dependent deviations and to enhance interpretability in both research and clinical contexts.

In conclusion, this study suggests that the smartphone application and wearable device, the hitoe system, may offer a practical means of monitoring and adjusting exercise intensity in individuals undergoing cardiac rehabilitation. While the findings do not confirm high accuracy, they indicate a promising direction for enabling remote and personalized rehabilitation support. However, further research involving cardiovascular patients in clinical settings in needed to validate the effectiveness and reliability of such technology.

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Contributions

MO, OS, YS, and TN conceptualized the study design and protocol, and determined the study institutions. MO and OS collected and assembled the data. MO and YS carried out the analysis and interpretation of data. MO drafted the manuscript. All authors have critically reviewed, revised and approved the manuscript.

Conflict of Interest

MO, YS, and TN declare no conflicts of interest. OS is an employee of Nippon Telegraph and Telephone Corporation (NTT).

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Figure Legends

Fig. 1. Belt-type physical activity measurement devices and smartphone application

A. hitoe®

B. Transmitter

C. hitoe® and transmitter (appearance)

D. Smartphone application

Fig. 2. Distribution of metabolic equivalents (METs) for each activity measured using the device and gas analyzer

A. Computational model specialized for sedentary and household activities

B. Computational model specialized for mobility activities

C. Computational model specialized for jogging

D. Computational model specialized for cycle ergometer

Abbreviation: METs, metabolic equivalents; CPX, cardiopulmonary exercise testing

The dotted lines in the figure represent the range of ± 1 MET difference between the METs measured by the device and those obtained as a reference using CPX.

Figure 3. Bland-Altman analysis of metabolic equivalents (METs) measured using the device and gas analyzer for each activity

Tables

Table 1. Activities performed during the validation

Number of activities	Activities		Implementation time	Contents of the activities
1	(Reference)	(Supine position)	10 min	Quietly lie down in the supine position and maintain rest to reset the condition
2	Sedentary activities	Supine position	10 min	Measure the basal metabolic rate in the supine position (lying face up)
3		Sitting	10 min	Measure the resting metabolic rate while seated in a chair
4		Desk work	7 min	Working on a computer
5	Household activities	Laundry	6 min	The action of taking a T-shirt out of the laundry basket and hanging it on a hanger to dry

6		Washing dishes	6 min	The action of washing dishes
7		Lifting a 5 kg weight	5 min	Lift a small 5 kg package, take a few steps, and then set it down
8		Vacuuming the floor	6 min	Clean the floor with a vacuum cleaner
9	Mobility activities	Slow walking	6 min	Slow walking (3.3 km/h, 55 m/min)
10		Normal walking	5 min	Normal walking (4.2 km/h, 70 m/min)
11		Brisk walking	5 min	Brisk walking (6.0 km/h, 100 m/min)
12		Jogging	5 min	Jogging (8.0 km/h, 140 m/min)
13	Cycle ergometer	Cycle ergometer	6 min	Cycle ergometer (with a load intensity of somewhat hard, around Borg scale 13)

Table 2. Characteristics of participants

Variables	Data
N	28
Male	26 (92.9%)
Age (years)	42.3 ± 11.2
Height (cm)	172.2 ± 6.0
Body weight (kg)	68.8 ± 10.0
Body mass index (kg/m^2)	23.2 ± 3.1
Smoking (never/ex/current)	19/5/4 (67.9/17.9/14.3%)
Hypertension	3 (10.7%)
Dyslipidemia	5 (17.9%)
Diabetes mellitus	0
Arrhythmia	0
Cardiovascular diseases	0
Respiratory diseases	1 (3.6%; bronchial asthma)
Musculoskeletal disorders	2 (7.1%; Achilles tendon rupture)

Data are presented as mean ± standard deviation or n (%).

Table 3. Intraclass correlation coefficients in each computational model and differences in metabolic equivalents (METs) for each activity measured using belt-type physical activity measurement device and gas analyzer

	Activities of daily living Model (i)	Mobility Model (ii)	Jogging Model (iii)	Cycle ergometer Model (iv)
Pearson's correlation coefficient	0.908	0.737	0.640	0.801
ICC (95% CI) for each activity				
2. Supine position	0.062 (-0.153–0.332)	N/A	N/A	N/A
3. Sitting	0.033 (-0.143–0.275)	N/A	N/A	N/A
4. Desk work	0.144 (-0.105–0.426)	N/A	N/A	N/A
5. Laundry	0.543 (0.180–0.767)	N/A	N/A	N/A
6. Washing dishes	0.245 (-0.078–0.544)	N/A	N/A	N/A
7. Lifting a 5 kg weight	0.614 (0.315–0.802)	N/A	N/A	N/A
8. Vacuuming the floor	0.693 (0.440–0.844)	N/A	N/A	N/A
9. Slow walking	N/A	0.179 (-0.216–0.518)	N/A	N/A

10. Normal walking	N/A	0.353 (-0.012–0.636)	N/A	N/A
11. Brisk walking	N/A	0.552 (0.226–0.765)	N/A	N/A
12. Jogging	N/A	N/A	0.620 (0.326–0.804)	N/A
13. Cycle ergometer	N/A	N/A	N/A	0.797 (0.607–0.901)

Abbreviations: ICC, intraclass correlation coefficient; N/A, not applicable

Table 4. The proportion of the absolute differences in metabolic equivalents (METs) measured using belt-type physical activity measurement device compared with that measured using gas analyzer falls within 1 MET

	Mean METs hitoe	Mean METs CPX	VO_2 CPX (mL/kg/min)	Relative difference (|hitoe – CPX| / CPX)	Activities of daily living Model (i)	Mobility Model (ii)	Jogging Model (iii)	Cycle ergometer Model (iv)
Activities								
2. Supine	1.18 ± 0.040	1.02 ± 0.20	3.58 ± 0.71	15.70	100.00	N/A	N/A	N/A
3. Sitting	1.24 ± 0.058	1.04 ± 0.20	3.65 ± 0.70	18.50	100.00	N/A	N/A	N/A
4. Desk work	1.30 ± 0.082	1.10 ± 0.22	3.85 ± 0.77	18.00	100.00	N/A	N/A	N/A
5. Laundry	2.15 ± 0.27	2.39 ± 0.61	8.37 ± 2.14	10.20	96.60	N/A	N/A	N/A
6. Washing dishes	1.87 ± 0.21	1.57 ± 0.37	5.51 ± 1.30	18.60	98.14	N/A	N/A	N/A
7. Lifting 5 kg	3.07 ± 0.52	3.04 ± 0.79	10.60 ± 2.77	10.20	91.36	N/A	N/A	N/A
8. Vacuuming the floor	2.76 ± 0.53	2.85 ± 0.72	9.98 ± 2.51	3.20	95.75	N/A	N/A	N/A

9. Slow walking	2.77 ± 0.24	2.76 ± 0.56	9.65 ± 1.94	0.39	N/A	93.57	N/A	N/A
10. Normal walking	3.28 ± 0.39	3.17 ± 0.57	11.1 ± 1.98	3.48	N/A	92.78	N/A	N/A
11. Brisk walking	4.16 ± 0.61	4.13 ± 0.72	14.4 ± 2.54	0.66	N/A	88.76	N/A	N/A
12. Jogging	7.96 ± 1.27	8.11 ± 1.70	28.4 ± 5.94	1.89	N/A	N/A	55.75	N/A
13. Cycle ergometer	5.54 ± 1.54	5.61 ± 1.80	19.6 ± 6.30	1.28	N/A	N/A	N/A	65.26

Data are presented as mean ± standard deviation or %.

Abbreviations: METs, metabolic equivalents; CPX, cardiopulmonary exercise testing; N/A, not applicable

Figure 1. Belt-type physical activity measurement devices and smartphone application

A. hitoe®

B. Transmitter

C. hitoe® and transmitter (appearance)

D. Smartphone application

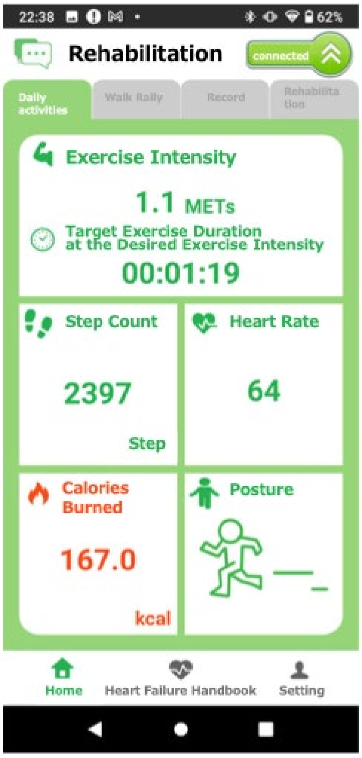
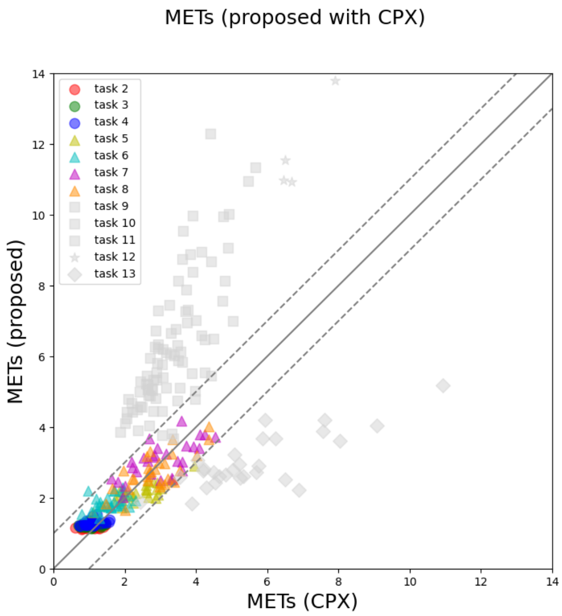
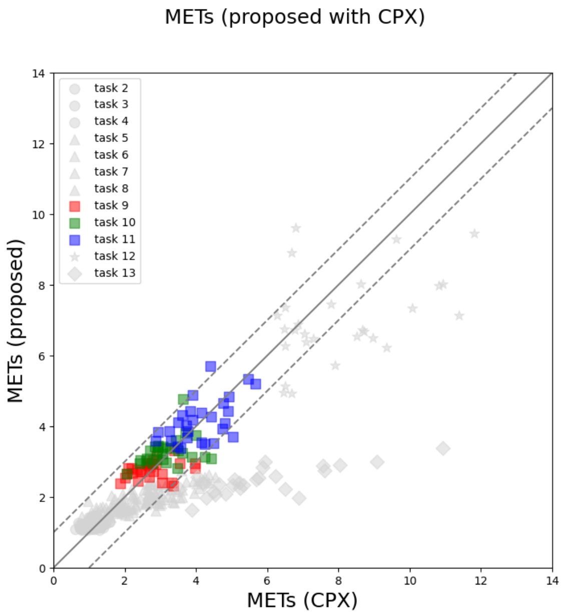


Figure 2. Distribution of metabolic equivalents (METs) for each activity measured using the device and gas analyzer

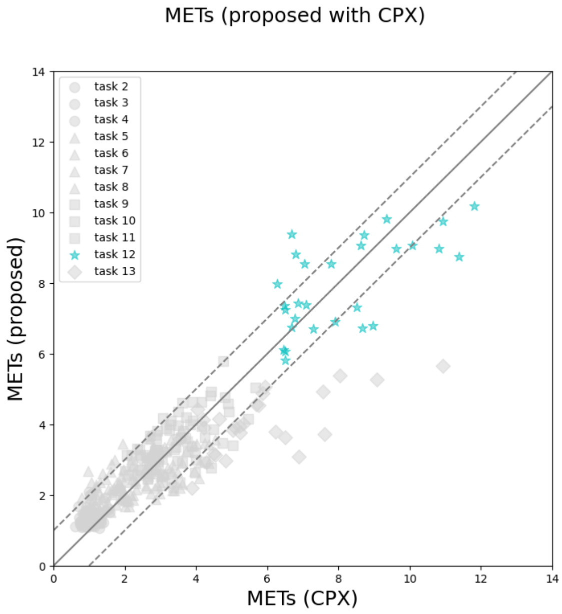
A. Computational model specialized for sedentary and household activities



B. Computational model specialized for mobility activities



C. Computational model specialized for jogging



D. Computational model specialized for cycle ergometer

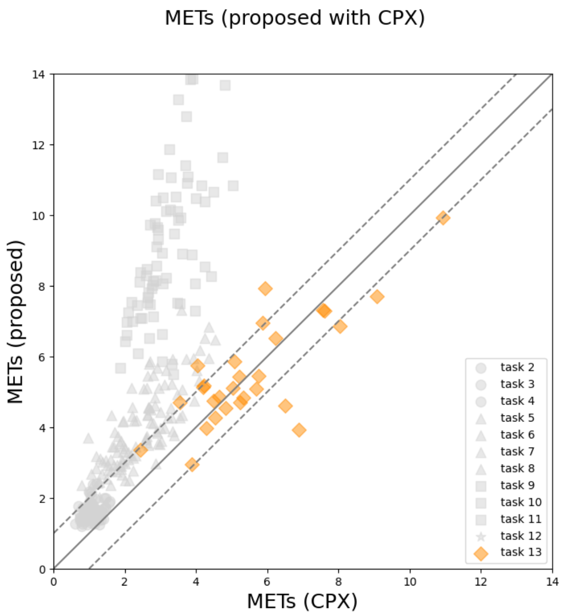
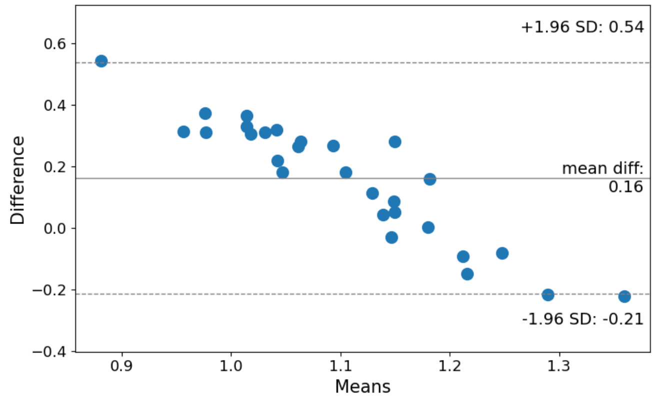
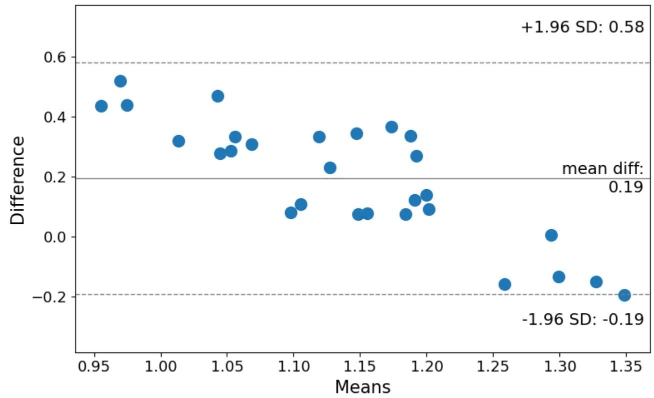


Figure 3. Bland-Altman analysis of metabolic equivalents (METs) measured using the device and gas analyzer for each activity

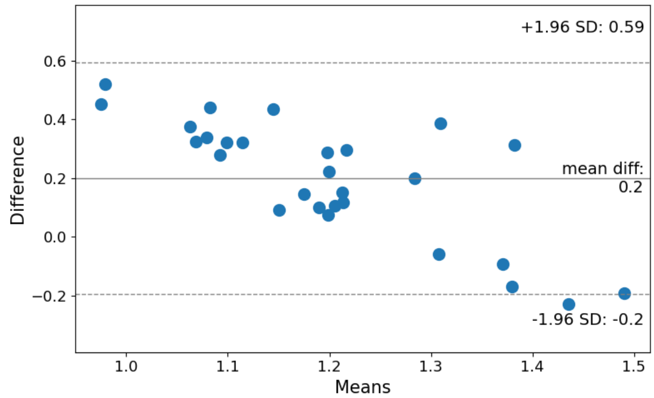
Activity 2. Supine position



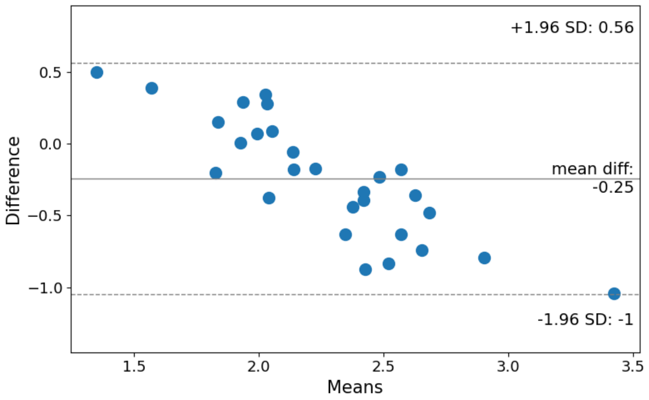
Activity 3. Sitting



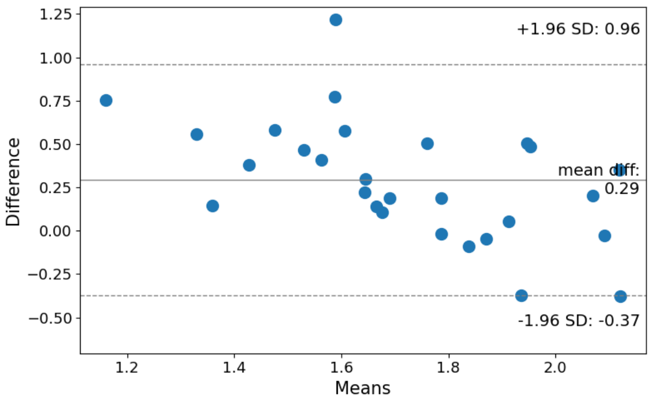
Activity 4. Desk work



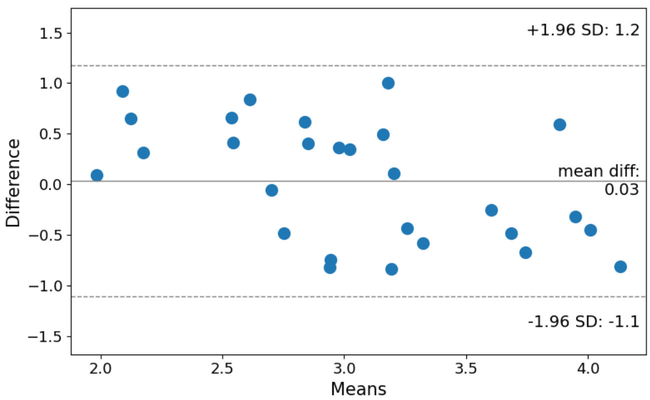
Activity 5. Laundry



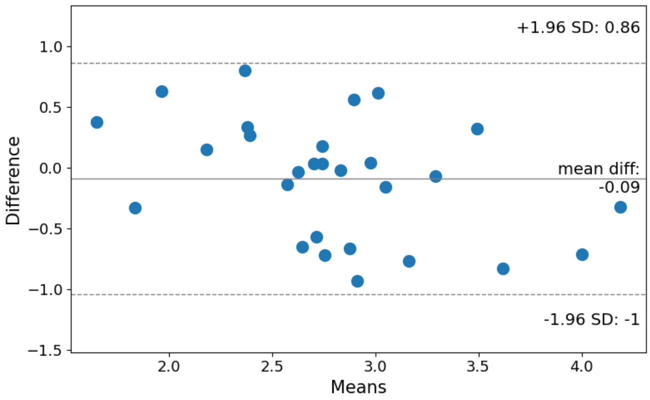
Activity 6. Washing dishes



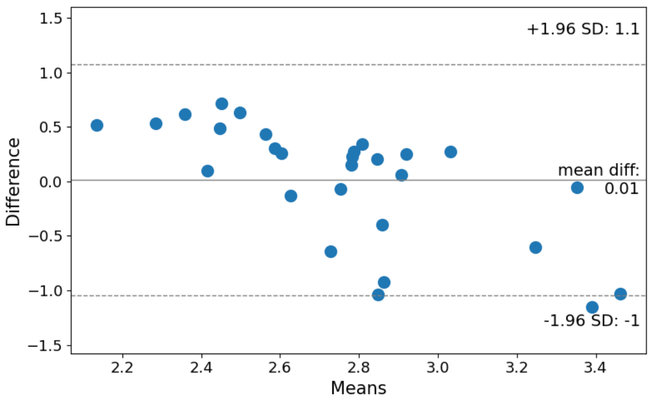
Activity 7. Lifting a 5 kg weight



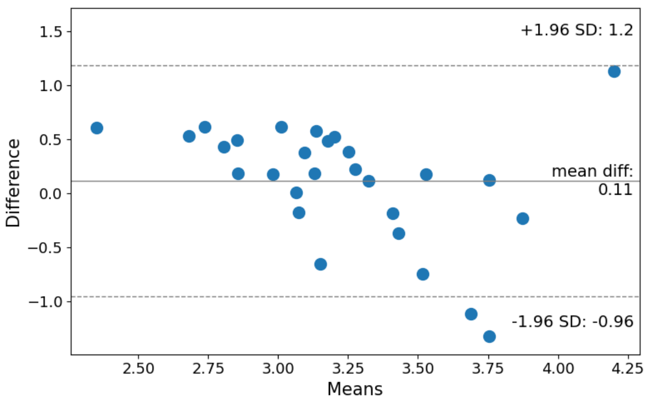
Activity 8. Vacuuming the floor



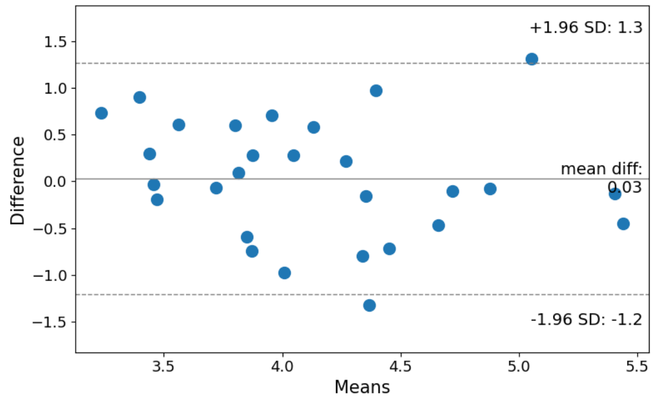
Activity 9. Slow walking



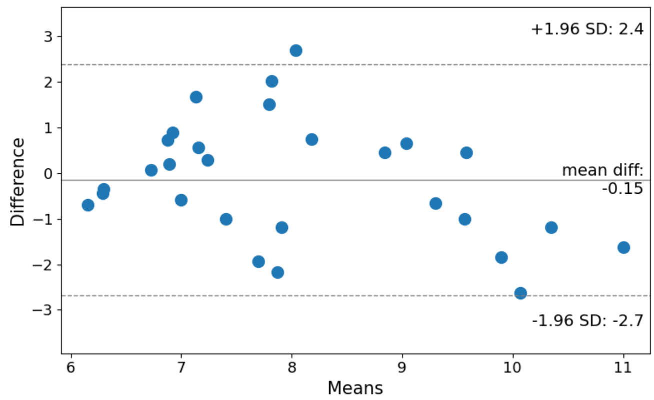
Activity 10. Normal walking



Activity 11. Brisk walking



Activity 12. Jogging



Activity 13. Cycle ergometer