ESTIMATING ENERGY EXPENDITURE BY USING FLOOR VIBRATION MONITORING TECHNOLOGY IN BEDROOM SETTINGS

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INTRODUCTION

Technology that enables the objective assessment of physical behaviors has evolved considerably over the two past decades. While activity tracker devices have been linked to inaccurate energy expenditure predictions [1-2], the emergence of the 5G and Internet of Things technology surely opens up room for more accurate and continuous monitoring. Nowadays, activity tracker devices can be paired with smartphone handsets, allowing collecting a wealth of information about people's physical behaviors throughout the day. In such a connected environment, and while housework-related activities account for a substantial proportion of daily physical activity in some populations [3], smart home systems could support the continuity of the monitoring of physical activity and sedentary behaviors when people stay at home. This would improve the accuracy of energy expenditure predictions related to activities that are performed at home, subsequently improving the daily PA estimates of activity tracking platforms. Recently, the Ocha-House project assessed the feasibility of using floor vibration monitoring to estimate the intensity of four activities(watching video, ironing, cooking and cleaning) commonly performed at home [4]. **The present study aims to develop a floor vibration monitoring system capable of predicting energy expenditure for activities commonly performed by children, adolescents or young adults in their bedroom.**

METHODS

An 13 m^2 experimental bedroom resembling the ones found in typical Japanese settings was build in the laboratory **(Figure 1)**. Eight high-sensitivity uniaxial accelerometers (Shear-type/vibration pickup PV-87, Rion Co., Ltd., Japan) were installed under the floor to measure vibrations . The PV-87 sensor characteristics are specified as follows by the manufacturer: charge sensitivity: $\pm$40 pC/(ms^{-2}), range of detection: 1–3000 Hz, peak measurement acceleration: 400m/s^2, dimensions: 24(Hex) x 30.5(H) mm, mass: 115 g. The range of measured acceleration can be set from 0.1m/s^2 to 30 m/s^2. In the present study, the range was chosen to be 0.3 m/s^2 based on preliminary experiments that confirmed sufficient resolution without signal saturation, as well as sufficient coverage of the whole area. The position of accelerometers was determined through preliminary experiments addressing the effect of the distance on the attenuation of floor vibrations. During the experiment the signal was collected at a sampling rate of 100 Hz with 12-bit resolution.

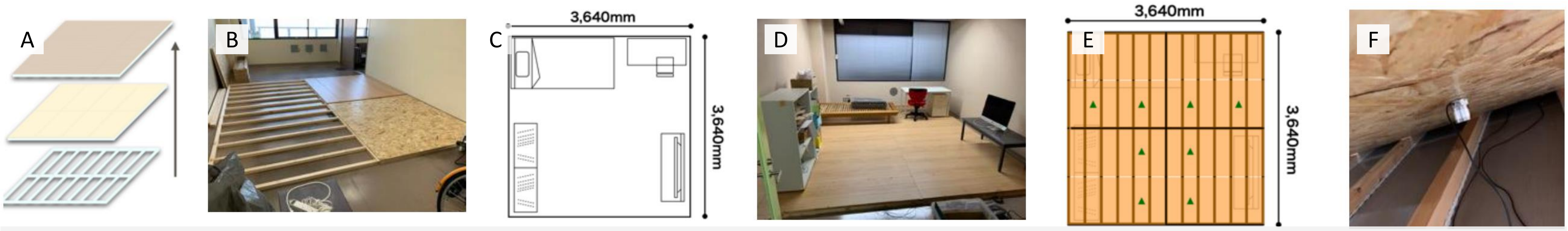

Figure 1. Overview of the experimental setting. A: the wooden floor of the 13 m^2 (8 tatamis) experimental bedroom is composed of 3 layers. The frame is composed of 32 pieces of lumbers (45 × 60). The mid layer is composed of 8 rectangular pieces of plywood (910 × 12 × 1820mm). The upper layer is composed of 24 pieces of flooring materials (300 × 12 × 1820mm). B: view of the wooden experimental floor under construction. C: furniture locations (view from above). D: view of the experimental bedroom (view from inside). E: location of the 8 sensors (interval between sensors: 910mm). F: View of one accelerometer sensor mounted under the mid layer.

Table 1. Participant characteristics

	Number of participants	Age (years)	Body weight (kg)	BMI (kg / m^2)^a
Women	8	27±19	50±7.5	20±2.5
Men	2	26±5.5	65±0.0	20±0.8
All	10	27±12	53±9.0	20±2.3

Ten participants (Table 1) performed **9 activities (Figure 2)** on the experimental floor. The participants fasted for at least six hours before the beginning of measurements. At the end of the experiment, each participant performed a short walking trial on the floor to collect the floor vibration information used for computing the walking-peak parameter used as a subject characteristic in the statistical analysis. The experiment was performed free of any footwear (no sleeper). The actual energy expenditure of each activity was measured using **indirect calorimetry** (K5, COSMED inc., Italy). Prior to the experiment, the resting metabolic rate of each participant was assessed. **The actual intensity of the activity was calculated as the ratio of energy expenditure on resting metabolic rate and is expressed in MET**. The participants were equipped with **two GT3X Actigraph monitors** (USA) worn at the wrist and the hip. **The floor vibration signal was collected using the 8 sensors described in Figure 1. The signal was treated as shown in Figure 3 to extract 7 features reflecting the intensity of the physical behaviors.**

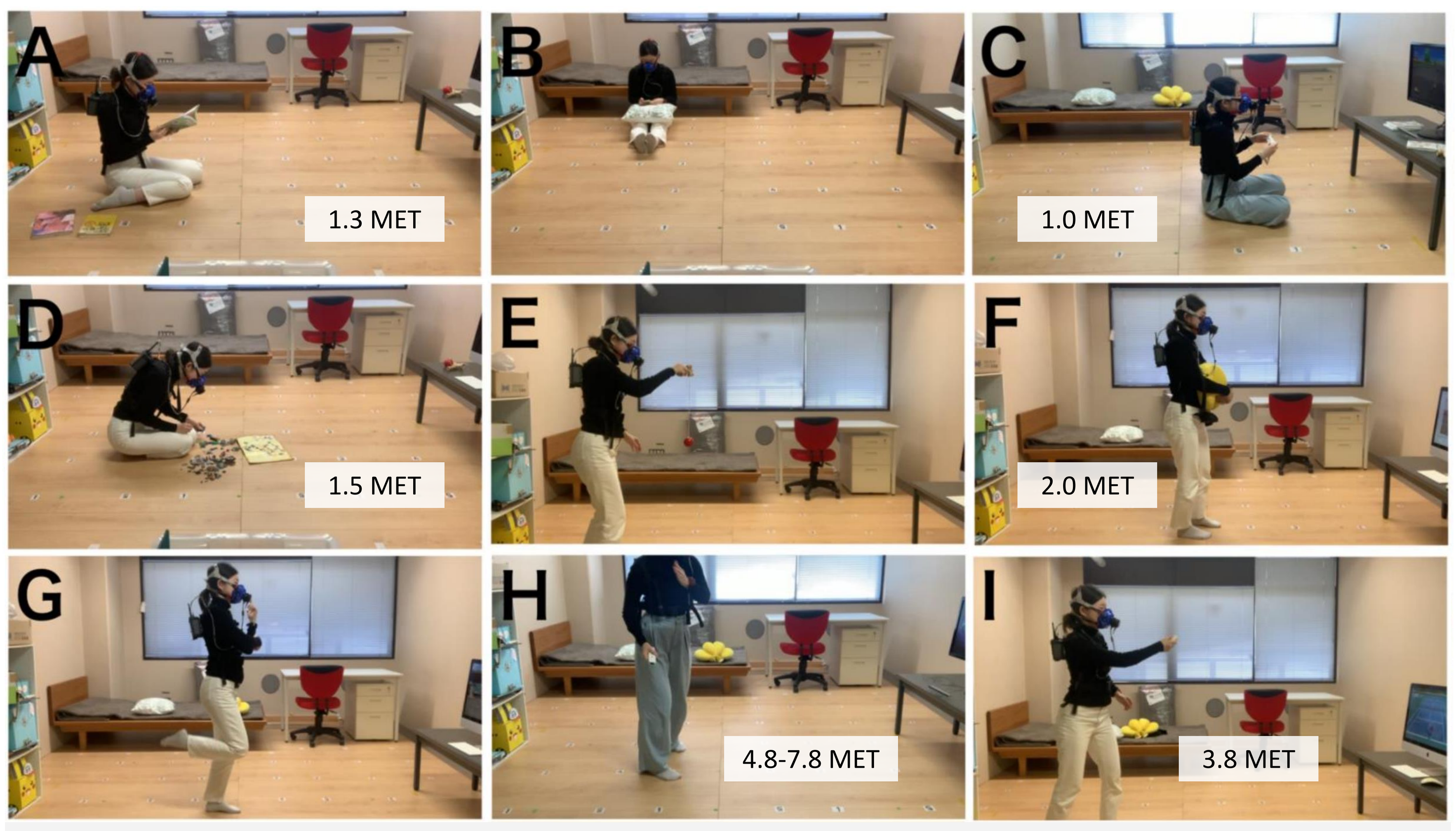

Figure 2. The nine activities. A: Sitting and reading books. B: Sitting and scrolling through the Smartphone. C: Sitting and playing video games. D: Playing with LEGO. E: Playing with Kendama. F: Singing. G: Tiktok dance tutorial. H: Interactive dance video game. I: Standing and playing active video games. Intensities found in the Compendium of PA are indicated in each panel when available.

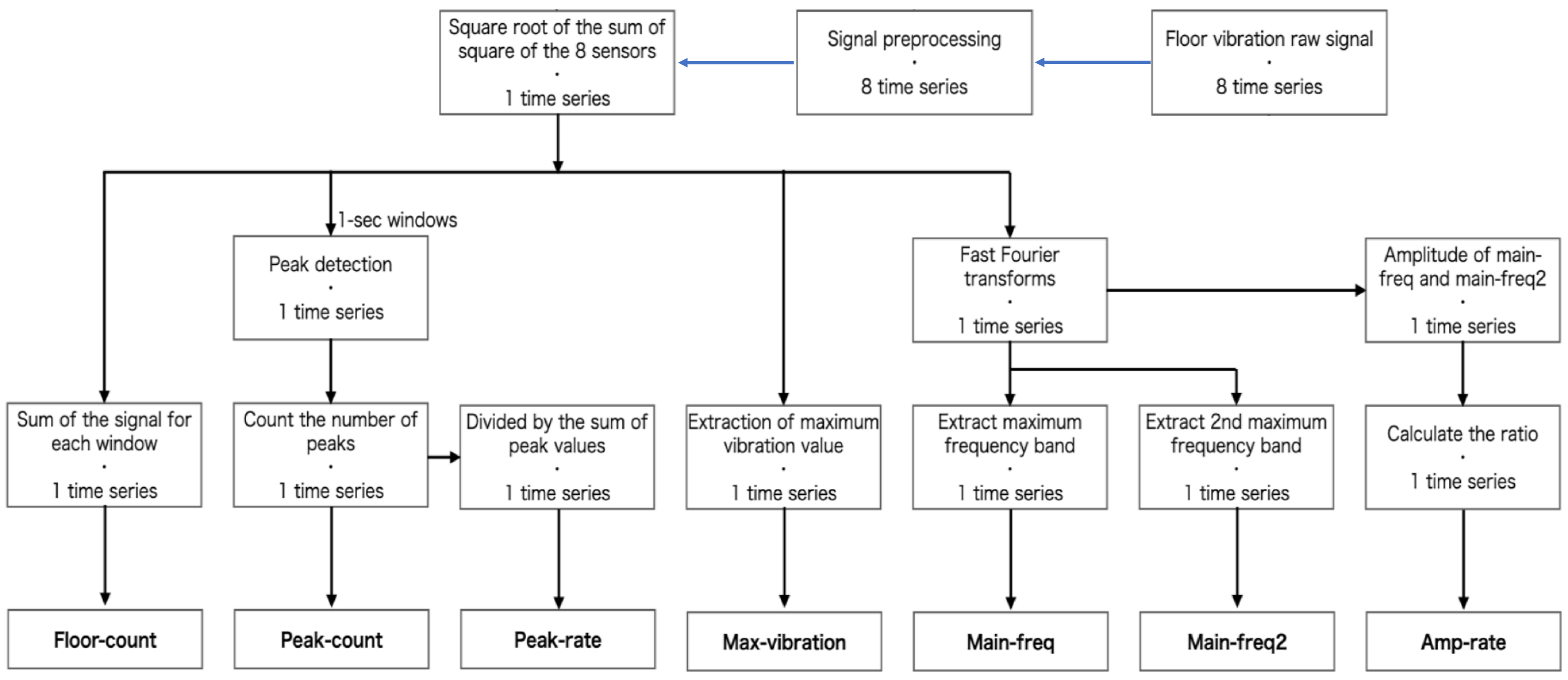

Figure 3. Floor vibration signal flow processing chart. From the raw 8-sensor signal time series to the extraction of 7 floor vibration-based data features.

RESULTS

Multiple regression models were used to examine relationships between these parameters and the actual activity intensities. The actual activity intensity averages ranged from 1.2 to 3.3 MET. Regression models combining parameters extracted from the floor vibration signal and including information related to subject characteristics explained up to 66% of activity intensity variance. The best model was compared to the outcomes of the wearable monitors. While the predictions of the wearable monitors showed significant deviations from the actual intensities (up to ~6.0 MET difference for the Tiktok dance tutorial activity) for 6 of the tested activities, the floor vibration system outcomes exhibited slight deviations for the Kendama and singing activities only.

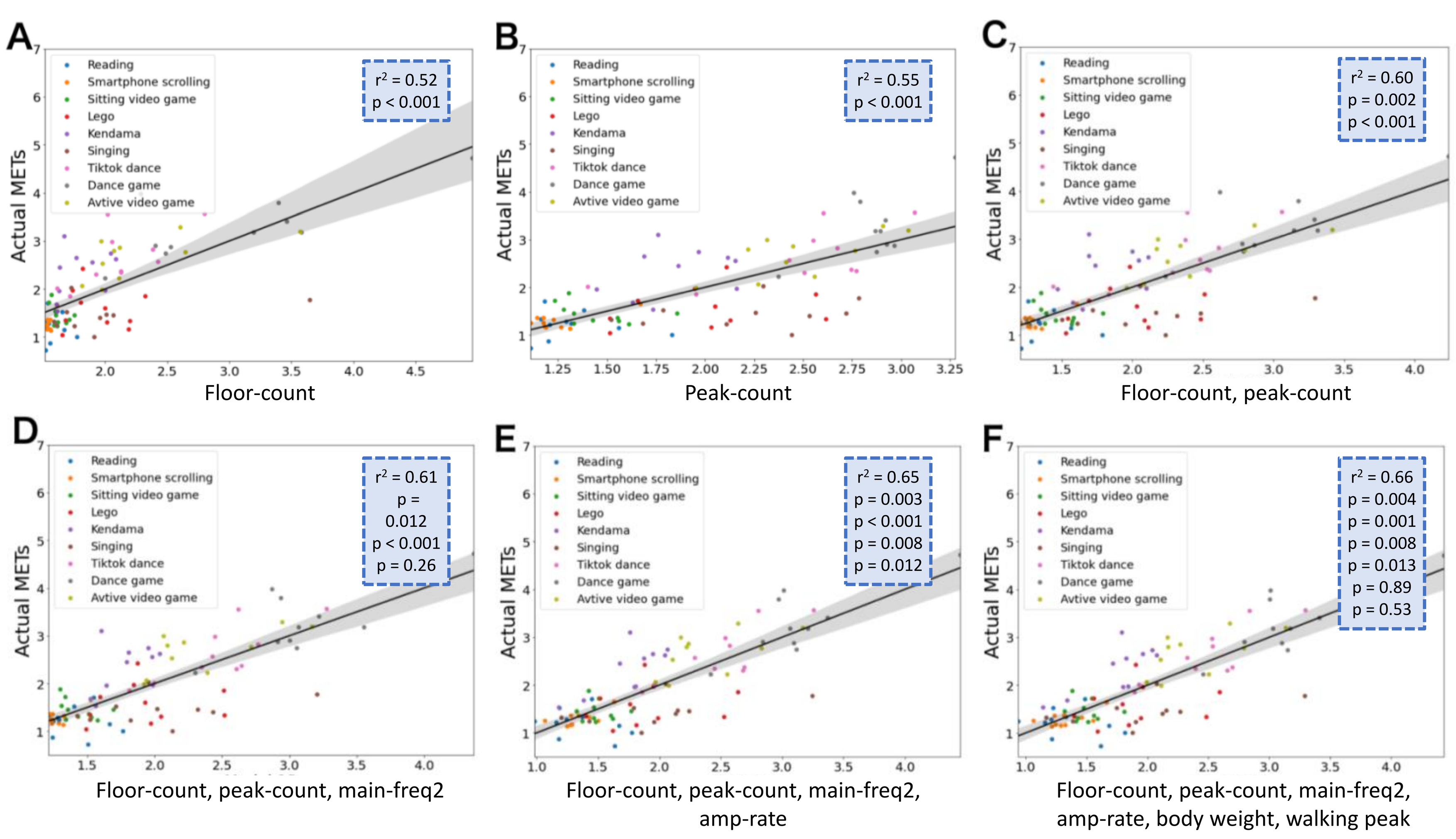

Figure 4. Relationship between some selected floor vibration-based models and actual activity. A and B: best single variable models. C, D and E: best multi-variable models (without inclusion of participant characteristics variables). F: Model that participant characteristics variables

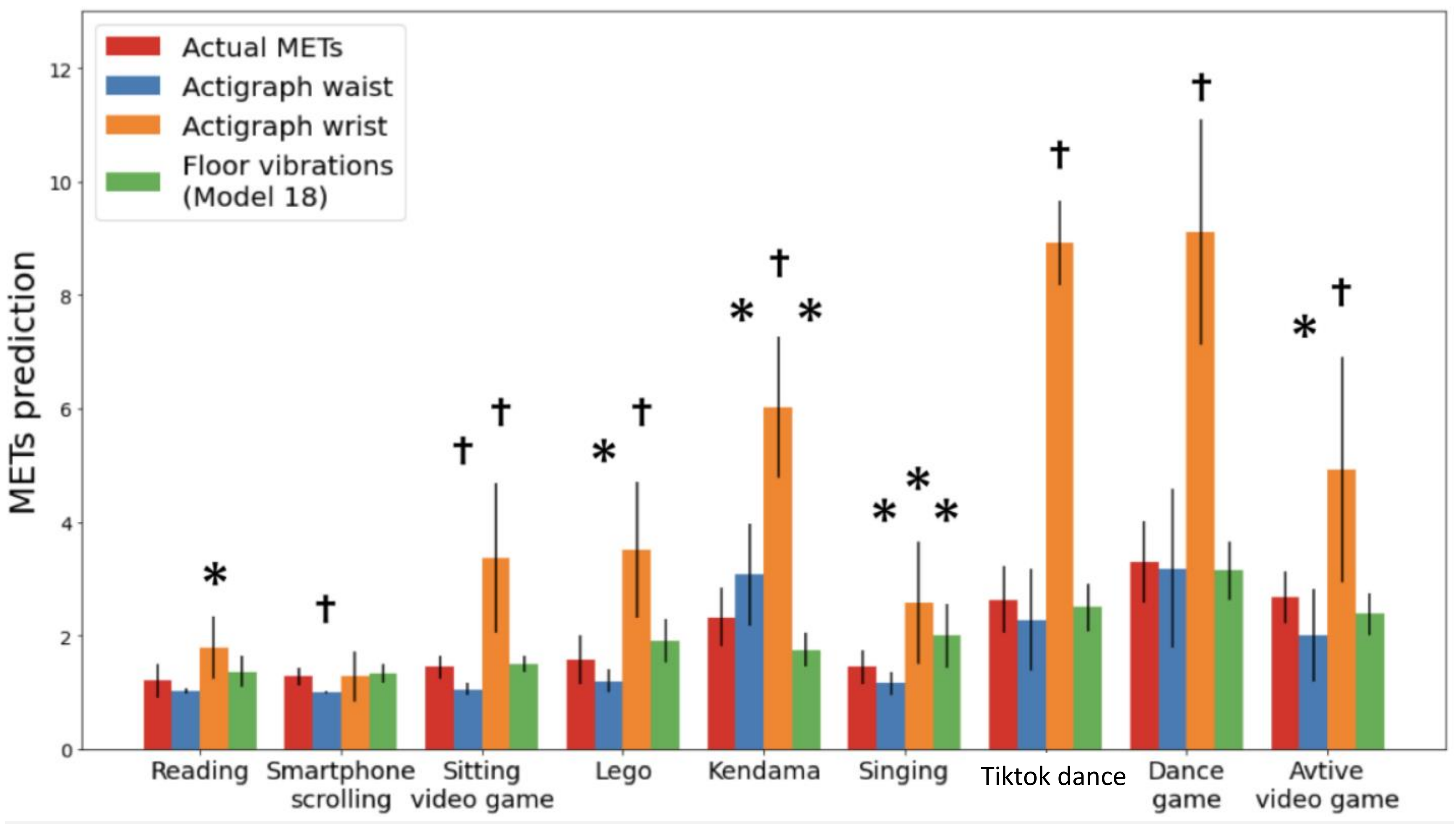

Figure 5. Comparisons between the predictions of the best floor vibration-based model, the outcomes of the wrist- and hip-worn Actigraph monitors, and the actual activity intensities. MET: metabolic equivalent of task. The marks indicate significant differences against the actual intensities. *: p<0.05, †: p<0.001

CONCLUSION

The floor vibration monitoring system computed activity intensity predictions that were more accurate than the ones produced by the Actigraph wearable monitors. Floor vibration-based smart home systems may be used as non-intrusive methods for quantifying physical behaviors in bedrooms and improve the daily estimates of PA.

Acknowledgments

The authors would like to thank the individuals who participated in this study. This study has received research grants from the Japan Society for the Promotion of Science (Grant-in-Aid for Scientific Research-C 21K11335 directed to JT and YO) and from the Japanese Foundation for the Promotion of Precision Measurement Technology (精密測定技術振興財団研究費).

The authors declare they do not have any conflict of interest

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