Table 3. Rate of correct discrimination of nonlocomotive from locomotive activities.

Threshold	1.12*		1.13		1.14		1.15		1.16#	
	Development group (48)	Cross-validation group (20)	Development group (48)	Cross-validation group (20)	Development group (48)	Cross-validation group (20)	Development group (48)	Cross-validation group (20)	Development group (48)	Cross-validation group (20)
Nonlocomotive										
desk work	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Nintendo DS	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
sweeping up	100.0	100.0	97.9	100.0	97.9	95.0	95.8	95.0	95.8	95.0
clearing away	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
washing the floor	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
throwing a ball	97.9	100.0	97.9	95.0	95.8	95.0	93.8	90.0	93.8	90.0
Locomotive										
climbing down	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
climbing up	100.0	90.0	100.0	95.0	100.0	95.0	100.0	100.0	100.0	100.0
normal walking	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
brisk walking	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
jogging	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Total discrimination	99.8%	99.1%	99.6%	99.1%	99.4%	98.6%	99.1%	98.6%	98.9%	98.6%

*shows the excellent cut-off value of children to discriminate between locomotive and nonlocomotive activity in this study.

#shows the cut-off value of adults to discriminate between locomotive and nonlocomotive activity which was proposed in our previous study [20].

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Table 4. Absolute and percentage differences between measured and predicted METs from each equation model for nonlocomotive and locomotive activities in the cross-validation group (n = 20).

	Predicted METs		Measured METs		Absolute difference		% difference		*P* value
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	
Nonlocomotive									
desk work	1.34	0.06	1.15	0.13	0.19	0.13	17.5	15.0	<0.01
Nintendo DS	1.30	0.03	1.11	0.09	0.18	0.10	17.9	9.1	<0.01
sweeping up	3.29	0.72	3.15	0.73	0.14	0.46	5.8	14.6	NS
clearing away	2.77	0.40	3.01	0.58	−0.25	0.42	−6.5	12.8	NS
washing the floor	3.91	0.40	4.41	0.69	−0.50	0.79	−9.0	18.9	<0.01
throwing a ball	4.26	0.78	3.76	0.82	0.48	0.45	14.9	13.4	<0.05
Locomotive									
climbing down	2.88	0.27	2.26	0.28	0.58	0.41	29.1	20.5	<0.01
climbing up	2.20	0.20	5.28	0.69	−3.08	0.61	−58.0	4.7	<0.01
normal walking	2.54	0.21	2.58	0.24	−0.04	0.36	−0.6	13.8	NS
brisk walking	3.21	0.25	3.16	0.25	0.05	0.36	2.1	11.3	NS
Jogging	6.44	0.48	6.20	0.77	0.23	0.83	5.2	14.7	NS

P<0.05 and <0.01 show that mean values were significantly different compared with measured METs.
METs; metabolic equivalents, SD; standard deviation, NS; not significant.
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Table 5. Effect of weight, age and sex on predictive ability by multiple regression analysis.

Independent variable	Intercept	Regression coefficient	*P* value	Adjusted R^2	RMSE
Nonlocomotive					
Model 1					
synthetic acceleration (mg)	1.220	0.013	<0.001	0.772	0.664
Model 2					
synthetic acceleration (mg)	−0.537	0.013	<0.001	0.816	0.596
weight			NS		
age		0.170	<0.001		
sex (boys:0, girls:1)		0.076	<0.05		
Locomotive					
Model 1					
synthetic acceleration (mg)	0.944	0.005	<0.001	0.880	0.639
Model 2					
synthetic acceleration (mg)	−0.925	0.005	<0.001	0.925	0.508
weight		0.032	<0.001		
age		0.085	<0.01		
sex (boys:0, girls:1)		0.092	<0.05		

RMSE; root mean square error, NS; not significant.
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the current study, we tried to examine whether the GRPACA, which was developed in our calibration model for adults, is able to discriminate various PAs in children, and to prove that this discrimination method improves the estimation accuracy of the prediction model for children using an accelerometer.

Our first key finding was that it might be possible to apply the discrimination procedures developed in adults to any participant with various activity components and patterns. In our previous study, we found that the percentage of correct discrimination with the GRPACA in adults was remarkable, 98.7%, when the ratio of USA/FSA was 1.16 [21]. In the present study, when the threshold of discrimination, which was similar to that in the previous study, was 1.12, the rate of correct discrimination was excellent, at 99.1% on average (Figure 1, Table 3). As the discrimination method that used the coefficient of variation in a previous study was 97% for locomotive activities and 89.5% for nonlocomotive activities [17], our discrimination procedure had a better rate of correct discrimination. It follows that our specific calibration model could evaluate the PA intensity of children with an estimation accuracy of a mean difference of −0.13 METs and limits of agreement (±2 SD) from +2.06 to −2.33 METs, similar to the success we obtained with the adult model in our previous study for adults [20,21]. This finding was supported by a strong linear relationship in the two prediction formulas and a cross-validation trial with another group of children (Table 4). These results suggested that our specific model, established according to the procedure of the adult model, was well suited to evaluate the PA of children.

We did not simultaneously compare our device with major devices, such as ActiGraph. However, our calibration procedures followed the procedures used in several calibration studies [11–17], which enabled comparison of the results in the present study with previous studies that used a common device. For example, a proposed single equation using a common device such as ActiGraph, Actical or RT3 provides average prediction errors of more than about 20% for nonlocomotive activities, calculated from average published values like VO_2 (ml/kg$^{0.75}$/min), activity energy expenditure (kcal/kg/min) and METs [14,33,34,35]. Moreover, when our model was compared with the 2 RM with ActiGraph proposed recently, the differences between the predicted METs and the measured METs in the current study were slightly smaller than those of the previous study [17]. To be more precise, the differences with ActiGraph for vigorous intensity PAs, such as sportwall and running, were −1.8 to METs and −1.1 METs [17], respectively, while the differences with our model were 0.23 METs for similar-intensity PAs like jogging. Furthermore, the difference with our model, which was within 0.50 METs for all PAs including sedentary to vigorous intensities, except for climbing up and down, was slightly smaller than in the previous study (within 0.6 METs) [17]. Actually, another study also indicated that the 2 RM with ActiGraph had a disadvantage for sedentary and high intensity PAs [36]. In the current study, although there were significant differences between the measured METs and the predicted values from standard equations in washing the floor, throwing a ball, and climbing down and climbing up, mean differences compared to the measured METs in overall activities were small (−0.13±1.09 METs). Mean differences between the predicted METs and the measured METs only in sedentary behaviors to light intensity PAs (<3.0 METs), which consumed the highest percentage of time per day [37], were still minimal (−0.20±0.33 METs) in the current study.

The finding that our procedure could lead to comparable estimation accuracy in both nonlocomotive and locomotive activities was also significant. The cause might depend on the fact that our model could assess upper-body activities such as sweeping up, clearing away, and throwing a ball accurately. Oshima et al. [21] indicated that when the acceleration sensor was attached to the waist of the individual, the USA/FSA ratio reflected dynamic changes in body posture. The waist is not in the upper body, but the inclination of the upper body accompanies that of the waist in most instances. Therefore, the gravitational acceleration signal at the waist reflects postural changes of the upper body during nonlocomotive activities, like household activities, to some degree.

Table 6. Comparison between predicted METs from each equation and measured METs (n = 68).

	Standard equation				Multiple regression equation				Measured METs		ANOVA
	Predicted METs		Difference*		Predicted METs		Difference*				
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
Nonlocomotive											
desk work	1.32	0.06	0.17	0.11	1.32	0.29	0.17	0.28	1.15	0.10	St, Mu>Me
Nintendo DS	1.30	0.04	0.18	0.10	1.30	0.28	0.28	0.27	1.12	0.09	St, Mu>Me
sweeping up	3.23	0.58	0.25	0.55	3.21	0.57	0.24	0.41	2.97	0.57	St, Mu>Me
clearing away	2.81	0.41	−0.23	0.58	2.80	0.46	−0.25	0.48	3.05	0.60	Me>St, Mu
washing the floor	3.98	0.48	−0.65	0.88	3.96	0.46	−0.66	0.70	4.62	0.78	Me>St, Mu
throwing a ball	4.20	0.80	0.53	0.60	4.19	0.80	0.53	0.47	3.69	0.65	Mu, St>Me
Locomotive											
climbing down	2.96	0.35	0.67	0.42	2.92	0.48	0.64	0.42	2.31	0.26	S, Mu>Me
climbing up	2.39	0.33	−2.91	0.74	2.39	0.52	−2.94	0.57	5.30	0.69	Me>S, Mu
normal walking	2.66	0.21	0.10	0.34	2.64	0.44	0.05	0.33	2.56	0.27	NS
brisk walking	3.34	0.34	0.16	0.36	3.29	0.45	0.09	0.32	3.16	0.33	S>Me
Jogging	6.69	0.59	0.26	0.99	6.46	0.76	0.02	0.75	6.43	1.04	NS

*Mean and SD mean the difference between predicted METs from each equation and meausred METs.
METs; metabolic equivalents, SD; standard deviation, ANOVA; analysis of variance, NS; not significant; St, standard equation; Mu, multiple regression equation; Me, measured.
>(a sign of inequality) means a significant difference among equations.
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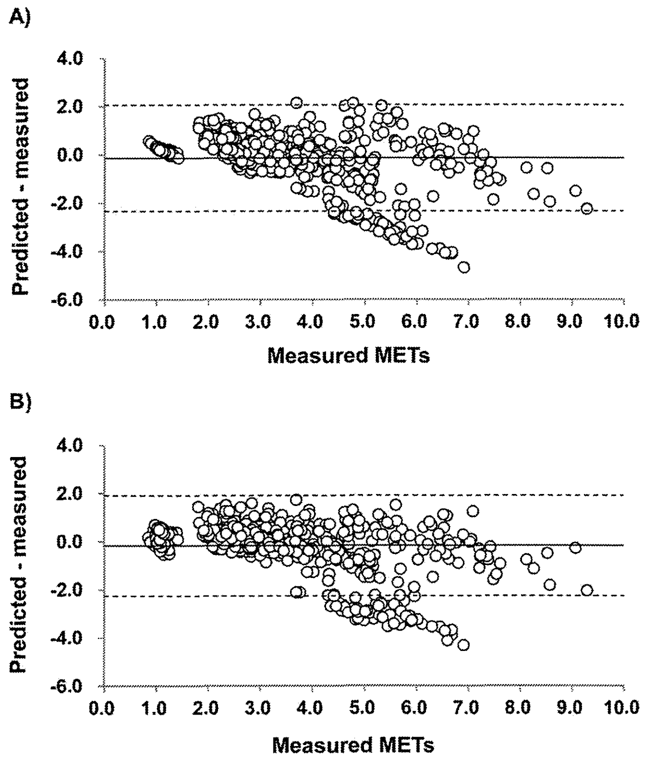

Figure 3. Differences between predicted and measured METs from each equation by Bland and Altman plot analysis. The solid line represents mean differences between measured and predicted values. The 2 dashed lines represent the upper and lower limits of agreement, calculated as mean difference ±2 SD. Upper figure (A) and lower figure (B) shows the standard equation's plots and the multiple regression equation's plots, respectively.
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In the present study, we also found that the adjusted determination coefficient (R^2) and the root mean square error (RMSE) were slightly better when weight, chronological age, and sex were added as independent variables into the standard predictive equations when combining the development group with the cross-validation group (Table 5). However, we did not observe significant differences between the multiple regression equation and the standard equation (not controlled) when looking at the average prediction error for each activity (Table 6). As this would mean that the integrated acceleration from the three dimensions associated with a child's motion includes the effects of biological factors, it might not be necessary to control for weight, age, and sex, similar to several other calibration studies [15,16].

Limitations

Given the limitations of this study, we must be very careful when interpreting our results. We cannot conclude that this predictive model is superior to previous calibration models proposed using common devices, because we did not directly compare our model to other models using the same experimental conditions (i.e. device, ethnic group, targeted activities, and calculation of energy expenditure in the resting state). To truly prove superiority, it would be necessary to compare the different methods under free-living conditions. Furthermore, in the future, we must determine whether our developed model is applicable for estimating PAs not including calibration tasks, because the predictive accuracy of the existing model is significantly reduced when applied to non-calibration activities [17,35].

Conclusions

The results of this study indicate that a specific calibration model that discriminates between nonlocomotive and locomotive activities for children can be useful to evaluate the sedentary to vigorous PAs of both nonlocomotive and locomotive activities. One of the main reasons why the differences between predicted and measured METs with our model were smaller than those reported in previous calibration studies using common devices may be the model's high rate of correct discrimination between locomotive and nonlocomotive activities.

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Author Contributions

Conceived and designed the experiments: YH CT KO KI ST. Performed the experiments: YH CT KO KI ST. Analyzed the data: YH YO. Contributed reagents/materials/analysis tools: YH CT YO ST. Wrote the paper: YH ST.

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