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Optimization Evaluation on Adolescent Cognitive Developmental Behavior Activity Measured by Digital Health Device

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ABSTRACT: The utilization of smart wearable devices in healthcare environments is expected to increase as digital technology advances. Smart wearables and the data they provide have become prevalent in medical care applications. However, evaluating clinical applications is challenging due to the need to accumulate more information and the limitations of technical approaches. By applying measures of the established digital health platform that incorporates smart wearables for adolescent brain cognitive development (ABCD), we investigated the optimization of ordinary physical activity as determined by the individual participants. It aims to provide reliable leverage for physical metabolic classification. First, the adolescent physical activity datasets are evaluated statistically for this analysis. Then, multi-dimensional Bayesian optimization (BO) is applied to extract optimized MET (metabolic equivalent of task) values to categorize physical development behavior. The result shows that the practical MET level is overestimated, and the real value is lower than expected.

KEYWORDS: Computational Biology and Bioinformatics; Smart wearable device; cognitive development; Bayesian optimization (BO); MET (metabolic equivalent of task).

Introduction

Smart wearable technology dramatically impacts the healthcare system and the quality of human life.[1] A smart device is regarded as an ultimate motivation tool that provides impetus to make key lifestyle changes for the long term. It is realized with advances in wireless hardware equipment like accelerometers, fitness trackers, body sensor devices, heart rate sensors, etc. Such technological promise redefines the assessment of human health behavior and daily activities. The global wearable technology market was valued at USD 61.30 billion in 2022 and is expected to extend at a compound annual growth rate (CAGR) of 14.6% from 2023 to 2030.[2] However, clinical implementation remains very challenging. Understanding how digital health data can be implemented for an equitable healthcare system is required. However, cost and a need for accumulated health information are the most striking barriers. In addition, the broad adoption of wearable devices further requires education, investment, and a high-tough method.[3]

Digital health devices, referred to as smart wearables or fitness trackers, can provide nearly uninterrupted information, for example, about physical activity, hydration, heart rate, sleep, and body compositions of weight/body fat percentage. The smart devices, usually worn as a wristband over the pulse, measure and analyze the personnel's biometric data in real time. They provide information about their body and lifestyle, from the number of steps they take daily, and calories burned, heart rate, and sleep quality. With increasing applications, data are integrated into clinical and research regimes. However, some bioinformation, especially blood pressure or oxygen level in the blood, has not been cleared by the FDA (Food and Drug Administration).[4] It is because blood pressure/oxygen level monitoring with smart wearable devices has not been proven in large-scale studies. For example, the values cannot depend only on a wrist monitor if one has a health condition like high blood pressure. There would be a significant lack of diversity in health outcomes.[5]

In January 2019, the National Institutes of Health (NIH) launched the Fitbit Bring-Your-Own-Device (BYOD) project, the first digital health technology initiative for the US Research Program.[6,7] There is great potential for digital health technologies in clinical and research settings in response to exploring the role of digital health in an unprecedented biotechnical category. The people who already own Fitbit devices and are willing to share their data with the program participated in the BYOD. The program has brought a novel data stream representing over a decade of innovation in smart wearable devices and revealed an opportunity to promote health equity. In this program, compelling questions were required to be answered: how can we best utilize data from technology for clinical integration? What clinical changes can be informed by the data? How can we bring health data into our daily lives? Accordingly, the future looks bright for healthcare biometrics with continuous innovation set to improve the range of devices, features, and services, the accuracy of captured data, and, importantly, the health and well-being of wearable consumers worldwide.

Physical activity is the most cost-effective measure via a smart wearable device. They count steps while measuring distance and estimate real-life functional physical performance that can be easily tracked. In applying a BYOD platform, the Adolescent Brain Cognitive Development (ABCD) study SM8 evaluated the physical behavior and health performance

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of adolescents aged between 8 and 14. ABCD is a research consortium consisting of a coordinating center, a data analysis, informatics and research center, and 21 research sites across the US. It promotes children's health, well-being, and success by sharing practical information with families, school superintendents, principals and teachers, health professionals, and policymakers. This is the most extensive long-term study of brain development and child health in the United States, supported by the National Institute of Health (NIH). As a part of the ABCD study program, scientists collected the physical activities of the participants at baseline using genetic and demographic data.

In this study, we evaluate the physical activities of adolescents collected from the ABCD study concerning individual metabolic scales by combining a quantile statistical approach with Bayesian optimization (BO). It aims to classify the trends of ABCD behaviors in terms of the metrics of the physical rate at which a person expends energy. Our study was accomplished by optimization of multidimensional input data. BO is an optimization technology that uses repetitive and efficient samples. It is an effective search method to implement hyperparameters not defined by any specific function, called the black box function. This BO completely differs from the random, grid, or hyperband searches requiring a pre-determined function. Thus, using the BO, a researcher can find the global optimum from a probabilistically principled function while performing multiple trial-and-error findings. In this study, we implemented the BO to classify and categorize patterns of ABCD behavior according to measures of a person's physical energy use.

Methods

Data:

Physical activities of a total of 167,488 children (male: 85,080 and female: 82,408) within a range of age from 8.92 to 14 years (adolescent: 11.9 years average age) were collected from the ABCD mobile technology program as a part of the BYOD platform. The activities were measured during a 3-week protocol, but 84.92% (142,230) of the total participants completed the program. The data is classified into three attributes (walk steps, heart rate, and MET: the metabolic equivalent of task). MET is defined as a ratio between rest metabolic rate and exercise metabolic rate. MET can calculate the maximum heart rate using the wearable device. The total walk steps were counted for 24 hours regardless of sleep, and heart rates were measured both during sleep and non-sleep. METs were evaluated regardless of sleep, but their values were subdivided based on activity class, i.e., sedentary (<1.5 METs), lightly active (1.5-2.9 METs), moderately active (3-5.9 METs), and vigorously active (>6.0 METs). Overall MET ranges from 0 to 12.5, and the average MET is presented as 1.976 with 0.4943 as the standard deviation. These MET values were estimated based on quantification of the percentage of maximum heart rate (MRT) that a wearable heart monitor can measure. Then, overall activities evaluated for each age category are normalized by MRT, and the range of upper or lower limits is selected as MET activity value. When mobile smart wearables are applied, this is considered more efficient than the typical MET calculation with oxygen consumption.

Table 1: This is part of the overall physical activity dataset acquired by Fitbit Smart Wearable based on the participant's activities and bioinformation, supported by ABCD (Adolescent Brain Cognitive Development) study 8. The meaning of each attribute is described in detail in the table below.

A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12
141	F	4/7/19	1	12479	1067	314	2.2	895	449	31	6
136	M	10/20/18	0	10801	799	392	2.44	827	276	71	17
149	M	4/1/19	1	8969	986	278	1.79	975	269	19	1
132	F	3/22/19	1	12282	878	552	1.94	1087	313	24	6
132	F	7/9/19	1	5721	690	573	1.69	1048	199	15	1
148	F	7/15/19	1	10763	759	482	2.37	825	402	13	1
135	F	11/13/18	1	5795	885	71	1.69	713	243	0	0
151	M	6/6/19	1	2712	261	434	2.14	585	110	0	0
151	F	12/19/19	1	2877	1112	328	1.53	1212	228	0	0
141	F	10/27/20	0	4567	840	581	1.49	1215	194	12	0
135	M	11/7/20	1	9714	896	521	2.19	965	452	0	0
131	M	5/6/19	1	40219	945	230	3.83	411	349	387	28
155	M	8/8/19	1	2815	787	651	1.63	1261	177	0	0
152	M	6/21/19	1	21299	799	624	4.96	786	184	139	314
133	M	5/25/19	1	20013	892	547	2.32	1009	358	69	3
132	M	8/19/19	1	15341	847	548	2.33	1057	266	58	14
147	M	8/9/19	1	10244	901	527	2.25	1057	338	32	1
136	M	2/10/20	1	7734	991	429	1.68	1159	250	11	0
136	M	2/13/20	1	3703	136	115	2.82	174	57	19	1
134	F	6/13/19	1	11462	907	463	1.94	1007	341	20	2
135	M	3/5/19	1	12086	853	0	2.44	476	342	20	15
160	F	9/3/19	1	5334	808	450	2.26	824	402	24	8

The attributes of Table 1

A1	Age in months at the time of the sampling.
A2	Sex of subject at birth
A3	First day of (expected) wear of 3-week protocol
A4	Is this day during the 3-week protocol period?
A5	Total number of steps observed in all minutes (no exclusions) from midnight (00:00) to 11:59 PM (23:59) regardless of sleep categorization
A6	Number of minutes with heart rate value from midnight (00:00) to 11:59 PM (23:59) not identified as sleep (at 60 second classic level) or exclusion rules
A7	Number of minutes with heart rate Value from midnight (00:00) to 11:59 PM (23:59) that ARE identified as sleep (at 60 second classic level) or exclusion rules
A8	Average METS during non-sleep (night) valid minutes
A9	Number of minutes of sedentary (<1.5 METS) time observed in all valid minutes after all exclusions from midnight (00:00) to 11:59 PM (23:59) regardless of sleep status
A10	Number of minutes of lightly active time (1.5-2.9 METS) observed in all valid minutes after all exclusions from midnight (00:00) to 11:59 PM (23:59) regardless of sleep status
A11	Number of minutes of moderately active (3-5.9 METS) time observed in all valid minutes after all exclusions from midnight (00:00) to 11:59 PM (23:59) regardless of sleep status
A12	Number of minutes of vigorously active (>6 METS) time observed in all valid minutes after all exclusions from midnight (00:00) to 11:59 PM (23:59) regardless of sleep status

Analysis:

First, the raw input data set is statically analyzed to overview the activity behavior trends. It is also compared for physical behavior based on each MET class. The statistical graphs are plotted with an observed cumulative percentage on the X-axis and an expected cumulative percentage on the Y-axis, such as quantile-quantile (Q-Q). The X-axis is marked for the total step number, and the Y-axis for the percentile. Distribution is calculated as a "normal Gaussian distribution", while the input data is ordered from smallest to largest based on the Bloom sort method.[9] This plot is an alternative way of graphical visualization to evaluate distribution so that it differs from the ordinal probability plot to show observed and expected values.

Bayesian optimization (BO)[13] is a data-driven optimization method used to find a function's maximum/minimum values whose input-output relationship is unknown. BO has attracted various research fields as a powerful probabilistic approach to solving optimization problems. The application of BO has been increasing in data analysis because it can efficiently optimize high-dimensional and non-differentiable functions. Recently, a graphical user interface (GUI) called BOXVIA, based on a Python application, was developed by Akimitsu

Ishii.[14] BOXVIA (BOXVIA stands for Bayesian Optimization Executable and Visualizable Application) enables us to visualize higher dimensional resultant functions of BO. Such visualization provides substantial information, such as the distribution of unsearched inputs and the location of the inputs, which may improve the output. BOXVIA offers significant help in understanding the distribution of high-dimensional objective functions, which is difficult for humans to imagine.

■ Result and Discussion

Figure 1 presents the pie diagram of the fraction of the MET values for (a) the total participants, (b) male, and (c) female. There is little difference between the groups. Light active 1.5-2.9 MET is a prevalent performance feature. The sum of moderate and vigorous intensities is less than 5%. However, the female group shows a slightly higher sedentary percentage. Table 1 shows a part of the overall physical dataset applied in this study and describes its attributes. From the pie diagrams in Figure 1, it is seen that the total amount of > 6.0 MET seems to be extraordinary, compared to below < 1.5 MET, and in general, the regime below < 1.5 MET (sedentary) or > 6.0 MET (vigorously active) are rare in consideration of adolescent physical activities. However, the fundamental MET definition suggests that detailed investigation is necessary even for such regimes, from which a full spectrum of physical activities can be evaluated in terms of MET. We included those values' ranges in our first statistical analysis and then discussed the values based on the optimization analysis.

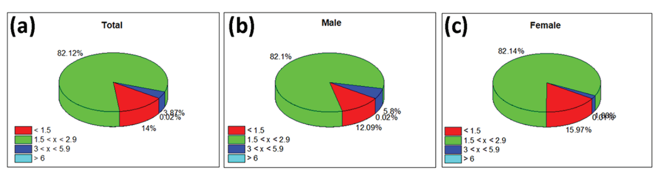

Figure 1: The fraction of the MET values for (a) the total participants, (b) male, and (c) female. (Updated)

Statistical Analysis:

Figure 2 shows the probability distribution of the total number of steps acquired from the ABCD participants for the 3-week protocol regardless of sleeping time. The graph is plotted with an observed cumulative percentage on the X-axis and an expected cumulative percentage on the Y-axis. The X-axis is the total step number, and the Y-axis is the percentile. The mean of the total step is 7919.1, with a 5384.3 standard deviation. Up to the bottom of the 9% percentile, "zero" steps appear because about 15.08% of the total participants did not complete this program. Over the range of 80-9% (percentile), the plot shows a linear behavior that can be fitted with a slope of 1.85E-4 (with std. of 1.85E-8) and intercept of -1.40 (with std. of 1.59E-4), expressed as $y = 1.85^{-4}x - 1.40$. However, the parabolic behavior appears to be above 80%, and exponential increase is dominant after 95%.

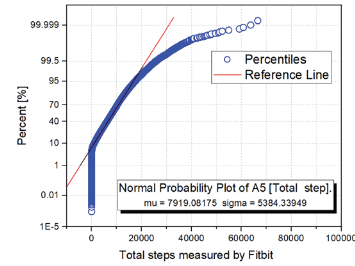

Figure 2: A Q-Q (Quantile-Quantile) plot for the distribution of the total number of steps observed at all times for a 3-week protocol (A5). This graph shows a linear trend from 9-80%, but the percentile increases from parabolic to exponential after 90%.

One MET (metabolic equivalent of task) is the energy consumed while sitting quietly, equal to 3.5 ml O_2 (oxygen) per kg of body weight x min.[10] The MET concept represents a simple, practical, and easily understood procedure for expressing the energy cost of physical activities as a multiple of the resting metabolic rate. MET can be calculated using the maximum heart rate (MHR) measured by a heart rate monitor or smart wearable devices.[11,12] Figure 3 exhibits the probability distributions of the physical activities of the ABCD participants according to each MET level. The profiles are plotted using the same statistical method applied to Figure 2. However, at this moment, the plots reflect the adolescent participants who completed the 3-week protocol of the ABSD mobile technology program. Interestingly, the amount (accumulated percentile) of "zero activity" increases as the MET value increases; likely, the length of the vertical line at "zero" MET becomes extended with an increasing MET category. It implies that the degree of physical activity becomes challenging as the category (class) requirement level increases. In the sedentary class, after 95% (percentile), two distinct linear transitions appear before the maximized minutes of MET. For light intensity, a linear behavior remains up to 98%. Any linear trend cannot be defined for both moderate and vigorous intensities. However, the rest of MET activities show rapid parabolic increases after 95%, except sedentary.

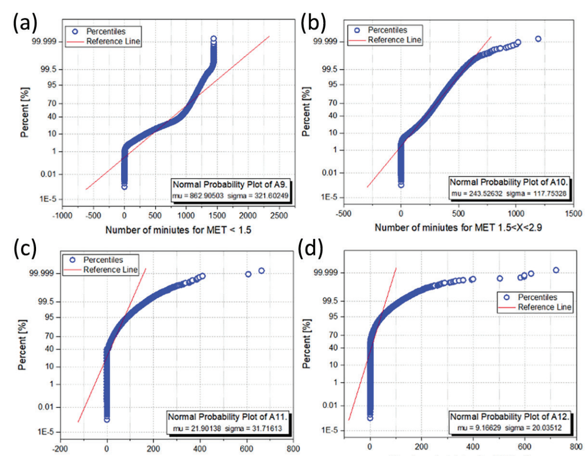

Figure 3: Q-Q (quantile-quantile) plots for overall valid minutes observed based on each MET category (class) (a) sedentary (MET < 1.5), (b) light active (MET 1.5-2.9), (c) moderate active (MET 3-5.9), and (d) vigorously active (MET >6). The red line is plotted for a reference. Distinct linear behaviors are clearly shown for both (a) and (b), but parabolic trends are more prevailing for both (c) and (d). (a) shows the limitation of the increase at 1500 minutes.

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From the statistical analysis, we could evaluate the distributions of the ABCD physical activities depending on the degree of MET. However, such a way could not provide the information on which MET values are required for actual activities during adolescent physical development. Hence, assessing the optimized MET value based on ordinary physical activities measured by the number of total steps directly from smart wearable device analysis is imperative. The MET values should also be estimated compared to heart rates for individual activities. This will generate the most efficient way to establish the goal of adolescent cognitive development rather than evaluating physical activities at each MET level (category), as exemplified in Figure 3. MET depends on the individual heart rate as the original heart rates collected for both awake (A6) and sleep (A7) conditions. Since the total steps (A5) are associated with the average MET (A8), we should optimize the MET value for individual percentile groups (Figure 2), which could be the shape of a 4-dimensional question. Bayesian optimization (BO) allowed us to estimate the optimized number with three variables (A5, A6, A7) and one target (MET value).

Optimization Analysis:

Using BOXVIA, we attempted to estimate optimized METs associated with the cumulative percentiles of the physical activity of the total participants. We imported the dataset in CVS format. As aforementioned, A5 (total step), A6 (heart rate value for daytime), A7 (heart rate value for nighttime) in Table 1 are used as the variables, and the average METs (A8) are assessed for the optimized target in each percentile group (above 99.5%, 99.5-90%, 90-80%, 80-75%, 75-70%, 70-67.27%, and 67.27-65% in order). Thus, a 4-dimensional BO analysis was performed. The percentile classification (grouping) relies on the behavior trends observed in Figure 2 (Quantile-Quantile statistical analysis). Rapid increases like exponential increase appear above 99.5%, parabolic behavior is shown between 99.5-80%, and linear behavior is significant up to 80%. Figures 4 and 5 show the results of BO analysis for the participants in the above 99.5% percentile. 3D plots (a) indicate input best with a suggested value highlighted by a red dot, as shown in 2D (b). The recommended value is the optimized MEM number in the 4D dimension. The bar legend in (b) depicts a color scale for the range of input data.

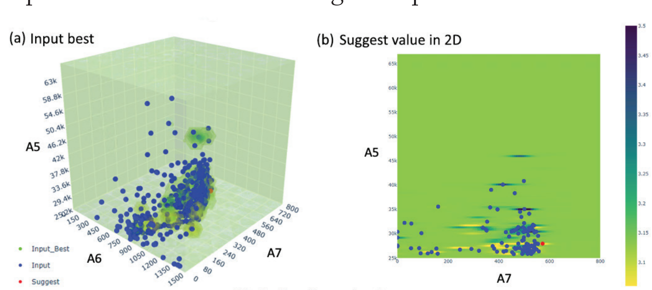

Figure 4: Visualized distribution of 4-dimensional mean function for (a) input best in 3D surface and (b) suggest value in 2D heat map surface, from BOXIA analysis on the participants who are in the above 99.5% percentile of the total number of steps measured by Fitbits (Figure 2). The suggested value is marked with a red dot, and its coordinates are shown in the sliced 2D heat map, corresponding to the optimized MET. For the 2D coordinate, A5 and A7 are shown here, but we could use other combinations, such as A5 & A6 or A6 and A7.

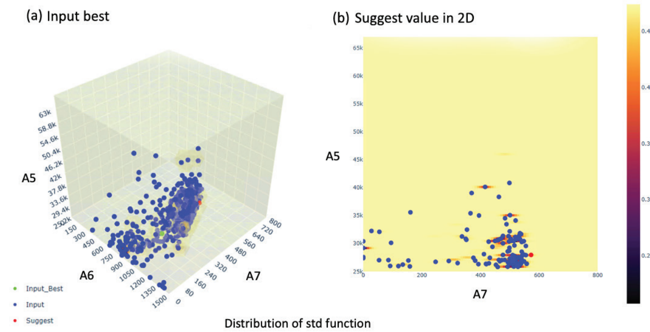

Figure 5: Visualized distribution of 4-dimensional standard deviation function for (a) input best in 3D surface and (b) suggest value in 2D heat map surface, from BOXIA analysis on the participants who are in the above 99.5% percentile of the total number of steps measured by Fitbits (Figure 2). These plots are supplementally obtained for the standard deviation distribution on the optimized suggesting number (Figure 4). Likewise, other coordinate combinations were collected, but A5 and A7 are shown here.

Figures 4 and 5, respectively, describe mean and standard deviation values optimized from BOXIA analysis. From these, we can estimate the best value (mean) with the affordable range (standard deviation) associated with each activity percentile category. When the multidimensional dataset is analyzed, these two values should be addressed together to meet statistical analysis purposes. As a result, as described below and in Table 2, no clear criteria exist to distinguish above the 90% percentile.

The Input best (best candidate) is suggested based on a global search. BOXVIA also provides a constraint function defining the correlation between two input parameters (variables). This option is set up for better optimization performance. However, such a case was not applied to our study because no apparent corresponding relations between the attributes of our input data sets are defined. In the same faction of this initial study, we completed BO evaluations for the rest of the percentile groups. Table 2 tabulates the obtained results. Suggested MET values are achieved from 3.13 to 0.32 for the eight different groups. They are referred to from moderate intensity to sedentary activity, corresponding to the total steps of 27,962.26 to 10,200.00. The number "1" in A6 and A7 is due to uncompleted optimization by the broad range of input data sets. This is another reason we did not specify details in the regime beyond < 1.5 MET or > 6.0 MET, as described previously. We confronted similar results for those ranges. From this optimization analysis, we can directly correlate adolescent physical activity and MET value for realistic application to behavior development. Even if high activity from the total counts of physical steps based on Figure 2 (>99.5%) is expected to represent above 6.0 MET, the top percentile group only refers to moderate activity MET value close to ~ 3.13. This means that the value of physical activity estimated during the behavior development of adolescents is likely overestimated. Our study shows that up to 70% of the participants remain sedentary, and their physical activities are transferred to light intensity between 70-80% (percentile). Afterward, the remaining participants showed moderate intensity. This newly suggested classification would provide systematic leverage for evaluating the physical development activity of the adolescent, rather than the simple sampling to categorize metabolic scales (MET) based on activity duration like Figure 3.

Table 2: The result of the BO (Bayesian optimization) analysis on the overall percentiles ranges from above 99.5% to 65% for the total participants in the ABCD program (Figure 2).

Percentile	MET Mean	Std	Acquisition	A5 (X1)	A6 (X2)	A7 (X3)
Above 99.5%	3.13	0.43	0.64	27,962.26	896.15	572.95
99.5%-90%	3.17	0.33	1.12	19,177.27	1	237.49
90%-85%	2.37	0.28	0	14,325.78	597.67	55.83
85%-80%	2.28	0.27	0.01	12,127.93	937.73	502.11
80%-75%	1.66	0.31	1.01	11,215.14	1	800
75%-70%	1.7	0.24	1	10,792.99	1500	1
70-67.27%	1.12	NaN	0	10,187.63	597.67	62.69
67.27%-65%	0.32	1.27	1	10,200.00	144.85	436.34

In addition, the statistical analysis shows that there is no significant difference between groups. However, the female group showed a higher sedimentary percentage. It is believed that the activity based on sex group would depend on the nature of the activity inclination. Thus, if some changes in physical circumstances are made, there would be a significant impact on health and activity in that group. Recently, physical activity could be considered a critical factor in preventing chronic diseases in adolescents and young adult childhood. In the current proliferation and popularity of smart wearables, our study introduces a persuasive technical direction to integrate such technology with the physical activity of young adults. In contrast, other systematic studies have reported the effects of wearing wearables or explicitly focused on examining MET value associated with physical activity. Our approach is to find the optimized value with multiple inputs and classify the value based on individual activity trends.

Conclusion

Smart wearable devices are becoming an increasingly popular form of identification using biometric measurements. They are set to replace traditional password and chip-and-pin authentication methods while continuing to assist both the fitness and medical industries. Physical activity is a well-established marker of current health status and future health risks. Health research has tracked it using body-worn sensors like smart wearables as a functional measure. Previous research suggests that digital health programs incorporating health behavior models are succeeding in future clinical applications. Yet, knowledge is likely limited regarding all factors that can drive the successful implementation of wearables in the healthcare environment.

In this study, we attempted to optimize the MET (metabolic equivalent of task) value of adolescents whose age ranges from 8.92 to 14 years based on the input data collected from the ABCD (Adolescent Brain Cognitive Development (ABCD) study^{SM}) program as a part of the Fitbit Bring-Your-Own-Device (BYOD) project supported by the National Institutes of Health (NIH). It aims to provide a more effective systematic MET value reflected on the ordinary physical activity of the adolescent development behavior, such as walking steps that smart wearables can measure. The MET values also included heart rates used to calculate individual metabolism. Before optimization analysis, a statistical evaluation was conducted to categorize each activity group into behavior trends. The total behavior was also compared with a type of MET class such as sedentary, light, moderate, high, and vigorous intensity. The comparison does not likely demonstrate the practical physical behavior during adolescent development. Thus, we applied Bayesian optimization (BO) in the shape of a 4-dimensional question, including three variables (total step, heart rates during day activity, and heart rates during sleep) and one target (MET). Our optimization analysis directly correlates adolescent physical activity and real MET value. Up to 70% (percentile) of the overall program participants for the total physical steps remain sedentary, corresponding below 1.5 MET. Light intensity with 1.5-2.9 MET appears from 70-80% (percentile). Above 90%, MET is represented as moderate intensity. From the evaluation with MET classes, as shown in Figure 3, the higher percentile (at least above 90%, which depicts an exponential increase) is supposed to be vigorous intensity marked with MET >6.0. However, our optimization analysis shows only moderate intensity, even for the case above 99.5%. It describes that our multi-dimensional optimization analysis provides effective systematic leverage for evaluating physical activity during adolescent development by applying smart wearable devices to a healthy behavior environment.

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Patrick Junhee Kim is an Asia Pacific International School senior interested in neuroscience and biology. He hopes to build his career as a pioneer in the neuroscience and bioengineering field using state-of-the-art IT technology, such as machine learning and artificial intelligence.

Andrew Gunhee Kim is a junior at Asia Pacific International School and is interested in STEM research, especially using machine learning and artificial intelligence technology. He hopes to be a researcher who utilizes advanced IT technologies for human life in the field of engineering.