Accuracy of the Huawei GT2 Smartwatch for measuring Physical Activity and Sleep among Adults during Daily Life: A Validation Study

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Abstract

Background: Smart wearable devices are increasingly popular for physical activity and health promotion. However, ongoing validation studies on commercial smartwatches are still needed to ensure their accuracy in assessing daily activity levels, which is important for both promoting activity-related health behaviors and serving research purposes.

Objective: This study aims to evaluate the accuracy of popular smartwatch, Huawei Watch GT2, in measuring step counting (SC), daily activity energy expenditure (TDAEE), and total sleep time (TST) during daily activities among Chinese adults.

Methods: A total of 102 individuals were recruited and divided into two age groups: young adults (YA) and middle-aged and elderly (MAAE). Participants' daily activity data were collected for one week by wearing the Huawei Watch GT2 on their non-dominant wrist and the Actigraph GT3X+ on their right hip as the criterion measure. The accuracy of the GT2 was examined using the intraclass correlation coefficient (ICC), Pearson product-moment correlation coefficient (PPMCC), Bland-Altman, mean percentage error (MPE), and mean absolute percentage error (MAPE).

Results: The GT2 demonstrated reasonable agreement with the Actigraph, as evidenced by an ICC consistency test of .88 ($P<.001$) and an MAPE of 25.77% for step measurement, an ICC of .75 ($P<.001$) and an MAPE of 33.79% for energy expenditure estimation, and an ICC of .25 ($P<.001$) and an MAPE of 23.29% for sleep time assessment. Bland-Altman analysis revealed that the GT2 overestimated SC, and underestimated TDAEE and TST. The GT2 is better at measuring SC and TDAEE among YA than among MAAE, and there was no significant difference between these two groups in measuring TST.

Conclusions: The Huawei Watch GT2 demonstrates good accuracy in step counting. However, its accuracy in assessing energy expenditure and sleep time measurement needs further examination. Therefore, the watch is suitable for daily activity monitoring, yet caution is advised for its use in research studies that require high accuracy.

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KEYWORDS

smartwatch; accelerometry; free-living; physical activity; sleep; validity

Introduction

Physical inactivity has been considered a major cause of chronic non-communicable conditions such as cardiovascular disease, malignancies, and type 2 diabetes [1], leading to increased mortality rates, impaired quality of life, reduced life expectancy [2-4], and a substantial financial burden on the healthcare system [5]. Hence, interventions aimed at increasing physical activity are critical to public health. In this regard, sustained efforts of regular and accurate monitoring of physical activity are necessary [6-8]. To achieve this goal, researchers and health practitioners have been continuously in search of physical activity measurement methods that best balance precision and cost. High-precision monitoring methods such as double-labeled water and indirect calorimetry are not suitable for daily life due to high cost and subject burden [9]. Pedometers and accelerometers are relatively easy to carry in daily life, but only offer limited indices that mostly focus on activity counts, rather than physiological measures (e.g., heart rate), and the latter is also expensive [8,9]. Questionnaires are commonly used, particularly in large sample surveys, but have often been questioned for being highly subjective [8-10].

With rapid technological advancements, smartwatches have become increasingly popular for monitoring and promoting health behaviors such as physical activity, sedentary behavior, and sleep. Such devices are valued for their multifunctionality, convenience, comfort, and cost-effectiveness. Specifically, smartwatches have multiple built-in sensor devices, such as accelerometers and optical heart rate sensors, which may achieve a high level of measurement accuracy and cover a variety of indices (e.g., duration of certain behavior, heart rate, oxygen saturation) than pedometers and accelerometers that are commonly used in research settings [11].

Recent studies highlight the role of smartwatches in enhancing exercise motivation and facilitating healthier lifestyle choices [12-15]. With the growing popularity, smartwatches provide the possibility for continuous, real-time monitoring and feedback, which has been shown effective in increasing physical activity engagement [7,12-16]. Nowadays, various types of smartwatches have been widely used in a variety of practical settings, such as physical activity programs, fitness training, physical education, and healthcare services [7,17-19]. They also have great potentials to serve research purposes [20,21]. However, the above-mentioned practical and research applications should be based on continuously examining and improving the validity.

Several studies have evaluated the accuracy of various smartwatch models in real-world settings, comparing them against established activity monitoring devices such as the Accelerometer GT3X+ [22,23]. Degroote et al [22] observed that while models such as the Polar M600 and Huawei Watch accurately measured steps, their ability to accurately capture moderate to vigorous physical activity (MVPA) varies. Tedesco et al [23] found that for an elderly population, both the Fitbit Charge 2 and Garmin Vivosmart HR+ were effective in step counting but only moderately accurate in measuring energy expenditure and sleep, with Fitbit performing slightly better in these areas. In addition, several studies examined the accuracy of smartwatches in different age groups in laboratory setting [24,25]. Chow et al [24] found that when performing aerobic exercise indoors, the Xiaomi Mi Band 2 and Garmin Vivosmart HR+ showed overall acceptable accuracy in heart rate measurements, which were independent of age. Magistro et al [25] suggested that the ADAMO Care Watch, with its algorithm tailored for slower pace, might be particularly effective for older adults in step counting.

While the accuracy of smartwatches has been explored in previous research studies, research specifically focusing on their performance across different age groups in a free-living environment remains scarce, particularly within the Chinese population. The Huawei smartwatch ranks second in global sales in Q2 2023 and holds a high market share of 39% in China [57], but received limited empirical research attention on its accuracy [22,43], especially with regard to measurements of energy expenditure and sleep duration [38,53,58]. Considering its significant market prominence, it is crucial to rigorously assess the accuracy of the Huawei smartwatch in measuring health-related indices to ensure its validity for users' health monitoring and lifestyle management. Clearly, researchers have long voiced out the need to regularly examine the accuracy of smartwatches in order to continuously improve their functions and better apply them to human health promotion. However, it appears that studies of validity examination are far from providing sufficient evidence that support the use of smartwatches for research and health promotion purposes [23,38,53,54].

Hence, this study aims to determine the validity of smartwatches for different populations under free-living conditions. Such efforts should bridge the above-mentioned research gap and offer insights that might facilitate the wider adoption of smartwatches in health promotion and monitoring.

Methods

Participants

A total of 102 adults were recruited (Campus and Community Flyer Recruitment; the 18 dropouts were excluded), including 44 young adults (YA; age range: 18-24 years) and 58 middle-aged and elderly (MAAE; age range: 55-91 years). All the participants were Chinese living in

Hangzhou, China, and volunteered to participate in this study. The inclusion criteria were: no neurological or cardiovascular disease that could affect the participants' daily exercise; no history of lower extremity injury or disability. A detailed verbal explanation was given by the researchers before participation in the study, and all the participants signed informed consent. Participants had the right to choose to continue or discontinue their participation at any time during the conduct of this experiment. The study was approved by the Medical Ethics Committee of the Department of Psychology and Behavioral Sciences, Zhejiang University ([2021]007).

Measures

Accelerometer

The Actigraph GT3X+ (ActiGraph, Pensacola, FL, USA) has been widely employed as a "gold standard" reference measure of physical activity because it has been consistently found to be both reliable and valid in physical activity studies [26-28]. The Actigraph accelerometer was set to collect data every 10 seconds, and the raw data and clinical reports of the accelerometer were downloaded using ActiLife V6.13.4 software (ActiGraph, Fort Walton Beach, FL, USA). The Freedson Adult (1998) cut-points were used to process the data [29-31]. The total sleep time was calculated using the Cole-Kripke algorithm [32].

Wearable Devices

The study aimed to examine the validity of the then-latest Huawei Watch GT2 (45.9×45.9×10.7mm) in daily life. The GT2 has a wrist coverage of 14-21cm and is equipped with the wearable chip Kirin A1 and sensors including an acceleration sensor, a gyroscope sensor, and an optical heart rate and geomagnetic sensor. In this study, the researcher used Huawei Sports Health software for data acquisition to examine the performance of the GT2 in terms of steps count (SC), total daily activity energy expenditure (TDAEE), and total sleep time (TST) in daily life.

Data Collection Procedure

All participants were first given verbal explanations of the study and signed written consent after being fully informed. The researchers measured and collected their physiological data (age, height, weight, etc.) on the first day and then fitted them with the Actigraph GT3X+ (right hip) and Huawei Watch GT2 (non-dominant wrist). Participants were told to maintain a normal daily routine but to wear both devices for 7 consecutive days (including 2 weekends and 5 workdays). The devices were worn at all times, except during water-based activities.

Statistical Analysis

The data were downloaded and recorded once the devices were returned. To ensure that the collected data were reliable, the researchers examined the data and excluded cases if the accelerometer was worn for less than 10 hours in a day and for fewer than 2 days [33,34]. Data analysis and graphical representation were performed using IBM SPSS 29 and GraphPad Prism 9. First, a descriptive analysis of the GT2 and GT3X+ accelerometers was performed. Second, the correlations between GT2 and accelerometer data were examined by calculating the Pearson product-moment correlation coefficient (PPMCC) and the intraclass correlation coefficient (ICC; two-way random, absolute consistency, 95% confidence interval, and single measurement). The critical values for the explanatory ICC were categorized as poor for less than .60, moderate for .60 to .75, good for .75 to .90, and excellent for greater than .90 [35]. Third, the agreement between GT2 and accelerometer was examined by calculating the mean percentage error (MPE) and the mean absolute percentage error (MAPE). The MPE quantifies the average percentage deviation between the GT2 and accelerometer, highlighting potential systematic discrepancies. Conversely, MAPE captures the absolute extent of these deviations, offering a comprehensive view of error magnitude without directional bias. These metrics are instrumental in assessing the GT2's precision across various physical activities. To determine whether the measurement errors of the GT2 against the Actigraph were statistically different between the two age groups, paired t-tests were used. Finally, to test the level of consistency between GT2 and convergence measures, Bland-Altman plots and the associated consistency restrictions were constructed.

Ethics statement

This study involving human participants was rigorously reviewed and received approval from the Ethics Committee of the Department of Psychology and Behavioral Sciences, Zhejiang University ([2021]007), ensuring adherence to ethical standards. All participants provided written informed consent, with a strong commitment to safeguarding personal data and privacy.

Results

A total of 102 participants met the inclusion criteria and participated in the experiment, spanning an age range of 18 to 91 years (mean 48.17 [SD=24.56]) and a BMI range of 16.68 to 31.64 (mean 22.52 [SD=3.13]) kg/m². The cohort was stratified into two age groups: young adults (YA), and middle-aged and elderly adults (MAAE), with a note that 5 participants in the MAAE group were under 60 years, constituting 8.62% of this group. Detailed demographic data are presented in Table 1.

Table 1. Participant characteristics (N=102).

Characteristic	**Total** (N=102)	**YA**[a] (N=44)	**MAAE**[b] (N=58)
Age (year), mean (SD)	48.17 (24.56)	20.89 (1.66)	68.86 (7.55)
Male gender, n (%)	37 (36.27)	22 (50)	15 (25.86)
Height (cm), mean (SD)	164.51 (8.57)	170.59 (7.38)	159.91 (6.25)
Weight (kg), mean (SD)	60.88 (9.07)	60.82 (8.53)	60.93 (9.54)
BMI[c] (kg/m^2), mean (SD)	22.52 (3.13)	20.86 (2.14)	23.78 (3.19)

[a]YA: young adult.
[b]MAAE: middle-aged and elderly.
[c]BMI: body mass index.

Table 2 shows the results of correlational analysis between the GT2 and the GT3X+ accelerometer, while Table 3 shows the results of the difference test between the GT2 and Actigraph in terms of SC, TDAEE and TST during daily life across different age groups. Figure 1 visualizes the Bland-Altman analysis comparison plot, and Figure 2 illustrates the overall accuracy of the Huawei Watch GT2 across various functions.

Table 2. Correlation coefficients, 95% confidence intervals between Huawei Watch GT2 and Actigraph GT3X+ measurements, and paired-sample t-tests on MAPE between the YA and MAAE groups.

Indicator, group	Correlation		Correlation		Paired	
	PPMCC[a]（95%CI）	*P* value	ICC[b]（95%CI）	*P* value	T-test[c]	*P* value
SC[d]					-2.79	=.006
Total	.92 (0.91, 0.93)	<.001	.88 (0.76, 0.93)	<.001		
YA[g]	.91 (0.89, 0.93)	<.001	.88 (0.79, 0.92)	<.001		
MAAE[h]	.92 (0.90, 0.94)	<.001	.88 (0.73, 0.93)	<.001		
TDAE[e]					-2.71	=.007
Total	.77 (0.74, 0.80)	<.001	.75 (0.67, 0.80)	<.001		
YA	.80 (0.75, 0.84)	<.001	.76 (0.67, 0.83)	<.001		
MAAE	.76 (0.71, 0.80)	<.001	.73 (0.65, 0.80)	<.001		
TST[f]					1.65	=.10
Total	.47 (0.40, 0.54)	<.001	.25 (-0.06, 0.49)	<.001		
YA	.49 (0.38, 0.59)	<.001	.21 (-0.07, 0.46)	<.001		
MAAE	.48 (0.39, 0.57)	<.001	.29 (-0.05,0.54)	<.001		

[a]PPMCC: Pearson product moment correlation coefficient.
[b]ICC: intraclass coefficient correlation. less than 0.60 (poor), 0.60 to 0.75 (moderate), 0.75 to 0.90 (good), greater than 0.90

(excellent).
[c]Paired T-test: paired samples t-test between YA and MAAE group MAPEs.
[d]SC: steps count.
[e]TDAEE: total daily activity energy expenditure.
[f]TST: total sleep time.
[g]YA: young adult.
[h]MAAE: middle-aged and elderly.

Table 3. Measured mean, mean percentage error, mean absolute percentage error, and deviation values in Bland-Altman for the Huawei Watch GT2 and Actigraph GT3X+ accelerometer for Steps Count, Total Daily Energy Expenditure (kcal), and Total Sleep Time (min), with associated standard deviations.

Indicator, group, device	Mean（SD）	MPE[a] (SD)	MAPE[b]（SD）	Bland-Altman analysis[c] Bias (SD)
SC[d]				
Total		-17.47 (30.56)	25.77 (23.98)	-1318.82 (2340)
Watch GT2	9585.29 (5947.50)			
Accelerometer	8266.47 (4919.71)			
YA[g]		-14.55 (27.80)	21.91 (22.43)	-1068.63 (2153)
Watch GT2	8870.82 (5333.84)			
Accelerometer	7802.18 (4418.34)			
MAAE[h]		-19.79 (32.44)	28.81 (24.74)	-1516.62 (2463)
Watch GT2	10150.17 (6342.52)			
Accelerometer	8633.55 (5260.39)			
TDAEE[e]				
Total		8.43 (39.64)	33.79 (22.34)	50.36 (148.40)
Watch GT2	307.76 (204.37)			
Accelerometer	358.13 (232.90)			
YA		4.48 (36.94)	30.32 (21.48)	44.39 (126.60)
Watch GT2	282.41 (172.53)			
Accelerometer	326.80 (212.99)			
MAAE		11.32 (41.33)	36.29 (22.68)	54.73 (162.50)
Watch GT2	326.27 (223.26)			
Accelerometer	381.00 (244.24)			
TST[f]				
Total		19.98 (18.20)	23.29 (13.71)	138.08 (123.80)
Watch GT2	476.68 (88.45)			
Accelerometer	614.76 (138.20)			
YA		22.13 (17.23)	24.39 (13.84)	156.33 (133.00)
Watch GT2	466.60 (77.06)			
Accelerometer	622.94 (153.17)			
MAAE		18.35 (18.77)	22.45 (13.58)	123.15 (114.70)
Watch GT2	484.37 (95.68)			

Accelerometer	608.52 (125.51)

[a]MPE: mean percentage error.
[b]MAPE: mean absolute percentage error.
[c]Bland-Altman analysis: bias of bland-altman.
[d]SC: steps count.
[e]TDAEE: total daily activity energy expenditure.
[f]TST: total sleep time.
[g]YA: young adult.
[h]MAAE: middle-aged and elderly.

Figure 1. Bland-Altman plots of the Huawei Watch GT2 and Actigraph GT3X+ in overall phases for different groups and indicators. The middle line represents the mean difference between the GT2 and accelerometer (negative values indicate an overestimation of the GT2, whereas positive values indicate an underestimation), and the upper and lower dashed lines indicate the limit of agreement (1.96×SD of the difference scores). The green dot indicates YA, and the red dot indicates MAAE.

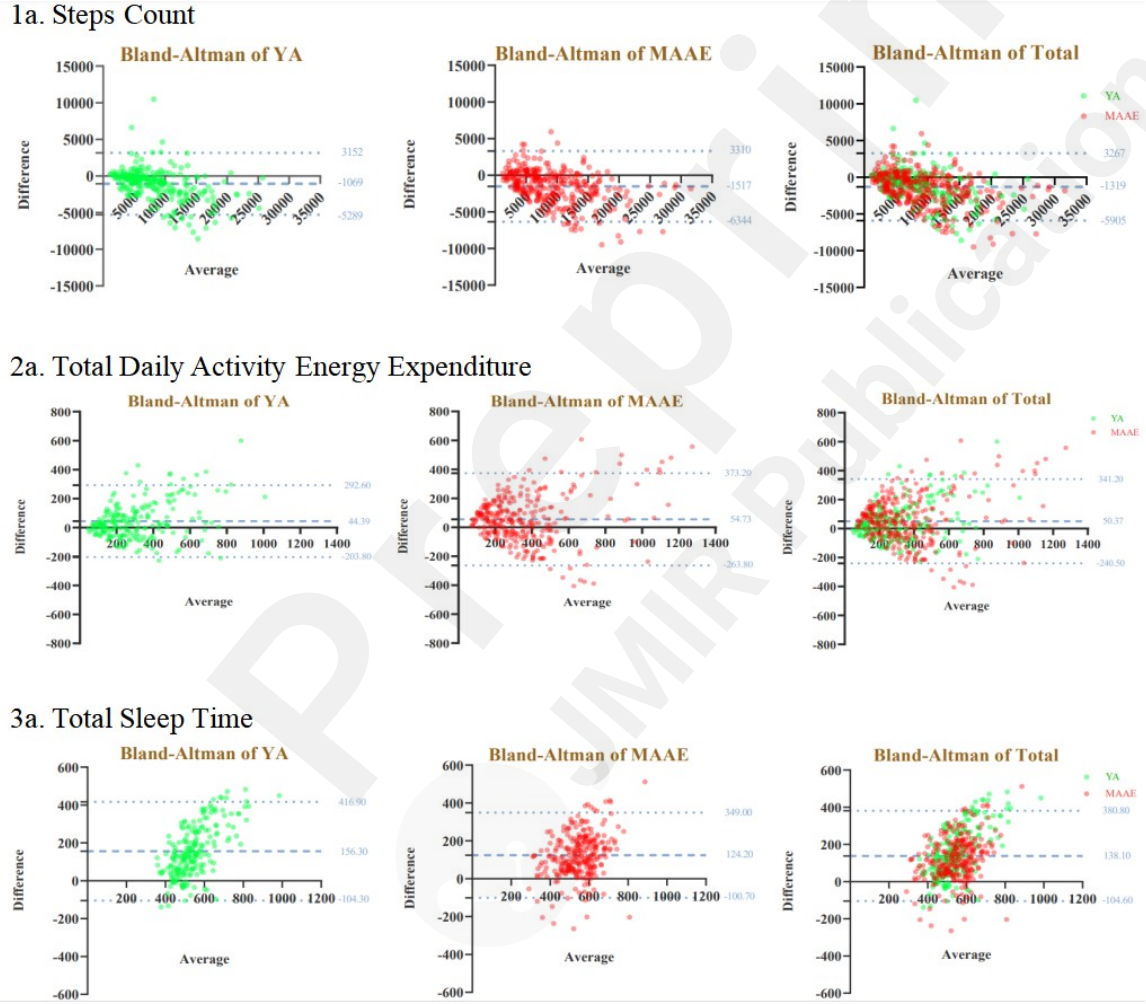
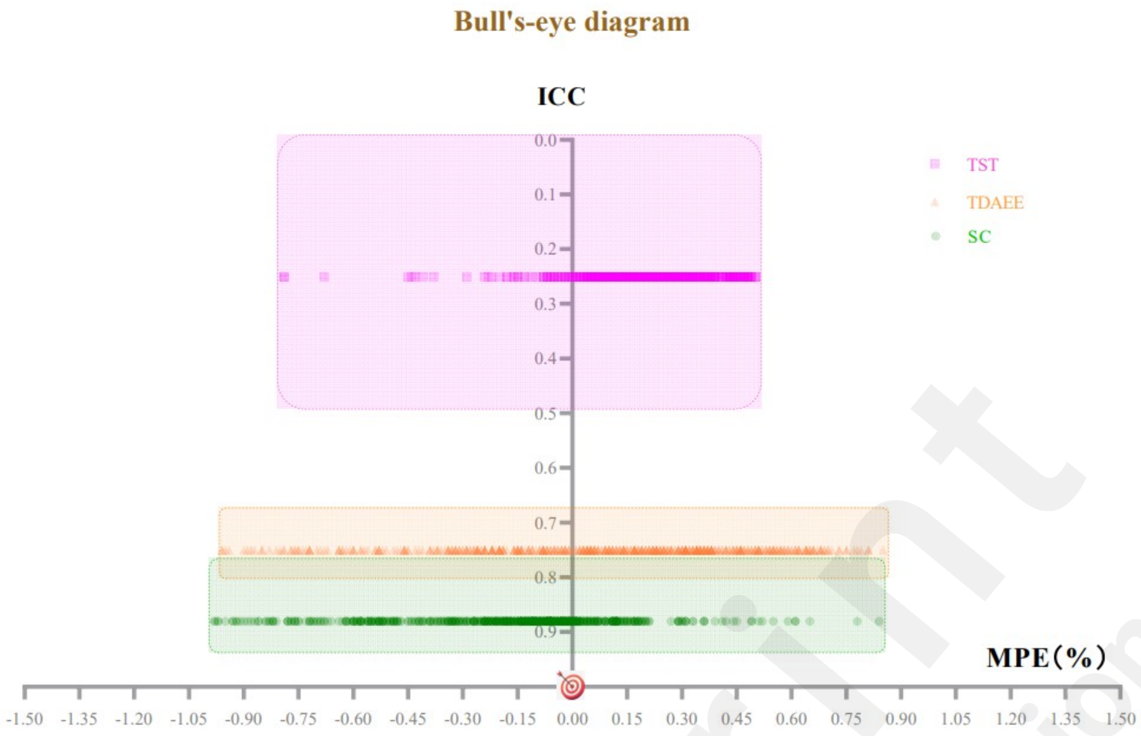


Figure 2. Bull's-eye diagrams with Actigraph GT3X+ as the gold standard. The X-axis represents the Mean Percentage Error (MPE), and the Y-axis represents the Intraclass Coefficient Correlation (ICC) between the GT2 and the accelerometer. The good accuracy of the Huawei Watch GT2's measurement is indicated when the scatter point falls steadily near the origin (MPE=0, ICC=1). TST=total sleep time, TDAEE=total daily activity energy expenditure, and SC=step count.



Steps Count

Firstly, Table 2 shows the correlation between GT2 and the accelerometer, with a PPMCC test score of .92 (*P*<.001, 95% CI=[0.91, 0.93]) and an ICC test score of .88 (*P*<.001, 95% CI=[0.76, 0.93]), which suggests that the GT2 possesses good to excellent validity in measuring SC. Secondly, the difference between GT2 and Actigraph in SC across age groups is presented in Table 3. Generally, the GT2 tends to overestimate SC compared to Actigraph accelerometer measurements (MPE=-17.47%, MD=-1318.82). This overestimation is more pronounced in the MAAE group (MPE=-19.79%, MD=-1516.62) than in the YA group (MPE=-14.55%, MD=-1068.63). Furthermore, the error results (MPE=-17.47%, MAPE=25.77%) confirm the GT2's validity for measuring SC in daily life. A paired t-test comparing MAPE between the YA and MAAE groups indicates a significant difference (t=-2.79, P=.006), with the YA group showing a lower measurement error (MAPE=21.91% [SD=22.43%]) than the MAAE group (MAPE=28.81% [SD=24.74]). Lastly, the Bland-Altman comparison plot (Figure 1[1a]) displays minimal scatter bias, suggesting good overall consistency in GT2's SC measurements. However, as the number of steps increases, the deviation becomes greater, implying a decrease in measurement consistency between the GT2 and Actigraph (Figure 1[1a]). Overall, the GT2 demonstrates good to excellent accuracy in SC measurement for both YA and MAAE groups in daily life settings.

Total Daily Activity Energy Expenditure

Firstly, Table 2 illustrates that TDAEE data measured by the GT2 and the accelerometer are correlated, evidenced by a PPMCC of .77 (P<.001, 95% CI=[0.74, 0.80]) and an ICC of .75 (P<.001, 95% CI=[0.67, 0.80]), indicating GT2's moderate to good validity in measuring TDAEE. Secondly, Table 3 summarizes the agreements between the GT2 and Actigraph in terms of TDAEE during daily life in different groups. In daily settings, GT2 typically underestimates TDAEE (MPE=8.43%, MD=50.36) compared to the Actigraph accelerometer. The underestimation seems to be more frequent among MAAE (MPE=11.32%, MD=54.73) than among YA (MPE=4.48%, MD=44.39). The error results (MPE=8.43%, MAPE=33.79%) suggest a moderate validity of the GT2 for measuring TDAEE in daily life. A paired t-test comparing MAPE between the YA and MAAE groups showed a significant difference (t=-2.71, P=.007), with the YA group exhibiting a lower measurement error (MAPE=30.32% [SD=21.48%]) compared to the MAAE group (MAPE=36.29% [SD=22.68%]).

Lastly, the Bland-Altman plot (Figure 1[2a]) indicates moderate consistency in GT2's TDAEE measurements, with a tendency to underestimate. In addition, the bias increases with increasing levels of energy expenditure, suggesting that the error in GT2 measurements tends to amplify as energy expenditure increases (Figure 1[2a]). Overall, the GT2 has moderate validity and may have limited measurement accuracy at high levels of energy expenditure.

Total Sleep Time

Firstly, Table 2 displays a significant correlations between the GT2 and the accelerometer, with a PPMCC of .47 (*P*<.001, 95% CI=[0.40, 0.54]) and an ICC test score of .25 (*P*<.001, 95% CI=[-0.06, 0.49]). Secondly, we tested the difference between the GT2 and Actigraph in terms of TST during daily life across different age groups, which is summarized in Table 3. The GT2 tends to underestimate TST (MPE=19.98%, MD=138.08) as compared to the Actigraph accelerometer measurements. The underestimation was evident among both YA (MPE=22.13%, MD=156.33) and MAAE (MPE=18.35%, MD=123.15). The error results (MPE=19.98%, MAPE=23.29%) suggest moderate validity of the GT2 for measuring TST in daily life. A paired t-test showed no significant difference in MAPE between the YA and MAAE groups (t=1.65, P=.10), indicating that the measurement error of the GT2 in the YA group (MAPE=24.39% [SD=13.84%]) was comparable to that in the MAAE group (MAPE=22.45% [SD=13.58%]). Lastly, the Bland-Altman plots (Figure 1[3a]) indicate that GT2 tends to underestimate TST and that the underestimation increases as sleep time increases. In total, when using the Actigraph GT3X+ as the criterion measure, the GT2 has poor to moderate validity in measuring TST among adults during daily life.

Discussion

This study assessed the accuracy of the Huawei Watch GT2 in measuring step count (SC), total daily activity energy expenditure (TDAEE), and total sleep time (TST) under free-living conditions, as well as exploring the validity differences between young adults (YA) and middle-aged to older adults (MAAE). The findings indicate that while the GT2 measures SC reasonably accurate, its accuracy in measuring TDAEE is less accurate, especially towards when the energy expenditure is high, and the assessment of TST requires further validation with more reliable criterion measures. Additionally, the GT2 demonstrated higher accuracy in measuring SC and TDAEE in the YA group compared to the MAAE group. However, the measurement errors for TST did not differ significantly between the two age groups.

For SC, the GT2 often reports higher counts than traditional accelerometers in daily scenarios (Mean difference=1318), yet it maintains a reasonable accuracy in SC, as evidenced by its high ICC value with accelerometer counts (ICC=0.88). This observation is in line with findings from prior research. For instance, Degroote et al [22] found that despite the Huawei watch's tendency to overestimate SC (MD=1478), its SC measurement accuracy remains robust, demonstrated by strong correlations with accelerometer data (ICC=0.88). The consistent overestimation observed across studies may be attributed to the differing placement of the devices [22,36]. Tudor-Locke et al [36] showed that wrist-attached devices tend to report higher SC than waist-attached devices in free-living conditions, with overestimations ranging from 2500 to 8700 steps per day. This phenomenon is particularly noticeable during sedentary and low-intensity intermittent activities, which are more prevalent than continuous walking in everyday life [37]. Consequently, while the GT2 accurately captures SC during regular walking (involving typical wrist and hip movements), it may also mistakenly count steps during wrist movements in non-walking activities (e.g., wrist oscillation without actual displacement), leading to higher counts than those recorded by waist-worn accelerometers. Further analysis through a paired t-test on MAPE revealed that the GT2's SC performance is superior in the YA group (MAPE=21.91%) compared to the MAAE group (MAPE=28.81%). This can be attributed to younger individuals' more consistent and predictable movement patterns, which correspond more closely with the GT2's step counting algorithm [37]. Additionally, younger adults typically engage more in vigorous activities, making their movements more detectable than those of older adults, resulting in better accuracy for the GT2. This is in line with previous research indicating that consumer-grade activity trackers tend to be more accurate at moderate to vigorous walking speeds than at slower speeds [45]. Future studies may consider improving the calibration of SC algorithms in smartwatches to account for the variability in activity types and intensities, which may potentially enhance their accuracy across a wider range of movements.

To our knowledge, this is the first study to assess the GT2 smartwatch's efficacy in measuring TDAEE in real-life settings. Aligning with findings from other smartwatch research on TDAEE [38,39-42], our results reveal that while the GT2 demonstrates moderate validity compared to the Actigraph, its in TDAEE measurements is still not ideal as shown by a high level of errors against Actigraph (MAPE>30%). Le et al [43] previously analyzed the GT2's EE accuracy against the Cosmed K5 in outdoor scenarios, reporting ICCs of .76 and .68, and MAPEs of 9.9% and 11.9% in walking (6 km/h, 2 km) and running (10 km/h, 2 km) scenarios, respectively. These findings generally agree with our results, underscoring the GT2's relative accuracy in energy expenditure measurement. Notably, our study extends the current findings by highlighting an increase in measurement error according to the rise in energy expenditure. Although the degree of error in our study appears to be higher than some previous findings (e.g., study by Le et al.), we applied the device in a daily-living setting with a long duration of seven full days. It has been shown that data collected in the context of daily life are often considered less accurate than those produced under controlled or short-term conditions, such as a laboratory setting [38,39,44]. This is because the accuracy of the device in daily life situations can be affected by various factors, such as complex terrain and more irregular activity patterns, making it difficult to identify the type of activity that is important to acceleration counts [44,45]. Hence, scholars have clearly articulated the necessity of testing devices in free-living contexts, as they are designed to monitor daily living activities [46]. Again, the current study emphasized that while the GT2 has good potentials for everyday health monitoring, users and researchers alike must remain cognizant of its limitations in accurately tracking TDAEE. They should take the potential underestimation into consideration when interpreting the readings of their TDAEE. Such findings underscore the ongoing need for technological refinement and validation.

Likewise, the issue of the measurement error in TST by GT2 warrants further research attention. We identified an underestimation of TST (138.08 min) for the GT2, and a similar case is reported on Fitbit [47,48]. Compared to polysomnography, Meltzer et al [47] showed that the Fitbit Ultra (sensitive mode) underestimated TST by 105 min on average in youth, and Cook et al [48] also found that the Fitbit Flex (sensitive mode) underestimated TST (86.3 min) in individuals with unipolar major depressive disorder. The degree of TST underestimation of Fitbit seems smaller than what we found in GT2. However, the reference measure used in this study (the accelerometer) is different from that used in Fitbit validation studies (polysomnography). Polysomnography is the gold standard for TST measurement, whereas accelerometers often overestimate TST too. For instance, Zinkhan et al [49] found that Actigraph GT3X+ (hip) overestimated TST (81.1 min) as compared to polysomnography. Therefore, when hip-worn accelerometers are used as measurement criteria, the degree of underestimating TST by smartwatch is likely to be exaggerated [49,50]. It is worth noting that different wearing positions resulting in different displacement data may be one of the reasons why the accelerometer and GT2 data are not in agreement [36,49]. Specifically, during bed rest, wrist activity tends to be higher than hip activity given that people may engage in activities involving use of wrists (e.g., reading books or using a mobile phone), in fact many participants orally reported habitual use of smartphones while lying in bed prior to fall asleep at night and getting up in the morning. In such cases, it is easy for smartwatch to capture wrist movements and accurately distinguish between awake and sleep states. However, hip-worn accelerometers are less able to monitor the above-mentioned activities and tend to recognize them as sleep time, and therefore are more likely to overestimate sleep duration, especially in insomniacs [49]. As described in the reviews by Guillodo et al [51] and Evenson et al [52], the current evidence from reliability studies on sleep is still limited. Therefore, although results of this study suggest the GT2 is likely to underestimate TST in reference to Actigraph, we should be cautious in drawing the conclusions. Future research is essential, and it should incorporate established standards like polysomnography to validate the accuracy of smartwatch measurements for TST.

Smart watches are becoming increasingly popular, but their use for monitoring and regulating health-related behaviors (e.g., physical activity, sedentary behaviors, and sleep) is hindered by insufficient evidence of accuracy [23,38,53,54]. In particular, the accuracy of the Huawei Watch GT2, as a very popular wearable device, remains uncertain in terms of TDAEE and TST monitoring in daily life, and few studies have been conducted on a large number of Asian individuals [38,53,54]. Therefore, we focused on gathering empirical evidence about the GT2's accuracy among the Chinese population. We consider such efforts are necessary and should be made on regular basis. First, with the fast advancement of digital technology, wrist-worn devices such as GT2 may become even more popular in the future given that growing technology acceptance in the public, and continuous upgradation of wearable devices can be expected. Accordingly, there may be a continuous need for verifying smartwatches' accuracy as they keep upgrading. Morever, such issue may not only be of interest to consumers, but also to researchers that aims to examine daily life activity patterns. To ensure study quality, high-precision devices (accelerometers indirect calorimeters, etc.) for assessing human activities are accurate, but are less desirable in collecting large-scale data with multiple timepoints in daily life considering factors such as price, convenience, and need for multiple indices[8,9]. In this regard, smartwatches are particularly advantageous as they cover a wide range of individuals, are able to collect data for a long duration as long as a person wears it. They can also offer real-time feedback through smartwatch screen and connected mobile apps, and thus help individuals become more motivated and better able to self-manage activities. This real-time feedback mechanism can be particularly beneficial in managing chronic conditions, promoting physical fitness, and enhancing overall well-being [55]. This represents great potentials for applying conducting population-based health behavior promotion [56]. Therefore, we call on mainstream smartwatch manufacturers to continuously improve their watch hardware devices by introducing advanced techniques such as deep learning and sensor fusion to refine their algorithms for more accurate health monitoring. Although it is difficult to have a one-size-fits-all measurement standard due to the variability of individual and environmental factors, studies that consistent evaluate the validity of smartwatches can offer informative feedbacks that help the algorithms of smartwatches improve, raise public recognition, and thus bring their potential use for health-related behavior management and health promotion into full play.

Strengths and Limitations

The study has several strengths. First, the Huawei Watch is a widely used smartwatch with a high market share, especially in China (39%) [57], but only several studies have provided empirical evidence of its accuracy [22,43]. The study examines the measurement accuracy of the GT2 in free-living setting. In particular, this is the first to examine the GT2's accuracy in measuring TDAEE and TST in daily life, which are quite important parameters that has not received sufficient attention. Second, this study has a sample size that is relative great among validation studies of smartwatches, and covers a wide age distribution of subjects (18 to 24 years in YA; 55 to 91 years in MAAE), evidence of such studies is rarely reported before[58]. Collectively, the results supported the accuracy of this device in measuring SC and TDAEE in daily life, such results may help users and researchers better determine how to use GT2 for practical and research purposes.

However, the results of the current study should also be interpreted with consideration for several limitations. First, the proportion of female subjects was higher in the MAAE group, and since we recruited a healthy population, the results may not be generalizable to populations with health conditions. Second, the gold standard of the study was research-grade accelerometers with known validity limitations of their own, especially in terms of sleep measures. Therefore, there is a risk that GT2's actual validity can be underestimated. Future studies should consider more appropriate and feasible criterion measures based on the target behaviors to be verified.

Conclusions

In summary, the Huawei Watch GT2 could be used as a reliable measure of SC, and has moderate accuracy when measuring TDAEE. However, it should be used with caution for studies requiring high precision of energy expenditure. Furthermore, its accuracy in monitoring TST awaits confirmation. With the development of a digital technology, smartwatches are constantly updated, their accuracy should be regularly evaluated in various settings and populations to ensure they can be properly applied in health-related behavior monitoring and promotion.

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Conflicts of Interest

None declared.

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Abbreviations

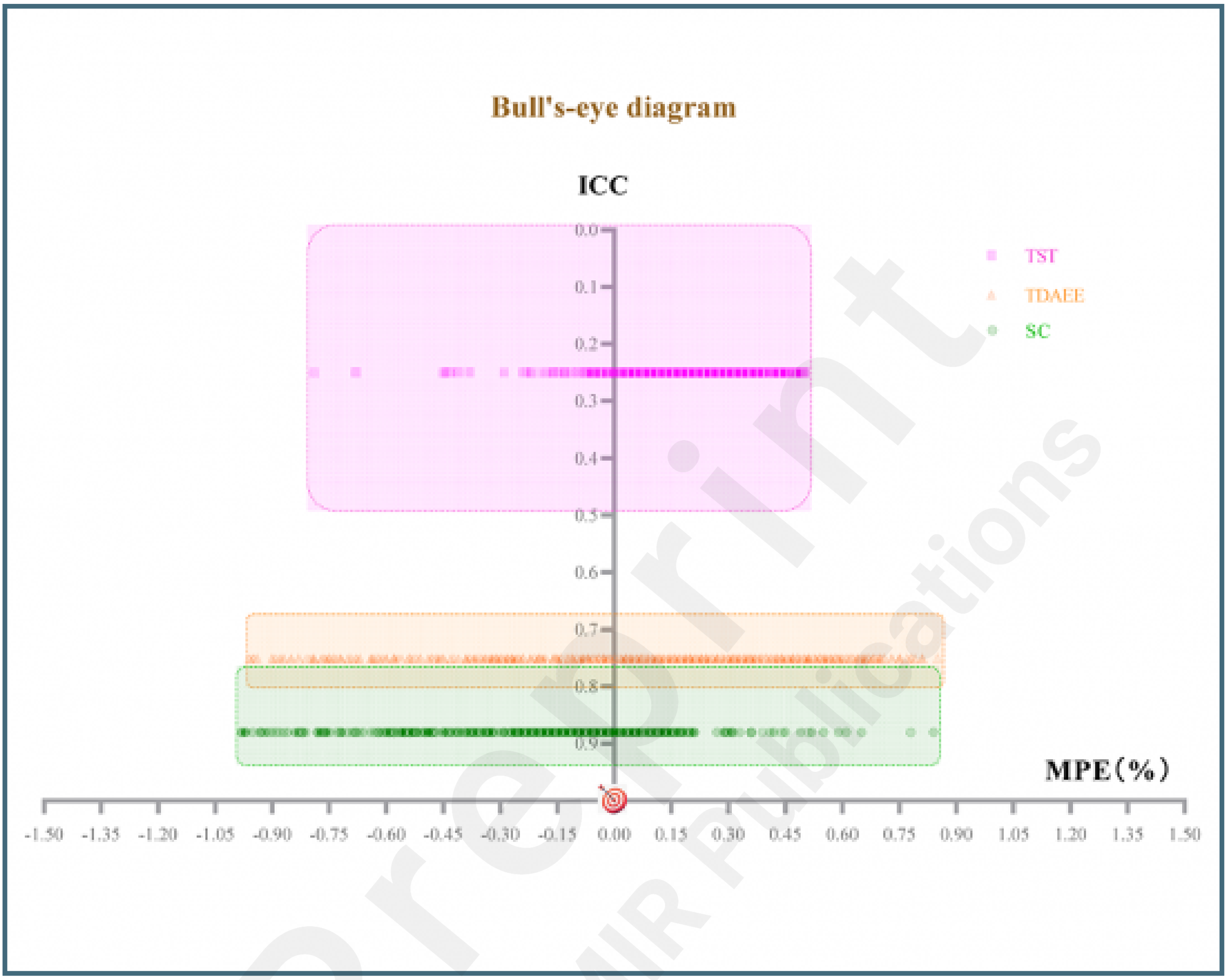
ICC: intraclass correlation coefficient
MAAE: middle-aged and elderly
MAPE: mean absolute percentage error
MPE: mean percentage error
PPMCC: pearson product moment correlation coefficient
SC: step count
TDAEE: total daily activity energy expenditure
TST: total sleep time
YA: young adult

Supplementary Files

Figures

Bland-Altman plots of the Huawei Watch GT2 and Actigraph GT3X+ in overall phases for different groups and indicators.

Bull's-eye diagrams with Actigraph GT3X+ as the gold standard.



TOC/Feature image for homepages

The smartwatch of our lives.