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Evaluation of a thigh-worn accelerometer for detecting leg fidgeting and estimating its energetic cost via indirect calorimetry

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Leg fidgeting, characterised by rhythmic lower limb movement while seated, is a spontaneous, low-intensity behaviour that may serve as a practical strategy to interrupt prolonged sedentary time. This study aimed to evaluate the feasibility of detecting leg fidgeting using a wearable thigh-mounted accelerometer, and to quantify its energetic cost in comparison to sitting, standing, and slow walking under controlled settings. Fifteen healthy adults (mean age = 35.6 ± 12 years; 33.3% male) completed five-minute bouts of sitting, fidgeting, standing, and slow walking while wearing a thigh-mounted accelerometer (SENS motion system). Behaviour classification was validated against direct observation, and energy expenditure was measured using breath-by-breath indirect calorimetry. The SENS classification of fidgeting was evaluated using sensitivity, specificity, and balanced accuracy metrics. Energy expenditure was compared across activities using linear mixed-effects models, controlling for age, gender, and BMI. A total of 305 min of activity data were recorded. Balanced accuracy for activity classification ranged from 90.6% (slow walking) to 99.1% (standing), with fidgeting classified at 95.0%. The energy expenditure of fidgeting (mean = 1.69 kcal/min) was significantly different from sitting (1.49 kcal/min), standing (1.47 kcal/min), and slow walking (mean = 4.10 kcal/min). This study demonstrates that leg fidgeting can be detected using wearable sensors under controlled conditions. Furthermore, leg fidgeting expends slightly greater energy expenditure compared to sitting and standing. Future research should examine its metabolic relevance in free-living settings and explore its role in daily movement patterns and in strategies to reduce prolonged sedentary time.

Keywords Sedentary behaviour, Energy expenditure, Accelerometer validation, Active sitting, Movement classification, Wearable technology

Prolonged sedentary behaviour is recognised as a risk factor for adverse health outcomes, with strong evidence linking higher sitting time to increased incidence of type 2 diabetes, cardiovascular disease, metabolic syndrome, certain cancers, and all-cause mortality, even after accounting for moderate-to-vigorous physical activity (MVPA)[1–5]. This body of evidence highlights that although regular exercise is beneficial, it does not fully mitigate the detrimental effects of prolonged sitting. These adverse outcomes may be attenuated by very high volumes of physical activity, but such levels are rarely achieved in the general population[6].

The physiological mechanisms underlying the health risks associated with sedentary behaviour have been widely investigated[7,8]. Extended sitting reduces skeletal muscle contractile activity, leading to downstream metabolic consequences. Notably, inactivity lowers lipoprotein lipase (LPL) activity, an enzyme critical for triglyceride metabolism and the regulation of high-density lipoprotein cholesterol, while also impairing glucose uptake through reduced GLUT4 translocation in skeletal[7,9]. These physiological disruptions can occur rapidly, even within hours of uninterrupted sitting, suggesting that sedentary behaviour exerts acute as well as chronic metabolic consequences.

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Importantly, it is not only the total duration of sedentary time that can affect health outcomes but also the way in which it is accumulated. Studies have shown that individuals who frequently break up their sitting with short bouts of movement exhibit more favourable cardiometabolic risk profiles compared to those who sit for long uninterrupted periods, even when overall sedentary time is similar[8,10]. Interrupting sitting with light activity breaks such as brief bouts of standing or walking, can reduce postprandial glucose and insulin responses and improve blood pressure and lipid regulation[8,11,12]. Collectively, these findings have informed public health guidelines that recommend avoiding prolonged sitting, ideally interrupting it every 20–30 min with physical activity[13,14].

However, in real-world environments, particularly in office or work settings, it may not always be feasible to take regular walking or standing breaks. These settings therefore require alternative strategies that allow individuals to remain seated while still engaging the lower limb muscles. One such behaviour is leg fidgeting while sitting (hereafter referred to simply as "fidgeting"), typically expressed as rhythmic foot tapping or bouncing while seated. Although often dismissed as a trivial or nervous habit, early research suggests that fidgeting may confer modest metabolic benefits, including improvements in vascular function as well as postprandial glucose and insulin responses[15,16].

Despite promising findings, research in this area remains limited. Fidgeting is rarely captured in standard accelerometery protocols and lacks validated classification algorithms[17]. Most accelerometers are designed to detect and classify conventional physical behaviours such as sitting, standing, walking, and running[18]. As a result, low-amplitude or sporadic movements like fidgeting are often misclassified or excluded from analysis. The SENS accelerometer system[19] includes inbuilt algorithms to classify a unique category called "sitting with movement", which is hypothesised to capture movement patterns consistent with fidgeting. Accurate measurement of fidgeting, including its occurrence and duration, is essential for understanding its role within the broader context of daily movement. The 24-hour movement paradigm conceptualises physical activity, sedentary behaviour, and sleep as interdependent components of a full-day behavioural composition[20]. Within this framework, even brief, low-intensity movements such as fidgeting may contribute to health outcomes by interrupting prolonged sitting or modestly increasing energy expenditure. Incorporating fidgeting into time-use models could enhance our understanding of how micro-movements influence the distribution of behaviours across the day and support more nuanced public health guidance.

While previous research has focused primarily on the physiological mechanisms underlying the risks of prolonged sitting, less is known about the energy cost of seated micro-movements such as fidgeting. Understanding its energetic contribution is important for evaluating whether fidgeting could serve as a physiologically meaningful sedentary-break strategy in contexts where standing or walking is not feasible. Evidence suggests that the health risks associated with prolonged sitting could be attenuated by very high volumes of MVPA[6], which are rarely achieved in the general population. In this context, even small increases in energy expenditure from seated micro-movements may offer a scalable complement to formal exercise, especially for individuals with constrained routines.

Therefore, the specific aims of this study are (1) to evaluate a thigh-worn accelerometer for detecting fidgeting, and (2) to quantify the energy expenditure of fidgeting and compare it with sitting, standing, and walking in controlled laboratory conditions.

Methods

Participants

Fifteen healthy adults were recruited from the university community via word of mouth and posted advertisements. Eligibility criteria included being free from physical disability and cardiometabolic conditions, and able to perform a range of physical activities, including sitting, standing, and walking. Participants' age, gender, height, and weight were recorded prior to data collection. All individuals provided written informed consent before participation. Ethical approval for this study was granted by the Auckland University of Technology Ethics Committee (approval number: 22/326). All methods were carried out in accordance with relevant guidelines and regulations.

Instrumentation

The SENS motion sensor[19] was employed to quantify fidgeting and other physical behaviours in this study. The sensor is a small, waterproof, thigh-worn accelerometer that captures triaxial acceleration data. It was worn on the outer side of the thigh, a few centimetres above the knee, secured within a single-use adhesive patch. The sensor connects via Bluetooth to the SENS smartphone application, while the linked web application is used for sensor set-up, control, and data download. Data were transmitted wirelessly to a secure cloud database, where the *SENS Activity algorithm (version 5.5)* was applied. This algorithm was selected at sensor initiation and automatically classified physical activities into four categories: sitting, standing, walking, and sitting with movement. The 'sitting with movement' category was hypothesised to capture fidgeting, given its sensitivity to subtle lower-limb movements during seated tasks and was therefore a focal point in evaluating the algorithm's classification accuracy. Sensor placement, activation, and data collection protocols adhered strictly to manufacturer guidelines to ensure reliable and valid measurement within the standardised activity protocol conducted during the study session. The output generated by the algorithm served as the basis for validation against observed behaviours in this study.

Energy expenditure was measured using a portable indirect calorimetry system (COSMED K5; COSMED, Rome, Italy), recording breath-by-breath oxygen consumption (VO_2) and carbon dioxide production (VCO_2). The K5 was paired via Bluetooth with the manufacturer's software to enable real-time acquisition; breath-by-breath data were recorded in the software throughout the protocol and exported immediately after completion for offline processing. Before each testing session, the system was calibrated according to manufacturer guidance.

Participants wore the device continuously for the duration of the laboratory protocol; all computations, including derivation of energy expenditure from gas-exchange data, were performed automatically by the COSMED software, with no additional processing or custom calculations undertaken.

Protocol

Participants completed a standardised protocol consisting of four activity conditions (see Fig. 1): (A) sitting still on a chair (they were permitted to use a computer or phone), (B) fidgeting (rhythmic foot tapping/bouncing while seated, on the leg where the thigh-worn accelerometer was attached), (C) standing still, and (D) walking at a comfortable, self-selected pace on a treadmill (~ 4–5 km/h). Each condition (sitting, standing, fidgeting, slow walking) was prescribed a total of approximately 5 min, achieved through the accumulation of multiple shorter bouts. Slow walking was completed in a single continuous 5-minute bout, whereas sitting, standing, and fidgeting were distributed across several shorter intervals. No fixed transition or washout periods were imposed between activities; however, transition periods were excluded from the timestamped dataset so that only discrete, activity-specific segments were analysed. Excluding these transition epochs minimised spillover from adjacent activities and prevented contamination of estimates. Furthermore, given the short, low-intensity nature of the activities and the breath-by-breath averaging applied in indirect calorimetry, any physiological carryover was expected to dissipate rapidly. To minimise sequencing effects, the order of sitting, fidgeting, and standing was randomised for each participant using a pre-generated sequence, while slow walking was always performed last to avoid residual fatigue influencing subsequent lighter activities. This design therefore ensured sufficient data capture for each condition and reduced potential sequencing effects. A sample protocol for one participant is shown in Supplementary Table S1.

To minimise potential confounding, participants were instructed to remain silent throughout the protocol, as verbal communication may affect energy expenditure. A researcher delivered brief verbal cues to initiate each activity, following a pre-determined randomised sequence. Activity start and stop times were recorded using a custom-built R Shiny application[21], enabling precise temporal alignment between behavioural transitions and accelerometery data.

Data processing and analysis

Accelerometer data from the SENS device were downloaded using the manufacturer's software and processed with the proprietary classification algorithm to generate behaviour predictions. The SENS outputs were compared with the study protocol activity log, which recorded the start and stop times of each condition and served as the gold-standard direct observation, to evaluate classification performance. Agreement was assessed at the epoch

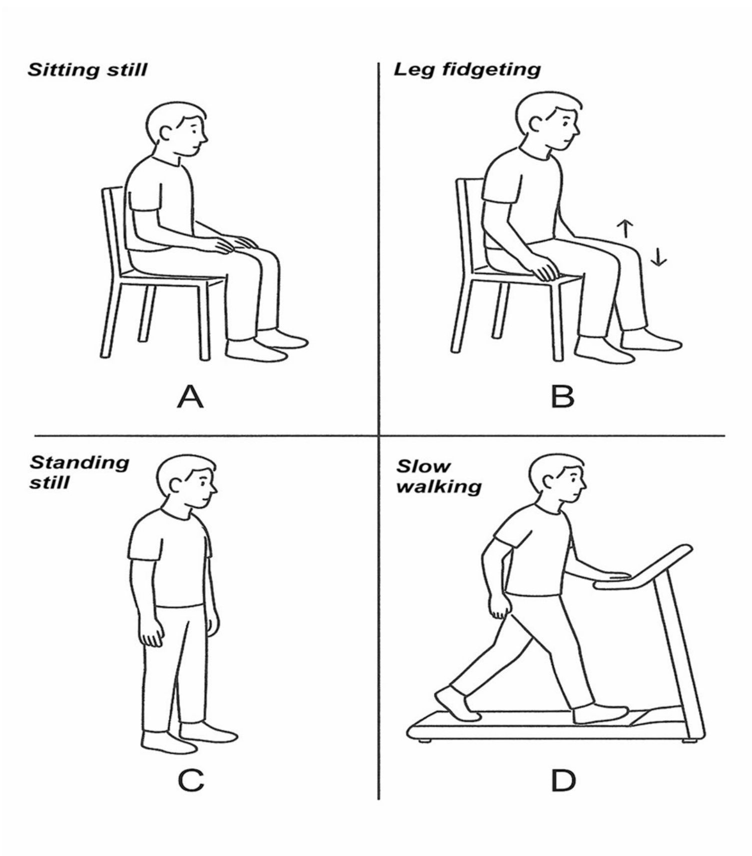

Fig. 1. Study protocol activities.

	Sitting	Fidgeting	Standing	Slow walking
Sensitivity	99.5 [98.8, 99.8]	90.2 [88.1, 92.1]	98.2 [97.1, 99.0]	83.2 [80.6, 85.6]
Specificity	92.5 [91.4, 93.5]	99.8 [99.5, 99.9]	100 [99.9, 100]	98.1 [97.5, 98.6]
Balanced accuracy	95.9 [95.1, 96.7]	95 [93.8, 96.0]	99.1 [98.5, 99.5]	90.6 [89.1, 92.1]

Table 1. Performance for each activity class. Sensitivity, specificity, and balanced accuracy are presented as percentages (%), with 95% confidence intervals in brackets.

				Predicted	
		Sitting	Fidgeting	Standing	Slow walking
Observed	Sitting	**947**	52	0	151
	Fidgeting	5	**820**	1	0
	Standing	0	0	**883**	0
	Slow walking	0	37	15	**746**
	Total	952	909	899	897

Table 2. Confusion matrix for activity predictions from the SENS accelerometer. Values represent the number of 5-second epochs correctly classified or misclassified; Bold values represent correct predictions.

level, with a default epoch length of 5 s, as defined by the SENS system. Overall percent agreement was calculated as the proportion of labelled epochs that matched the direct observation. Confusion matrices were generated to illustrate classification outcomes for each condition, and performance metrics were calculated, including sensitivity (true positive rate for each behaviour), specificity (true negative rate), and balanced accuracy (the mean of sensitivity and specificity). Performance was summarised both as pooled epoch-level metrics and as participant-level averages to capture within-participant variability. Binomial confidence intervals (95%) were computed using the exact method via *binom.test()* in R and expressed as percentages. These intervals were used to quantify uncertainty around each accuracy estimate.

Breath-by-breath calorimetry data were quality-checked, averaged into 10-second epochs, and merged with the activity log using synchronised timestamps. All epochs were clearly labelled according to the activity being performed (sitting, fidgeting, standing, or slow walking). Energy expenditure was represented in kilocalories per minute (kcal/min).

The primary analysis examined whether energy expenditure differed across the four activity conditions. To account for repeated measures, linear mixed-effects models with a random intercept for participant were fitted, with activity as a fixed effect and participant ID as the clustering unit, controlling for age, gender, and body mass index (BMI, as weight divided by height squared). All continuous covariates were mean-centred prior to model fitting to improve interpretability. Contrasts comparing fidgeting with each of the other conditions (sitting, standing, and slow walking) were calculated using estimated marginal means and are reported as mean differences with 95% confidence intervals. Multiple comparisons were adjusted using the Holm method[22], with statistical significance set at $p < 0.05$. To explore whether model accuracy varied by individual, residuals (difference between observed and fitted energy expenditure) were calculated for each observation and summarised by participant. These residuals were visualised using boxplots to assess whether error was disproportionately concentrated in any one individual.

All statistical analyses were performed using R (version 4.5.1; R Foundation for Statistical Computing, Vienna, Austria)[23]. The analysis code is provided as a supplementary file.

Results

A total of 15 adults successfully completed the study (mean age = 35.6 ± 12 years; 33.3% male; mean BMI = 23.7 ± 2.7 kg/m^2). Across all participants, 3,657 epochs of 5-second duration were recorded, representing approximately 305 min of accelerometery data. The distribution of epochs by participant and activity type is detailed in Supplementary Table S2. The performance metrics of the SENS motion accelerometer for each activity class are summarised in Table 1. Balanced accuracy ranged from 90.6% for slow walking to 99.1% for standing. These results indicate strong classification, even for subtle movements such as fidgeting.

The confusion matrix for activity predictions is presented in Table 2. Correct classifications are indicated in bold, showing that misclassifications occurred primarily between sitting and fidgeting or slow walking.

Table 3 presents the results of the linear mixed model predicting energy expenditure (kcal/min). Sitting was specified as the reference activity, and both age and BMI were mean centred prior to analysis. Consequently, the intercept represents the estimated energy expenditure (in kcal/min) during sitting for individuals coded as female (the reference gender) with average age and BMI. This centring allows the intercept to represent a meaningful baseline rather than implausible values corresponding to zero age or BMI. All other fixed-effect estimates indicate deviations from this baseline, accounting for individual-level differences through random intercepts. The estimates for slow walking, standing, and fidgeting represent the adjusted differences in energy expenditure relative to sitting. Model residuals were calculated to assess individual-level error patterns, with residuals ranging from −0.0170 to 0.8302 kcal/min across participants. The intraclass correlation coefficient

Predictor	Estimate (kcal/min)	SE	t value	95% confidence intervals	*p*-value
(Intercept)	1.29	0.09	13.7	[1.11, 1.47]	< 0.001
Fidgeting	0.2	0.04	5.05	[0.12, 0.27]	< 0.001
Slow walking	2.6	0.04	67.09	[2.53, 2.68]	< 0.001
Standing	-0.02	0.04	-0.51	[-0.10, 0.06]	0.612
Age (centred)	-0.001	0.006	-0.18	[-0.01, 0.01]	0.86
Male	0.4	0.16	2.53	[0.09, 0.72]	0.012
BMI (centred)	0.11	0.03	3.94	[0.06, 0.17]	< 0.001

Table 3. Estimated fixed effects from linear mixed model predicting energy expenditure. The intercept reflects energy expenditure during sitting for an average-aged, average-BMI female participant. Random intercepts were included for participants.

Activity	Mean (kcal/min)	95% CI	t value
Sitting	1.49	[1.33, 1.65]	18.14
Fidgeting	1.69	[1.53, 1.85]	20.48
Slow walking	4.1	[3.93, 4.26]	49.7
Standing	1.47	[1.31, 1.63]	17.85

Table 4. Estimated marginal means of energy expenditure by activity.

Level 1	Level 2	Difference (kcal/min)	SE	95% CI	t value	*p*-value
Sitting	Fidgeting	-0.2	0.04	[-0.27, -0.12]	-5.05	< 0.001
Slow walking	Fidgeting	2.41	0.04	[2.33, 2.49]	61.25	< 0.001
Standing	Fidgeting	-0.22	0.04	[-0.29, -0.14]	-5.48	< 0.001

Table 5. Pairwise contrasts of fidgeting with other activities. Negative differences indicate lower energy expenditure in Level 1 relative to Level 2. p-values adjusted using Holm's method.

(ICC) was 0.185, indicating modest clustering of energy expenditure within individuals. Residual distributions by participant are shown in Supplementary Figure S1.

Estimated marginal means of energy expenditure for each activity are presented in Table 4. Among the four conditions, slow walking elicited the highest energy expenditure. Sitting and standing produced similar energy demands, both of which were lower than those observed during fidgeting. These findings suggest that fidgeting, while performed in a seated posture, may represent a metabolically distinct behaviour with modest energetic cost.

Lastly, pairwise comparisons of energy expenditure between fidgeting and each of the other activity conditions are presented in Table 5. Energy expenditure during slow walking was significantly higher than during fidgeting, while both sitting and standing were significantly lower (all $p < 0.001$).

Discussion

The primary aims of this study were to evaluate a thigh-worn accelerometer for detecting fidgeting, and to quantify and compare the energy expenditure associated with fidgeting, sitting, standing, and slow walking using indirect calorimetry. Collectively, the findings demonstrate the potential of accelerometery for detecting fidgeting behaviours and highlight the distinct energy cost profile of fidgeting relative to other low-intensity activities.

The SENS algorithm showed strong performance in distinguishing fidgeting from other sedentary behaviours. Overall balanced accuracy was ~ 95%, with particularly high accuracy for sitting (95.9%) and standing (99.1%). Importantly, fidgeting was identified with high sensitivity (90.2%) and very high specificity (99.8%). These results suggest that the algorithm is well-suited for capturing leg fidgeting during sitting in controlled settings.

Previous work has demonstrated that accelerometers are highly effective in identifying gross motor behaviours such as walking or running, but they often misclassify low-intensity activities or posture transitions[24,25]. In this study, we evaluated the performance of the proprietary SENS classification algorithm, focusing on its ability to distinguish between sitting still and sitting with movement, a distinction operationalised as fidgeting. While it would be relatively straightforward to develop a bespoke algorithm for this binary classification, our objective was to examine whether the existing 'active sitting' category within the SENS system reliably captures fidgeting behaviour. This approach extends earlier work demonstrating the feasibility of detecting fidgeting using wearable sensors. For instance, Esseiva et al. (2020) reported 95% accuracy in classifying sitting with versus without fidgeting, although their sample comprised only five participants[17]. Similarly, more recent research on leg bouncing achieved 90% accuracy in identifying everyday movements and 94% accuracy in distinguishing four types of leg bouncing using ankle-mounted accelerometers and a Random Forest classifier[26]. However, that study also highlighted the limited understanding of optimal sensor placement and the challenge of differentiating leg bouncing from other seated movements. In contrast, our findings indicate that the SENS algorithm's 'active sitting' category provides a practical and scalable solution for detecting fidgeting using a single thigh-worn device.

Many previous approaches have relied on custom machine learning pipelines, which can be resource-intensive and require substantial expertise in feature engineering, model tuning, and validation. In contrast, the current study demonstrates that a thigh-worn accelerometer can achieve similarly high accuracy using existing algorithms. This underscores the potential for scalable, low-burden methods to detect subtle variations in sedentary behaviour without the need for bespoke model development.

Fidgeting was found to modestly increase energy expenditure compared with both sitting and standing (approximately 0.20 to 0.22 kcal·min^{-1}), while slow walking produced a substantially higher expenditure (around 2.41 kcal·min^{-1} above fidgeting). These findings highlight the intermediate energetic role of fidgeting, which requires more energy than static postures but remains far below ambulatory behaviours. Interestingly, in our sample the mean energy expenditure of standing was slightly lower than sitting, although not statistically significant. This contrasts with prior literature, which typically reports a modest increase in standing compared to sitting (0.1–0.19 kcal·min^{-1} across females and males)[27]. We suggest that this subtle difference may be due to methodological factors, including the absence of a fixed transition or washout period, which may have contributed to minor carryover effects. Other factors such as the short bout duration and the structured nature of the protocol may also have influenced the estimates. In addition, while participants remained silent throughout, many used phones or laptops while sitting, which may have introduced subtle arm or postural movements that slightly elevated sitting expenditure. Taken together, these considerations advise caution in interpreting the results.

Although the energy cost of fidgeting is small in absolute terms, it may still have a cumulative impact on energy balance when sustained over longer periods, such as across a day or a week[28]. For example, if a person spends two hours fidgeting in a day rather than sitting completely still, this could result in an additional 24 to 26 kcal expended. Sustained over a week, that same daily pattern could accumulate to approximately 170 to 180 kcal. While the energy expenditure from fidgeting is modest compared to purposeful movement, these small increments may still influence overall daily energy balance, particularly in contexts where prolonged sedentary behaviour is common. Fidgeting should be considered a complement to, rather than a substitute for, more deliberate activity breaks.

Fidgeting may also serve as a spontaneous interruption of sedentary stillness, rather than a structured activity[28]. Physiological mechanisms provide plausible pathways through which even low-intensity contractions might benefit metabolic health. Previous studies have shown that breaking up sitting with light activity can reduce postprandial glucose and insulin responses[8,12] and improve vascular function[15]. Repeated small muscle contractions during fidgeting may promote local blood flow, stimulate glucose uptake, and enhance lipoprotein lipase activity. While our results demonstrate an energetic effect of fidgeting, further research is needed to determine whether these physiological benefits occur in free-living contexts and translate into measurable improvements in health outcomes.

While this study provides initial evidence on the sensor-based feasibility of detecting fidgeting and estimating its energetic cost, several limitations must be acknowledged. The small and homogeneous sample of healthy adults limits generalisability to broader populations. The laboratory protocol involved short, structured five-minute bouts of activity (although accumulated through randomly ordered segments), which may not reflect the sporadic and intermittent nature of fidgeting in free-living settings. No fixed transition or washout periods were imposed between activities, which may have introduced carryover effects between activities and also limits comparability with studies that employ longer steady-state protocols. Behaviour classification was validated against an activity log rather than continuous video, which, although practical, may be less precise. The proprietary nature of the SENS algorithm also constrains independent evaluation and reproducibility. Finally, the study focused exclusively on energy expenditure; no metabolic biomarkers (such as glucose, insulin, triglycerides, or endothelial function) were collected, which precludes inferences about the potential health benefit of fidgeting-related movement.

Future work should extend validation of accelerometer-based detection of fidgeting to naturalistic settings, incorporating free-living observation or video verification. Although the energetic cost of fidgeting is modest, even small increases in muscle activity may influence metabolic processes such as glucose regulation, lipid metabolism, and vascular function. Randomised trials that integrate metabolic endpoints such as continuous glucose monitoring, postprandial triglyceride and insulin responses, or endothelial function are needed to test whether the modest energetic increases from fidgeting confer tangible health benefits. Larger and more diverse samples will also help to clarify whether these effects differ by age, sex, body composition, or metabolic risk status.

Conclusion

This study demonstrates that fidgeting can be accurately detected using a thigh-worn accelerometer and shows that fidgeting elicits a small but consistent increase in energy expenditure compared with sitting and standing. Although it may not match the energy expenditure or broader health benefits of walking or other light-intensity breaks, fidgeting may represent an accessible and practical micro-movement strategy to interrupt sedentary time in contexts where standing or walking is not feasible. Future work incorporating metabolic markers will be critical for determining its relevance as part of strategies to reduce the health risks associated with prolonged sitting.

Data availability

The data that support the findings of this study are available upon reasonable request from the corresponding author.

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Author contributions

AN was responsible for study design with assistance from MW, TS and SD. Data cleaning and processing were performed by AN. AN performed the analysis and drafted the manuscript, with critical feedback provided by all authors.

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Declarations

Competing interests
The authors declare no competing interests.

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