Journal of Endocrinology and Diabetes Research
2026 Volume 4, Issue 1
DOI: 10.59657/2996-3095.brs.26.024

BioRes Scientia
Value your Research

Research Article

Open Access

Do Wearable-Derived Activity Measures Predict Glycemic Control? Evidence from NHANES 2003-2006

Kolade Folami[1]*, Sesan Micheal Johnson[2]

[1]*Monroe University, Bronx, New York, United States.* [2]*University of Calgary, Calgary, Canada.*

**Corresponding author: Kolade Folami.*

Abstract

Background: Wearable technologies are increasingly used to capture real-time physical activity and physiological signals, offering a promising non-invasive approach for monitoring chronic conditions such as Diabetes. Despite growing adoption, the extent to which wearable-derived activity metrics predict glycemic control remains uncertain, particularly in population-level studies.

Objective: To evaluate whether accelerometer-derived measures of physical activity and sedentary behavior are associated with glycemic control among U.S. adults with diagnosed Diabetes.

Materials and Methods: This cross-sectional study analyzed data from 664 adults aged ≥20 years with diagnosed Diabetes from the National Health and Nutrition Examination Survey (NHANES) 2003-2006. Physical activity and sedentary behavior were assessed using hip-worn ActiGraph accelerometers over 7 days. Key exposure variables included mean daily sedentary time and moderate-to-vigorous physical activity (MVPA), examined both continuously and through derived movement phenotypes. The primary outcome was glycated hemoglobin (HbA1c), analyzed as both a continuous variable and a binary indicator of poor glycemic control (HbA1c ≥7%). Survey-weighted linear and logistic regression models were used, adjusting for demographic and socioeconomic covariates.

Results: Participants had high sedentary time (mean 568 minutes/day) and low MVPA (mean 11 minutes/day). In adjusted models, neither sedentary time nor MVPA was significantly associated with HbA1c ($p > 0.05$) or with odds of poor glycemic control. Movement phenotype analysis showed that the Active + High sedentary group had lower HbA1c compared to the reference group; however, this subgroup was small, and findings were not consistent in continuous models. Overall, accelerometer-derived activity measures explained little variation in glycemic outcomes.

Conclusion: Wearable-derived activity metrics, including sedentary time and MVPA, were not independent predictors of glycemic control in this nationally representative sample of adults with diagnosed Diabetes. These findings suggest that short-term movement data alone may be insufficient to capture the complex determinants of glycemic regulation in clinical populations.

Keywords: wearable devices; glycemic control; hba1c; physical activity; sedentary behavior; accelerometer

Introduction

Globally, Diabetes affects approximately 529 million adults and leads to 1.7 million deaths [1]. The growth in the prevalence of Diabetes is not abating, and a significant portion of the US population is undiagnosed and pre-diabetic. Glycemic control is essential to the overall treatment and management of Diabetes.

Not unlike other chronic diseases, early detection and lifestyle offers the most effective method of prevention and management. Undoubtedly, physiological signals like heart rate, blood pressure, and temperature, among others, have consistently provided necessary insights into the physical health condition of an individual [2]. Accordingly, there is a growing number of systems and methods for predicting and diagnosing Diabetes across the full spectrum, from invasive to non-invasive approaches. Indeed, with the ascendance of Artificial Intelligence and Machine Learning, health data from different sensors like the Electrocardiograms (ECG), electroencephalogram (EEG), gyroscopes, and accelerometers can be used in a way that will reduce hospitalizations and remotely monitor patients' health [3].

Wearable technologies offer a transformative opportunity to fill gaps in care by facilitating real-time measurement and personalized feedback, combined with improvement in glycemic control [4]. In the specific case of Diabetes and glycemic control, wearables are either wrist-worn or waist-worn, and while waist-worn wearables are less expensive, they collect less activity information in comparison to wrist-worn wearables [5]. Bent et al. [6] noted that

non-invasive and wrist-worn biometric sensors or wearables have seen accelerated growth in adoption in the United States, with 117 million in use as of 2021 and an estimated 100 percent projected growth over the course of the next three years after their study.

Central to the development of non-invasive wearable devices for glycemic control is the need to minimize trauma, enhance convenience, and simplify monitoring of vital signs in Diabetes management. Specifically, wearable devices largely adopt sensors often deployed in clinical settings, and with Artificial Intelligence, the data from these devices show demonstrable promise of estimating, analyzing, and predicting glucose, glucose monitoring, and glycemic control [7]. However, across all studies, there is a variation in the efficacy of wearable devices, coupled with a low number of studies with stronger levels of evidence [8].

Despite growing use of wearable-derived activity data in predictive models, there is limited population-level evidence on whether accelerometer-measured movement behaviors are independently associated with glycemic control in adults with diagnosed Diabetes. This study examines whether objectively measured sedentary time and moderate-to-vigorous physical activity are independently associated with glycemic control among U.S. adults with diagnosed Diabetes using nationally representative NHANES data. By evaluating both categorical movement phenotypes and continuous activity measures, this study provides a population-level assessment of the extent to which wearable-derived movement metrics correspond to a clinically relevant outcome.

Review of Literature

Extant studies have examined the impact of wearable and non-invasive methods for glycemic control and their impact on the quantification of physical activity and sedentary behavior. These studies can be broadly divided into studies of wearable-device-based interventions for glycemic control, those that measure glucose excursions or variability, and those that quantify physical activity and measure sedentary behavior. Across this spectrum, devices ranged from Actigraph [9] to Fitbits, FreeStyle Libre, and Continuous Glucose Monitoring devices, among others. Under the first category are studies that emphasize the value of data from wearable devices for the training of machine learning/ artificial intelligence models for the prediction of glycemic control. Additionally, wearables and glycemic control studies largely focus on people without Diabetes, pre-diabetes, and individuals with either Type 1 or Type 2 Diabetes.

Data from wearable devices have supported glycemic prediction and the associated development of machine learning models. However, while studies have emphasized the predictive value of data harnessed from wearables, focus has been on models' predictive performance comparison [10,5], or the development of machine learning models for predicting glycemic control [6]. As such, while the comparative evaluation of models developed with wearable data, or the use of data for glycemic control prediction models, are necessary steps in the development of Diabetes digital health tools, there is a need for the examination of the predictive value of wearable-derived activity measures in glycemic control.

Undoubtedly, measures of physical activity, such as Light to Intense Physical Activity [LIPA], Moderate-to-Vigorous-Physical Activity [MVPA], sleep time, and sedentary time, are central to both Diabetes and glycemic control debates. Indeed, studies have shown that reduced sedentary time, increases in LIPA/MVAP, physical exercise, accelerometer-derived physical activity data, are all associated with decreased odds of Type 2 Diabetes, reduction of glucose level, design of non-invasive personalized detection of hypoglycemia from physiological sensors, and development of automated and personalized user behavior mechanisms [11-14]. However, these studies assume, in most parts, that wearable-derived activity measures predict glycemic control.

Wearable-derived physical activity/inactivity measures have been associated with different health outcomes, including next-day glycemic excursions/control [15], incidence of Diabetes, and improvement of cardiovascular health indicators [16]. Furthermore, longer sleep duration derived from wearable activity measures has been linked with higher glycemic control [17]. This is in addition to the enhancement of motivation for adherence to/continuity of physical activity, and reduction of sedentary behaviour, both traceable to wearable-device-based activity interventions [18-22].

Despite the demonstration of the efficacy of wearable-derived activity measures/data in the development of glycemic prediction models' comparison, design of personalized detection of hypoglycemia, glucose level measurements, capture of sedentary behavior/physical inactivity among at-risk

populations, and lower odds of Diabetes, existing studies have not adequately examined whether wearable-derived activity measures are predictors of glycemic control at the Diabetes' population level. For example, in a study that used wearable Continuous Glucose Monitoring devices to suggest that glycemic control among patients with Type 1 Diabetes is associated with seasonal variations [23], there is the further question of whether changes in physical activity or fasting are associated with the seasonal changes in glycemic control. Furthermore, the existing studies are not nationally representative of the population of US adults with Diabetes, have small sample sizes, and in a few cases where higher glycemic control was reported, a single measure of wearable-derived activity, like sleep duration, was the predictor variable.

Materials and Methods

Study Design and Data Source

This study used data from the National Health and Nutrition Examination Survey (NHANES), a nationally representative, cross-sectional survey of the non-institutionalized U.S. population conducted by the Centers for Disease Control and Prevention. NHANES employs a complex, multistage probability sampling design with oversampling of key demographic groups.

Data from the 2003-2004 and 2005-2006 survey cycles were analyzed, the only NHANES cycles with objectively measured accelerometer data using ActiGraph devices. These cycles were combined following NHANES analytic guidelines, and appropriate 4-year sample weights were constructed.

Study Population

The analytic sample included adults aged ≥20 years with:

1. Self-reported diagnosed Diabetes, defined by an affirmative response to the question of whether a doctor or health professional had ever told the participant they had Diabetes;
2. Valid accelerometer data;
3. Available laboratory measurement of glycated hemoglobin (HbA1c).

Participants with missing data on key covariates or HbA1c were excluded. The final analytic sample consisted of 664 individuals.

Outcome Variable

The primary outcome was glycated hemoglobin (HbA1c), measured in NHANES laboratory examinations as a continuous variable (LBXGH, %).

A secondary binary outcome, poor glycemic control, was defined as HbA1c ≥7%, consistent with widely used clinical thresholds.

Accelerometer Data Processing

Physical activity and sedentary behavior were assessed using hip-worn ActiGraph accelerometers, which recorded movement counts in 1-minute epochs over a 7-day monitoring period.

Data processing followed standard NHANES protocols:

- Non-wear time was defined using sustained periods of zero counts.
- Valid days required sufficient wear time (typically ≥10 hours/day).
- Participants were required to have multiple valid days of data.

Daily summaries were constructed for each participant:

- Mean sedentary time (minutes/day): defined using established cut-points for low activity counts.
- Mean moderate-to-vigorous physical activity (MVPA; minutes/day): defined using higher count thresholds.
- Mean wear time (minutes/day): included as a covariate to adjust for differences in device usage.

Movement Phenotype Construction

Participants were categorized into four movement phenotypes based on:

1. Physical activity status (meeting vs. not meeting MVPA thresholds); and
2. Sedentary time (dichotomized using sample-based thresholds).

The resulting phenotypes were:

- Active + Low sedentary (reference group)
- Active + High sedentary
- Inactive + Low sedentary
- Inactive + High sedentary

This classification allowed joint evaluation of activity and sedentary exposure.

Covariates

All models adjusted for key demographic and socioeconomic variables:

- Age (continuous; RIDAGEYR)
- Sex (male/female; RIAGENDR)
- Race/ethnicity (categorical; RIDRETH1)

- Educational attainment (categorical; DMDEDUC2)
- Poverty-income ratio (continuous; INDFMPIR)

Mean accelerometer wear time (minutes/day) was included in all models to account for differences in device adherence.

Statistical Analysis

All analyses incorporated the NHANES complex survey design, including stratification, clustering, and sample weights. A 4-year MEC examination weight (WTMEC4YR) was constructed by dividing the 2-year weights (WTMEC2YR) by two, consistent with NHANES guidance for pooled cycles. Survey design variables (SDMVPSU and SDMVSTRA) were used to specify primary sampling units and strata. Descriptive statistics were calculated as survey-weighted means and proportions with standard errors. Multivariable regression models were estimated using survey-weighted generalized linear models:

1. Linear regression models with HbA1c as a continuous outcome:
- Model with movement phenotypes;
- Model with sedentary time and MVPA as continuous variables;
- Model including interaction between sedentary time and MVPA.
2. Logistic regression models (quasibinomial) with poor glycemic control (HbA1c ≥7%) as the outcome.

All models were adjusted for the covariates listed above. Statistical significance was assessed at a two-sided $\alpha = 0.05$ level. Analyses were conducted using R (survey package).

Ethical Considerations

NHANES protocols were approved by the National Center for Health Statistics Research Ethics Review Board, and all participants provided informed consent. The present analysis used publicly available, de-identified data and was exempt from additional institutional review.

Results

Study Population

The analytic sample included 664 adults aged ≥20 years with diagnosed Diabetes, valid accelerometer data, and available HbA1c measurements from the National Health and Nutrition Examination Survey (NHANES) 2003-2006.

The survey-weighted mean age was 59.8 years (SE 0.8), and 53.1% (SE 2.3%) were female (Table 1). The weighted racial/ethnic distribution was 66.5% non-Hispanic White, 14.8% non-Hispanic Black, 8.0% Mexican American, 4.7% other Hispanic, and 6.0% other race/multiracial. Approximately 45.7% had at least some college education, while 26.3% had less than a high school education.

The weighted mean HbA1c was 7.16% (SE 0.08). Participants accumulated an average of 568 minutes/day of sedentary time (SE 6.3) and 11.3 minutes/day of moderate-to-vigorous physical activity (MVPA) (SE 0.9). Mean accelerometer wear time was 875 minutes/day (SE 5.9).

Table 1: Sample characteristics (NHANES 2003–2006; adults with diagnosed Diabetes; n = 664); Values are survey-weighted means or percentages (SE), with 95% CI.

Continuous Variables

Characteristic	Weighted mean	SE	95% CI
Age (years)	59.75	0.80	58.19-61.32
Poverty-income ratio (PIR)	2.73	0.09	2.56-2.89
Wear time (min/day)	875.31	5.87	863.80-886.82
Sedentary time (min/day)	567.96	6.29	555.63-580.29
MVPA (min/day)	11.26	0.94	9.42-13.09
HbA1c (%)	7.16	0.08	7.00-7.32

Categorical Variables

Characteristic	Weighted %	SE (%)	95% CI (%)
Sex			
Male (RIAGENDR=1)	46.90	2.31	42.37-51.43
Female (RIAGENDR=2)	53.10	2.31	48.57-57.63
Race/ethnicity (RIDRETH1)			
Mexican American (1)	8.05	1.88	4.36-11.73
Other Hispanic (2)	4.73	1.35	2.09-7.38

Non-Hispanic White (3)	66.49	3.45	59.72-73.25
Non-Hispanic Black (4)	14.76	2.29	10.27-19.25
Other race/multiracial (5)	5.98	1.27	3.49-8.47
Education (DMDEDUC2)			
<9th grade (1)	13.14	1.20	10.79-15.49
9–11th grade (2)	13.19	1.64	9.97-16.40
High school/GED (3)	27.97	2.43	23.20-32.73
Some college/AA (4)	29.61	2.41	24.89-34.33
College graduate+ (5)	16.09	2.05	12.07-20.11

Notes: Estimates incorporate NHANES complex survey design with pooled 4-year MEC weights (WTMEC4YR). CI computed as estimate ± 1.96×SE.

Movement Phenotype Distribution

Using physical activity guideline status and sedentary time quartiles, four movement phenotypes were defined (Table 2).

Table 2: Movement phenotype distribution (unweighted counts and survey-weighted%).

Phenotype	Unweighted n	Weighted %	SE (%)	95% CI (%)
Active + Low sedentary	81	13.11	2.48	8.25-17.97
Active + High sedentary	13	1.76	0.54	0.70-2.82
Inactive + Low sedentary	417	64.29	3.68	57.08-71.50
Inactive + High sedentary	153	20.84	2.36	16.22-25.47
Total	664	100.00	-	-

Weighted prevalence estimates were:

- Active + Low sedentary: 13.1% (SE 2.5%)
- Active + High sedentary: 1.8% (SE 0.5%)
- Inactive + Low sedentary: 64.3% (SE 3.7%)
- Inactive + High sedentary: 20.8% (SE 2.4%)

Thus, fewer than 15% of U.S. adults with diagnosed Diabetes were both physically active and low in sedentary time, and fewer than 2% met physical activity guidelines while also falling in the highest sedentary quartile.

HbA1c and Movement Metrics by Phenotype

Weighted mean HbA1c differed modestly across phenotypes (Table 3). The Active + Low sedentary group had a mean HbA1c of 7.52% (SE 0.36), whereas the Active + High sedentary group had a lower mean HbA1c of 6.09% (SE 0.08). The two inactive groups showed similar mean HbA1c values (7.13% and 7.12%).

As expected, sedentary time was substantially higher in the High sedentary groups (approximately 746-773 minutes/day) compared to the Low sedentary groups (approximately 443-522 minutes/day). MVPA levels were highest among active participants (approximately 36-39 minutes/day) and lowest among the Inactive + High sedentary group (4.4 minutes/day).

The Active + High sedentary group was small (unweighted n=13), and subgroup estimates should be interpreted cautiously.

Table 3: Survey-weighted means of HbA1c and movement metrics by phenotype.

Phenotype	HbA1c %	Sedentary min/day	MVPA min/day	Wear min/day
Active + Low sedentary	7.52 (0.36) (6.82-8.22)	442.72 (15.09) (413.14-472.30)	39.26 (1.69) (35.94-42.58)	873.01 (12.32) (848.85-897.16)
Active + High sedentary	6.09 (0.08) (5.93-6.25)	745.66 (27.39) (691.98-799.35)	36.19 (3.91) (28.52-43.87)	1100.18 (50.19) (1001.81-1198.56)
Inactive + Low sedentary	7.13 (0.10) (6.93-7.33)	522.04 (4.71) (512.81-531.28)	7.07 (0.42) (6.26-7.89)	831.67 (5.80) (820.30-843.05)
Inactive + High sedentary	7.12 (0.20) (6.73-7.52)	773.41 (11.76) (750.35-796.46)	4.44 (0.53) (3.40-5.48)	992.39 (14.81) (963.38-1021.41)

Values are weighted mean (SE), with 95% CI; Note: The Active + High sedentary group is small (unweighted n=13), so estimates for that subgroup should be interpreted cautiously.

Multivariable Associations with HbA1c

In survey-weighted linear regression models including phenotype categories, the Active + High sedentary group had a lower HbA1c than the Active + Low sedentary reference group (β = −1.10, SE = 0.46, p = 0.0299). No significant differences were observed for the inactive groups relative to the reference.

Table 4: HbA1c (%) by movement phenotype (survey-weighted linear regression; full analytic sample) Outcome: HbA1c (%); Reference phenotype: Active + Low sedentary, Model: Adjusted for age, sex, race/ethnicity, education, PIR, and mean wear time.

Predictor	β (Estimate)	SE	t	p-value
Intercept	8.713	0.941	9.258	<0.001
Active + High sedentary (vs Active + Low sedentary)	-1.105	0.460	-2.399	0.0299
Inactive + Low sedentary (vs Active + Low sedentary)	0.028	0.357	0.077	0.9393
Inactive + High sedentary (vs Active + Low sedentary)	0.166	0.389	0.427	0.6757
Age (years)	-0.0268	0.00680	-3.943	0.0013
Sex (Female vs Male)	-0.141	0.134	-1.048	0.3112
Race/ethnicity cat2 vs ref	0.403	0.915	0.440	0.6663
Race/ethnicity cat3 vs ref	-0.593	0.292	-2.034	0.0600
Race/ethnicity cat4 vs ref	-0.165	0.314	-0.525	0.6070
Race/ethnicity cat5 vs ref	-1.160	0.340	-3.407	0.0039
Education cat2 vs ref	0.306	0.321	0.953	0.3555
Education cat3 vs ref	-0.408	0.299	-1.364	0.1925
Education cat4 vs ref	-0.445	0.323	-1.380	0.1879
Education cat5 vs ref	-0.901	0.312	-2.892	0.0112
Poverty-income ratio (PIR)	0.0926	0.0419	2.210	0.0431
Mean wear time (min/day)	0.000745	0.000876	0.850	0.4085

When sedentary time and MVPA were modeled as continuous variables, neither was independently associated with HbA1c:

- *Sedentary Time:* β = -0.000105 (SE 0.000629, p = 0.87)
- *MVPA:* β = -0.00537 (SE 0.00961, p = 0.58)

Table 5: HbA1c (%) with sedentary time and MVPA as continuous predictors (survey-weighted linear regression); Outcome: HbA1c (%); Key exposures: mean sedentary minutes/day; mean MVPA minutes/day; Model: Adjusted for age, sex, race/ethnicity, education, PIR, and mean wear time.

Predictor	β (Estimate)	SE	t	p-value
Intercept	8.851	0.962	9.197	<0.001
Mean sedentary minutes/day	-0.000105	0.000629	-0.167	0.8693
Mean MVPA minutes/day	-0.00537	0.00961	-0.559	0.5841
Age (years)	-0.0274	0.00760	-3.607	0.0024
Sex (Female vs Male)	-0.146	0.138	-1.060	0.3049
Race/ethnicity cat2 vs ref	0.471	0.920	0.513	0.6152
Race/ethnicity cat3 vs ref	-0.588	0.298	-1.970	0.0664
Race/ethnicity cat4 vs ref	-0.162	0.325	-0.498	0.6252
Race/ethnicity cat5 vs ref	-1.173	0.333	-3.521	0.0028
Education cat2 vs ref	0.273	0.321	0.849	0.4083
Education cat3 vs ref	-0.435	0.297	-1.464	0.1626
Education cat4 vs ref	-0.459	0.316	-1.452	0.1658
Education cat5 vs ref	-0.910	0.316	-2.874	0.0110
Poverty-income ratio (PIR)	0.0918	0.0419	2.192	0.0435
Mean wear time (min/day)	0.000822	0.000891	0.923	0.3697

Similarly, in survey-weighted logistic regression models predicting poor glycemic control (HbA1c ≥7%), neither sedentary time nor MVPA was significantly associated with the odds of poor control.

Table 6: Poor glycemic control (HbA1c ≥7%): adjusted odds ratios (survey-weighted logistic regression); Outcome: Poor control (HbA1c ≥7%); Model: quasibinomial; adjusted for age, sex, race/ethnicity, education, PIR, and mean wear time; Reported as: OR = exp(β), 95% CI = exp(β ± 1.96×SE).

Predictor	OR	95% CI	p-value
Mean sedentary minutes/day	0.9996	0.9973 – 1.0019	0.7398
Mean MVPA minutes/day	0.9846	0.9625 – 1.0073	0.2015
Age (years)	0.9647	0.9436 – 0.9863	0.0058
Sex (Female vs Male)	0.9098	0.6347 – 1.3040	0.6137
Race/ethnicity cat2 vs ref	0.9716	0.3890 – 2.4265	0.9516
Race/ethnicity cat3 vs ref	0.8346	0.4358 – 1.5985	0.5931
Race/ethnicity cat4 vs ref	1.1349	0.5470 – 2.3549	0.7384
Race/ethnicity cat5 vs ref	0.3360	0.1138 – 0.9919	0.0658
Education cat2 vs ref	0.8911	0.4295 – 1.8489	0.7609
Education cat3 vs ref	0.3655	0.1515 – 0.8816	0.0396
Education cat4 vs ref	0.3259	0.1624 – 0.6537	0.0061
Education cat5 vs ref	0.2135	0.0984 – 0.4632	0.0013
Poverty-income ratio (PIR)	1.1684	1.0284 – 1.3275	0.0295
Mean wear time (min/day)	1.0006	0.9984 – 1.0028	0.6192

Across models, older age was consistently associated with lower HbA1c. Higher educational attainment and selected race/ethnicity categories were also significantly associated with glycemic control.

Discussion

Wearable devices are a category of non-invasive physiological measurement devices that aid in diagnosing and predicting both acute and chronic health conditions. Studies have shown that wearable devices, directly or indirectly, via activity tracking or motivating physical activity, have an association with improved glycemic control, reduction in the presence of comorbidities of Type 1 and Type 2 Diabetes, obesity, and cardiovascular risk factors [7, 26-30].

In this nationally representative sample of U.S. adults with diagnosed Diabetes, objectively measured sedentary time and moderate-to-vigorous physical activity (MVPA) were not independently associated with glycemic control after adjustment for demographic and socioeconomic factors.

Participants accumulated, on average, 568 minutes per day of sedentary time and only 11 minutes per day of MVPA. Despite this substantial sedentary exposure and low activity levels, neither continuous sedentary time nor MVPA predicted HbA1c in multivariable models. These findings were consistent across linear models of continuous HbA1c and logistic models of poor glycemic control (HbA1c ≥7%).

Although the Active + High sedentary phenotype showed a lower mean HbA1c compared with the Active + Low sedentary group, this subgroup represented only 1.8% of the weighted population (unweighted n=13), and the association did not persist when sedentary time was modelled continuously. The apparent difference, therefore, probably reflects instability in small subgroup estimation rather than a robust biological pattern. However, while this may be the case, this finding reinforces the findings in a study on Fitbit-based intervention, where a statistically significant increase in daily step count and MVPA was found, and a significant decrease in weight, in conjunction with a non-significant decrease in sedentary behavior [21].

Movement behavior as captured by 7-day accelerometry did not meaningfully explain variation in HbA1c among adults with established Diabetes. However, this may not have affected the overall outcome because a study that measured the effectiveness of wearable trackers on physical activity, where the mean intervention duration was 21.4 weeks, while usage of wearable trackers showed modest short-term increases in physical activity in healthy adults, subgroup analysis of the same sample showed no clear benefit of wearable trackers for both physical activity and weight loss [31].

Overall, these findings suggest that short-term accelerometer-derived activity measures may not capture the dominant determinants of glycemic control in treated Diabetes, where pharmacologic management and long-term behavioral patterns likely play a larger role.

Interpretation of The Descriptive Patterns

The descriptive data provide important context for these findings. First, most adults with diagnosed Diabetes were inactive (approximately 85% when

combining inactive phenotypes), and over 20% were both inactive and highly sedentary. The weighted mean MVPA of 11 minutes per day corresponds to approximately 77 minutes per week - well below recommended guidelines.

Second, the average HbA1c of 7.16% suggests a treated diabetic population with moderate glycemic control. In such populations, pharmacologic management, disease duration, insulin use, and dietary patterns likely exert stronger influences on HbA1c than short-term movement variation.

Third, sedentary exposure was high across all phenotypes, even among physically active individuals. For example, the Active + Low sedentary group still accumulated over 440 minutes per day of sedentary time. This indicates that meeting MVPA guidelines does not eliminate prolonged sitting exposure, but in this dataset, that exposure was not independently associated with HbA1c. The descriptive and multivariable findings suggest that cross-sectional accelerometer-derived activity metrics may not capture the dominant determinants of glycemic control in treated Diabetes.

Implications for Wearable-Derived Activity Metrics

These findings carry important implications for the interpretation of wearable sensor data in clinical and public health contexts. Wearable devices increasingly generate detailed activity metrics that are used in health monitoring and predictive modeling. However, this study demonstrates that sedentary time and MVPA, measured objectively and analyzed within a nationally representative framework, were not reliable standalone predictors of HbA1c in adults with diagnosed Diabetes.

This does not diminish the value of physical activity for cardiovascular health, weight management, or overall metabolic function. Rather, it highlights a measurement limitation: a single week of movement data may not adequately represent the long-term behavioral patterns relevant to three-month glycemic exposure reflected in HbA1c.

Additionally, glycemic control in treated Diabetes is shaped by medication adherence, insulin therapy, and clinical management strategies - variables not captured by accelerometry. Any system that attempts to infer glycemic status solely from movement data is therefore likely to omit critical explanatory factors.

In short, wearable-derived movement metrics should be interpreted cautiously when used as proxies for glycemic control in established Diabetes.

Strengths

This study has several methodological strengths:

- Use of objectively measured accelerometer data rather than self-report.
- Nationally representative sampling with appropriate survey weighting.
- Clear reporting of weighted descriptive statistics.
- Multiple model specifications (continuous, categorical, interaction, and binary outcome).
- Transparent identification of small subgroup limitations.

By grounding inference in survey-weighted analysis, the findings reflect population-level patterns rather than convenience samples.

Limitations

Several limitations warrant consideration. First, the cross-sectional design prevents causal inference. Second, accelerometer data capture short-term behavior and may not reflect long-term movement habits. Moreso is the fact that the Actigraphy tool is hip-worn, which poses a challenge of device variability in the measurement of activity intensity, and the body location of devices has been reported to have the possibility of not reflecting the intensity of some activities like cycling and swimming [25]. Third, medication use, insulin status, and Diabetes duration were not incorporated into the primary models and likely explain substantial variability in HbA1c.

Fourth, the Active + High sedentary phenotype was small, limiting precision in subgroup comparisons. Finally, the accelerometer technology used during NHANES 2003–2006 differs from contemporary wearable devices, which may capture additional physiological signals. Indeed, while this may be true and there is a lack of a gold standard for the validation of devices, it is noteworthy that the Actigraphy technology remains the primary measurement tool [25].

Conclusion

In this nationally representative cohort of U.S. adults with diagnosed Diabetes, objectively measured sedentary time and moderate-to-vigorous physical activity were not independently associated with HbA1c after adjustment for demographic and socioeconomic factors.

Despite high sedentary exposure and low average MVPA, movement behavior measured over seven days did not explain variation in glycemic control. These findings suggest that wearable-derived activity

metrics alone may be insufficient indicators of glycemic status in treated diabetic populations and should be interpreted within broader clinical and behavioral contexts. Nonetheless, the data from wearable devices and sensors should be harnessed because they are valuable for developing models, algorithms, and strategies for the optimization of new inputs for the general management of Diabetes.

References

1. Cao, Z., Min, J., Chen, H., Hou, Y., Yang, H., et al. (2024). Accelerometer-derived physical activity and mortality in individuals with type 2 Diabetes. *Nature Communications*, 15(1):5164.
2. Li, X., Dunn, J., Salins, D., Zhou, G., Zhou, W., et al. (2017). Digital health: Tracking physiomes and activity using wearable biosensors reveals useful health-related information. *PLOS Biology*, 15(1):e2001402.
3. Site, A., Nurmi, J., Lohan, E. S. (2021). Systematic review on machine-learning algorithms used in wearable-based eHealth data analysis. *IEEE Access*, 9:112221-112235.
4. Jamil, S., Mohammadnezhad, M., Abdulrahim, A., Muhammad, F., Khan, H. T. A. (2025). Managing Diabetes one step at a time in low- and middle-income countries: The promise of wearable devices. *Chronic Diseases and Translational Medicine*, 11(4):279-283.
5. Patel, M. S., Polsky, D., Small, D. S., Park, S.-H., Evans, C. N., et al. (2021). Predicting changes in glycemic control among adults with prediabetes from activity patterns collected by wearable devices. *NPJ Digital Medicine*, 4(1):172.
6. Bent, B., Cho, P. J., Wittmann, A., Thacker, C., Muppidi, S., et al. (2021). Non-invasive wearables for remote monitoring of HbA1c and glucose variability: Proof of concept. *BMJ Open Diabetes Research & Care*, 9(1).
7. Ahmed, A., Aziz, S., Abd-alrazaq, A., Farooq, F., Sheikh, J. (2022). Overview of artificial intelligence–driven wearable devices for Diabetes: Scoping review. *Journal of Medical Internet Research*, 24(8):e36010.
8. Piet, A., Jablonski, L., Onwuchekwa, J. I., Unkel, S., Weber, C., et al. (2023). Non-invasive wearable devices for monitoring vital signs in patients with type 2 Diabetes mellitus: A systematic review. *Bioengineering*, 10(11):1321.
9. Tryon, W. W., Williams, R. (1996). Fully proportional actigraphy: A new instrument. *Behavior Research Methods, Instruments, & Computers*, 28(3):392-403.
10. Dave, D., Vyas, K., Branan, K., McKay, S., DeSalvo, D. J., et al. (2024). Detection of hypoglycemia and hyperglycemia using noninvasive wearable sensors: Electrocardiograms and accelerometry. *Journal of Diabetes Science and Technology*, 18(2):351-362.
11. Shi, Q., Jang, H., Collings, P. J., Wang, M., Chen, Z., et al. (2025). Different intensities of physical activity substituted for sedentary time and risk of type 2 Diabetes: Integration of genetics and wearable data. *Mayo Clinic Proceedings*.
12. Jacobs, P. G., Resalat, N., Hilts, W., Young, G. M., Leitschuh, J., et al. (2023). Integrating metabolic expenditure information from wearable fitness sensors into an AI-augmented automated insulin delivery system: A randomised clinical trial. *The Lancet Digital Health*, 5(9):e607-e617.
13. Cescon, M., Choudhary, D., Pinsker, J. E., Dadlani, V., Church, M. M., et al. (2021). Activity detection and classification from wristband accelerometer data collected on people with type 1 Diabetes in free-living conditions. *Computers in Biology and Medicine*, 135:104633.
14. Hu, X., Wei, L., Xiaoling, C., Yu, Z., Mingxia, Z., et al. (2025). A smart wearable device-based model for identifying hypoglycemia in type 1 Diabetes. *Diabetes Research and Clinical Practice*, 230:112841.
15. El Fatouhi, D., Héritier, H., Allémann, C., Malisoux, L., Laouali, N., et al. (2022). Associations between device-measured physical activity and glycemic control and variability indices under free-living conditions. *Diabetes Technology & Therapeutics*, 24(3):167-177.
16. Pesola, A. J., Brakenridge, C. J., Lamberg, S., Gao, Y., Finni, T., et al. (2025). Silence of the muscles: Wearable electromyography, sitting, and type 2 Diabetes. *Exercise and Sport Sciences Reviews*, 53(4):169-177.
17. Lee, D. Y., Lee, J.-B., Jung, I., Park, S. Y., Yu, J. H., et al. (2026). Association of daytime circadian-aligned activity with glycemic control in type 2 Diabetes. *Metabolism: Clinical and Experimental*, 179:156570.
18. Wu, P.-T., Baltich, A. A., Chu, I.-H., Chui, K. K. (2025). Wearable activity trackers to improve physical activity and cardiovascular risk in type 2 Diabetes: A randomized pilot study. *Diabetology*, 6(9).

19. Qiu, S., Xing, Z. (2025). Dose-response relationship between accelerometer-measured physical activity and depression: Evidence from the UK Biobank. *Translational Psychiatry*, 15(1):297.
20. Khurshid, S., Weng, L.-C., Nauffal, V., Pirruccello, J. P., Venn, R. A., et al. (2022). Wearable accelerometer-derived physical activity and incident disease. *NPJ Digital Medicine*, 5(1):131.
21. Ringeval, M., Wagner, G., Denford, J., Paré, G., Kitsiou, S. (2020). Fitbit-based interventions for healthy lifestyle outcomes: Systematic review and meta-analysis. *Journal of Medical Internet Research*, 22(10):e23954.
22. Wang, Y.-H., Lai, T.-F., Liao, Y., Cheng, I.-L., Hsueh, M.-C. (2026). A randomized controlled trial of wearable accelerometer-based feedback and behavior change techniques. *Experimental Gerontology*, 213:112979.
23. Belsare, P., Bartolome, A., Stanger, C., Prioleau, T. (2023). Understanding temporal changes and seasonal variations in glycemic trends using wearable data. *Science Advances*, 9(38):eadg2132.
24. Goode, A. P., Hall, K. S., Batch, B. C., Huffman, K. M., Hastings, S. N., et al. (2017). The impact of interventions that integrate accelerometers on physical activity and weight loss. *Annals of Behavioral Medicine*, 51(1):79-93.
25. Rosenberger, M. E., Fulton, J. E., Buman, M. P., Troiano, R. P., Grandner, M. A., et al. (2019). The 24-hour activity cycle. *Medicine and Science in Sports and Exercise*, 51(3):454-464.
26. de Oliveira, V. L. P., de Paula, T. P., Viana, L. V. (2024). Pedometer- and accelerometer-based interventions in type 2 Diabetes. *Nutrition, Metabolism and Cardiovascular Diseases*, 34(3):548-558.
27. Levenson, J. N., Dias, C. G., Shah, J., Kovacs, K. D. (2025). Association of accelerometer measured physical activity with diabetic retinopathy. *Journal of Vitreoretinal Diseases*.
28. Luo, J., Zhang, K., Xu, Y., Tao, Y., Zhang, Q. (2021). Effectiveness of wearable device-based intervention on glycemic control. *Journal of Medical Systems*, 46(1):11.
29. Ruissen, M. M., Torres-Peña, J. D., Uitbeijerse, B. S., et al. (2023). Clinical impact of an integrated e-health system (POWER2DM). *Diabetologia*, 66(12):2213-2225.
30. Shen, C., Du, Z., Lai, C., et al. (2025). Association of wearable device-measured physical activity with diabetic retinopathy. *Diabetology & Metabolic Syndrome*, 17(1):230.
31. Tang, M. S. S., Moore, K., McGavigan, A., Clark, R. A., Ganesan, A. N. (2020). Effectiveness of wearable trackers on physical activity. *JMIR mHealth and uHealth*, 8(7):e15576.

Cite this article: Folami K, Johnson SM. (2026). Do Wearable-Derived Activity Measures Predict Glycemic Control? Evidence from NHANES 2003-2006, Nigeria, *Journal of Endocrinology and Diabetes Research*, BioRes Scientia Publishers. 4(1):1-10. DOI: 10.59657/2996-3095.brs.26.024

Article History: **Received:** April 14, 2025 | **Accepted:** April 30, 2026 | **Published:** May 13, 2026