

Improving Context-Aware Personalized Nudging:

Using Wearable Sensors to Reduce Sedentary Behavior

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Abstract

Objectives. To improve nudge outcome classification accuracy in a context-aware personalized nudging framework using wearable sensor data targeted to reduce sedentary behavior using Just- in-Time Adaptive Interventions (JITAI). **Methods.** Data were collected using a custom smartwatch application in a free-living observational study conducted at the University of Delaware (Newark, Delaware, USA) between Spring 2021 and Fall 2022. A total of 18 participants were enrolled. The system continuously recorded motion, physiological, and contextual data and delivered adaptive behavioral prompts. A decision- tree model was trained using sitting and walking bouts enriched with contextual features such as time, location, physiological state, and prior intervention outcomes. Behavioral responses were automatically evaluated using sensor-derived outcomes. **Results.** The proposed model improved classification accuracy for nudge outcomes from 0.42 to 0.78 across 787 sitting bouts. A walking-nudge model achieved an accuracy of 0.70 on 207 walking bouts. Nudged walking bouts were longer in duration, covered greater distances, and exhibited higher average speeds than non-nudged bouts. **Conclusions.** Context-aware adaptive nudging can improve both the timing and behavioral effectiveness of wearable-based interventions. Incorporating contextual and historical features enables personalized and behaviorally meaningful intervention delivery. **Policy Implications.** Wearable-based adaptive interventions offer a scalable and cost-effective strategy to reduce sedentary behavior and support population-level health promotion.

Introduction

Sedentary behavior is increasingly recognized as a major public health concern, contributing to cardiovascular disease, obesity, diabetes, and premature mortality worldwide.¹⁻³ Modern work and lifestyle patterns have led to prolonged periods of sitting, often exceeding recommended limits, even among individuals who meet daily physical activity guidelines.⁴ Evidence suggests that interrupting sedentary time with brief bouts of movement can produce measurable metabolic and health benefits, highlighting the importance of timely behavioral interventions in everyday settings.⁵ Wearable devices such as smartwatches provide a promising platform for addressing this challenge, as they enable continuous monitoring of activity and delivery of real- time feedback or prompts to encourage movement.^{6,7} However, the effectiveness of such interventions depends not only on detecting sedentary behavior accurately but also on delivering prompts at moments when individuals are most receptive. Just-in- time adaptive interventions (JITAI) offer a framework for delivering personalized, context-aware nudges that aim to reduce sedentary time and promote healthier activity patterns in real-world environments.^{8,9}

Wearable technologies such as smartwatches and fitness trackers have created new opportunities to monitor activity and deliver interventions in real time. These devices enable continuous sensing of

physiological and behavioral signals, allowing researchers to study physical activity patterns in naturalistic environments and deliver context-aware feedback.^{6,10} Systematic reviews indicate that consumer wearables can increase physical activity and support behavior change, although their effectiveness depends on engagement, personalization, and timely feedback.^{7,11} Moreover, recent studies have demonstrated that behavioral nudges delivered through wearable devices, such as prompts to stand or move, can significantly increase short-term activity levels.¹² The concept of nudging originates from behavioral economics and refers to subtle interventions that influence behavior without restricting choices or providing strong incentives.¹³ In digital health, nudges are increasingly delivered through mobile and wearable systems, where notifications and feedback can be tailored to individual behavior patterns and contexts.¹⁴ Personalized nudging approaches have been shown to improve adherence and engagement compared to static interventions, highlighting the importance of adaptive and context-aware systems.¹⁵

JITAI provides a principled framework for delivering such personalized, context-aware behavioral support. JITAI aims to deliver the right type of intervention at the right time, based on an individual's current state and environment.^{8,16} Systematic reviews demonstrate that JITAI can effectively promote physical activity and other health behaviors when interventions are triggered at moments of high receptivity.^{9,17} Recent trials and protocol studies further show the feasibility of using wearable sensors and mobile applications to implement JITAI-based systems in real-world settings.^{18,19}

Despite these advances, several challenges remain. First, accurately detecting activity states such as sitting, standing, and walking in free-living environments requires reliable sensing and robust machine learning models.^{20,21} Second, determining the optimal timing and context for delivering nudges remains an open problem, as poorly timed interventions may reduce effectiveness or lead to notification fatigue. Third, integrating sensing, decision-making, and intervention delivery into a single on-device system introduces constraints related to energy consumption, computational resources, and real-time processing.

To address these challenges, a pilot study was conducted using an adaptive sedentary interruption framework that leverages wearable sensor data to detect user activity and deliver context-aware nudges designed to reduce prolonged sitting and promote walking behavior.¹⁹ By combining continuous sensing, machine learning-based activity recognition, and a decision-making component grounded in JITAI principles, the proposed system aimed to deliver timely and personalized interventions in real-world settings. However, several issues were encountered that hindered nudge contextual accuracy. A post-hoc analysis using a new decision tree approach that better integrates contextual, physiological, and behavioral features was developed that has much higher accuracy than the deployed system. These results contribute to the growing body of research on wearable health technologies and demonstrate the feasibility of adaptive, sensor-driven behavioral interventions for reducing sedentary behavior.

Methods

This work builds on data collected as part of the Walking with JITAI (WWJ) study, a pilot deployment evaluating a context-sensitive wearable intervention framework designed to reduce sedentary behavior in free-living conditions.¹⁹ In this framework, a nudge refers to a brief, real-time smartwatch notification intended to prompt the user to interrupt prolonged sitting, or to walk longer or faster.¹³ Nudges were designed as lightweight, non-coercive behavioral prompts grounded in evidence that extended sedentary behavior is associated with adverse cardiometabolic outcomes, and that timely micro-interventions can promote meaningful increases in physical activity.²²

The decision to deliver a nudge is governed by the user's context, defined as the multidimensional state of the individual at a given moment. Context includes temporal factors (e.g., time of day, study phase), physiological state (e.g., heart rate), behavioral indicators (e.g., duration of inactivity), environmental attributes (e.g., weather and location semantics), and historical information such as prior nudge outcomes.²³ Within a Just-in-Time Adaptive Intervention (JITAI) framework, context determines both the appropriateness and the potential effectiveness of a behavioral prompt.

To meaningfully represent context, behavior should be structured into interpretable units. A behavioral bout is defined as a continuous, time-bounded episode of a dominant activity, such as uninterrupted sitting bouts, or walking bouts. Bout-level representation captures accumulated exposure (e.g., how long an individual has been sedentary), temporal continuity, and transitions following intervention attempts. Momentary row-level sensor readings alone do not sufficiently reflect behavioral trajectories or receptivity patterns.²² Segmenting behavior into bouts therefore enables a more accurate understanding of contextual dynamics and supports adaptive decision-making.

The present work focuses specifically on improving the learning and decision-making components of the system by refining contextual feature modeling and extending the decision-tree framework for more accurate nudge outcome classification.

Data Collection for Results

Data were collected using the **WWJ** (Walking With JITAI) watchOS application (app), deployed as part of a longitudinal pilot study designed to evaluate the feasibility of real-time, wearable-based nudging for physical activity.¹⁹ The app continuously recorded motion, heart rate, and some contextual signals, including inferred activity type, location semantics, and user responses to nudges.

Importantly, the original WWJ dataset consisted of continuous row-level sensor logs and contextual annotations without explicit bout-level segmentation. Behavioral episodes (e.g., sitting periods or walking periods) were not pre-constructed in the prior version of the dataset.

Raw sensor and context streams were transmitted to a secure server and post-processed offline in the present work to construct structured behavioral segments, referred to as *bouts*. Consecutive rows with consistent activity labels were aggregated into sitting bouts and walking bouts, each annotated with summary statistics such as duration, mean heart rate, average speed, environmental context, and nudge outcomes.

Transformation to Bout-Level Datasets

The primary methodological contribution of this preprocessing stage was the transformation of continuous, noisy sensor streams into discrete, interpretable behavioral units suitable for learning and evaluation.

The raw dataset contained hundreds of thousands of time-stamped rows per participant at second-level granularity, but without explicit boundaries between distinct behavioral episodes. To enable meaningful modeling of intervention timing and behavioral outcomes, we constructed validated sitting bout and walking bout datasets through rule-based segmentation, integrity validation, and feature summarization.

Contextual Feature Modeling

Context was defined as a multidimensional representation of the user's state at the time a potential intervention decision was considered. Contextual features included temporal variables (time of day,

study stage, duration of inactivity), physiological measures (heart rate and derived indicators), environmental and situational attributes (location semantics, weather conditions, activity context), and behavioral history (prior nudges and observed outcomes).

Context-aware decision making is fundamental to JITAIs, in which intervention timing and content are tailored to an individual's momentary state and environment.^{8,9} However, instantaneous row-level sensor readings do not adequately reflect accumulated behavioral exposure or sustained inactivity. Receptivity to a behavioral prompt is influenced not only by what a participant is doing at a single second, but by the trajectory and duration of behavior preceding that moment.

To capture these dynamics, we implemented a bout-centric feature engineering strategy. Continuous sensor streams were segmented into sitting and walking bouts, each representing a time-bounded episode of dominant activity. For every bout, summary statistics were computed, including duration, mean and maximum heart rate, average walking speed, cumulative distance, and aligned contextual attributes such as temporal markers and environmental variables. Aggregating features at the bout level reduces noise, preserves behavioral continuity, and provides interpretable units for modeling intervention timing.

Two enriched outcome variables were derived to enhance contextual sensitivity:

- ***hasFollowingWalkingRow***: indicates whether a walking bout began within three minutes following the end of a sitting bout, serving as an objective marker of behavioral transition.
- ***Overall Success***: integrates the app-detected success label with post-hoc behavioral evidence derived from subsequent activity transitions. Specifically, outcomes are categorized as True (immediate walking transition following a nudge), False (no observed behavioral response within the predefined response window), or Post-hoc success (a delayed walking transition occurring shortly after the response window). This enriched categorization reduces misclassification of delayed receptivity and provides a more behaviorally faithful representation of intervention effectiveness.

The *hasFollowingWalkingRow* variable captures transitions that may not be reflected in explicit user responses, while *Overall Success* extends binary labeling to account for delayed receptivity. These enriched representations allow the learning framework to model behavioral responsiveness as a graded and context-dependent process rather than a simple instantaneous outcome.

Extended Decision Tree Learning Framework

Building on the bout-level contextual representation, a decision-tree-based model was used to predict whether a nudge should be delivered within a given behavioral bout. Decision trees were selected because they partition data based on attributes with high information gain, yielding interpretable rule structures well suited to heterogeneous behavioral datasets.²⁴⁻²⁶ Interpretability is particularly important in behavioral intervention systems, where transparent decision logic supports clinical reasoning and iterative refinement.

In the original WWJ pilot deployment, a decision-tree model guided real-time nudge delivery. That implementation primarily relied on row-level contextual features and treated outcomes as binary (success vs. failure). It did not incorporate structured bout-level representations, missed intervention opportunities, or delayed behavioral responses. The present work extends that implementation by introducing a bout-level learning framework with an expanded outcome space. The model was trained using labeled behavioral bouts and contextual features, including:

- Successful nudges (immediate transitions following a prompt),
- Failed nudges (no observed transition within the response window),
- Missed intervention opportunities (walking transitions occurring without a preceding nudge),
- Post-hoc successes (delayed transitions initially classified as non-success).

Incorporating missed opportunities allows the system to learn contexts in which an intervention might have been beneficial but was not delivered. Accounting for post-hoc successes enables detection of delayed receptivity that would otherwise be misclassified as failure. By expanding beyond binary outcome labels and operating at the bout level, the model captures a more nuanced representation of behavioral responsiveness within sustained sitting and walking episodes.

Although this extended model has not yet been deployed in a live intervention study, its computational structure remains fully compatible with real-time implementation within the existing WWJ system architecture. The decision-tree inference process is lightweight and interpretable, enabling immediate integration into on-device or server-side nudge delivery pipelines. Decision rules were refined iteratively as additional bout-level evidence accumulated, enabling adaptive modification of intervention logic over time. This extension represents a methodological refinement of the pilot decision framework, enhancing learning fidelity while preserving the overall system architecture.²⁷

Two-Stage Nudge Decision Policy

The learned decision model was embedded within a two-stage nudge decision policy integrating opportunity detection with context-sensitive delivery filtering.

Stage 1: Opportunity Identification

Potential intervention opportunities were identified using bout-level thresholds, such as prolonged sitting duration or suboptimal walking patterns. Because bouts reflect accumulated behavioral exposure rather than transient fluctuations, opportunity detection is grounded in sustained inactivity patterns. This aligns with JITAI principles, in which behavioral and contextual signals determine when support may be most beneficial.⁸ Missed nudge opportunities identified during offline analysis were incorporated into model refinement, allowing retrospective improvement of opportunity timing.

Stage 2: Delivery Filtering

Candidate nudges were filtered using contextual suppressors and learned decision rules to avoid inappropriate delivery during driving, sleep, meetings, or user-defined quiet periods. Context-aware filtering reduces burden and preserves engagement.^{9,28}

The extended framework further adjusted delivery decisions based on historical bout-level responsiveness, including prior successes, failures, and post-hoc responses. By integrating learned receptivity patterns into delivery filtering, the system prioritizes moments of higher predicted effectiveness and mitigates notification fatigue, a known barrier to long-term sustainability of wearable-based interventions.¹¹

Evaluation Metrics

Model performance was evaluated using:

- Precision

- Recall
- F1-score
- Overall accuracy

These metrics are widely used in activity recognition and behavioral prediction tasks to assess classification performance across heterogeneous datasets.²² Performance metrics were computed separately for sitting-nudge prediction and walking-nudge prediction tasks.

Behavioral impact was further assessed by comparing walking duration, distance, and speed between nudged and non-nudged bouts. Evaluating post-intervention behavioral changes is a standard approach in wearable and JITAI studies to determine the real-world effectiveness of interventions.^{7,18}

Ethical Considerations

All behavioral data were collected through voluntary participation in a pilot deployment of the wearable system. Participants provided informed consent prior to data collection. Data were anonymized prior to analysis and used solely for research purposes in accordance with institutional review board (IRB) guidelines and established ethical practices for digital health and wearable research.¹⁰

Results

Dataset Summary

The dataset used for evaluation consisted of approximately 488,501 rows of data collected during pilot deployment of the wearable system, that were re-analyzed as described above into 787 sitting bouts and 207 walking bouts. Each bout was enriched with contextual features, physiological measures, and intervention outcomes, enabling analysis of both nudge effectiveness and post-intervention behavior.

Both successful and unsuccessful nudges, as well as post-hoc successes and missed opportunities, were included in the dataset to support learning of contextual receptivity patterns.

Sitting Bout Nudge Prediction Performance

Sitting Bout. A sitting bout is defined as a continuous episode of sedentary behavior that terminates upon:

- the onset of walking,
- reaching a protocol-defined maximum duration threshold (30-45 minutes), after which a nudge is expected to interrupt the bout, or
- the occurrence of a nudge event. Sitting bouts constitute the primary analytic unit for sedentary intervention decisions.

Model Comparison Overview. The context-aware decision tree model demonstrated substantial improvement compared with the earlier pilot implementation.¹⁹ The prior model relied primarily on row-level features and binary outcome labeling, whereas the extended framework incorporated bout-level representations and enriched outcome variables, including post-hoc success and explicit *No Nudge Decision* classification.

Tables 1 and 2 summarize performance across $N = 787$ sitting bouts.

Performance of the Previous Model. In the earlier implementation (Table 1), recall for Successful Nudge was 0.13 (F1=0.23), indicating limited sensitivity to true behavioral transitions. The model exhibited strong bias toward predicting Unsuccessful Nudge (recall=0.95) and did not meaningfully represent No Nudge Decision. Overall accuracy was 0.42.

Table 1. Previous Model Classification Report (N=787)

Class	Precision	Recall	F1-score	Support
Unsuccessful Nudge	0.82	0.95	0.54	279
Successful Nudge	0.38	0.13	0.23	508
No Nudge Decision	0.00	0.00	0.00	0
Accuracy = 0.42				

Performance of the Improved Model. The new bout-centric model (Table 2) improved classification across outcome categories. Recall for *Successful Nudge/Post Hoc* increased substantially to 0.85 (F1=0.86), reflecting improved sensitivity to meaningful behavioral responses, including delayed transitions. The *No Nudge Decision* class achieved balanced precision and recall (0.49/0.51), indicating that the model no longer defaulted to intervention-heavy predictions. Although precision for *Unsuccessful Nudge* decreased (0.82 → 0.71), its overall F1-score improved to 0.73, suggesting better calibration across competing classes. Overall classification accuracy increased from 0.42 to 0.78.

Table 2. Proposed Model Classification Report (N=787)

Class	Precision	Recall	F1-score	Support
Unsuccessful Nudge	0.71	0.75	0.73	183
Successful Nudge/Post Hoc	0.87	0.85	0.86	508
No Nudge Decision	0.49	0.51	0.50	96
Accuracy = 0.78				

Interpretation. From an intervention perspective, accurately identifying *Successful Nudge/Post Hoc* cases is critical for timely behavioral interruption and minimizing unnecessary prompts. Incorporating enriched outcome variables (*hasFollowingWalkingRow*, *Overall Success*) reduced mislabeling and aligned classification with observed behavioral transitions. These findings are consistent with prior evidence demonstrating that contextual and behavioral feature integration improves precision and personalization in adaptive interventions.

Walking Bout Nudge Prediction Performance

A walking bout is defined as a continuous episode of ambulatory activity beginning at detected walking onset and ending when movement ceases, transitions to another activity, or exceeds pre-defined inactivity thresholds. Walking bouts represent sustained periods of movement and serve as the analytic unit for evaluating post-intervention activity quality. The original WWJ model focused exclusively on sitting bouts as the decision unit for nudging and did not explicitly incorporate walking behavior into the learning framework.¹⁹ While the system effectively identified opportunities to interrupt prolonged sitting, it did not evaluate the quality, sustainability, or intensity of the resulting walking activity. Walking bouts were examined only descriptively and were not incorporated into model training or adaptive refinement. Across the full 6-week deployment involving 18 participants, only 23 walking nudges were recorded, underscoring the limited scope of walking-related intervention modeling in the prior implementation.

Extension to Walking-Aware Learning. In the present work, we extend the decision-tree framework to explicitly incorporate walking-related outcomes into the adaptive feedback loop.

Rather than relying solely on predefined time or distance thresholds to trigger walking prompts, the proposed model dynamically evaluates walking bouts using contextual and physiological features. A total of 207 walking-bout instances were analyzed, each characterized by start and end time, cumulative distance, average heart rate, average user speed, and contextual attributes.

By integrating walking bouts with sitting and contextual data, the model can learn not only when a nudge precedes movement, but also whether that movement reflects meaningful behavioral engagement. This enables evaluation of intervention effectiveness beyond simple transition detection.

Behavioral Outcome Dimensions. We defined two walking-related behavioral dimensions representing distinct manifestations of engagement:

- **Walk Faster (during walk):** $\bar{v}_{\Delta} \geq V_{\text{base}}$, where \bar{v}_{Δ} denotes the post-nudge mean walking speed relative to baseline.
- **Walk Longer:** post-nudge walking duration exceeds participant-specific baseline walking duration.

These outcome dimensions expand the intervention objective from merely initiating movement to improving movement quality and intensity. Walking performance therefore becomes an explicit learning target rather than an indirect byproduct of sitting interruption.

Model Performance. The walking-nudge decision tree achieved an overall accuracy of 0.70 across $N = 207$ walking bouts (Table 3). The precision ranged from 0.53 to 0.54 in the two active walking classes, with high recall values (0.86 to 0.87). The *No Nudge Decision* class demonstrated moderate balance (precision=0.50, recall=0.63).

High recall indicates that the model successfully identifies most contexts in which walking performance could be enhanced. In adaptive behavioral systems, prioritizing sensitivity is often desirable during early-stage learning to avoid missing potential opportunities for meaningful engagement.⁸ The moderate precision observed here reflects the exploratory nature of walking-outcome modeling in a relatively small dataset, and is consistent with reported performance in wearable-based activity classification systems leveraging contextual features.

Table 3. Performance of Walking-Nudge Decision Tree Model (N=207)

Class	Precision	Recall	F1-score	Support
Walk Faster Nudge	0.53	0.87	0.70	73
Walk Longer Nudge	0.54	0.86	0.70	73
No Nudge Decision	0.50	0.63	0.56	61
Overall Accuracy: 0.70				

Behavioral Impact of Nudging

Comparative analysis of nudged and non-nudged walking bouts in the original data revealed substantial differences in activity outcomes. Nudged bouts were longer in duration, covered greater distances, and exhibited higher mean walking speeds than non-nudged bouts. Prior studies have similarly reported that wearable-delivered prompts and behavioral nudges can increase activity levels and improve behavioral outcomes in real-world settings.⁷

Table 4 presents a summary of these differences.

Table 4. Comparison of Nudged and Non-Nudged Walking Bouts

Metric	Nudged	Non-Nudged
Average Duration (minutes)	10.57	3.26
Average Distance (m)	1167.93	115.08
Average Speed (m/s)	1.14	0.99

These findings suggest that nudges were associated not only with increased likelihood of movement but also with improvements in the quality and intensity of walking behavior, consistent with prior evidence that timely, context-aware interventions can influence both activity initiation and performance.¹⁸

Effect of Contextual Modeling

Integrating contextual dimensions, including temporal, physiological, and environmental features, substantially enhanced both prediction accuracy and behavioral relevance of interventions. Context-aware modeling is a core principle of JITAIs, where decisions are tailored to an individual's momentary state and environment.^{8,9}

The decision tree framework was able to learn from successes, failures, and missed opportunities, allowing the system to refine intervention strategies and better align nudges with user receptivity. Adaptive learning from behavioral outcomes has been shown to improve personalization and effectiveness in wearable health coaching systems.²⁷

Overall, the results demonstrate that context-aware nudging is both technically feasible and behaviorally meaningful, influencing real-world activity patterns in measurable ways. Prior studies of wearable-based interventions have similarly reported measurable changes in activity behavior following context-aware prompts and nudges.¹⁸

Discussion

This study evaluated a context-aware wearable nudging framework designed to improve the timing and effectiveness of behavioral prompts aimed at reducing sedentary behavior. The results demonstrate that incorporating contextual information and behavioral feedback substantially improves both prediction accuracy and behavioral outcomes compared with static or rule-based approaches.

Principal Findings

The proposed decision-tree framework achieved substantial improvement in sitting-bout classification accuracy, increasing overall accuracy from 0.42 in earlier rule-based approaches to 0.78. This improvement reflects the benefit of integrating contextual, physiological, and behavioral features into the decision process. In particular, the ability to learn from both successful and unsuccessful nudges, as well as missed opportunities, enabled the model to develop a more nuanced understanding of user receptivity.

Analysis of walking outcomes further demonstrated that nudged walking bouts were longer, covered greater distances, and exhibited higher average speeds than non-nudged bouts. These findings suggest that context-aware nudges can influence not only whether individuals initiate activity but also the quality and intensity of that activity.

Together, these results indicate that adaptive nudging frameworks can improve both intervention relevance and behavioral impact, addressing a key limitation of many commercial wearable reminder systems.

Comparison with Prior Work

Previous studies of wearable-based interventions have demonstrated the feasibility of JITAIs but have reported mixed evidence regarding long-term effectiveness. Many earlier systems relied on fixed thresholds or limited contextual information, reducing their ability to personalize intervention timing.

The present work extends prior research by incorporating richer contextual modeling and explicitly evaluating post-intervention walking outcomes. By considering walking duration and speed as outcome dimensions, the framework provides a more comprehensive assessment of behavioral response than binary movement detection alone.

In addition, the use of interpretable decision-tree models enables transparent reasoning about intervention timing, which is important for both clinical acceptance and user trust.

Implications for Behavioral Intervention Design

The findings highlight several design principles for wearable-based behavioral interventions.

First, intervention timing is critical. Delivering prompts during periods of low receptivity may reduce engagement and contribute to notification fatigue. The two-stage nudge decision policy implemented in this study demonstrates how contextual filtering can improve the appropriateness of intervention delivery.

Second, learning from both successes and failures improves model performance and behavioral relevance. Traditional systems often evaluate only successful interventions, overlooking valuable information contained in unsuccessful or missed opportunities.

Third, evaluating behavioral quality rather than only activity initiation provides a richer understanding of intervention effectiveness. Measures such as walking duration and speed provide insight into whether behavioral changes are meaningful from a health perspective.

Public Health Relevance

Sedentary behavior is highly prevalent in modern work and home environments, particularly among individuals engaged in desk-based occupations. Scalable and cost-effective strategies for reducing sedentary time are therefore of considerable public health interest.

Wearable-based adaptive interventions have the potential to deliver personalized behavioral support at population scale without requiring intensive clinical supervision. By improving both the timing and effectiveness of nudges, context-aware systems may help individuals incorporate more frequent movement into daily routines, potentially reducing long-term risk of chronic disease.

Limitations

This study has several limitations. First, the dataset was derived from a pilot deployment with a limited number of participants and a relatively short observation period. Larger and more diverse cohorts will be needed to evaluate generalizability across populations and environments.

Second, although the decision-tree framework provides interpretable rules, behavioral responses may be influenced by unobserved factors such as social context, mood, or competing activities that were not captured in the dataset.

Third, long-term adherence and sustained behavior change were not evaluated in this pilot study. Future longitudinal studies will be required to assess whether adaptive nudging produces durable changes in sedentary behavior.

Future Work

Future work will focus on expanding the dataset through larger-scale deployments and integrating additional contextual signals, including environmental and calendar-based features. More advanced adaptive learning approaches, including ensemble methods and reinforcement learning strategies, may further improve intervention timing and personalization.

In addition, integrating user feedback and preference modeling may improve acceptance and long-term engagement with wearable-based interventions.

Conclusions

This study demonstrates the feasibility of a context-aware wearable nudging framework that learns from behavioral data and contextual signals to deliver adaptive interventions. The results indicate that incorporating contextual modeling and behavioral feedback can improve prediction accuracy and enhance the behavioral impact of nudges.

These findings support the potential of wearable-based adaptive interventions as a scalable approach to reducing sedentary behavior and promoting physical activity in real-world settings.

Public Health Implications

Sedentary behavior is a widespread and growing public health concern associated with increased risk of cardiovascular disease, metabolic disorders, and premature mortality.^{3,29} Interventions that can be delivered at scale and integrated into daily life are needed to help individuals reduce prolonged sitting and increase physical activity.¹²

The findings of this study suggest that context-aware wearable interventions can improve both the timing and effectiveness of behavioral prompts compared with static reminder systems. By incorporating physiological, temporal, and behavioral context, adaptive nudging systems may increase user engagement while reducing notification fatigue.

Wearable-based adaptive interventions have the potential to support population-level health promotion by providing personalized, low-cost, and continuously available behavioral support. As wearable device adoption continues to increase, integrating intelligent intervention strategies into consumer and clinical technologies may offer a scalable approach to reducing sedentary behavior and promoting healthier daily activity patterns.

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