Shizuoka University

Graduate School of Integrated Science and Technology

Master's Thesis

Predicting Daily Physical Activity from Morning Activity Patterns to Optimize Intervention Delivery

by

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ABSTRACT

Background: Physical inactivity remains a major public health concern globally, particularly among both adult and elderly populations, contributing to chronic conditions such as cardiovascular disease, obesity, and diabetes. While previous interventions targeting physical inactivity have shown effectiveness in increasing physical activity levels, many lack timely personalization. They often adopt a one-size-fits-all approach or rely on fixed daily schedules, disregarding individual behavioral patterns. Morning physical activity has been shown to be a strong behavioral signal for predicting total daily physical activity, with early movement increasing the likelihood of meeting daily physical activity goals due to both physiological and psychological momentum effects. Using morning activity data allows for timely, actionable decisions providing a wide time window to deliver interventions while there is still sufficient opportunity for users to adjust their behavior. However, prior research has rarely explored early-day predictions using wearable data to guide intervention timing. This study addresses these gaps by developing a machine learning (ML) based method to predict total daily physical activity using morning behavior and sleep patterns. It also introduces a rule-based intervention logic tailored to individual physical activity goals. By identifying low physical activity days early, while there is still time to intervene, this approach facilitates the delivery of interventions only when predictive indicators suggest insufficient physical activity, thereby ensuring timely and targeted support while minimizing unnecessary interventions.

Objective: The objective of this study was to predict total daily physical activity from morning activity patterns and sleep features, and to develop a simple decision logic for the delivery of interventions.

Methods: A total of 44 healthy adults aged 20-85 years (mean ± Standard Deviation (SD): 53.5 ± 18.2 years; 28 males and 16 females) participated in this study. Each participant wore a wristwatch-type wearable device (Fitbit Sense 2; Fitbit Inc., San Francisco, CA, USA) continuously over a three-week period. The device continuously tracked various physical activity and sleep-related data throughout the day, such as step count, distance traveled, sleep duration, and sleep efficiency. From this comprehensive dataset, key features were extracted, including morning physical activity (i.e., total distance traveled between 6 AM and 12 PM), average morning distance, sleep duration, and sleep efficiency. Each participant's daily physical activity goal was calculated as the average of their total distances across the entire data collection period, and a personalized physical activity goal was set using mean and goal threshold. To predict total daily physical activity, three ML models (i.e., Random Forest Regression, Light Gradient Boosting Machine (LightGBM), and Extreme Gradient Boosting (XGBoost)) were trained and compared. The Random Forest model showed the best performance and was used for final analysis. Based on the predicted total daily physical activity and user-specific physical activity goal, a simple rule-based logic was applied to determine whether and when to deliver an intervention message. The intervention categories were "Definitely Send Intervention," "May be Send Intervention," and "No Intervention Needed".

Results: The results of this study demonstrated a significant positive correlation between morning (9:00 AM-12:00 PM) physical activity and total daily physical activity ($r = 0.52$, $p < 0.001$). Among the ML models tested, the Random Forest model yielded the best predictive performance, achieving a coefficient of determination (R^2) of 0.86, Root Mean Square Error (RMSE) of 1.36, and Mean Absolute Error (MAE) of 0.88. The predicted and actual total daily distances traveled were highly correlated ($r = 0.93$, $p < 0.001$), confirming strong predictive power. Using a personalized goal-setting approach based on each participant's average i.e., mean and goal threshold, a simple rule-based decision logic was developed to categorize intervention needs. This resulted in 149 days classified as "Definitely Send Intervention," 158 days as "May be Send Intervention," and 616 days as "No Intervention Needed", demonstrating the model's potential to provide timely and individualized intervention support.

Conclusion: This study demonstrates the feasibility of predicting total daily physical activity using morning and sleep data collected from a wearable device. A Random Forest model achieved strong predictive performance, enabling early identification of low physical activity days. A rule-based decision logic based on user's average individual goals was developed to determine whether and when to deliver an intervention. This approach supports timely, low-burden, and practical intervention delivery, offering a scalable solution for promoting physical activity in real-world settings.

Keywords: Physical activity; Machine learning; Random Forest; Just-in-Time Adaptive Intervention (JITAI); Wearable devices; Sleep data; Intervention timing; Personalized goal setting.

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1 INTRODUCTION

1.1 Background

Physical activity is one of the most significant factors influencing general health and wellbeing. Prior studies indicate that it protects against a wide range of chronic illnesses, including heart disease, obesity, type 2 diabetes, and some types of cancer (Lee, 2012). Besides, it has been shown to have a positive effect on mental wellbeing by decreasing depressive and anxiety symptoms and improving cognitive function (Schuch, 2016). International health organizations, such as the World Health Organization (WHO), highly recommend adults to undertake a minimum of 150 minutes of moderate or 75 minutes of vigorous aerobic physical activity every week (WHO, 2020). Despite these guidelines, a large percentage of the population across the world is physically inactive. More than 25% of adults fail to achieve the minimum recommended physical activity, as per global studies (Hallal, 2012). Even in Japan, despite growing health and fitness consciousness in recent years, sedentary lifestyle is prevalent, particularly among working people who live structured and time-constrained lives (MHLW, 2021). Since physical inactivity not only leads to ill health but also causes a huge economic cost, encouraging physical activity has become a priority for public health (Ding, 2016).

To this problem, numerous solutions have been tried, from education campaigns and community interventions to digital interventions. Of these, technology-based tailored interventions including mobile applications, SMS reminders, and wearable devices have been particularly popular given their scalability and usability (Patel, 2015). Yet there is still one issue: how to provide interventions at the most suitable moment when the user is most in need of them. Recent advancements in wearable devices such as Fitbit, Garmin, and Apple Watch have made it easier to collect real-time physical activity data. These devices monitor several indicators such as steps taken, calories expended, distance traveled, and heart rate variability (HRV) continuously, providing a rich source of information about user's activity levels (Bent, 2020). It is now possible to examine trends in behavior and even predict future activity levels using data-driven models (Wang, 2022). While prior studies like (Wang, 2022) focused on various machine learning (ML) models for predicting health behaviors, but did not focus on the use of early-day data for immediate prediction or intervention. This study simplifies this concept by applying a rule-based decision logic to determine whether to send a daily physical activity intervention based on predicted physical activity versus a personalized physical activity goal.

In most current behavior-change programs, interventions are provided one-size-fits-all style i.e., reminders to walk at the same time every day independent of context. Although some users might benefit from this, others might find these kinds of interventions mismatched or inappropriate (Nahum-Shani, 2018). In contrast to Nahum Shani's theoretical framework for Just-in-Time Adaptive Interventions (JITAI), this study applies a simpler, rule-based method to classify each day's intervention need using actual predicted physical activity relative to a personalized physical activity goal. Additionally, high-frequency messaging might cause alert fatigue or disengagement (Klasnja, 2015). Therefore, low-burden and high-impact solutions for simplicity versus personalization must be found.

Morning physical activity serves as a strong behavioral signal for forecasting total daily physical activity. Previous research has consistently shown that individuals who engage in higher levels of physical activity during the morning are more likely to meet or exceed their overall daily physical activity goal (Zhaoyang, 2017; Schumacher, 2020). This is explained in part by the "momentum effect", where early movement in the day initiates a positive feedback loop-once physical activity has begun, the likelihood of continuing throughout the day increases. From a psychological standpoint, early success in meeting part of a daily physical activity goal can increase self-efficacy, motivation, and adherence to an active lifestyle. Morning activity also fosters a sense of accomplishment and can set a positive tone for the rest of the day (Rhodes, 2010). This aligns with behavioral science findings that early reinforcement increases the probability of sustained behavior (Bandura, 1997). From a physiological standpoint, engaging in morning activity stimulates metabolism, improves blood circulation, and enhances alertness. Physical activity in the early hours also promotes the release of endorphins and other mood-enhancing neurochemicals, which can improve overall energy levels and reduce perceived fatigue throughout the day (Feng, 2023). From an intervention design standpoint, morning physical activity provides a time advantage for behavioral feedback systems. If low activity is detected early, there is a wider time window available for delivering targeted interventions allowing users to adjust their behavior before the day ends. Afternoon or evening activity patterns may be accurate indicators, but they leave little opportunity to influence daily totals. Therefore, morning distance not only serves as a predictive indicator but also as a strategic decision point for delivering timely, actionable prompts that maximize the potential for behavior change (Chaudhari S, 2022).

One potential is a single, early-day intervention. The idea is to look at an individual's morning activity (e.g., 6 AM to 12 PM) and predict whether they are likely to meet their daily physical activity goals. If the prediction indicates low physical activity compared to the physical activity goal, a motivational message or prompt can be delivered to encourage movement during the remainder of the day. If the model predicts high physical activity, no message is sent, thereby avoiding unnecessary interventions.

This approach was chosen due to its simplicity, feasibility, and user-centered design. In real-world settings, particularly for elderly or general populations, high-frequency or context-aware interventions can be challenging to deploy and may increase user burden (Nahum-Shani, 2018; Klasnja, 2015). By contrast, a single daily decision offers a low-burden and easily interpretable solution that still provides support based on early day physical activity data. This strategy also reduces the risk of alert fatigue and increases the likelihood of user engagement over time (Dennison, 2013). Rather than aiming to dynamically adapt in real-time, the focus here is to provide just enough support, just once, when it's most likely to be helpful.

While many studies have tried to examine complex intervention systems or adaptive messaging in real time, none have explored the possibility of predicting total daily physical activity using just morning data. Predictive modeling can be the solution to this problem by acting as the missing link between continuous monitoring and effective intervention delivery. Recent advancements in wearable technology have enabled the continuous collection of physical activity and sleep data, making it possible to apply ML models to support health behavior change. Prior studies have demonstrated the use of ML to analyze and predict physical activity patterns for the purpose of delivering timely interventions. For example, (Wang, 2022) reviewed various ML approaches for health behavior prediction, highlighting their role in personalizing interventions. (Mair, 2022) developed a smartphone-delivered intervention system that used behavioral data to deliver personalized physical activity interventions to older adults. Similarly, (Molina-García, 2019) employed wearable sensors to assess sedentary behavior and physical activity trends in older adults. These studies show the growing interest in leveraging ML to optimize when and to whom interventions should be delivered.

This study will create and evaluate a ML model that predict the total daily physical activity based solely on morning activity patterns. The study involves data collection from wearable sensors, data preprocessing and feature engineering, training and testing of the model, and finally, creation of a simple rule-based intervention logic. It is not just to be more predictive but to provide a guideline of operation on when and if to act based on insight at the beginning of the day. Finally, this study contributes to current digital health research by creating a data-driven, non-invasive strategy for physical activity intervention improvement. From the study, there is insight into how morning routine can practically be a prelude to the rest of the day and how prediction can be better to improve the timing of intervention, particularly in low-intervention-frequency or resource-constrained settings.

1.2 Problem Statement

Despite the increasing availability of wearable technology and its demonstrated usefulness in tracking physical activity (Bent, 2020) (Zhang, 2015), a significant challenge remains: determining when and if to intervene to effectively support behavior change. Most existing interventions use fixed-timing or one-size-fits-all approaches, which often fail to consider daily variability in user behavior or contextual factors (Chaudhari S, 2022). While predictive modeling techniques, including ML algorithms such as Random Forest regression model and Extreme Gradient Boosting (XGBoost), have been employed to estimate physical activity levels (Bampakis, 2022), few studies have focused specifically on morning data to anticipate whether a person is on track to meet their physical activity goals for the day. This early prediction window is crucial, as it allows for the possibility of proactive intervention while there is still time to influence behavior.

Furthermore, prior studies have rarely translated these predictions into simple, actionable frameworks for real-world use. High-burden or overly complex JITAI may be impractical for certain populations, and scalable, low-burden alternatives remain limited (Nahum-Shani, 2018).

To address these gaps, this study proposes a personalized, rule-based decision logic informed by morning physical activity and sleep features to forecast daily outcomes and trigger timely interventions only when necessary. This approach aims not just to improve prediction accuracy but to guide operational decision-making that supports more effective and user-sensitive intervention delivery.

1.3 Objectives

Despite the prevalence of a wristwatch-type wearable device and the established benefit of physical activity, many people continue to be under physical activity guidelines. While interventions like messages or motivational reminders can faster behavior change, their delivery for optimal effect particularly at low frequency, once daily depends on predictive insight into a participant's anticipated physical activity level. For this purpose, the present study aims to predict total daily physical activity based on morning behavior patterns, with the long-term overall aim of facilitating timely and minimally obtrusive intervention provision.

The following are the specific research goals:

- To develop a ML model that can predict a participant's total daily physical activity based on morning activity features alone.
- To evaluate the prediction accuracy of various machine learning models, including Random Forest, LightGBM, and XGBoost.
- To obtain a decision rule for delivering intervention based on prediction outputs (e.g., below goal threshold) so that one targeted message could be delivered when physical inactivity risk is high.
- To assess the practical applicability of this approach for application in real-life environments, prioritizing simplicity, effectiveness, and prospects for use in low-resource digital health programs.

1.4 Research Question and Hypothesis

This study investigates the potential of using morning activity data, captured from a wearable device, to predict total daily physical activity and enable the provision of timely single interventions. A sequence of research questions and related hypotheses has been developed to underpin this study. These are based on available literature in the fields of physical activity monitoring, predictive modeling, and rule-based intervention.

Research Questions: The study is structured on the following questions:

RQ1: To what degree can total daily physical activity be accurately predicted based on morning activity data collected by wearable devices?

RQ2: Which among the features derived from morning activity data (e.g., step count, distance, heart rate, physical activity intensity) are the best predictors of total daily physical activity?

RQ3: How well can alternative prediction model strategies (e.g., linear regression, decision tree-based models such as Light Gradient Boosting Machine (LightGBM), Extreme Gradient Boosting (XGBoost), Random Forest predict total daily physical activity outcomes from early-day behavior?

RQ4: What is the optimal type of physical activity goal strategy (e.g., group mean, percentile-based, user-specific baseline) for determining whether a one-time intervention should be administered?

RQ5: Can model predictions be used to model intervention delivery scenarios, and how well can low physical activity days be forecasted before the day ends?

These questions attempt to assess both the technical potential and practical use of predicting daily levels of physical activity from morning activity patterns in a real-world, low-burden intervention setting.

Hypotheses: Driven by the research questions and based on previous empirical studies, the study confirms the following hypotheses:

H1: Physical activity measures in the morning (e.g., distance) are positively and significantly related to total daily physical activity.

H2: Total daily physical activity can be predicted with reasonable accuracy (e.g., $R^2 > 0.60$ and Mean Absolute Error (MAE) within 15% of the mean daily physical activity) by ML models trained on morning data alone.

H3: Tree-based models (e.g., Random Forest model) will outperform linear models in predictive accuracy due to their ability to capture non-linear relationships in physical activity behavior.

H4: A decision rule based on the 25th percentile of predicted total daily physical activity can identify at least 70% of low physical activity days (true positives) with few false positives.

H5: Among all the features, cumulative morning steps and distance covered will have more predictive power for total daily physical activity than other features such as intensity minutes.

Together, these research questions and hypotheses provide systematic guidance to the methodology design, model development, and analysis phases of the study.

2 LITERATURE REVIEW

Physical activity is widely recognized as a vital component of health maintenance and chronic disease prevention. According to the (WHO, 2020) adults should engage in at least 150 minutes of moderate-intensity physical activity per week. However, global data indicates that many individuals fail to meet this recommendation, particularly in aging populations (Hallal, 2012). Physical inactivity has been linked to elevated risks of cardiovascular disease, type 2 diabetes, obesity, depression, and other mental health disorders (Lee, 2012).

Morning activity has been identified as a strong predictor of total daily physical activity. Individuals who accumulate more activity in the morning are more likely to achieve higher overall totals, reflecting a "momentum effect" (Zhaoyang, 2017; Schumacher, 2020). Psychologically, morning accomplishments foster self-efficacy, which enhances motivation for continued behavior (Bandura, 1997; Rhodes, 2010). Physiologically, early movement stimulates metabolism, circulation, and mood, providing both energy and psychological readiness for the day (Feng, 2023). Importantly, from an intervention design perspective, using morning activity data allows for timely, actionable decision-making, as afternoon or evening data provide less opportunity to influence the same day's outcome. Thus, focusing on morning data bridges predictive insight with practical feasibility for real-world interventions (Klasnja, 2015; Nahum-Shani, 2018).

The increasing availability of wearable technology, such as Fitbit, Apple Watch, and Garmin, has made it easier to monitor real-time physical activity. These devices collect diverse metrics, including steps, heart rate, calories burned, sleep duration, and distance traveled (Bent, 2020). Researchers have leveraged these data streams to explore behavioral trends and build predictive models. For example, (Bent, 2020) used wearable sensor data to predict physical activity and mental stress, indicating the potential of such technology in health interventions.

Moreover, studies have demonstrated that wearables not only support self-monitoring but also improve intervention outcomes. (Huang Z, 2025) found that wearable-based interventions significantly increased physical activity in older adults. Similarly, (Black M, 2021) showed that combining wearable trackers with weekly behavioral email support enhanced moderate-to-vigorous physical activity in overweight women. WheelFit, a wearable-based mobile health intervention for wheelchair users, further confirmed the feasibility and engagement benefits of such technology (Jin, 2022).

Despite these advances, limitations remain in current approaches. Many interventions are delivered uniformly, such as fixed daily reminders, without considering contextual cues or individual behavior patterns. This one-size-fits-all method often leads to user disengagement or alert fatigue (Chaudhari S, 2022). Personalized, context-aware strategies such as JITAI have emerged as a response, aiming to deliver support when it is most needed (Nahum-Shani, 2018). However, implementing JITAI at scale remains complex, requiring continuous data capture, real-time modeling, and high computational resources.

Predictive modeling of physical activity has shown promise in enabling timely intervention. Techniques like linear regression model, Random Forest, LightGBM, and XGBoost have been employed to forecast step counts, physical activity levels, and health outcomes (Bampakis, 2022) .Some research also highlights the relevance of features such as HRV, sleep quality, and early day physical activity in predicting behavior (Zhang, 2015) .However, very few studies have explored the use of morning data alone for same-day predictions or connected these predictions to actual intervention logic.

In summary, prior literature demonstrates the potential of wearable data and ML for physical activity prediction, but gaps remain in timing, simplicity, and operationalization of interventions. The present study seeks to address these by focusing on morning data-based prediction, personalized goal thresholds, and a practical rule-based decision system to determine whether and when to intervene there by bridging predictive insight with real-world intervention feasibility.

3 METHODOLOGY

3.1 Research Approach

This research is quantitative observational and predictive modeling. The primary objective is to predict total daily physical activity from morning measurements alone (i.e., distance, sleep) to guide optimal timing for future health interventions. In this research, variables are not manipulated or subjects assigned to conditions but rather investigated as naturally collected behavioral and physiological measures using a wearable device and self-report surveys. This data-driven approach allows pattern recognition and model-based prediction without the introduction of intervention bias. The obtained results can be utilized to inform the design of adaptive, personalized intervention systems for future application.

3.2 Participants

Participant recruitment involved healthy adults aged 20-85. The inclusion criteria were age 20 years old and above, phone ownership or access (Android device provided if needed), capacity to use a wearable device Fitbit sense 2 (Fitbit Inc., San Francisco, CA, USA) continuously, and capacity to complete twice-daily mood/schedule surveys. The exclusion criteria included: cognitively or psychiatrically diagnosed impairments that may potentially affect participation, acute impairment of mobility, and inability to offer consistent data for a period of more than 3 days.

A total of 44 participants were able to complete the process of data collection successfully, offering valid data for a period of at least two consecutive weeks. Of these, 28 were male (63.6%) and 16 were female (36.4%). The mean age of participants was 53.52 years with a Standard Deviation (SD) of 18.20 years which is shown in Table 3.1, reflecting a mix of both working age and older individuals.

Table 3.1: Participant Demographics

Category	Value
Number of Participants	44
Male	28 (63.6%)
Female	16 (36.4%)
Mean Age (years)	53.52
Standard Deviation (SD)	18.20

3.3 Data Collection Procedure

The data collection process was conducted over a three-week period. During the first week, participants engaged in benchmark setup and familiarization with the devices and procedures. The second and third weeks constituted the primary phase of data collection and logging. Each participant was provided with a wearable device to continuously monitor their physical activity. Additionally, for those who did not have a compatible smartphone, a Motorola Moto G24 (Motorola Mobility LLC, 2024) was issued, pre-installed with a custom mobile survey application. Participants were instructed to always use a wearable device and to complete brief self-report questionnaires twice daily once in the morning between 6:00 AM and 10:00 AM, and once in the evening between 8:00 PM and 11:00 PM. All collected data were either automatically synced or stored locally and securely transmitted to a centralized server for further analysis.

3.4 Data Types and Variables

The following data were collected for analysis:

- Morning Activity: Step count, distance, and sedentary minutes
- Total Daily Physical Activity: Total distance 00:00 AM-23:59 PM
- Sleep Data: Last night's sleep duration (minutes of sleep) and sleep efficiency
- Heart Rate Variability: Root Mean Square of the Successive Differences (RMSSD), Low Frequency (LF), and High Frequency (HF) recorded in the early morning
- Subjective State: Self-rated mood, motivation, and availability

3.5 Measurement Instruments

A commercially available a wristwatch-type wearable device Fitbit Sense 2 was used to record various physical activity and physiological metrics, including steps, distance, sleep patterns, heart rate, and HRV, making it suitable for health and behavioral research. Smartphone Surveys were conducted to capture self-reported mood states (based on Russell's Circumplex Model of Affect), motivation, availability in one's schedule, and environmental/weather context. Surveys used Likert-scale items (0-10) to allow for numerical modeling and correlation analysis.

3.6 Data Preprocessing

The exported data was saved in CSV format and underwent a structured preprocessing pipeline to ensure quality and consistency. First, days with missing Fitbit or survey data were excluded to maintain the integrity of the dataset. Next, time-window filtering was applied to define morning data strictly as physical activity recorded between 6:00 AM and 12:00 PM, aligning with the study's focus on early-day prediction. Feature engineering steps were then performed to derive relevant variables, including the average morning distance and individualized daily goal thresholds. Finally, data from multiple sources including survey responses and Fitbit measurements were merged using user IDs and corresponding timestamps to form a unified dataset for analysis.

3.7 Predictive Modeling

The objective of this study is to predict the total daily physical activity (e.g. distance) from morning distance, sleep duration and sleep efficiency. To achieve this, multiple supervised ML models were developed and compared. The models reveal how early day physical activity is associated with overall behavior activity and can be used to support proactive decision-making in future intervention systems.

3.7.1 Light Gradient Boosting Machine (LightGBM)

LightGBM is an open-source gradient boosting framework from Microsoft based on histogram-based decision tree learning algorithms. It is highly optimized for performance, scalability, and low memory usage, which makes it very suitable for large, high-dimensional datasets. LightGBM was utilized in this research as a competitive benchmark because of its established performance on tabular regression problems. Some of its most important features are the support of missing values, intrinsic feature importance, and parallel computation efficiency (Ke, et al., 2017). The learning rate, max depth, and number of leaves were hyperparameters that were tuned using grid search with 5-fold cross-validation.

3.7.2 XGBoost (Extreme Gradient Boosting)

XGBoost is also a powerful ensemble learning technique based on the concepts of gradient boosting. It uses second-order gradients along with regularization to prevent overfitting and promote generalization. XGBoost has been used very widely in ML competitions as well as actual prediction problems because of its accuracy, efficiency, and predictability (Chen & Guestrin, 2016). There, it was used to test how efficiently gradient-based tree ensembles performed with small- to medium-sized behavioral data sets. Tuning entailed the application of early stopping rounds as well as regularization tuning (L1/L2).

3.7.3 Random Forest Regression Model

Random Forest model is a collection of decision trees that predicts by taking the average output of numerous trees, where each tree is trained on bootstrapped samples of the data (Breiman, 2001). Its advantages are Robustness against overfitting because of averaging, capacity to model non-linear feature interactions, less sensitivity to noise or missing values and simple feature importance estimation.

The model was trained on 80% of the data and evaluated on the remaining 20%, with internal validation by 10-fold cross-validation. Hyperparameters such as the number of estimators, max depth, and minimum samples per leaf were optimized by grid search.

3.8 Prediction Procedure Using Random Forest Regression Model

Among all three models, Random Forest model was selected as the primary predictive model in this research. This section describes the process to predict total daily physical activity levels from morning activity and sleep data using the Random Forest model. The goal of this model is to predict the total daily distance (in kilometers) a user will walk from the computation of early-day available data, i.e., morning distance, sleep duration and sleep efficiency. This prediction capability is essential for enabling early-day interventions and personalized feedback.

3.8.1 Variable Definition

The prediction task was posed as a regression problem with one dependent variable and several independent variables:

- Dependent Variable (Target):
  - Total Distance: Total distance (in kilometers) covered by a user in a day.
- Independent Variables (Predictors):
  - Morning Distance: Distance traveled during the morning hours (6:00 AM-12:00 PM).

- User Average Morning Distance: Mean distance covered by a user during the morning across all recorded days.
- Sleep Duration: Amount of sleep on the night before.
- Sleep Efficiency: The proportion of time a sleep to time in bed.

3.8.2 Regression Principle and Equation

Random Forest model averages the outputs of numerous decision trees. Each tree learns to predict a function that maps the input features to the output variable. The final prediction is an average of all the tree's outputs. Algebraically, this can be expressed as:

$$\hat{Y} = \frac{1}{T}\sum_{t=1}^{T} f_t(X)$$

where $\hat{Y}$ is the predicted total distance. T is the total number of decision trees in the forest. $f_t(X)$ is the output of the t^{th} regression tree for input feature vector X.

3.8.3 Modeling Workflow

The prediction model was developed using a multi-step pipeline to ensure robustness and accuracy. First, the data preprocessing phase involved imputing missing values, scaling features where appropriate, and identifying and treating outliers using interquartile range (IQR) methods. The cleaned dataset was then split into training and testing sets, with 80% allocated for model training and 20% reserved for testing. A Random Forest model was selected for model development due to its ability to handle non-linear relationships and complex feature interactions. Key hyperparameters, including the number of trees (n_estimators), maximum tree depth (max_depth), and minimum samples per leaf (min_samples_leaf), were tuned using GridSearchCV combined with 10-fold cross-validation. After training, the model was evaluated on the test set by predicting the daily total physical activity distance. Model performance was assessed using multiple regression metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and a coefficient of determination (R^2). Finally, feature importance scores were extracted to identify the most influential predictors contributing to the model's performance.

3.9 Evaluation Metrics

The following evaluation metrics were used to assess the performance of the regression models: MAE measures the average magnitude of the errors in a set of predictions, without considering their direction, RMSE represent square root of the average squared differences between predicted and actual values; penalizes larger errors more heavily. R^2 represents the proportion of the variance in the dependent variable that is predictable from the independent variables. R^2 values closer to 1.0 indicate better model fit.

In addition to regression metrics, this study also employed classification evaluation metrics to assess the performance of the binary goal achievement prediction. The classification task was based on whether users reached 80% of physical activity goals. Accuracy was used to measure the overall proportion of correct predictions across both classes. Precision was used to evaluate the proportion of true positive predictions among all positive predictions, reflecting how many users predicted to achieve their physical activity goals did so. Recall measured the proportion of true positive predictions among all actual physical activity goal achievers, indicating how well the model captured positive cases. F1-score, the harmonic mean of precision and recall, was utilized to provide a balanced measure that considers both false positives and false negatives, especially useful in cases of class imbalance.

These metrics were chosen to balance interpretability and sensitivity to prediction error magnitudes, particularly in a real-world context where overestimation or underestimation can influence intervention decisions (Chicco, Totsch, & Jurman, 2021).

3.10 Decision Logic for Intervention Recommendation

While this study does not involve the delivery of real-time interventions, an intervention decision logic was designed to simulate how such recommendations could be generated based on individual physical activity and sleep patterns. This logic was created to support future JITAI systems or rule-based digital health solutions.

The intervention logic is based on goal threshold mechanisms using personalized data. Specifically, three categories were defined to represent the likelihood or necessity of an intervention: “Definitely Send Intervention”, “May be Send Intervention”, and “No Intervention Needed”.

3.10.1 Goal Definition and Calculation

In this study, a daily physical activity goal was defined individually for each user to reflect their typical physical activity level. Rather than assigning a fixed target across all participants, a personalized physical activity goal setting approach was adopted based on each participant's physical activity behavior, calculated as the average of their total distances recorded over the entire study period. To determine whether a user was "on track" for the day, goal thresholds were applied. These thresholds were expressed as percentages of the user's daily physical activity goal (e.g., 60%, 70%, 80%, 90%, 110%), representing the minimum proportion of the physical activity goal that must be achieved. After evaluating intervention outcomes across different threshold levels, clear patterns emerged. At higher thresholds (e.g., 90%, 110%), users were less likely to reach their physical activity goals, resulting in a larger number of interventions being triggered. Conversely, at lower thresholds (e.g., 60%, 70%), users were more frequently classified under the "No Intervention Needed" category, potentially missing opportunities for timely support.

Considering these results, the 80% threshold was selected as the most balanced and effective criterion for intervention. This level provided an optimal trade-off by maintaining sufficient sensitivity to detect users at risk of underperforming while avoiding excessive or unnecessary interventions, thereby improving the accuracy and relevance of the intervention delivery.

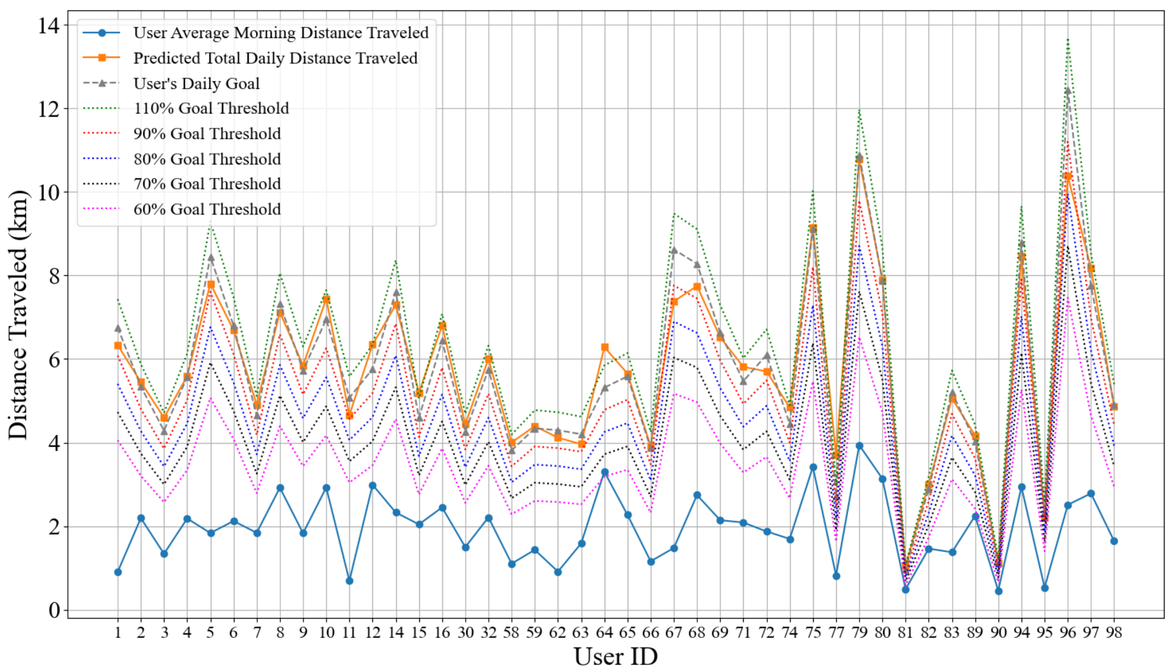

Figure 3.1: Predicted Total Daily Distance and Goal Threshold Variations

Figure 3.1 illustrates the comparison between each user's predicted total daily distance, their personalized daily physical activity goal, and various goal thresholds expressed as percentages (60%, 70%, 80%, 90%, and 110%). The blue line represents the user's average morning distance traveled, while the orange line indicates the predicted total daily distance. The grey dashed line marks the user's personalized daily physical activity goal, and the dotted lines above and below represent different threshold levels.

As shown, higher thresholds (e.g., 90%, 110%) result in more users falling short of the target, which would trigger more interventions. Conversely, lower thresholds (e.g., 60%, 70%) classify more users as "No Intervention Needed," potentially overlooking cases that could benefit from support. Based on these patterns, the 80% threshold was selected for this study as it provided the best balance between sensitivity and avoiding unnecessary interventions.

3.10.2 Logic Overview

To determine whether an intervention message should be delivered, a rule-based logic was applied using predictions of total daily physical activity, sleep duration and sleep efficiency.

First, a prediction of the user's total distance for the day is made based on morning distance and sleep data. To account for uncertainty in prediction, two bounds upper and lower are calculated around the predicted total distance using an error margin (± error rate). These bounds provide a range within which the actual daily physical activity is likely to fall.

- Upper Bound: Represents the optimistic scenario (predicted total distance × 1.10 if 10% error margin).
- Lower Bound: Represents the conservative scenario (predicted total distance × 0.90).

Next, 80% Goal threshold of the user's individual daily physical activity goal, allowing for slight under performance while still meeting a reasonable level of physical activity.

Based on the comparison between the error bounds and the goal threshold, the following decisions are made:

- Definitely Send Intervention: If even the upper bound is below the user's goal threshold and the user has poor sleep duration (less than 6 hours), this indicates a high likelihood that the physical activity goal will not be met. An intervention message is triggered.

- No Intervention Needed: If the lower bound is already higher than the goal threshold, it suggests that the user is well on track to meet their physical activity goal without support.
- May be Send Intervention: If the prediction falls in between the two bounds, the model expresses uncertainty. A light prompt or monitoring may be considered, as the outcome is not clearly above or below the target.

Table 3.2: Rule-Based Intervention Decision Logic

Condition	Decision
If the Upper Bound is less than the user's goal threshold and the user slept less than 6 hours (360 minutes)	Definitely Send Intervention
if the Lower Bound is greater than the user's goal threshold	No Intervention Needed
Otherwise	May be Send Intervention

Table 3.2 shows a rule-based logic allowed for classifying each participant-day into intervention categories, enabling both real-time decision support and the potential for future model training or evaluation.

3.11 Ethical Considerations

This research was undertaken in accordance with full ethical standards for human participant research. All participants were informed of the nature and purpose of the research and gave voluntary consent in writing prior to participation. For privacy protection, personal identifiers were stripped, and each participant was given a unique anonymized ID. Physical activity data, sleep, and HRV measures captured through a wearable device were kept secure and utilized solely for educational ends. The study remained non-invasive, represented the least amount of risk, and involved no invasive procedures. The appropriate institutional review board received ethical approval, and all procedures adhered to university policy.

4 RESULTS

Empirical results of the predictive modeling efforts in predicting user's total daily physical activity from morning behavior patterns are introduced in this chapter. The study utilized a dataset collected from both adult and elderly participants, such as physical activity (morning distance) and sleep variables. The main aim was to establish whether early-day data could be used to predict total daily physical activity accurately and therefore, allow for improved timing of behavioral interventions.

The main modeling approach utilized was a Random Forest model due to its ability to handle non-linear relations and feature interactions. Other approaches such as LightGBM and XGBoost were attempted for comparison. Model performance was validated using the conventional regression metrics of MAE, RMSE, and R^2. Feature importance analysis was also conducted to identify the variables contributing most to the prediction outcome.

The results indicate that morning distance and user-specific averages distance were the most predictive characteristics, then sleep duration. Random Forest model was observed to be performing well, achieving high R^2 value and low error metrics, supporting the feasibility of early prediction for the delivery of personalized intervention.

Later parts of this chapter describe dataset characteristics, prediction accuracy, feature importances scores, comparative comparison across models, and visualization of predicted versus actual physical activity levels.

4.1 Descriptive statistics

This section illustrates the summary statistics of the primary variables used in the analysis of predictive modeling. The data are physical activity and sleep data that were collected from a representative sample of adult and elderly participants over three weeks. The key variables include total daily distance, morning distance, sleep duration, and sleep efficiency.

Summary statistics are listed in Table 4.1, mean and SD. They help in understanding the central tendency and variability of the data set.

Table 4.1: Mean and SD of Key Variables

Variable	Mean	Standard Deviation (SD)
Total Distance (kilometers)	5.76	3.59
Morning Distance (kilometers)	1.92	1.57
Sleep Duration (minutes asleep)	214.43	190.76
Sleep Efficiency (%)	57.75	45.09

The mean values indicate the average daily physical activity and sleep patterns, while the SD highlights substantial variability among participants, especially in sleep duration.

4.2 Correlation Analysis

To explore the ability of morning activity features to predict total daily physical activity, a correlation analysis was conducted. To be precise, correlation between morning physical activity (broken down to hourly bands) and total daily distance was evaluated. This step had to be executed to determine which components of morning activity correlated most linearly with total daily physical activity to provide support for feature selection in predictive modeling.

Figure 4.1 is a line plot of correlation coefficients between hourly morning distance and daily total distance. The x-axis is each one-hour interval from midnight to noon, and the y-axis is the corresponding correlation value. From the figure, we observe that:

- Early morning time periods (00:00-05:00) have poor correlations ($r < 0.10$, $p > 0.05$), which can be attributed to no or negligible physical activity during sleeping hours.
- Starting from 05:00, the correlation values increase sharply, peaking at 9:00 AM-12:00 PM, where $r = 0.52$, $p < 0.001$.
- This suggests that mid to late morning physical activity profiles are far more indicative of the user's daily physical activity.

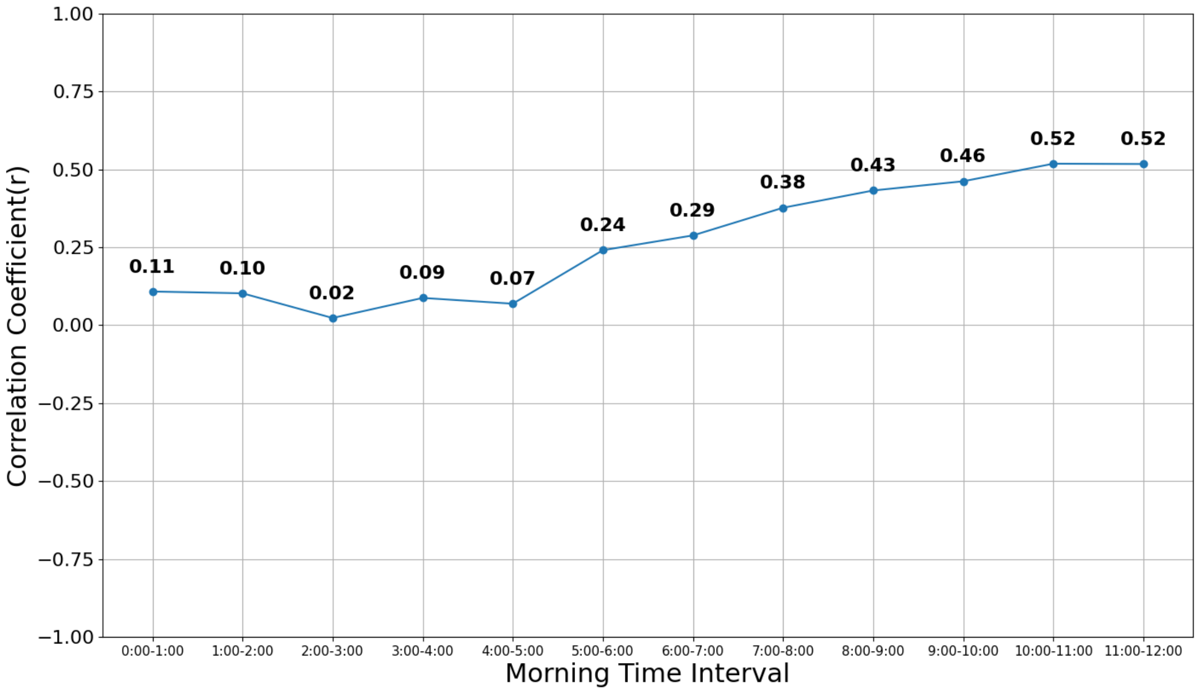

Figure 4.1: Correlation between Morning Hourly Distance and Total Daily Distance

4.3 Prediction Results

4.3.1 Model Performance Comparison

Before the application of the predictive modeling approach, three of the most widely used ML algorithms were attempted regarding their efficiency when it came to predicting total daily physical activity: Random Forest, LightGBM, and XGBoost. All three models utilized the same features morning distance, user average morning distance, sleep duration, and sleep efficiency to be able to compare them accordingly. These models were validated with the standard regression measures like MAE, RMSE, and R^2.

Table 4.2: Comparison of Model Performance Metrics

Model	MAE	RMSE	R^2
Random Forest	0.88	1.36	0.86
LightGBM	1.20	1.74	0.76
XGBoost	1.03	1.48	0.80

The findings show that Random Forest model performed better than the rest of the models on all major evaluation metrics with the highest R^2 value (0.86) and lowest error rates (MAE = 0.88, RMSE = 1.36) shown in Table 4.2. Although LightGBM and XGBoost also showed moderate performance, their comparatively higher error values and moderately lower explanatory power rendered them less appropriate for this dataset. Random Forest model was therefore chosen as the final model to be used for further analysis and intervention logic development as it presented an acceptable balance between accuracy and interpretability.

4.3.2 Final Model: Random Forest Regression Model Results

This section represents the result of regression modeling done for the problem of predicting user's total daily physical activity against features of morning data. Different models were experimented with, including Random Forest, LightGBM, and XGBoost, out of which Random Forest model was selected as the final model due to its better prediction performance and interpretability. The model's performance was gauged against standard regression measures: MAE, RMSE and R^2. These are tabulated in Table 4.3.

Table 4.3: Evaluation Metrics for Random Forest Regression Model

Metric	Value
MAE	0.88
RMSE	1.36
R^2	0.86

The R^2 of 0.86 indicates that approximately 86% of the variability in total daily physical activity is explained by the features in the model. The low MAE and RMSE values also indicate that the model had accurately predicted the outcome variable with very minimal error.

Figure 4.2 illustrates the relationship between the actual and predicted total daily distance values as modeled by the Random Forest regression algorithm. Each point in the scatterplot represents an individual data instance, with the x-axis showing the actual total distance and the y-axis showing the predicted distance. The red dashed line represents the ideal prediction line where the predicted values perfectly match the actual values (i.e., predicted = actual). The majority of the data points cluster closely around this ideal line, especially in the lower to mid-range distance values, indicating strong predictive accuracy. The Pearson correlation coefficient ($r = 0.93$, $p < 0.001$) further confirms a very high linear correlation between the actual and predicted distances. Although a few outliers exist, particularly at higher distance values, the overall tight distribution suggests that the model generalizes well to most users. This visual evidence reinforces the quantitative performance results of the Random Forest model, supporting its selection as the final predictive model.

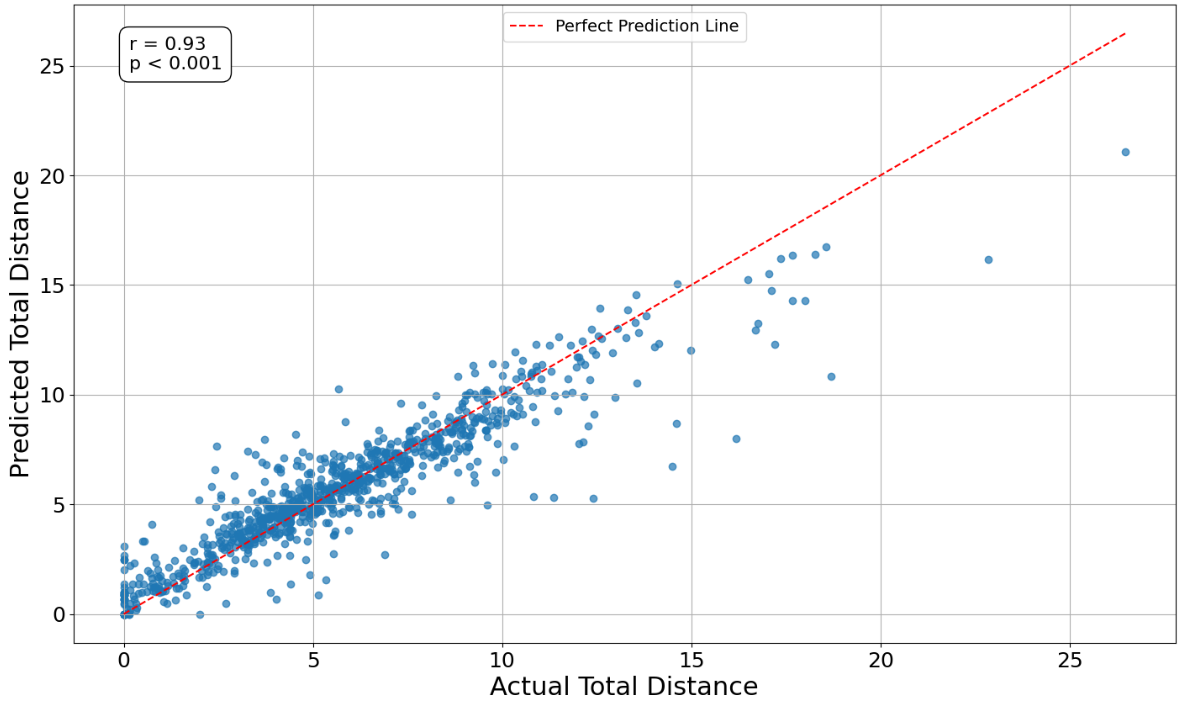

Figure 4.2: Actual vs Predicted Total Distance Using Random Forest Regression Model

These results validate the effectiveness of the selected input features and the suitability of Random Forest model as a robust modeling approach for this prediction task.

4.4 Classification Performance

To continue assessing the predictive model's practical utility, a classification analysis was performed. The objective was to classify if a user would reach a minimum level of physical activity goal, in this case, completing at least 80% of their daily physical activity goal. This binary classification framework aids in converting the regression outputs to intervene with deliverable insights. The accuracy of the model classification was assessed using a confusion matrix, i.e., predicted vs. actual outcomes. The results are given in Table 4.4

Table 4.4 Confusion Matrix for Binary Classification Based on Goal Achievement Threshold

	Predicted Positive	Predicted Negative
Actual Positive	196	33
Actual Negative	76	618

The classification results indicate that the model correctly identified 196 daily instances as True Positives cases where correctly predicted not reaching goal and getting Definitely send intervention and 618 instances as True Negatives, where users meet their physical activity goals getting no need interventions. In contrast, there were 33 False Negatives and 76 False Positives, reflecting a modest level of misclassification. These values correspond to daily prediction instances across all participants and days, rather than unique individuals. Despite some misclassification, the high proportion of correctly classified cases highlights the model's strong performance and its potential utility in supporting goal-based intervention strategies.

To test the model's capacity for classifying if a user is likely to achieve their daily physical activity goal, the predicted total distance was compared against a threshold of 80% of each user's specified physical activity goal. The classification problem labeled users as either achieving (positive class) or failing to achieve (negative class) their physical activity goals. The classification performance of the model was measured using conventional evaluation metrics such as precision, recall, F1-score, and accuracy.

Table 4.5: Classification Evaluation Metrics Based on Goal Achievement

Class	**Precision**	**Recall**	**F1-Score**	**Support**
0 (Reached Goal)	0.89	0.95	0.92	651
1 (Not Reached Goal)	0.86	0.72	0.78	272
Accuracy	-	-	0.88	923

As shown in Table 4.5, the model achieved a level of around 88% accuracy. Class 0, users who achieved their physical activity goal, exhibited high recall (0.95) and precision (0.89), indicating good detection performance. Class 1, users who did not achieve their physical activity goal, exhibited poorer recall (0.72), suggesting some missed cases. However, the model has an even F1-score on both classes, determining its viability for intervention support.

Other than confusion matrix and classification evaluation metric, Receiver Operating Characteristic (ROC) curve has also been drawn Figure 4.3 to presents the binary classification task of predicting whether users would meet their physical activity goals. The ROC curve illustrates the model's performance across various classification thresholds by plotting the True Positive Rate (Sensitivity) against the False Positive Rate (1 - Specificity).

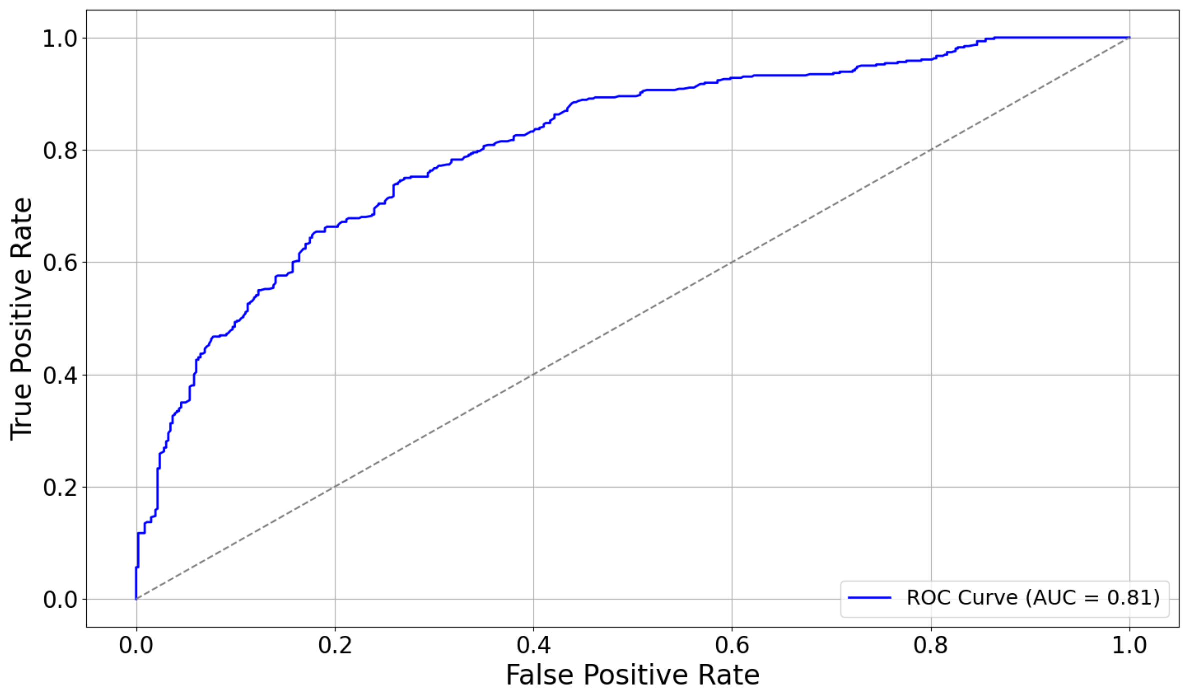

Figure 4.3: ROC Curve for Binary Classification Based on Predicted Total Daily Physical Activity Outcomes

In Figure 4.3, the blue curve represents the performance of the Random Forest model. The diagonal dashed line indicates a model with no discriminative ability with Area Under the Curve (AUC) value 0.5, effectively equivalent to random guessing. The ROC curve shown bows significantly above the diagonal, indicating strong classification capability.

The AUC value is 0.81, which signifies good discriminative power. This means the model has an 81% chance of correctly distinguishing between a randomly selected positive (goal not reached) and negative (goal reached) instance. In practical terms, it confirms that the model is effective in differentiating between users who will likely meet their physical activity goal and those who will not.

ROC curve complements other evaluation metrics such as accuracy, precision, recall, and F1-score, by demonstrating the model's robustness across different thresholds and reinforcing its suitability for decision-making in intervention contexts.

4.5 Intervention Logic Results

The intervention logic was designed to categorize users into three categories “Definitely Send Intervention”, “May be Send Intervention”, and “No Intervention Needed” based on their predicted total distance for the day. The categorization was computed using rule-based decision logic considering the predicted total distance, morning activity levels, and user-specific goal thresholds from user physical activity goal. This was achieved by facilitating certain interventions corresponding to the user's expected behavior, increasing the responsiveness and dynamism of the process.

Figure 4.4 show the actual intervention decisions scattered over the decision space formed by morning activity and predicted total physical activity. Users are data points colored according to intervention type. Green dots represent users with no need for intervention, red denotes those who need intervention for sure, and orange represents those in the uncertain region. The visualization lends itself to the effectiveness of the decision logic in successfully grouping users according to their physical activity patterns.

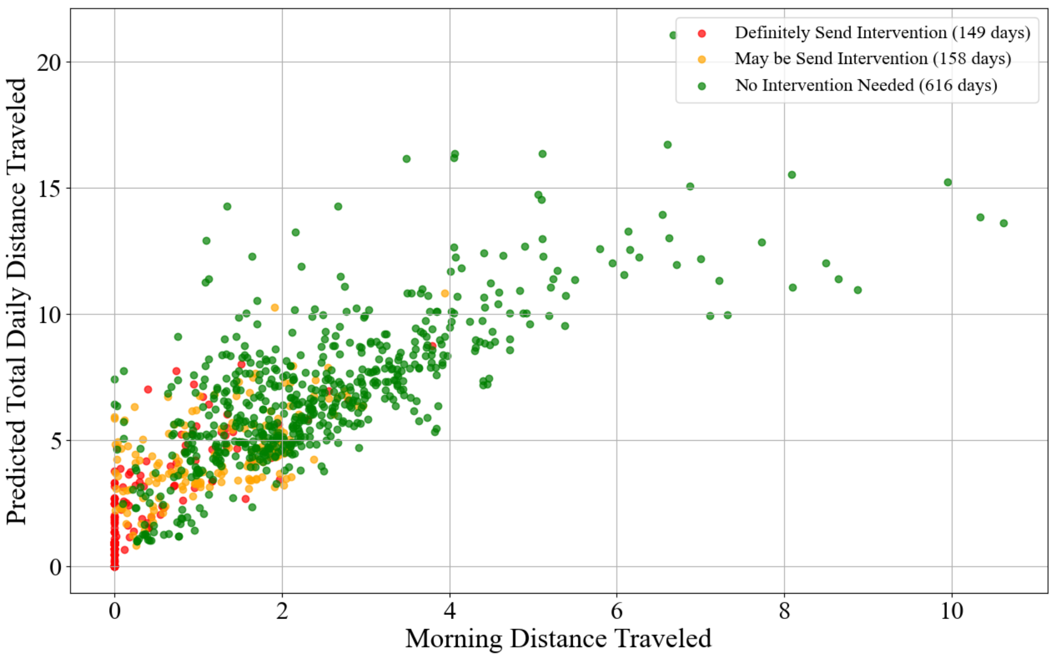

Figure 4.4: Intervention Decisions Based on Predicted Total Daily Physical Activity

To quantify the effectiveness and distribution of the intervention logic, the number of daily instances assigned to each intervention category is summarized below. This helps in understanding how the logic classifies each day based on predicted physical activity levels compared to their personalized physical activity goals.

Table 4.6: Intervention Decision Distribution

Decision Category	Number of Days
Definitely Send Intervention	149
May be Send Intervention	158
No Intervention Needed	616

As shown in Table 4.6, many days, user did not require any intervention, indicating predicted values aligned well with user's physical activity goals. However, a significant number of days were identified as needing definite intervention, emphasizing the relevance of early prediction. The "May be Send Intervention" category signals the need for additional data or adaptive strategies for borderline cases.

5 DISCUSSION

5.1 Overview of Key Findings

In this study, I aimed to predict total daily physical activity levels using morning activity patterns and sleep features, with the goal threshold of supporting timely and effective intervention delivery. I collected and analyzed data from both adult and elderly participants, including variables such as total distance, morning distance, sleep duration, and sleep efficiency. To model this relationship, I applied several ML approaches, including Random Forest, LightGBM, and XGBoost. And I found that the Random Forest model produced the most accurate predictions with an MAE of 0.88, an RMSE of 1.36, and an R^2 score of 0.86. These measures indicate that morning and sleep features can explain a significant portion of daily physical activity outcome variance, supporting the validity of using early-day data to predict total daily physical activity, which is crucial for planning timely interventions (Milo, 2022).

To understand this prediction even more into the intervention context, I transformed the regression outputs as a binary classification problem with an 80% threshold of each user's daily physical activity goal. I labeled users as Reached Goal (class 0) and Not Reached Goal (class 1) their targets based on actual and predicted values. The model was 88% accurate, and class 0 contained extremely high precision (0.89) and recall (0.94), indicating extremely high capability in the identification of those users likely to meet their physical activity goal.

Based on the classification results, I framed and applied a rule-based decision logic to assist in intervention planning. The intervention days were segmented into three actionable decision groups: “Definitely Send Intervention”, “May be Send Intervention” and “No Intervention Needed” Among the total cases examined, 149 days belonged to the “Definitely Send Intervention” category, 158 to “May be Send Intervention” and 616 to “No Intervention Needed”. These findings demonstrate the applied value of predictive modeling for the identification of users at risk of low physical activity and provide a clear, scalable approach to inform personalized health behavior interventions.

5.2 Interpretation of Results

This study confirms that morning behavior and sleep patterns are strong predictors of total daily physical activity. The Random Forest model achieved high predictive performance ($R^2 = 0.86$), indicating that up to 86% of the variance in total daily physical activity can be explained using early-day data alone. This finding supports the hypothesis that morning activity and sleep features such as morning distance, sleep duration, and sleep efficiency are crucial indicators of overall activity levels, aligning with previous studies on the predictive potential of early behavioral markers (Wang, 2022).

These findings directly address the first objective of the study, which was to determine whether partial-day features can predict total daily physical activity. Additionally, mapping the regression outputs to a binary classification framework using an 80% goal threshold enhanced the model's applicability for real-world interventions. The classification achieved an overall accuracy of 88% and a strong F1-score of 0.92 for users who met their physical activity goals, providing a robust framework for identifying individuals at risk of low activity and achieving the second study objective of goal-based user segmentation.

The integration of rule-based intervention logic further demonstrates the potential of this approach to inform actionable decisions. By categorizing days into "Definitely Send Intervention," "May be Send Intervention," and "No Intervention Needed," the model provides a transparent and interpretable mechanism for planning interventions. Notably, 149 days were classified as requiring definite intervention, highlighting the model's potential to support personalized health promotion strategies. Overall, these results emphasize that early prediction of daily activity allows interventions to be delivered at the most effective time, maximizing the likelihood of positively influencing user behavior before the day concludes.

5.3 Comparison with Previous Studies

The findings of this study are consistent with previous research on the use of ML models to predict health behaviors such as physical activity. Prior studies have demonstrated that early-day metrics, such as morning step counts or sleep quality, are significantly correlated with end-of-day outcomes, making them valuable for predictive modeling and intervention planning (Wang, 2022; Milo, 2022). Compared to traditional methods using full-day data for physical activity assessment, this study offers a new direction that predicts using partial data for early intervention. The performance of the Random Forest model in this study ($R^2 = 0.86$) is consistent with other ML applications in other domains. For example, (Rezaei, 2021) reported R^2 ranges of 0.60-0.80 for predicting physical activity from a wearable device data when they included contextual features like sleep, suggesting that predictive performance increases with the addition of contextual features. Unlike study that exclusively examines step counts or physical activity minutes, this study also incorporated sleep metrics such as sleep duration and sleep efficiency, which have been demonstrated to impact physical activity behavior (Molina-García, 2019). The fact that these variables were included may account for the better model performance and greater classification accuracy realized herein. Additionally, the rule-based intervention logic used in this study is consistent with a body of research on adaptive intervention systems. While this research targeted a one-time, goal-based logic instead of a JITAI approach, the results are consistent with the notion that timely, data-driven interventions can be used to enhance user outcomes and engagement, a concept reflected in (Milo, 2022).

5.4 Implications for Research and Practice

The results of this study offer several important implications for both future research and real-world practice in the field of digital health and behavior change.

5.4.1 Implications for Research

Firstly, the study shows that the ML models, specifically Random Forest model in this instance, can accurately predict total daily physical activity outcomes based on early-day data. This opens the door for future research to explore real-time prediction processes and more advanced time-series or sequential modeling strategies. Future studies can also test the addition of contextual features such as weather, location, or heart rate variability to the model to determine if it would enhance performance and generalizability. Furthermore, the fact that sleep metrics (sleep duration, sleep efficiency) are part of the predictive model illustrates the interrelatedness of behavior and physiological state, one that should be explored more in interdisciplinary research that connects health informatics, behavioral science, and wearable technology. Finally, while this study employed rule-based decision logic, future research can contrast this with data-driven or adaptive intervention systems, like JITAI, to compare behavioral outcome and participant engagement differences (Ikegaya, 2024).

5.4.2 Implications for Practice

In practice, this research provides a basis for early warning systems in physical activity interventions. For app developers, fitness trainers, or health professionals, having the ability to identify users at risk of failing to achieve their physical activity goal of total daily physical activity by noon is a beneficial time to deliver specialized alerts or motivational pushes. Additionally, the interpretable and straightforward rule-based logic developed here can be integrated into low-computation demanding mobile health (mHealth) platforms with scalable deployments. It is, therefore, especially ideal for workplace or community wellness programs where real-time decisions need to be taken but technical resources may be limited. In general, the research concludes in favor of a proactive, evidence-based intervention planning approach, as opposed to reactive or end-of-day analysis, and this potentially would greatly increase the effectiveness of health behavior change interventions.

5.5 Limitations of the Study

While this study achieved promising results in predicting total daily physical activity from morning behavior and sleep data, several limitations should be acknowledged. The dataset included only 44 participants, which may restrict the generalizability of the findings. A larger and more diverse sample could capture broader behavioral patterns, reduce overfitting, and improve the robustness of the model. Although the sample included both adults and elderly participants, age-related differences were not analyzed in detail. Physical activity patterns can vary with age due to changes in physiology, mobility, and daily routines. Younger adults may show higher and more variable activity, while older adults often have steadier but lower-intensity patterns. These differences could influence the relationship between morning and total daily physical activity, suggesting that future models might benefit from age-specific analysis. The model also relied primarily on morning distance, average morning distance, and basic sleep features (sleep duration and sleep efficiency), while other potentially relevant factors such as heart rate variability, weather conditions, mental state, stress levels, or previous-day physical activity were excluded, potentially limiting the model's predictive power.

This study evaluates daily physical activity, while the WHO guidelines are expressed in weekly cumulative terms. This difference in measurement timeframe introduces a gap: participants might fail to meet the daily prediction physical activity goal yet still achieve the WHO's recommendation through higher activity on other days, or vice versa. While daily evaluation enables timely feedback and same-day interventions critical for behavior change it does not directly equate to weekly compliance. Future work could bridge this gap by calibrating daily physical activity goals to align with weekly goals, aggregating daily predictions into weekly summaries, or applying rolling 7-day physical activity windows to combine the benefits of daily responsiveness with public health guideline consistency.

Additionally, total daily distance was used as the sole target variable, which does not fully represent health-related movement metrics like intensity, step counts, or Moderate-to-Vigorous Physical Activity (MVPA). The classification approach, based on achieving 80% of self-defined daily physical activity goals, may not account for individual differences in physical activity goal difficulty or motivation, especially among elderly participants who may set lower physical activity goals due to physical constraints. Furthermore, although sleep data were included as predictors, the causal relationship between sleep and physical activity was not examined, leaving uncertainty about their interaction. Finally, the rule-based intervention logic was implemented as a one-time decision based on morning data, without considering day-of-week patterns or user responsiveness. Future research could explore more adaptive strategies, such as JITAI, to improve personalization and effectiveness.

5.6 Recommendations for Future Work

This study demonstrates promising results in predicting daily physical activity using morning behavior and sleep patterns; however, several improvements can enhance its accuracy and practical utility. Future research should involve a larger and more diverse sample, as the current dataset of 44 users limits generalizability. Expanding the feature set to include contextual and physiological factors such as weather, prior-day physical activity, mood, stress, and HRV would provide a more comprehensive understanding of user behavior. Additional outcome metrics like step count, active zone minutes, or movement intensity could better capture overall health behavior beyond distance. Investigating the causal relationship between sleep quality and physical activity through time-lagged or causal inference methods may reveal deeper behavioral insights. Moreover, transitioning from one-time rule-based logic to adaptive approaches such as JITAI could deliver more personalized and effective interventions. Finally, incorporating explainable ML techniques, such as SHAP, would improve interpretability and build user trust in model predictions.

6 CONCLUSION

This study examined how early morning activity and sleep habits can be utilized to predict total daily physical activity. Data from 44 participants, including both adults and elderly individuals, were analyzed using variables such as morning distance, user average morning distance, sleep duration, and sleep efficiency. Several prediction models: Random Forest, LightGBM, and XGBoost were evaluated, with the Random Forest model achieving the highest predictive performance ($R^2 = 0.86$, RMSE = 1.36, MAE = 0.88).

To make the predictions actionable, a simple rule-based intervention logic was developed to classify days into “Definitely Send Intervention,” “May be Send Intervention,” and “No Intervention Needed” based on predicted distances relative to personalized goal thresholds. This approach demonstrated interpretability and practical value, supported by high performance in classification metrics such as precision, recall, and F1-score. The findings highlight the feasibility of using early-day behavioral and sleep features to support timely, data-driven interventions aimed at promoting healthier physical activity levels.

However, the study is limited by its small sample size, limited feature set, and the absence of adaptive intervention strategies. Future research should focus on including richer behavioral and contextual variables, expanding the participant pool, and exploring dynamic approaches like JITAI to improve generalizability and real-world applicability.

In conclusion, the results demonstrate that even with simple data and models, accurate predictions of daily physical activity can be achieved, providing a foundation for the development of personalized and timely health interventions.

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