# Explaining Decision-Making between Exploration and Repetition: Key Factors for Physical Activity Recommendations*

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**Abstract**

A challenge in promoting physical activity with recommender systems lies in balancing repeat recommendations to create habits, with exploration to prevent boredom. This study aims to identify the key variables influencing users' decision-making between the two. Through the analysis of data from an eight-week Micro-Randomized Trial conducted via a mobile health app, using random forest variable importance measures and SHAP analyses, we identified factors affecting these decisions. Our findings reveal that participants were more likely to explore new activities during the first two weeks of the intervention, in the afternoons and evenings, on Sundays, and when activities involved specific locations or workouts. These findings provide valuable insights into the transition from exploration to repetition, contributing to more effective recommender systems for physical activity promotion.

**Keywords**

recommender systems, physical activity, decision-making, variable importance analysis, random forest, repetition, exploration,



## 1. Introduction

Insufficient physical activity (PA) is associated with adverse health outcomes [1]. To support motivation and long-term health benefits, individuals with low activity levels may benefit from engaging in enjoyable activities. Recommender Systems (RSs) can automatically personalize such enjoyable PAs by utilizing a wide range of information about users and their preferences [2, p 9].

As these physically inactive people might not have established healthy habits yet, the RS should repeat some activities to create habits, because repetition makes the behavior more automatic [3], increasing the chances for long-term engagement and positive health outcomes. However, the RS should also provide sufficient opportunity to explore new and varied activities to prevent boredom [4, 5, 6].

In addition to their recommended minimum of 150 minutes of moderate-to-vigorous PA (MVPA) per week, the World Health Organization (WHO) also recommends a mix of aerobic and muscle-strengthening activities [1]. As such, both exploration for variety and repetition for habit formation are important for healthy behavior. The challenge lies in determining when an RS should prioritize one approach over the other.

This study focuses on identifying the key variables that impact users' decision-making process to choose either an exploration or repetition PA item, arguing that future RSs can integrate these variables in their own decision-making processes as well. The research question is:

*RQ: Which variables affect users' decision to choose an exploration or repetition PA recommendation, and in which conditions are they more likely to choose one over the other?*

By analyzing data from an eight-week Micro-Randomized Trial (MRT) conducted with a mobile health (mHealth) app, we aim to uncover the most important factors, determined with Random Forests' (RFs) variable importances [7] and SHapley Additive exPlanations (SHAP) [8] analyses. RFs are a machine

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learning technique used for classification or regression to predict an outcome variable based on several input variables by aggregating the results from multiple decision trees. RFs are widely used for data exploration and understanding using variable importance measures [7].

This paper merges two study waves: one that ran from October 2023 until January 2024 (started in autumn), and one from March until June 2024 (spring). Our previous research was solely conducted on the data from the study starting in autumn [9]. To increase participation and dataset, we replicated the study in spring and combined both study's data. In a previous paper [10], we already conducted a first analysis on the subjective perceptions and preferences measured with star rating of the repetition vs. exploration PA recommendations. The current paper dives deeper in the decision-making of the users using a set of factors that might influence their decision, contributing to the design of more effective RS algorithms in the PA domain.

The rest of the paper is organized as follows. Section 2 covers previous work on RFs in the domain of PA. The methods are discussed in Sect. 3. Next, the results and their discussion are elaborated in Sect. 4, followed by the conclusion in Sect. 5.

## 2. Related work

Previous work with RFs in the domain of PA mainly focused on the classification and recognition of the activity using sensors, such as accelerometers [11, 12, 13]. In those RFs, the input data consists of the data collected from the sensors and the predicted outcome variable is the detected type of PA. In our study, the input data is a combination of manual information (e.g., the self-reported motivation of the user at that time) and automatic information about the context (e.g., the weather).

Other studies used PA as an input variable in the RF to predict a certain outcome variable. In [14], body mass index and depressive symptoms are predicted with sedentary time and MVPA. Another study investigated severity of menopausal symptoms with an RF regression and found that PA level was in the top four of variable importances [15]. In [16], COVID-19 death rates were estimated with 29 socioeconomic and health-related factors with an RF.

PA amount was also used as outcome variable in several studies. Meeting the guidelines for sufficient aerobic PA in a target group of adults with autism was assessed in [17]. Another study found that greenery in the streets impacts the duration of light intensity PA the highest for older adults [18]. In [19], an RF algorithm performed best to predict the probability of achieving a daily steps threshold. In our study, the predicted outcome class is whether the user decides to engage in an exploration or repetition item, thus resulting in a binary classification.

Previous work has also investigated the exploration and repetition decision in next basket recommendations [20] and sequential recommendations [21]. While these are mainly focused on e-commerce and grocery shopping, our study is situated in the health domain and PA promotion with mHealth interventions.

## 3. Methods

An Android app was created to display the personalized PA recommendations as shown in Fig. 1. Our PA dataset is based on activities from the compendium of physical activities [22], for which we distinguish between *workout* and *location* PA types. In our dataset, we also integrated *general* PA tips from the Belgian website for health (www.gezondleven.be), which contains small-effort activities people can integrate in all four PA situations of their daily life (*free time, during work, household task, active transport*). The resulting dataset contains 237 PA items, connected to the corresponding PA type and situation. For the content-based RS algorithm, all PA items were manually extended with 24 binary attributes to describe their content. For a full implementation description of content-based RS algorithm, we recommend reading our previous paper [23]. The exact same RS algorithm was used in this study, with an adjustment of the dataset and output list that now shows six recommendations.

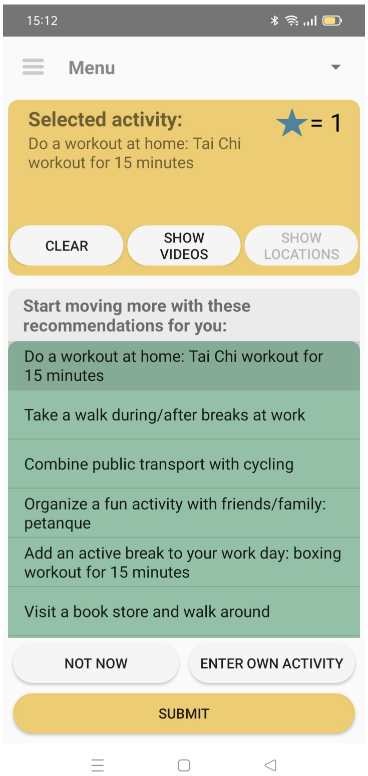


**Figure 1:** The main screen of the app displays six recommendations in a random order, corresponding to the six combinations of exploration versus repetition and the PA type.

A list of six items was chosen because six combinations can be made in our MRT study design: 2 from the outcome variable (repetition vs. exploration) x 3 from the PA type (general vs. location vs. workout). A repetition item refers to a personalized recommendation for an activity that the user has previously submitted during the study, while an exploration item is a personalized recommendation for an activity that the user has not yet submitted. By randomly positioning each of the six combination in the list for every participant at every delivery time, the micro-randomization of this study is achieved [24] and position bias effects are prevented. As a result, the user can freely choose between a repetition or exploration item of all three PA types at any time.

We recruited healthy adults (between 18 and 65 years old), who have less than 150 min of MVPA per week, via the Sona Platform and Facebook groups for paid studies of Ghent University. For both study waves (starting in autumn and spring), participants were asked to use the app for at least eight consecutive weeks, after which they receive 30 EUR. To prevent false submissions about their PA behavior, participants were informed that they do not receive more money for submitting more PAs, but only qualify for the incentive if they actively use the app for eight weeks and complete all questionnaires. At the start and after eight weeks, they answer the pre-test and post-test questionnaire, respectively, both containing the European Health Interview Survey - Physical Activity Questionnaire (EHIS-PAQ) to measure weekly PA [25] and a question about their age group (18 − 44 or 45 − 65 years). The study received ethical approval from the Ethical Committee (www.ugent.be/pp/en/research/ec) on August 22, 2023 (reference number: 2023-061A).

An RF classifier is tuned with Randomized Search and trained using scikit-learn (scikit-learn.org/) version 1.5.1. Table 1 provides an overview of all 15 input variables of the RF model. The predicted output of the RF is whether the user engaged in a repetition or exploration item (binary classification). SHAP provides an explanation for this output by assigning feature importance values to each variable for a specific prediction [8]. For the variables with the highest feature importance, we apply the dependence plot function from SHAP package version 0.46.0 to show the relation between the input variable and the corresponding SHAP value for the RF's prediction [8]. For an additional statistical analyses on the

EHIS-PAQ answers, SPSS Statistics v. 28 is used for the analyses with a Linear Mixed Model (LMM) using the MIXED procedure [26].

**Table 1**
We put 15 input variables in the RF, which can be categorized in eight categories and originate from various sources.

| category | type | input variables for the RF | source |
|---|---|---|---|
| Time | continuous | day in study | device's clock |
| | | hour of day | |
| | categorical | start season: spring / autumn | |
| | | day of week | |
| | | weekend / week day | |
| Weather | continuous | outdoor temperature | GPS + weather API |
| | categorical | clear sky | (OpenWeatherMap) |
| | | clouds | |
| | | rain | |
| Situation | categorical | free time / work / household / transport | dataset |
| PA type | categorical | general (e.g., walk during breaks) / location (e.g., minigolf) / workout (e.g., pilates) | dataset |
| Company | categorical | alone / with a buddy | self-reported |
| Motivation | continuous | score on 4 | self-reported |
| Location | categorical | indoors / outdoors | self-reported |
| Step count | continuous | amount of steps already detected that day | accelerometer |

# 4. Results and Discussion

Of the 62 participants who started the study (100% in the age group of 18 - 44 years), 34 continued for at least eight weeks. Throughout the study, the participants submitted 457 recommended items, of which the amounts are categorized in Table 2.

**Table 2**
The amount of submits per situation and per PA type, including the percentage of the situation.

| situation | PA type | amount | % of situation |
|---|---|---|---|
| transport | exploration | 17 | 94% |
| | repetition | 1 | 6% |
| during work | exploration | 45 | 75% |
| | repetition | 15 | 25% |
| household | exploration | 73 | 55% |
| | repetition | 59 | 45% |
| free time | exploration | 153 | 62% |
| | repetition | 94 | 38% |

Firstly, the hyperparameters of the model were tuned with Randomized Search with 5-fold cross validation and a max depth of 6 to prevent overfitting. The resulting optimal hyperparameters are: n estimators = 493, min samples split = 10, min samples leaf = 10, max features = sqrt, max depth = 6, bootstrap = True, resulting in a train accuracy of .764 and test accuracy of .663. The corresponding feature importances are shown in Fig. 2, in which the time in study showed the highest relevance.

Figure 3 shows the SHAP dependence plots that visualize the relation between the six input variables with the highest feature importances and their corresponding SHAP value. We added a color legend to show possible interaction effects with days in study, as this variable ranked highest on the variable importances.

## 4.1. The input variables

### 4.1.1. Day in study

The first dependence plot shows that days in the beginning of the study are associated with a higher prediction for an exploration item (above the y=0 line). The threshold at which the model switches

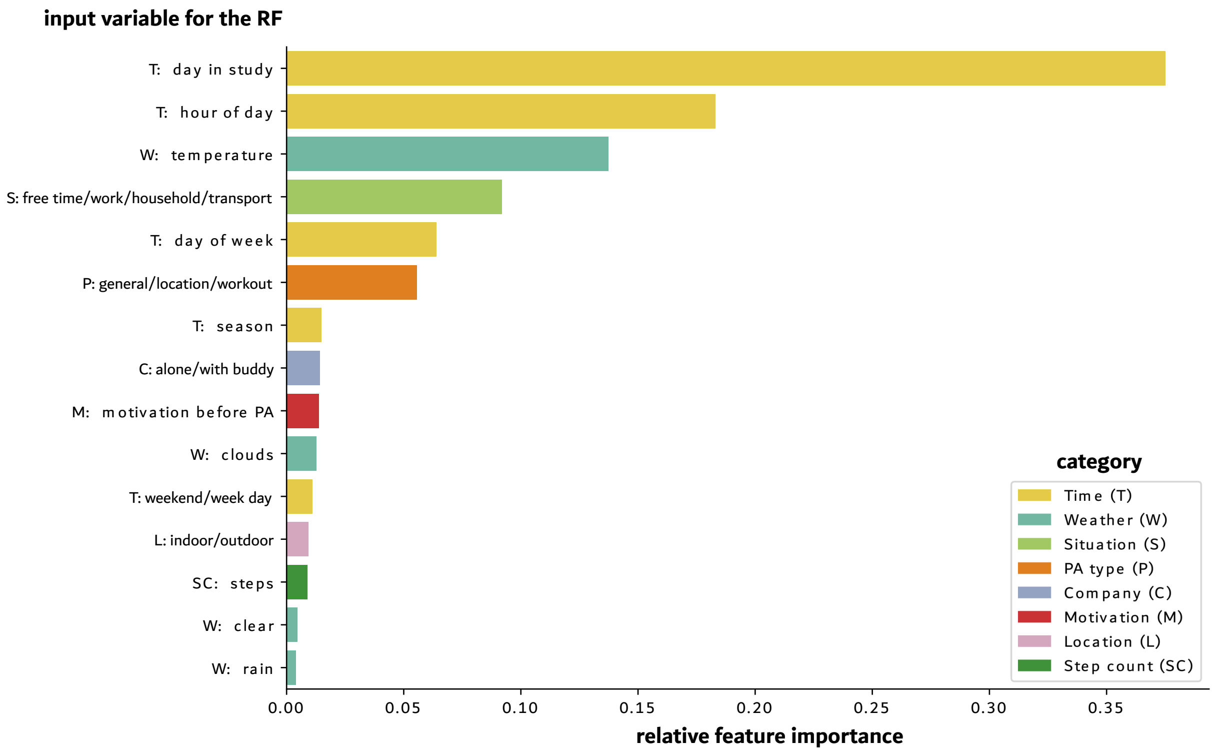


**Figure 2:** The feature importances show that day in study, hour of day, outdoor temperature, PA situation, day of week, and PA type score the highest on the feature importances in the RF's exploration/repetition prediction.

from predicting exploration to repetition lies around day 15 in the study.

The switch from exploration to repetition after two weeks was also found in our previous study, which showed a significant interaction effect on the star rating feedback after this two-week mark for general PAs [10]. In this previous study [10], we referred to the lower effort and complexity of general PAs as the reason for the quicker shift to repetition, based on [3].

#### 4.1.2. Hour of day

The second dependence plot reveals that exploration predictions are associated with afternoon and evening hours, but not with mornings or nights, with this effect becoming more pronounced later in the study. The highest predictions for explorations are between 4 and 10 pm, especially for later days in the study. An explanation for this pattern could be that our participants (who all belong in the age group of 18 - 44 years) prefer fixed routines in the morning before they go to work or school, and are more likely to explore new activities when they finished their daytime commitments.

This pattern could also be attributed to people's circadian rhythm and the distinction between morning chronotypes who rise and peak early in the day, and evening chronotypes who experience arousal in the afternoon or evening [27]. However, as we did not collect the chronotype of our participants, nor an exact age or occupation, we cannot derive a clear explanation from this.

#### 4.1.3. Outdoor temperature

The third plot suggests a larger prediction for exploration when the outdoor temperature is around 10 degrees Celsius, with two threshold values around 5 and 15 degrees. According to [28], the first and last warm days of the year may motivate people for more PA, which could explain why they are more open to exploration in this temperature range, unlike higher temperatures above 20 degrees.

### 4.1.4. PA type and situation

High variable importance was also found for PA type and situation, of which the dependence plots are shown at the bottom of Fig. 3. The higher association with repetition in free-time, household, and general contexts can be due to established habits in these contexts. For example, exploration could be less preferred in household tasks because people already have their own routine for these.

Exploration was mostly associated with activities for transportation, during work, at a location, and as a workout. The results of our previous analysis [10] showed that exploration for general PAs was only preferred in the first two weeks of the study, after which higher star ratings were given to repetitions. This can explain why general PAs are mostly associated with repetition prediction in the SHAP dependence plot. Similarly, the star rating was consistently higher for exploration of location and workout PAs in the LMM [10], which corresponds to the conclusions of this SHAP analysis.

As 94% of the active transport and 75% of during work submits were an exploration, as displayed in Table 2, this explains the higher association with exploration. Nonetheless, submits in the situations of active transport and during work are limited, thwarting reliable analyses for these situations.

### 4.1.5. Day of week

The fifth plot shows that exploration predictions are more associated with Sundays, likely because more people have time off then, allowing more time for exploration. As Saturdays are not associated with more exploration, this can explain the lower variable importance of the “weekend/week day” variable.

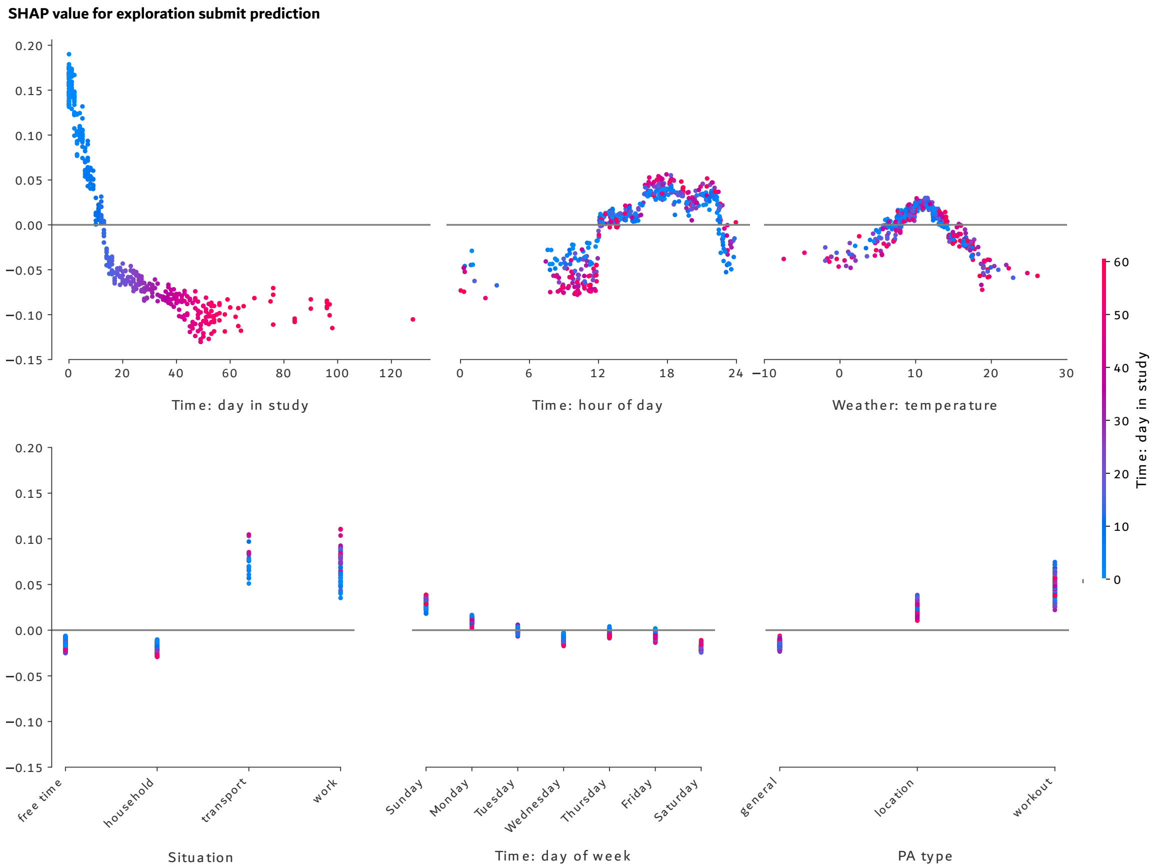


**Figure 3:** The dependence plots from SHAP show a switch in predicting an exploration item (above the y=0 line) to a repetition item (under the y=0 line).

#### 4.1.6. Season

The season in which the participant started the study (autumn vs. spring) ranked seventh in the variable importances. We did not create a dependence plot for this variable, but conducted an LMM analysis with this variable to investigate the effect on the amount of weekly MVPA.

To investigate the increase in weekly PA, we compare the total MVPA measured by the EHIS-PAQ (Q4*Q5 + Q7) in the pre-test and post-test questionnaires [25]. An LMM was fitted with the time (pre-test vs. post-test), the season in which the participant started (autumn vs. spring), and their interaction as fixed effects [26, 29]. To account for possible variations between users, the user ID was considered as a random effect in a random coefficient model with a random slope [26].

We found a significant interaction effect, of which the mean fixed predicted values are shown in Fig. 4, illustrating that the group of participants who started the study in spring had a higher increase in weekly MVPA, on average ($F$(1,46.094)=4.079, $p$=.049). While a general increase in MVPA in both study groups was expected [30, 31], the stronger increase in the spring group can be explained because PA is higher in warmer months [28].

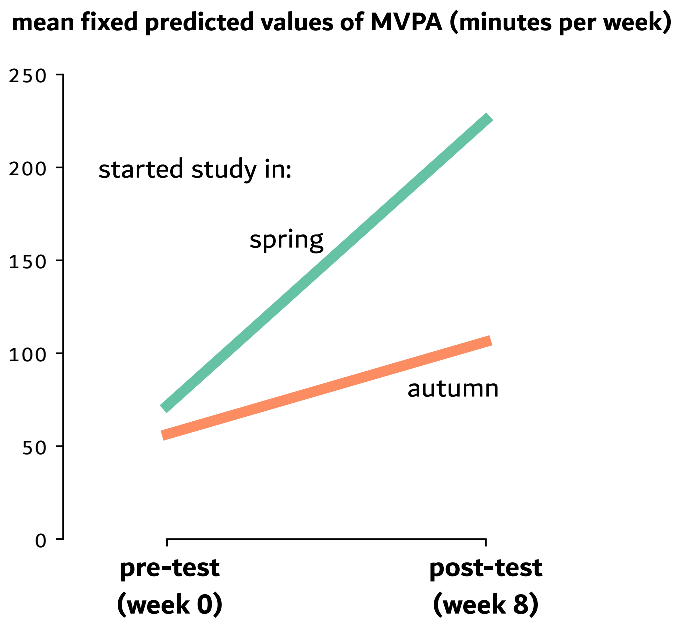


**Figure 4:** This interaction plot shows the significant interaction effect of the starting season on the increase in weekly MVPA from pre-test to post-test.

### 4.2. Limitations and future work

As only 34 participants finished the full eight-week study, a large amount of data of the later weeks are missing. Additionally, the study was not conducted year-round or across different climate zones, limiting reliable conclusions about the impact of outdoor temperature. Given the limited submissions for transportation and work PAs, we suggest future research to include longer studies with a larger participant pool.

Our results show that the variables company, location, and motivation had lower importance. However, this company variable could be extended with the presence of a human trainer, as their supervision and guided workout plans, often containing repetition of activities, increase engagement in trainings delivered via mobile apps [32].

Nonetheless, our results indicate that time-related factors primarily drive the decision to explore new activities. We suggest integrating these time-related variables in future RSs for PA promotion. Although we identified specific conditions for exploration, we propose to tailor these conditions to the user. For example, an RS could learn at what moments a user prefers to explore a new activity.

Additional information could be integrated in the system, such as the user's chronotype to take into account moments at which the user is most active [27].

## 5. Conclusion

Two eight-week user studies with a total of 62 physically inactive participants (<150 minutes MV-PA/week) were conducted to investigate factors influencing people's decision to either repeat or explore a PA recommendation. In the MRT, repetition and exploration PAs were provided to the user in an mHealth app at random positions, allowing participants to freely choose between the options at each delivery time.

The RF and SHAP approach identified key factors and conditions influencing the likelihood of exploring a new activity: in the first two weeks of the mHealth intervention, in afternoons and evenings, on Sundays, and for activities at a location or as a workout. Other factors scored lower on the variable importances of the decision between an exploration or repetition item, such as the season, company, motivation, and location. However, we did find a significant higher increase in weekly MVPA for the group that started the study in spring, suggesting that the season might not largely influence the exploration/repetition decision, but does affect the amount of PA.

By defining moments and contexts at which people are more open to explore new activities, this study contributes to future PA recommenders to balance between repeating favorite activities and introducing new ones.

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