HHAI 2023: Augmenting Human Intellect
P. Lukowicz et al. (Eds.)

doi:10.3233/FAIA230122

WeHeart: A Personalized Recommendation Device for Physical Activity Encouragement in Cardiac Rehabilitation

Rosa VAN TUIJN [a,1], Tianqin LU [a], Emma DRIESSE [a], Koen FRANKEN [a], Pratik GAJANE [a] and Emilia BARAKOVA [a]

[a] *Eindhoven University of Technology, Eindhoven 5612 AZ, the Netherlands*

ORCiD ID: Rosa van Tuijn https://orcid.org/0000-0003-1731-3743, Tianqin Lu https://orcid.org/0000-0001-8033-4024, Emma Driesse https://orcid.org/0000-0003-3099-2242, Koen Franken https://orcid.org/0000-0003-3534-616X, Pratik Gajane https://orcid.org/0000-0002-8087-5661, Emilia Barakova https://orcid.org/0000-0001-5688-4878

Abstract. We introduce WeHeart, a personalized recommendation device that aims to gradually increase physical activity levels in cardiac rehabilitation. The importance of physical activity in cardiac rehabilitation as a means of reducing associated morbidity and mortality rates is well-established. However, forming physical activity habits is a challenge, and the approach varies depending on individual preferences. Our solution employs a Random Forest classification model that combines both measured and self-reported data to provide personalized recommendations. We also propose to make use of Explainable AI to improve transparency and foster trust.

Our Contibutions: We introduce WeHeart, a personalized recommendation device that aims to gradually increase physical activity (PA) levels in cardiac rehabilitation. The importance of physical activity in cardiac rehabilitation as a means of reducing associated morbidity and mortality rates is well-established. Our solution employs a Random Forest classification model that combines both measured and self-reported data to provide effective recommendations for physical activity. We also propose to make use of Explainable AI to improve transparency and foster user trust.

Our Solution and Results: Our system consists of a recommendation model and a physical prototype called "WeHeart" (see Figure 1 for its graphical visualization[2]). We make use of PMData [4], a publically available dataset containing logging data measured with a Fitbit Versa 3 smartwatch and self-reporting of 16 healthy adults over a period of 5 months. The dataset was split into a training set (80%) and a testing set (20%).

Our model makes use of the step count, active minutes, sleep indicators, and self-reported data (consisting of fatigue, mood, stress etc) as input variables. The PA score is

[1] Corresponding Author: Rosa van Tuijn, r.c.m.m.v.tuijn@student.tue.nl.
[2] For more details including that of the physical prototype, click here.

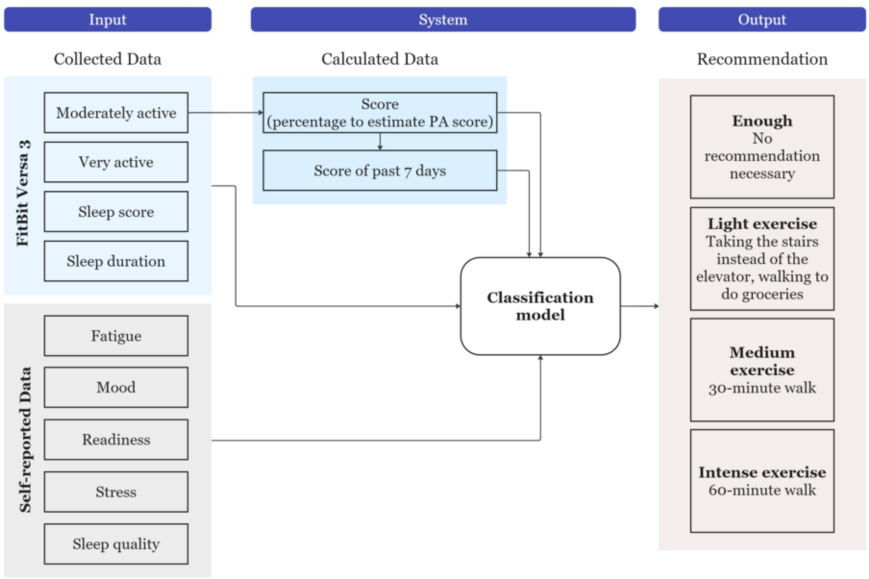


Figure 1. Input and output of the classification model.

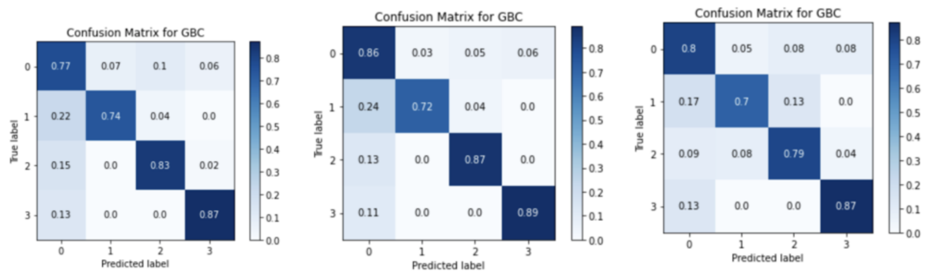
calculated in Equation (1) using the moderately active minutes based on a recommendation of the World Health Organization [3].

$$score = \frac{\text{sum of the moderately active minutes of the past 7 days}}{150} * 100\% \qquad (1)$$

The model is trained using the collected data and the calculated data to predict the category of recommended exercise for each observation: *Enough*, *Light exercise*, *Medium exercise* and *Intense exercise*. We compared three algorithms: Decision Tree classifier, Decision Tree regressor, and Random Forest classifier. As seen in Figure 2, the Random Forest classifier has the highest accuracy of 0.86.

Explainable AI: Considering the importance of these recommendations, it is crucial that the users can trust the employed recommendation system. To achieve trust, we adopted the Shapley Values to visually explain the predictions by calculating feature importance, which provides a framework to interpret Decision Trees and Ensemble Tree models. WeHeart uses the global interpretability of the Shapely Additive exPlanations (SHAP) model [1] to demonstrate the extent to which each input variable contributes positively or negatively to the output. This greatly increases the transparency of our proposed model by explaining to users why they received a particular recommendation and the extent to which various factors influenced the recommendation.

Current Limitations and Future Work: Firstly, the dataset for this model contains data from healthy adults. To further evaluate the model's effectiveness, data should be collected from cardiac rehabilitation patients. Secondly, instead of classifying if someone did or did not do enough exercise, other models such as a regression model could be used to actually predict someone's progress and improvements. Reinforcement learning (RL) can address some of the these limitations by recommending gradual improvements,



(a) Decision Tree classifier; Accuracy: 0.80.

(b) Random Forest classifier; Accuracy: 0.86.

(c) Decision Tree regressor; Accuracy: 0.81.

Figure 2. Confusion matrices of the different classification models.

considering long-term effects and capturing dynamic sentiments of the users (which traditional recommendation systems fail to consider)[2,5].

References

[1] Lundberg, S.M., Allen, P.G., Lee, S.I.: A unified approach to interpreting model predictions. Advances in Neural Information Processing Systems **30** (2017)

[2] Mulani, J., Heda, S., Tumdi, K., Patel, J., Chhinkaniwala, H., Patel, J.: Deep reinforcement learning based personalized health recommendations. Studies in Big Data **68**, 231–255 (2020)

[3] Organization, W.H.: Physical activity (2022), https://www.who.int/news-room/fact-sheets/detail/physical-activity

[4] Thambawita, V., Hicks, S.A., Borgli, H., Stensland, H.K., Jha, D., Svensen, M.K., Pettersen, S.A., Johansen, D., Johansen, H.D., Pettersen, S.D., Nordvang, S., Pedersen, S., Gjerdrum, A., Grønli, T.M., Fredriksen, P.M., Eg, R., Hansen, K., Fagernes, S., Claudi, C., Biørn-Hansen, A., Nguyen, D.T.D., Kupka, T., Hammer, H.L., Jain, R., Riegler, M.A., Halvorsen, P.: Pmdata: A sports logging dataset. MMSys 2020 - Proceedings of the 2020 Multimedia Systems Conference pp. 231–236 (5 2020)

[5] Zheng, H., Ryzhov, I.O., Xie, W., Zhong, J.: Personalized multimorbidity management for patients with type 2 diabetes using reinforcement learning of electronic health records. Drugs **81**, 471–482 (3 2021).