Article

Feedback Collection and Nearest Neighbor Profiling for Recommendation Systems in Healthcare Scenarios

João António* [1], Ricardo Malheiro [2], Sandra Jardim [3]

[1] Techframe-Information Systems, SA, 2785-338 São Domingos de Rana, Portugal; joao.antonio@techframe.pt;
[2] School of Technology and Management of the Polytechnic Institute of Leiria; University of Coimbra, Centre for Informatics and Systems of the University of Coimbra; rsmal@dei.uc.pt
* Correspondence: joao.antonio@techframe.pt

Abstract: The rise in the dimension and complexity of information generated in the clinical field has motivated research on the automation of tasks pertaining to personalized healthcare. Recommendation systems are a type of filtering method that utilize patterns and data relationships to generate items of interest for a particular user. In healthcare, these systems can be used to potentiate physical therapy by providing the user with specific exercises for rehabilitation. In this study, we propose a physical activity recommendation system that utilizes a KNN sampling strategy and feedback collection modules to improve the adequacy of recommendations at different stages of the rehabilitation period, improving over traditional Collaborative Filtering (CF) or human-constrained methods. Results from a trial show significant improvements in the quality of initial recommendations, achieving 81.2% accuracy before optimization. Moreover, the introduction of short-term adjustments based on frequent player feedback can be an efficient manner of improvement recommendation accuracy over time, achieving overall better convergence periods than those of human-based systems.

Keywords: Recommendation Systems, Collaborative Filtering, KNN, Physical Activity, Knowledge Extraction, Machine Learning, Feedback Collection

Citation: António, J., Malheiro, R., Jardim, S. To Decide. *J. Imaging* **2022**, *1*, 0. https://doi.org/

Received:
Accepted:
Published:

1. Introduction

Developing some form of physical activity is a basic need for human physical and mental well-being and is essential in combating a sedentary lifestyle and its harmful effects. Around 80% of the population does not practice enough physical activity to meet the recommendations of the World Health Organization (WHO). Regular physical activity speeds up metabolism, allowing for more effective fat burning and consequently weight loss, helping prevent and combat obesity. Prevents cardiovascular diseases as plays an important role in cardiac rehabilitation as a means of reducing morbidity and mortality rates associated with cardiovascular disease [1]. It also helps control diabetes, high blood pressure and cholesterol levels, as improves sleep quality and increases the ability to concentrate, leading to better academic and professional performance.

Health recommendation systems have the ability to encourage and engage users in modifying their behavior by providing improved options and practical knowledge, which derive from the analysis of user behavior [2]. According to the technical taxonomy recently proposed by Etemadi et al. [3], healthcare recommendation systems can be classified into collaborative, content-based, knowledge-based, context-based, and hybrid techniques. When it comes to evaluating healthcare recommendation systems, about half of the studies focused exclusively on the performance of the algorithms using several metrics, while others conducted comprehensive randomized controlled trials or studies in the wild to assess their impact in human health conditions [2]. This reality suggests a still slow progression of health recommendation systems, where their maturity and validation is not yet sufficient for their applicability in a real context.

Among the several possible applications of healthcare recommendation systems, such as recommending nutritional diets [4–8] or medicinal drugs [9–12], recommending physical activities as promoters of well-being or integrated into rehabilitation processes, is one that has aroused interest, both in the technical-scientific community, and by experts in the medical health sector, as a tool that potentially promotes better lifestyle habits.

In this study, a new rehabilitation exercise recommendation system is proposed as a intermediate layer between patients' activity sessions. The system is capable of generalizing patient profiles using KNN analysis, thus predetermining an initial exercise configuration that adequately matches user's physical capacities. The method is expanded with a second operation mechanism, which periodically collects explicit feedback from patients. Using a bidirectional weight system, the system can model feedback directly into the recommendation logic, adjusting some aspects of the activity to patients' needs and preferences.

This paper is organized by sections as follows. Section 2 introduces existing work in the context of healthcare recommendation algorithms, particularly those focused on rehabilitation practices. Section 3 follows, presenting the method described herein, focusing on the technical aspects of components that make up the system's functionality. In Section 4, the results from a practical trial of the proposed method are presented and discussed. Finally, Section 5 presents conclusive statements and introduces potential lines of future research.

2. Related Work

The employment of recommendation systems covers a wide range of techniques and problem areas. In the past two decades, the growth in both the quality and quantity of systems is notable, namely in applications areas related to streaming services, but also in industries such as healthcare and education. Below, an initial analysis is made to existing approaches for recommendation systems, further detailing those applied to healthcare topics, identifying the most popular techniques and limitations of such methods.

Collaborative Filtering (CF) is one of the more common techniques in building recommendation systems. In these approaches, items are recommended based on similarities in traits or actions with past users [13]. Moreover, recommendation systems based on CF are often designed to act on implicit or explicit feedback from the users, enabling personalized experiences [14].

As early as 2006, Aberg [15] proposed a meal planning recommendation system for the elderly population. The method utilizes a mix of weighted soft constraints and traditional hard constraints for modelling patient satisfaction, meal preparation difficulty, and dietary restrictions, showcasing theoretical usability in real-world scenarios, although several drawbacks in algorithm speed and user experience are pointed out by the author. In 2010, Freyne and Berkovsky [16] present a study on the sensitivity of a recipe recommendation system for groups of people to changes in weighing models and data aggregation heuristics, proposing that the best group recommendation performance is achieved when user's interests are individualized and scaled to group-based models.

The most common implementation for CF in healthcare is related to recommendation systems for connecting patients and doctors. In 2015, Narducci et al. [17] introduce HealthNet, a social network with a built-in recommendation system for creating recommendations between a patient and the doctor or medical institution that can provide them with the best possible service, by utilizing proprietary measures of similarity between patient profiles, and suggesting a ranked list of available doctors for the given patient's profile. Similarly, Guo et al. [18] developed a recommendation system in which the recommended doctors are ranked by their impact regarding the patient's specific health topic. The method has been extensively tested in China and shown to outperform benchmarks, supporting the usage of professional achievements as a key factor in making good recommendations. Later, in 2018, Han et al. [19] hybridize a traditional recommendation system to present patients with high-compatibility family doctors. Their approach is based on historical data and proposes the addition of a measurement of trust, having achieved superior performance than baseline heuristic or CF approaches.

Improvements to clinical decision support are also achievable with CF methods, namely in the field of therapy prescriptions. Gräßer et al. [20] propose a therapy recommendation system which aims to suggest efficient systematic therapies for skin condition treatment based on a similarity measure between the current consultation and a large set of recorded consultations.

Recommendation systems for physical rehabilitation are closely linked to this study, and despite it being a relatively immature sub-field of research, some works support their real-world implementation. Gmez-Portes et al. [21] propose the application of fuzzy logic to improve the quality of therapeutic monitoring and guidance, suggesting a recommendation model that enables the remote rehabilitation of stroke patients through interactive exercises. Ishraque et al. [22] leverage an AI-supported chatbot for interfacing users with a recommendation system for cardiac rehabilitation exercises. Initial evaluation suggests that allowing users to personalize their therapy plans may induce better adherence and efficacy, though a real evaluation of these effects is not yet available. Also for cardiac rehabilitation scenarios, Tuijn et al. [1] introduced a tailored recommendation tool designed to incrementally boost physical activity and circumvent a sluggish start. The authors' proposed system harnesses a Random Forest classification model, amalgamating both measured and self-reported data to furnish individualized suggestions for physical activity. Moreover, the utilization of explainable Artificial Intelligence enhances clarity and fosters confidence in the system. The study underscores the capacity of Machine Learning in tailoring recommendations for physical activity, advocating for a reinforcement learning strategy to refine system personalization as time progresses. Ferreto et al. [23] proposed a personalized physical activity recommendation system for hypertensive patients, with the aim of improving their lifestyle and health outcomes. The system uses a user profile model and a recommendation system, which considers cardiovascular risk factors, physical activity history and physical activity result indices. Through validation by specialist doctors, 75% of the system's recommendations were approved, indicating its potential to help hypertensive patients improve their health through regular physical activity. The study also emphasizes the importance of personalized recommendations in promoting the well-being of individuals with hypertension.

3. Methods

In this paper, I propose a hybrid approach for recommending physical activities to elderly players of a gaming platform that targets the rehabilitation of upper limbs. Traditional CF strategies are employed for the initial sampling of patient profiles and the generation of baseline recommendations, while a built-in explicit feedback recovery system gradually models patients' specific preferences for a more personalized approach in subsequent iterations.

3.1. Data Characterization

All data was collected as a result of a clinical trial, aiming to assess the usability of a handheld dynamometer as a controller for augmented reality (AR) games. Participants were asked to play a number of games and consent to the respective data to be collected and analyzed. Each activity is comprised of a set of parameters that dictates its inherent difficulty level (length of the activity, proposed targets for grip strength, grip cadence and number of grip presses). After each activity, participants could optionally provide feedback in the form of a 1-to-5 rating for that particular game. Exclusively elderly patients with indicative traits of frailty were asked to participate in trial.

3.1.1. Data Sources

Two data sources are considered for the current study. For ease of explanation, they will be referred to as *PD* and *AD* in the characterizations below.

Patient Data, (*PD*) has 860 patient profiles, containing rows pertaining to general health and the degree of affliction with risk factors for frailty. Personal information is also present in the data, though it has been omitted for the purpose of this study.

Activity Data, (*AD*) has 3525 rows of recorded game sessions performed by the patients in *PD*. These rows correspond to every valid activity collected during the trial, providing information about a relatively extensive range of game parameter combinations, from patient behaviour to the achieved scores.

3.2. Hybrid KNN Sampling

First recommendations are based on the CF principle that similar users will have similar preferences. A K-Nearest Neighbors approach is used to model the input feature array (new patient information) with a number, K, of previously existing features. Feature arrays are uniform in size, always containing 10 numerical and 6 categorical values pertaining to various physical and psychological measurements and the presence of frailty risk factors. Due to the coexistence of both categorical and continuous attribute types in the data, a single distance metric could not be used. Instead, categorical variables are transformed into binary arrays through attribute indication (dummy variable creation), and a weighted average of two measures is adopted when calculating neighbors.

The similarity score between numerical arrays, A and B, is given by the *Euclidean Similarity* formula given by Eq.1. To avoid scale unbalance, the continuous variables in the data were scaled with a mean-based scaling formula, where the scaled value for a value, X_i is given by $Xs = \frac{X_i - X_{mean}}{X_{sd}}$, where X_{mean} is the average value for the attribute, and X_{sd} is is the standard deviation for the attribute.

$$S_{A,B} = \frac{1}{1 + d(A,B)}, \tag{1}$$

where d is the *Euclidean Distance* (Eq.2) between both vectors:

$$d_{A,B} = \sqrt{\sum_{i=1}^{n} (A_i - B_i)^2} \tag{2}$$

Contrarily, the binary arrays corresponding to categorical variables in the data are evaluated with an adapted *Jaccard* similarity coefficient, shown in Eq. 3.

$$J_{A,B} = \frac{a}{a+b+c}, \tag{3}$$

whereby a is the count of attributes equal to 1 for both objects A and B; b is the count of attributes equal to 0 for object A and 1 for object B; and c is the count of attributes equal to 1 for object A and 0 for object B.

Finally, a weighing strategy was implemented to counter unfair similarity scores originating from having a larger number of continuous variables than categorical values (10 and 6, respectively). The corresponding weights were calculated as the relative fraction of total attributes per data type, or $10/16 = 0.625$ for continuous and $6/16 = 0.375$ for categorical data. As an example, if the euclidean similarity between two patient rows is 0.95 but the *Jaccard* similarity is 0.50, the final similarity is given by $(0.95 * 0.625) + (0.50 * 0.375) = 0.78125$, or approximately 78.1%.

3.2.1. Determining *K*

The selection of an adequate number, K, of neighbours for generating classifications is often an overlooked decision when developing neighbour based heuristic approaches. Selecting too small of a sample size makes the system much less resistant to noise and other data quality inconsistencies, whereas an exaggerated K value is counter intuitive to the original premise of KNN itself. To find the best possible value for this problem, K was tested for all integer values in range $[5, 86]$, with the upper limit corresponding to 10% of the dataset size. The metric used for this test pertains to the classification accuracy of the KNN algorithm in predicting previously assigned labels with a K-Means clustering algorithm (number of clusters, $N = 4$).

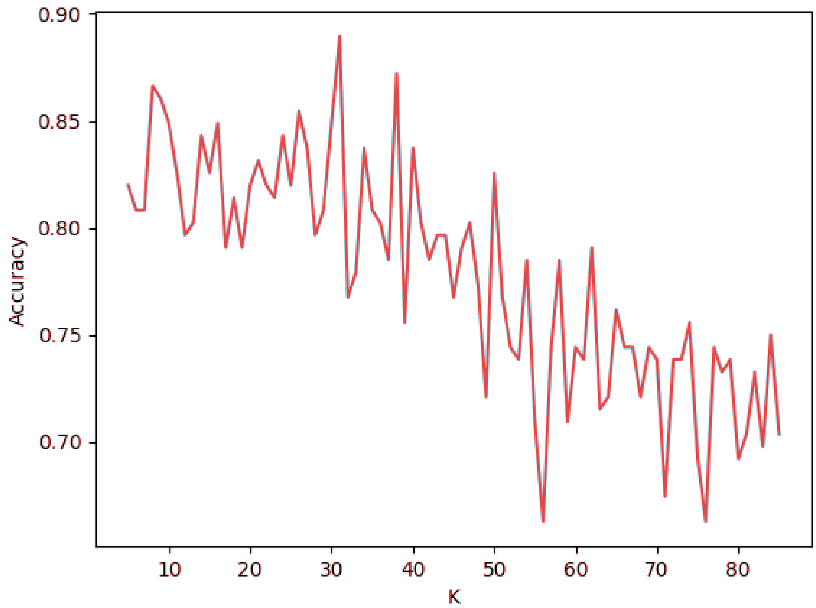

Figure 1. KNN Classification Accuracy for $K \in [5, 86]$

Despite not following a predictable pattern, the highest observed classification accuracy for this range is 88.9%, and relates to $K = 31$. For the purposes of this study and the foreseeable scope of the project, this value will be used. However, a reiteration of the process outlined above may be necessary in the event of a significant expansion in the size of the dataset.

3.3. Generating Recommendations

The recommendations generated by the system are essentially a set of activity rules that should align with a patient's therapeutic needs, physical capacity, and, notably, their preferences. Two working modes were devised to generate recommendations, depending on whether the user has previously interacted with the system or not. Initially, implicit feedback is taken from the patient's overall health profile, whereby the activities played by a number of high similarity neighbours are analyzed. Subsequent interactions with the recommendation system are built on explicit feedback, collected at frequent intervals. The usage of both implicit and explicit feedback ensures that recommendations made with no prior knowledge of a patient can still be relevant, but promotes a gradual change into a personalized experience as more feedback is collected.

3.3.1. Nearest-Neighbor Based Recommendations

First recommendations are generated in accordance to the general tendencies of the $K = 31$ nearest neighbors to that particular user. The workflow for instantiating first recommendations can be consulted in Fig. 2.

All neighbors' activity history is initially mean aggregated by rating, meaning that the game with the highest average satisfaction among the current demographic is identified first. To create a therapeutic experience that is cohesive with the user's physical capabilities, all individual difficulty levels for the game are tabulated in regards to their Quality Score, Qs, given by Eq. 4, where the user's average engagement and satisfaction

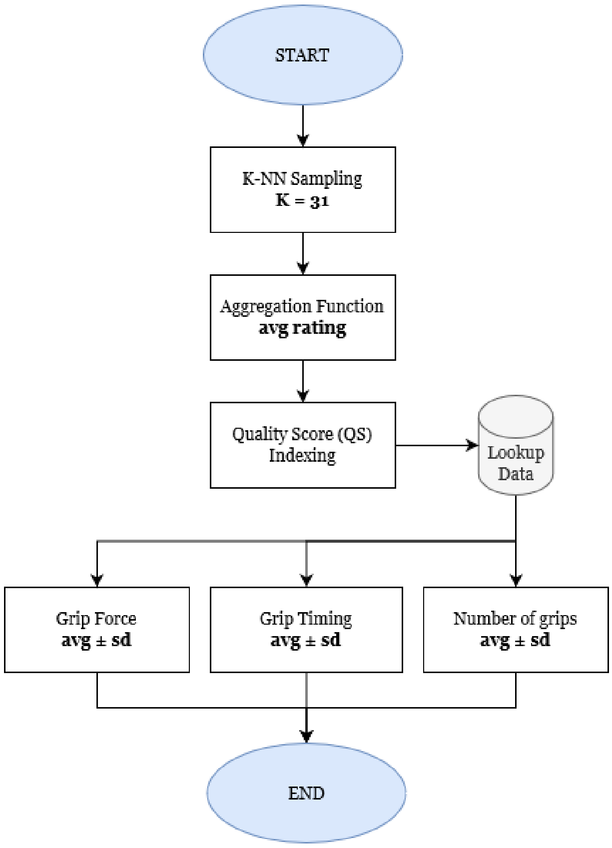

Figure 2. Workflow for $N = 1$ recommendations

scores for that particular difficulty, x, are weighed. Note that since the satisfaction score, $S \in [0, 5]$, while the engagement score, $E \in [0, 1]$, the former is multiplied by a factor of 0.2 to avoid outweighing the latter by scale differential.

$$Qs_x = (S_x \times 0.2) \times 0.5) + E_x \times 0.5 \tag{4}$$

Upon finding the difficulty level with the highest Quality Score, the specific targets for grip force, grip timing and grip instances are generated randomly within the constraints defined for that difficulty.

3.3.2. Weighed Feedback Based Recommendations

After the first recommended activity is played, the recommendation workflow changes into a feedback-based approach, based on the immediate impressions the user had about the activity they have just participated in. For this, a set of weights, W, is initialized for the current user. Weights are used to track the user's sentiment towards specific components of the activity, and are gradually adjusted through the application of a short questionnaire. The different questions, choice paths, and respective effects on the weights can be consulted in Fig. 3. The questionnaires are designed with ease-of-use in mind, predicting an environment in which the majority of players are elderly, and thus less accustomed to complex technology.

Any given weight set has a fixed number of positions (5), corresponding to the different activity elements that can be gradually fine-tuned to the user's preference. The weight shifting mechanism can incur changes on:

- The game, either to avoid patient burn-out or to correspond to their preferences.
- The session duration, depending on whether the user found it to be excessive or insufficient. This makes the system responsive to the patient's energy levels and disposition to partake in longer activities.

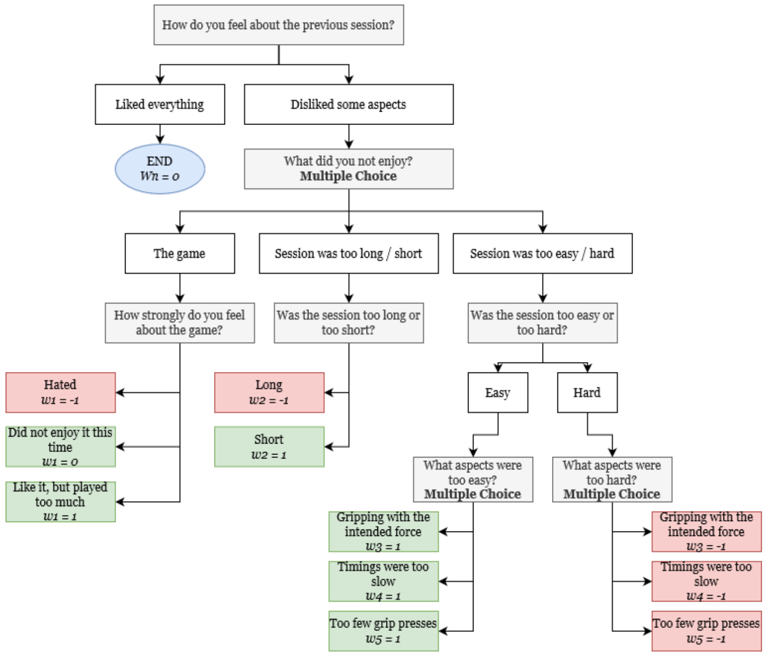

Figure 3. Feedback collection workflow, with respective bidirectional weight shifting operations

- The session's grip targets, namely the recommended average grip force, the correct grip cadence (interval at which grips are meant to be pressed), and the total number of times the patient needs to perform a grip. All of these parameters are initially bound by a predetermined difficulty level ranging from 0 to 10, however, to favour a personalized experience, individual targets are gradually optimized to the patient's specific needs. For example, a patient whose initial activity corresponds to a difficulty of 6 might possess a much steeper level of lethargy, requiring far fewer grips to account for their reduced energy, hence gradually having only that target adjusted accordingly.

A bidirectional shift is used to inflict changes in weights, depending on whether the patient's sentiment towards a question is positive or negative. Generally, answers that indicate that the patient is struggling to achieve the proposed goals (negatively connoted) correspond to the respective weights being shifted to -1. Contrarily, if any goal is too easy to achieve (positively connoted), the corresponding weight is shifted to 1. Finally, when patients are are satisfied with a particular setting, its weight is not altered from 0 (neutrally connoted).

4. Results

The proposed method was used by 71 returning patients from the original trial, enabling a comparative evaluation of the before and after states of the system. The trial was done under no supervision, with participants having full access to the recommendation system throughout its 3-day duration. At the end of the trial, participants answered some questions about their overall experience.

4.1. Recommendation Accuracy

An activity is considered correct when the patient, after playing it, does not request changes to any of its difficulty settings. As such, accuracy is expected to grow as the number of iterations increases, which corresponds to the number of parameter adjustment cycles needed to achieve an adequate fit to the patient's needs. For the purpose of this evaluation, convergence is considered at 97% accuracy. The proposed system is hereby compared to the previous method, in which activity parameters are defined by human therapists. The data in Fig. 4 suggests that the proposed system is far superior in N_1 accuracy (i.e. first recommendations), supporting the usage of KNN for generalizing patient profiles from historical data.

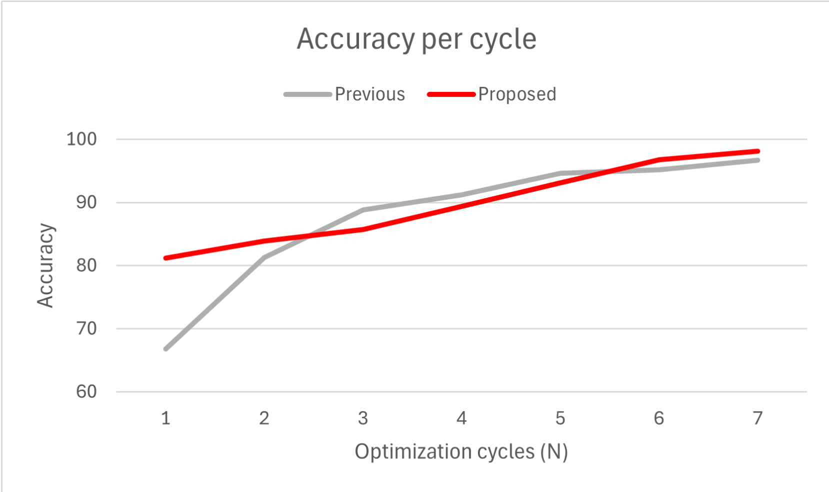

Figure 4. Average Accuracy: Previous vs Proposed method

Notably, the human-based approach has a faster convergence speed in the earlier iterations, facing an increase of 22% accuracy from N_1 to N_3, and stabilizing from there onwards. Disregarding the N_1 iteration, the previous method has a slightly higher average convergence rate per cycle (2.56%) than the proposed method (2.36%). This is likely due to the previous method not being limited by a learning rate (with it being human-bound), which also explains why the proposed method's accuracy increases steadily across iterations. Despite the slower convergence, the proposed method generally converges quicker ($N = 5$) than the previous method ($N = 6$) due to it having superior N_1 accuracy.

Due to limitations in the scope and timeline of the trial, we are unable to determine the evolution of accuracy curves for $N > 7$, raising questions about the adequacy of the system for extended usage. To provide reasoning for this question, a predictive analysis was performed, using logarithmic functions to predict the growth of accuracy for $N \in [8, 10]$. Logarithmic curves tend to stabilize as the x axis increases, correctly reflecting the notion that accuracy will also top-up and stabilize after a certain number of iterations (convergence). The graph depicted in Fig. 5 contains the logarithmic extension of curves, alongside the modelled logarithmic functions.

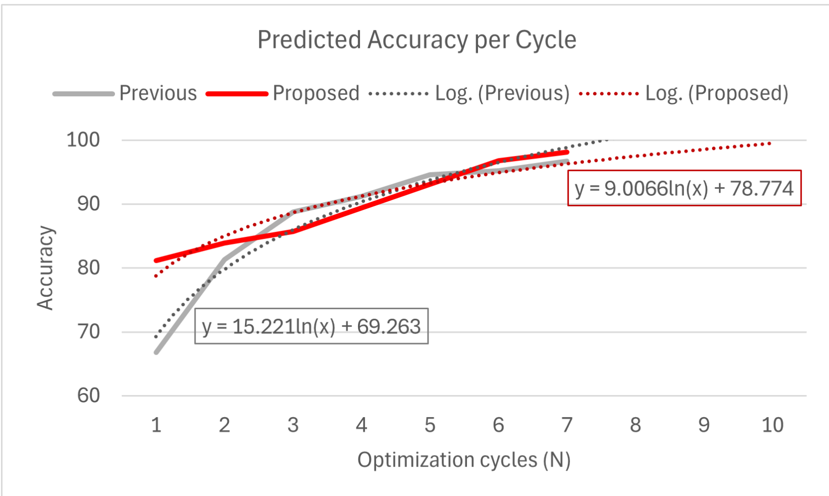

Figure 5. Logarithmic prediction of accuracy: Previous vs Proposed method

Logarithmic prediction favours the previous method to converge quicker due to the initial spike in accuracy observed after the first iteration. Moreover, mathematical prediction of recommendation systems does not account for situations that can not be modelled into data, such as the player's mood (The player may dislike activities they enjoyed in the past) and uncertainty (The player may not be sure about certain aspects of the activity), which will ultimately affect accuracy at irregular intervals.

4.2. Behavioral Evaluation

An indirect way of measuring the quality of the recommendations is by analyzing patients' behaviour and adherence to the activities before and during the trial. Engagement is a metric that relates the each activity's proposed duration with the actual time spent by the patient partaking in it, and can indicate situations of early quitting due to exhaustion or boredom. For the purpose of the study, a patient is considered engaged with the activity when they participate in at least 95% of its duration, meaning that an implied goal of the system is to improve the ratio of players over this threshold.

Additionally, a patient's self-perception of improvement is a psychological indicator that the underlying system is working as intended. After participating in the trial, patients are asked to rate their performance subjectively, on a scale from 0 to 100. Below, the proposed approach is compared with the previous solution in regards to the two behavioural metrics. First, the proportion of patients that match or exceed the proposed engagement score, and secondly, the average self-rating score. The results from this comparison can be consulted in Fig. 6.

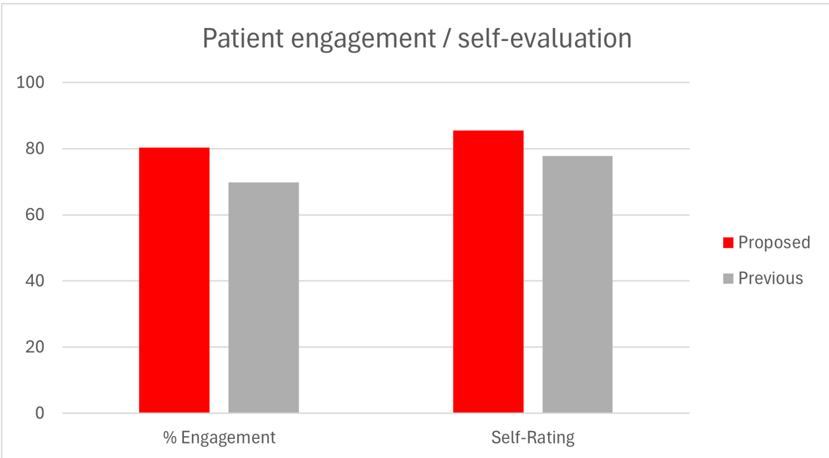

Figure 6. Behavioural Indicators: Previous vs Proposed method

The data depicted in the graph indicates a slight improvement on both indicators over the previous method. A 10.5% increase in the percentage of patients who achieved the proposed engagement scores is consistent with the uptick in first recommendation accuracy observed before, meaning that when patients are initially suggested a better activity, they tend to have better adherence for the remainder of the rehabilitation plan. Patients also appear to rate their performances, on average, 8% higher than with the previous method, which could indicate a situation were activities are better suited to patient's capabilities and preferences.

Feedback collected from patients after the trial revealed that significant portion (66%) of players felt noticeable positive changes in difficulty between activity cycles. Generally, the bidirectional weight shifting mechanism seems appropriate at instantiating adjustments according to patient's specific needs. However, 11 participants claimed that the feedback questionnaire is too frequent and disruptive to a seamless experience, suggesting that an alternative optimization frequency might benefit user experience in detriment of convergence speed.

5. Conclusions and Future Work

Engaging in frequent physical activity is proven to improve quality-of-life in a variety of aspects, but despite the outlined benefits, a large portion of the population lacks sufficient exercise levels, leading to physical and psychological complications, especially in the latter stages of life. Physical therapy a type of health rehabilitation practice that aims to reduce pain and improve motor function, promoting recovery from injury, medical intervention, and age-related loss of mobility. Recommendation systems play an important role in enabling personalized healthcare, and thus can be leveraged to improve the efficacy of physical therapy through autonomous prescription of rehabilitation exercises according to patients' specific needs.

The proposed method's functionality is defined by two distinct modes. First, a Nearest Neighbor-Based Collaborative Filtering strategy is used to generate initial recommendations based on patient profile similarity. Then, explicit feedback collection interacts with a personalized weight system, gradually fitting newer recommendations to the patient's preferences. The weight shifting mechanism is designed to provide the patient with an immediate and tangible change in the way their next activity plays out, enabling a degree of positive or negative adjustment to activity goals, depending on perceived difficulty.

Evaluation of the proposed method shows significant improvement in first recommendation accuracy when compared with a human-based approach, supporting the role of multiple feature weighing for improving nearest neighbour analysis precision. Indicators of success can also be derived from behavioural data, which suggests that having high quality recommendations in the earlier stages of the program can lead to better adherence to the activities. Consequently, when players' feedback has noticeable effects on recommendations, their understanding of self improvement is improved. Overall, these results support the introduction of explicit feedback collection as a means of enhancing the personal aspect of recommendation systems applied to healthcare, in particular, physical activity recommendation systems.

As indicators for future work, it is necessary to conduct further research into the limitations of the feedback collection method. In particular, it is essential to implement measures to prevent the exploitation of feedback collection. One such instance occurs when a patient knowingly and untruthfully reports their activities as being too difficult, thereby inducing changes that are not aligned with their actual physical capabilities. Moreover, a solution for preventing disruptive feedback collection needs to be explored, potentially involving the evaluation of alternative optimization periods to reduce interruption of the player's experience. Finally, a subsequent study is planned to introduce periodic inference of patients' performance. This will add another layer of feedback whereby patients can better understand their rehabilitation progress over time.

Author Contributions: Conceptualization, J.A.; Formal analysis, J.A.; Funding acquisition, S.J.; Investigation, J.A.; Methodology, J.A. ; Project administration, R.M.; Software, J.A.; Supervision, R.M.; Validation, J.A., R.M.; Writing—original draft, J.A.; All authors have read and agreed to the published version of the manuscript.

Funding: Not Applicable

Institutional Review Board Statement: Not Applicable

Informed Consent Statement: Not Applicable

Data Availability Statement: The data presented in this study is available on request from the corresponding author. The data are not publicly available due to privacy matters, and none of the data contained in the dataset mentioned in the manuscript is publicly available.

Acknowledgments: Not Applicable

Conflicts of Interest: The authors declare no conflict of interest

Abbreviations

The following abbreviations are used in this manuscript:

References

1. van Tuijn, R.; Lu, T.; Driesse, E.; Franken, K.; Gajane, P.; Barakova, E. WeHeart: A Personalized Recommendation Device for Physical Activity Encouragement and Preventing “Cold Start” in Cardiac Rehabilitation. *Lecture Notes in Computer Science* **2023**, *14144*. doi: https://doi.org/10.1007/978-3-031-42286-7_11.
2. Croon, R.D.; Houdt, L.V.; Htun, N.N.; Štiglic, G.; Abeele, V.V.; Verbert, K. Health Recommender Systems: Systematic Review. *Journal of Medical Internet Research* **2021**, *23*. doi: https://doi.org/10.2196/18035.
3. Etemadi, M.; Abkenar, S.B.; Ahmadzadeh, A.; Kashani, M.H.; Asghari, P.; Akbari, M.; Mahdipour, E. A systematic review of healthcare recommender systems: Open issues, challenges, and techniques. *Expert Systems With Applications* **2023**, *213*. doi: https://doi.org/10.1016/j.eswa.2022.118823.
4. Zhang, J.; Wang, Z.; Liu, W.; Liu, X.; Zheng, Q. A unified approach to designing sequence-based personalized food recommendation systems: tackling dynamic user behaviors. *International Journal of Machine Learning and Cybernetics* **2023**, *14*, 2903–291. doi: https://doi.org/10.3390/bioengineering10111241.
5. Rostami, M.; Aliannejadi, M.; Oussalah, M. Towards Health-Aware Fairness in Food Recipe Recommendation. Proceedings of the 17th ACM Conference on Recommender Systems, 2023, p. 1184–1189. doi:https://doi.org/10.1145/3604915.3610659.
6. Kobayashi, A.; Mori, S.; Hashimoto, A.; Katsuragi, T.; Kawamura, T. Functional Food Knowledge Graph-based Recipe Recommendation System Focused on Lifestyle-Related Diseases. Proceedings of the IEEE 18th International Conference on Semantic Computing, 2024, pp. 261–268. doi:https://doi.org/10.1109/ICSC59802.2024.00048.
7. Brintha, N.C.; Nagaraj, P.; Tejasri, A.; Durga, B.V.; Teja, M.T.; Pavan, M.N.V. A Food Recommendation System for Predictive Diabetic Patients using ANN and CNN. Proceedings of the 7th International Conference on Communication and Electronics Systems, 2022, pp. 1364–1371. doi:https://doi.org/10.1109/ICCES54183.2022.9835808.
8. Thongsri, N.; Warintarawej, P.; Chotkaew, S.; Saetang, W. Implementation of a personalized food recommendation system based on collaborative filtering and knapsack method. *International Journal of Electrical and Computer Engineering* **2022**, *12*, 630 638. doi: https://doi.org/10.11591/ijece.v12i1.pp630-638.
9. Suryadevara, C.K. Towards Personalized Healthcare - An Intelligent Medication Recommendation System. *International Engineering Journal for Research Development* **2020**, *5*.
10. Bhoi, S.; Lee, M.L.; Hsu, W.; Tan, N.C. REFINE: A Fine-Grained Medication Recommendation System Using Deep Learning and Personalized Drug Interaction Modeling. *Advances in Neural Information Processing Systems* **2024**, *36*.
11. Tan, W.Y.; Gao, Q.; Oei, R.W.; Hsu, W.; Lee, M.L.; Tan, N.C. Diabetes medication recommendation system using patient similarity analytics. *Scientific Reports* **2022**, *12*.
12. Yue, W.; Wang, M.; Zhang, L.; Zhang, L.; Huang, J.; Wan, J.; Xiong, N.; Vasilakos, A.V. A-GSTCN: An Augmented Graph Structural–Temporal Convolution Network for Medication Recommendation Based on Electronic Health Records. *Bioengineering* **2022**, *10*. doi: https://doi.org/10.3390/bioengineering10111241.
13. Pazzani, M.J.; Billsus, D. Content-based recommendation systems. In *The adaptive web: methods and strategies of web personalization*; Springer, 2007; pp. 325–341.
14. Hu, Y.; Koren, Y.; Volinsky, C. Collaborative filtering for implicit feedback datasets. 2008 Eighth IEEE international conference on data mining. Ieee, 2008, pp. 263–272.
15. Aberg, J. Dealing with Malnutrition: A Meal Planning System for Elderly. AAAI spring symposium: argumentation for consumers of healthcare, 2006, pp. 1–7.
16. Berkovsky, S.; Freyne, J. Group-based recipe recommendations: analysis of data aggregation strategies. Proceedings of the fourth ACM conference on Recommender systems, 2010, pp. 111–118.
17. Narducci, F.; Musto, C.; Polignano, M.; de Gemmis, M.; Lops, P.; Semeraro, G. A recommender system for connecting patients to the right doctors in the healthnet social network. Proceedings of the 24th international conference on World Wide Web, 2015, pp. 81–82.

18. Guo, L.; Jin, B.; Yao, C.; Yang, H.; Huang, D.; Wang, F.; others. Which doctor to trust: a recommender system for identifying the right doctors. *Journal of medical Internet research* **2016**, *18*, e6015.
19. Han, Q.; Ji, M.; De Troya, I.M.D.R.; Gaur, M.; Zejnilovic, L. A hybrid recommender system for patient-doctor matchmaking in primary care. 2018 IEEE 5th International Conference on Data Science and Advanced Analytics (DSAA). IEEE, 2018, pp. 481–490.
20. Gräßer, F.; Beckert, S.; Küster, D.; Abraham, S.; Malberg, H.; Schmitt, J.; Zaunseder, S. Neighborhood-based Collaborative Filtering for Therapy Decision Support. HealthRecSys@ RecSys, 2017, pp. 22–26.
21. Gmez-Portes, C.; Castro-Schez, J.J.; Albusac, J.; Monekosso, D.N.; Vallejo, D. A fuzzy recommendation system for the automatic personalization of physical rehabilitation exercises in stroke patients. *Mathematics* **2021**, *9*, 1427.
22. Ishraque, M.T.; Zjalic, N.; Zadeh, P.M.; Kobti, Z.; Olla, P. Artificial intelligence-based cardiac rehabilitation therapy exercise recommendation system. 2018 IEEE MIT Undergraduate Research Technology Conference (URTC). IEEE, 2018, pp. 1–5.
23. Ferretto, L.R.; Bellei, E.A.; Biduski, D.; Bin, L.C.P.; Moro, M.M.; Cervi, C.R.; De Marchi, A.C.B. A physical activity recommender system for patients with arterial hypertension. *IEEE Access* **2020**, *8*, 61656–61664.