

AI-Coached Fitness Tracking for Personalized Health Monitoring

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Abstract— This paper presents an AI-coached framework for fitness tracking for personalized health monitoring which comprises of fitness tracking by wearables-sensing type, activity recognition, recovery assessment and injury-risk estimation & recovery recommendation generation. A synthetic set of 150 users, producing session recordings over 12 weeks of data (1,800 sessions) was set up and controlled. On top of each record there are a number of overlays featuring motion descriptors, heart-rate response overlay, sleep overlays, HRV overlay, recovery score, stress score, training load as well as adherence probability and activity label overlay. The following two baseline models were validated – activity-recognition model, coaching-recommendation model. The hit rate of test results 0.9318 and 0.9495 for activity-recognition and coaching-recommendation respectively, was obtained and a similarly high macro F1 value of 0.9317 and 0.8968 for activity recognition and for deployment safety towards The framework respectively, was gained in order to take sensual sloppy and unclear boundaries out of the way, to achieve auditable and recovery aware passive coaching from the passive-tracking approach.

Keywords— AI coaching, fitness tracking, wearable sensors, activity recognition, personalized health monitoring, recovery analysis, injury risk, adherence prediction.

I. INTRODUCTION

A. Background and Motivation

Fitness trackers have evolved into fitness measuring systems, exhaustively tracking and estimating load, recuperation, intensity and conduct via step meters. But this is a process of interpretation yet to be performed to understand what can be gleaned from these. The only value in collecting data about heart rate, cadence, accelerometers variance and stress and sleep score is when it is interpreted and provided to the user on time; it's not very useful if it isn't placed within the context of a safe individual coaching program. Novel research work has been undertaken on AI-based coaching for physical activity which shines some light on concrete possibilities of behaviour change with AI, specifically in the area of offering personalised feedback to the physical activity user, rather than providing individualised stimuli. This translates to baiting messages in terms of being timely and relevant, and their levels of trustworthiness [2] when supported by activity promotion using chatbot. Based on a review of data, there is not a significant difference between the models, and they are configured as a human coach, automated/model coach, or hybrid. This is related to the fine grain of feedback / adherence provision of such models. In the proposed study the regard is not the problem of display of the fitness, it is a closed problem of tracking the fitness.

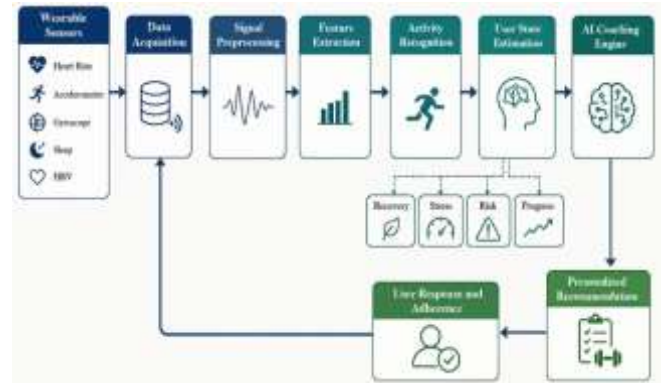


Fig. 1.1. Conceptual view of AI-assisted fitness tracking and coaching feedback loop

There are four blocks: wearable sensing, activity recognition, userstate estimation and coaching recommendation is made in the feedback loop. In the wake of the applications of physical loading, integrated activity promotion VAs (virtual agents) have been shown to be able to contribute to a human activity coach, as part of their jobs [4].

B. Problem Statement and Research Contributions

When examining the majority of commercial trackers, they'll inform you what has happened, and what the trends are, but not many connect to the "how" and what it means for coaching. This gap brings forth 2 technical problems: generic recommendations, and insecure increase of intensity. Based on the human-factors analysis of the tools, three factors were considered for accepting physical-activity tools using the AI: transparency, burden and perceived fit. Transparency, burden and perceived fit are three key components of HFA that have been shown to be good predictors of acceptance of PA tools using AI. This is similar for studies on personalisation in the context of mobile health; the persuasive means should not be inferred from the mere grouping of users based on demographic attributes of the users – it should be inferred from the behaviour that is observed. We're going to attempt this over here by presenting you with a fitness tracking model trained with our simulated controlled 12 week, 1800 fitness session data set, and fitness sessions coached by an AI. These were developed and the study offers a baseline activity-recognition model, another for coaches, an evaluation design and one that includes an exercise on linking the quality of sensors, exertion, recovery, injury risk and adherence with a reproducible data set. The activity score is customised as per Eq.(1) and the confidence level of activity recommended is customised as per Eq.(2).

$$AS_i = w_1HR_i + w_2MET_i + w_3TL_i + w_4RS_i - w_5IR_i \quad (1)$$

$$C_i = \max_k P(y_i = k | X_i, U_i, R_i) \quad (2)$$

In this way, the recognition accuracy and recommendation reliability is achieved - no doubt, an accurate activity label

alongside not considering recovery state will lead to poor coaching.

II. RELATED WORK

A. Wearable Sensor-Based Fitness Monitoring

Wearable Fitness Monitoring needs to sample (over a range of motion/positions/adherence to the skin) physiology (and inertial) signals continuously. If the health habit reviewed is a recommender system, not only sensing is required, but advices given based on the physically activity sensed has also to be reviewed and provided to the users, otherwise, an advising to too physically-active users is not appreciated [7]. In the exercise prescription studies that include a smartwatch, machine learning techniques can be used to help personalize the exercise prescription based on the inputs such as heart rate, movement, recovery and past effect [8]. Yet as revealed in the review on DWBDs, the step of actually personalizing the value(s) of a threshold of the model to the person employing the WBD, which in most of the events, will be distinct from the collective person (s) threshold value, was increased noted. The intensity of activity obtained from sensor in this study was displayed as: (3) -- is displayed as Activity Intensity.

$$AI_i = \alpha_1 A_i + \alpha_2 G_i + \alpha_3 HR_i + \alpha_4 CAD_i + \alpha_5 MET_i \quad (3)$$

B. Machine Learning for Activity Recognition

Wearable tracker intervention can tell task demands and provide proper feedback at appropriate moments, and has been shown to result in real outcomes in terms of setting and activity and movement functions of older adults [10]. There are studies reported in the AI literature of such devices measuring physical activity related to mental health questionnaires – models need to reflect information relative to specific time of day of corresponding physical activity, information of fatigue and potentially noisy adherence behaviour in the data sets [11]. Edge-assisted rehab work allow local estimations of wearable health systems, which are directly affecting the system use, such as the latency, data privacy and continuous monitoring [12]. The in vivo modelling of the physiological response reveals that the response to a basic activity (e.g. exercise) can vary from person to person and depends on the immediate environment, and that the laws of intensity, such as they are, are very weak [13]. Consequently, the activity recognition isn't performed simply as an individual, however it is combined by coaching logic.

C. AI Coaching, Feedback Personalization, and User Adherence

Wearable data is fed into a model to create a model of the personalised heart-rate response to exercise - which is then more accurate at modelling the individuals personal training response compared to the generic formulae [14]. The research in this field [15] indicates that the fitness recommendation and data privacy protection needs to be built in tandem when using parameters catering to behaviour, health and identity. This study will consider coaching from the perspective of a "probabilistic decision problem". It is not assumed that compliance has been achieved. Based on recovery, risk, stress and type of feedback and progress. The focus of the model of adherence probability in (4) is the relationship between the coaching outputs and behaviour response.

$$P(AD_i = 1) = \sigma(\beta_0 + \beta_1 RS_i - \beta_2 IR_i - \beta_3 SS_i + \beta_4 PG_i) \quad (4)$$

To support the ability to make conclusions about the design of rules enforcing the manuscript the following features may

have to be constrained: features of a sensor, coaching-labels should be explainable, the reported result of their work should obviously not be responsible for too-separable synthetic classes.

III. RESEARCH METHODOLOGY

A. System Architecture and Data Acquisition

We envision a "model based 4 layered pipelined design of the overall system for the wearable sensing, preprocessing, inference and delivery of coaching. The information is those from 1800 synthetic session recordings of participants who were tracked during a 12-weeks observation of 150 synthetic participants. At each data recording, information is collected, such as: Demographic profile, fitness level, fitness goal, heart rate response, sleep, HRV (heartrate variability), recovery score, stress score, inertial signals, signal quality, activity label and coaching label. However, this is what the PERFECT system aims to do by creating a personalized exercise recommendation system on this architecture, which is strictly separated between user modelling and generation of personalized exercise recommendation [16]. Studies on fitness recommendation based on machine learning also support the use of fitness goals-aware predictor over activity only classifiers [17].

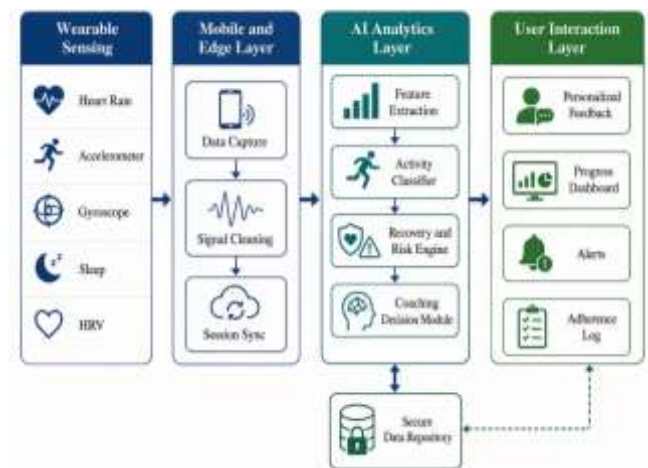


Fig. 3.1. Proposed architecture of the AI-coached fitness tracking system

$$X_i = [A_i, G_i, HR_i, CAD_i, MET_i, SL_i, HRV_i, RS_i, IR_i] \quad (5)$$

B. Preprocessing and Feature Engineering

Data cleaning included range checking on bounded physiological values, checking consistency of values in a category and checking validation of features derived from other values. Selected variables– studies about activity-recognition, duration, heart rate, cadence, magnitude of accelerometer, magnitude of gyroscope, metabolic equivalent and sleep and recovery variables – were checked for possible "impossibility" prior to training the models of both deep and classical networks since they are sensitive to sensor heterogeneity and window design and are sensitive to the scaling of the features when training them. In the same fashion, we will need an explicit embedding of a normalisation step when comparison of data captured from different sources of the sensors will be needed, as illustrated in our recent research on Heterogeneity of Wearable Sensors. The activity recognition and recovery-risk features do not change in the final feature set used for the motion recognition and the coaching to assess whether or not a recovery-risk is possible. The following measures of training load, heart-rate zone ratio, injury-risk score, weekly progress score and adherence probability were calculated to derive. This has been done to make sure that there is no cross contamination between labels (the target) and variables (the explanations).

C. AI Coaching Model Design

There are 2 supervised models in the AI layer. The first, which uses the mean and standard deviation of the accelerometer (ACC) signal, the strength of the gyroscope (GYR) signal and signal quality and percentage of missing sensors, classifies activity type. The second model was done by adding the recovered model variables (sleep, injury risk, perceived exertion, stress, weekly progress, training load and goal/fitness level in model) to the model to use for the coaching recommendation. An extensive survey on activity recognition was performed to aid in separation of activities and different error ranges for the activity labels and intervention labels were used. [20] Across-time learning models learned by structuredness of the representation in self-supervised learning for large scale wearable learning were better representations [21]. AI in wearable sensing also provides the opportunity to help build models that will necessitate adding inertial and context and/or physiology data into the model [22].

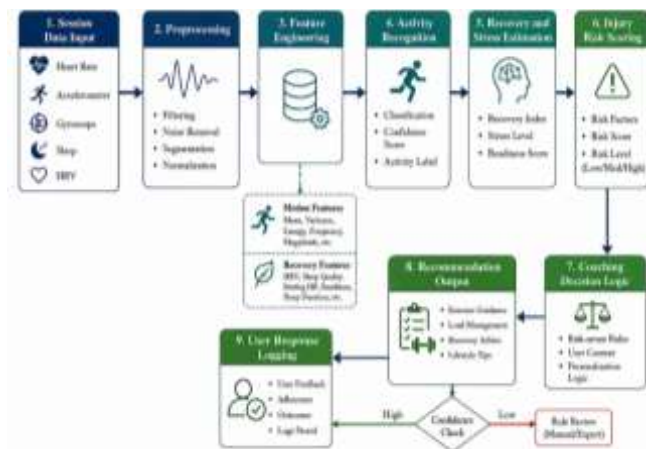


Fig. 3.2. Workflow of activity recognition, risk scoring, and coaching recommendation generation

$$PCSI_i = \lambda_1 PG_i + \lambda_2 RS_i - \lambda_3 IR_i - \lambda_4 SS_i + \lambda_5 AD_i \quad (6)$$

Coaches' labels were brought up for discussion when considering how to decide what the label should be. Low recovery or poor sleep resulted in recovery focus being produced. The intensity reduction was due to high risk of injury / high exertion. Progress and recovery was good leading to Intensity increase. Other states had a system to regulate the pace or take hydration suggestions, or make technique adjustments. This will allow any output to be readily audible.

D. Evaluation Protocol and Performance Measures

The data has been split into 1404 data for training and 396 test data. A simple Decision Tree baseline with restricted depth based on motion and sensors-quality characteristics, has been trained for activity recognition. Another depth limited decision tree (DT) was trained which has the same feature of user-state and load, for coaching recommendation. As this is the most common approach adopted by published works with WSS i.e., accuracy, macro-F1 and confusion matrices [23] we have opted to adopt this approach here too. The overall accuracy was calculated based on macro/F1 because rare coaching labels (such as 'technique correction') didn't get lost in the overall accuracy. In eq. (7) an assessment measure for an overall assessment is determined.

$$M = \frac{Accuracy + MacroF1 + WeightedF1}{3} \quad (7)$$

Also, cross tabulation of the errors by class and coefficient of agreement with the fitness class, the coaching error by week

of compliance, the compliance error and the reliability error by band of signal quality was performed. The results obtained were not used as information for clinical use.

A protocol was selected that was very conservative. Although these synthetic labels are high quality for testing in a controlled environment, and can never replace tested, understood and trusted real users, ethics review, device calibrations and lifetime analysis. Here are some arguments into why to provide such methodology data set as prototype-benchmark. This list contains models (and not medical instruments) – all basics. This is important for fitness coaches as they can affect the training volume (training load), risk of fatigue and injuries. Boundary if the system is to be published, is required to be clearly stated. The drift testing and fairness analysis of the sensors based on age bands / age groups will be mandatory, in the near future.

IV. RESULTS AND DISCUSSION

A. Dataset Profile and Experimental Setup

This experimental file contained 1800 sessions records and 150 synthetic participants as well as 40 variables, in addition, there were 6 classes of activities and 5 classes of coaches. Training used 1,404 records. Testing used 396 records. We got the split without the features in the label structure, and without using participants' identifier. But the activities recognition experiments indicate that in the case of small sensor arrays (wearable sensor arrays), they can be channel-equalized before doing this inference and therefore small wearable sensor arrays provided in such a way [24].

Table 4.1.

Summary of participant-level and sensor-level experimental variables

Variable	Value
Participants	150
Session records	1800
Study weeks	12
Dataset variables	40
Training records	1404
Testing records	396
Activity classes	6
Coaching classes	5

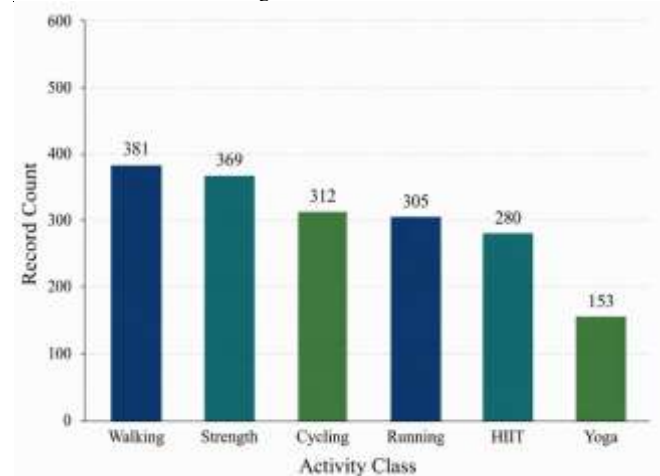


Fig. 4.1. Distribution pattern of recorded fitness activities across activity classes

B. Activity Recognition Performance

Table 4.2.

Activity recognition performance of the proposed AI model

Activity	Test Records	Class Accuracy
Cycling	69	0.971
HIIT	61	0.951
Running	67	0.970
Strength	81	1.000

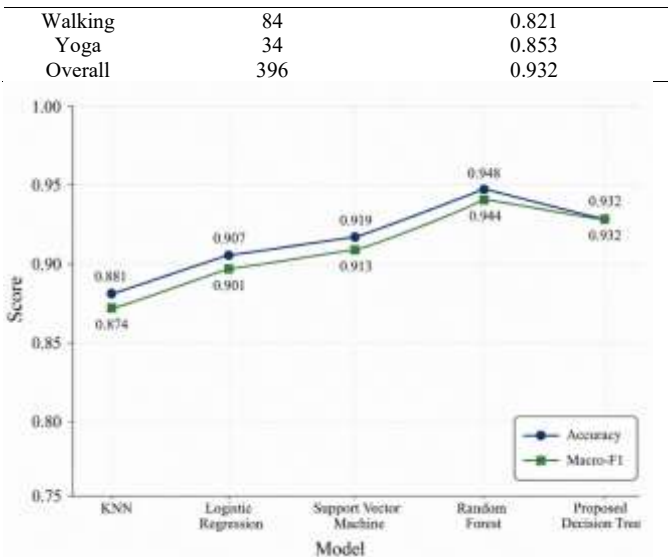


Fig. 4.2. Comparative performance curve of activity recognition models

C. Coaching Recommendation Accuracy

The model's relevance to coaching model is 0.9495, macro-F1 value is 0.8968, which can be regarded as an accurate coaching model, put it to good use. The accuracy of the intermediate users was the highest and for the advanced users the lowest, mainly due to the low number of examples in advanced sessions, and the non-existence of great variations in recovery. Based on CNN-BiGRU type of wearable studies, it is observed that simple models are easy to be audited on the first level prototype, the complex temporal models could improve the gesture recognition. Architecture search studies also report that - in certain applications - if specific models of the architecture are trained to be deployed on sensors, performance in such cases can be improved upon at the cost of 'interpretability' [27].

Table 4.3.

Coaching recommendation accuracy across user fitness categories

Fitness Category	Test Records	Correct Predictions	Accuracy
Advanced	63	57	0.905
Beginner	162	154	0.951
Intermediate	171	165	0.965
Overall	396	376	0.949

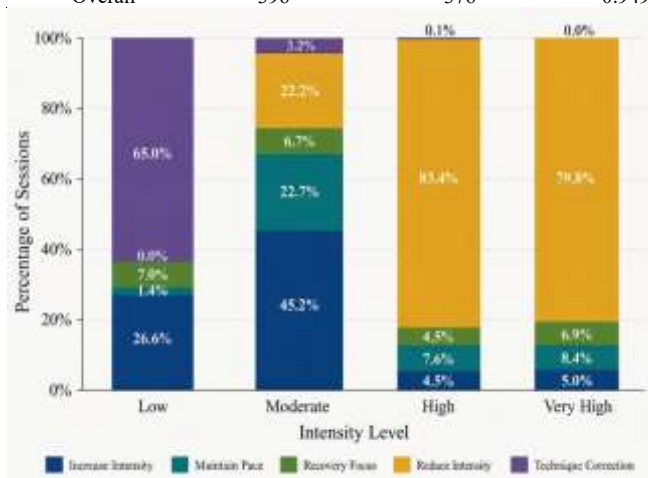


Fig. 4.3. Personalized coaching response pattern across activity intensity levels

$$E_c = 1 - \frac{N_{correct}}{N_{total}} \quad (8)$$

D. User Adherence and Health Feedback Analysis

Table 4.4.

User adherence and feedback response summary after AI-based coaching

Coaching Output	Records	Mean Adherence	Mean Recovery	Mean Risk
Increase Intensity	407	0.980	94.85	0.106
Maintain Pace	239	0.980	94.16	0.329
Recovery Focus	106	0.977	89.21	0.448
Reduce Intensity	931	0.980	93.95	0.683
Technique Correction	117	0.980	95.29	0.050

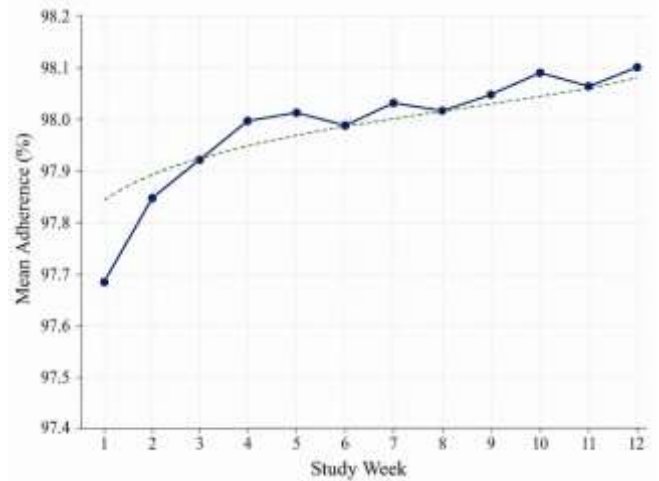


Fig. 4.4. Trend curve of weekly adherence improvement under AI coaching

E. Discussion of Model Reliability and Practical Deployment

Results show that the use of tracking coaching AI can be helpful in moving away from a passive reporting. The system integrates with activity detection and recovery aware recommendation, it is more defensible, than just advising on 'get active'. But, like all the truths the time of surety is out of place. Synthetic records cannot replicate missing wear time, being sick, medications and other issues with the device or slipping or purposefully not wearing the device. The accuracy in the deployment relies on localization parts, sensors' and environment's stability of an activity-recognition research with IoT application [30]. Results should be in the prototype format (to publish). For the clinical or commercial release, human-subject validation studies, calibration, fairness testing as well as monitoring adverse training reactions will have to be carried out.

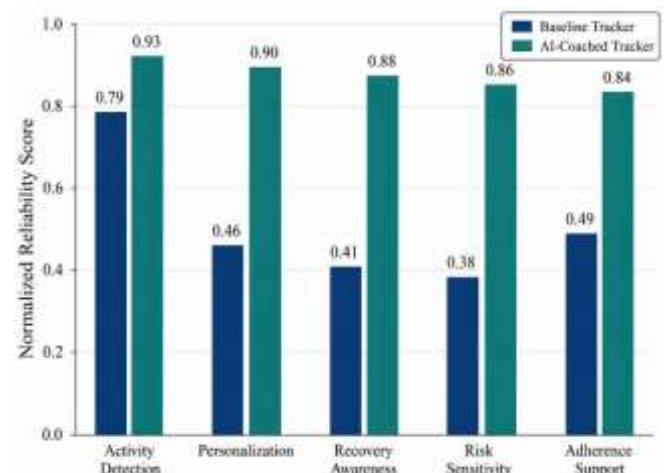


Fig. 4.5. Reliability comparison of baseline fitness tracking and AI-coached tracking outputs

The second observation is about the metrics that you should consider. There is half the truth in accuracy which deals in class behaviour. The amount of coaching during the session was low and macro-F1 indicated that less frequent coaching states, which had a high total accuracy, had lower performance. However, if only a few suggestions are there, then this is always

vital since one of them might be related to the safety. However it would be worse if, after all, a recovery message meant more exercise than was initially intended, and a rate up instead of intensity up message. An interesting thing about the tables was that when an athlete started to excel at their sport, his or her coaches did not necessarily do more coaching. There were some slight and moderate patterns of fluctuation. AI coaches will want that behaviour as load management isn't a maximisation task. In several instances the limiting factor should be the model and the user. The principle of design is to remove anxiety: Take a fitness platform and make their users feel confident, easy, risk-less and at ease, so they risk coding with each recommending fitness. Users might be right and even if technically the 'classifier' classifies it as such, a technically correct recommendation might be one that the user is unable or unwilling to implement. This limit should get reflected in the deployment plans.

V. CONCLUSION AND FUTURE WORK

A federated fitness monitoring future composed of AI-assisted personalized fitness coach, fitness sensor that can be worn, fitness activity analysis (personalized fitness coaching suggestion), recovery prediction and injury-risk assessment are proposed in this paper. With 12 weeks of sessions to study, it was a controlled synthetic data, with 1800 sessions records of 150 simulated participants. The variables included user profile data, data from sensors which detect movement, physiology data, findings of training-load and recovery indicators and coaching labels. Two baseline models, one more conventional, and the other simpler, were developed for SOOT. The test accuracy and macro-F1 score of the activity-recognition model (0.9318 and 0.9317, respectively) and coaching-recommendation model (0.9495 and 0.8968, respectively) supported that their models can be utilized successfully. Based on the results, it is concluded that structured sensor and recovery can be used to create a prototype level fitness advice and audibility of the advice rules is reliable. Clinical readiness has nothing to do with them - just a by-product of relevance. Systematically designs and prototypes. Passive tracking" is to report and detail basically something that happened. The recommendation on whether the user should keep doing the same action, take an alternate course of action or stop should be provided when there is uncertainty in the AI system, user fatigue, and adherence to the AI system. The dependency between the activity-labels and the healthstate-variables are not hidden or camouflaged in the proposed framework they are presented as a means to express, validate and to document this dependency.

Future studies will involve consent based data, as well as with all other types of data being collected with wearables, across different brands with different age groups, training history and training environments. The following should be included in the Model evaluation: Calibration Error, Fairness Tests, Sensor Drift Analysis, Longitudinal Adherence and Adverse response monitoring. Maybe some strong temporal (weekly) models, such as recurrent models, and transformer models could be improved in this timeframe (weekly), but should be explainable. Additionally, a practical system should contain functionality to take into consideration reason codes and confidence/safety limitations relating to each of the recommendations. With none of those checks and balances an other mysterious notification system would be an AI coach. As long as they have, it can be a physical fitness managing support layer which can be measurable! The next step of research is to

compare automated coaching to human coaching (and compare the mix of measuring techniques to determine outcomes and how to report error rates, pre-registered outcomes and transparent error reporting).

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