

CAREX: Comprehensive Adaptive Rehabilitation Expert – A Proposed AI-Powered Personalized Rehabilitation Platform

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Abstract

Effective rehabilitation following surgery, fracture, stroke, or sports injury occurs when rehabilitation is continuous, well-monitored, and adjusted according to the patient's recovery progress. In actual practice, however, continuous personalized care is hard to deliver: it is difficult for clinicians to see patients often enough to make accurate assessments and patients often need to report their own progress. The same standard exercise regimen is usually prescribed to patients regardless of their individual recovery progress. This article presents CAREX (Comprehensive Adaptive Rehabilitation Expert), an AI-based rehabilitation program aimed at overcoming this shortcoming. CAREX creates a rehabilitation profile of the patient based on the patient's age, medical condition, stage of recovery, and medical history, and combines this profile with data on the extent of exercise and the rate of progress made in order to develop a personalized exercise plan. With every new progress report, CAREX reads the patient recovery situation once again so that it can re-evaluate its recommendations and offer estimates of the expected recovery progress. A doctor dashboard serves as a communication point that allows medical professionals to monitor and modify the treatment plan. Taken together, these components are intended to make rehabilitation more consistent for the patient and easier to monitor for the clinician, without removing the clinician from the decision-making process.

Keywords: Adaptive rehabilitation; Artificial intelligence; Digital health; Recovery prediction; Telerehabilitation

1. Introduction

Rehabilitation is often the deciding factor in how well a patient recovers from an injury, a surgical procedure, or a neurological event such as a stroke. Good outcomes generally require regular exercise to be carried out by the patient, along with periodic reviews with a clinician. The way this has traditionally been delivered, however, involves in-person supervision plus the patient's honest and accurate reporting of their progress, and it is genuinely difficult for a clinician to know where they are between visits. Some patients find it challenging to keep up with their exercises, medications, and appointments amongst their other commitments. Artificial intelligence and digital health solutions can help to close this gap. Instead of prescribing the same rehabilitation pathway to all patients with the same diagnosis, a system which has an understanding of the patient's individual condition, age, recovery status, and treatment history can personalise its

recommendations to that person and update itself as the recovery progresses. It can also store a complete history of the patient's progress and display it to the clinician in a way that aids more informed decision-making, rather than relying on what a patient can remember at a short consultation. CAREX (Comprehensive Adaptive Rehabilitation Expert) is proposed in this proposal as a platform to connect patients and clinicians through the same digital interface. It generates a personalised schedule of exercises from patient information, tracks the rehabilitation progress continuously, and provides an outlook on the recovery that could be utilised by a clinician to aid in their own judgement. A dedicated dashboard for doctors allows the clinician to assess performance, review analytics, and modify a treatment plan from a remote location, reducing the amount of patient progress to be tracked manually. Medication and appointment reminders, structured

health reports, and an AI-based virtual assistant complement the platform. Together, they are intended to make life easier for the rehabilitation journey for the patient and for oversight to be provided by the clinician, while still remaining in the control of the clinician to make treatment decisions.

1.1.Related Work

Telerehabilitation has been investigated as an alternative to traditional forms of personal therapy for some time now. Laver et al. (2020) conducted a review of telerehabilitation services for post-stroke patients, evaluating effectiveness relative to traditional institutional therapy. Their analysis demonstrated that remote rehabilitation produced comparable results to conventional therapy in a number of considered settings, thus proving to be an effective substitute in terms of reducing the frequency of a patient's visits to a healthcare facility. However, none of the reviewed studies attempted to tackle the issue of personalized recommendations, focusing primarily on the logistics of delivering therapy from a remote location. An emerging body of research has devoted its attention to the role of artificial intelligence in physical rehabilitation as a tool for enabling personalized recommendations. Sumner et al. (2023) performed a systematic review of AI-enabled physical rehabilitation technologies. Their work provides an overview of the current state-of-the-art in the field, outlining the various methods, applications, and tools. In their review, Sumner et al. note the general ability of AI technologies to facilitate accessibility in physical rehabilitation and enable remote supervision while identifying a number of barriers stemming from technology readiness, technical literacy, fatigue, and the absence of clinical evaluation of such technologies. The issue of personalized recommendations has been approached from multiple angles in the literature. Kim et al. (2021) designed an AI-based recommendation system that employs a graph neural network to recommend personalized therapeutic exercises based on the individual patient's characteristics. The focus of their research was on the recommendation algorithm itself and the architecture of the graph, without considering broader aspects of therapeutic management, such as tracking of therapeutic progress, reminders, or post-therapeutic analysis and

evaluation in conjunction with medical professionals. On the other hand, Campagnini et al. (2022) performed a systematic review of the role of machine learning in outcome prediction in post-stroke rehabilitation. Their review identified a variety of studies employing ML technologies to predict patient outcomes based on various clinical and demographic features, utilizing both conventional statistical models and complex machine learning algorithms. The review highlighted the general limitations of the ML-based approach in this domain, including the lack of extensive validation data and consistency between studies, small sample sizes, and issues with generalizability stemming from inconsistencies between input variables and clinical predictors. The focus of Davigne et al.'s (2023) review was on digital interventions providing personalized video exercises, which analyzed the effect of such applications on adherence and outcomes through a meta-analysis. Their work demonstrated the general benefits of such personalized digital interventions while highlighting heterogeneity between the included studies. Similarly, Nussbaum et al. (2019)'s review focused on the role of mobile technologies in post-stroke rehabilitation, analyzing the current applications and evaluating their effectiveness. Their review highlighted the present limitations of mobile technologies in post-stroke rehabilitation, focusing on the lack of comprehensive tools, which are typically limited to providing a single function, such as tracking or training, as opposed to integrated solutions incorporating assessment, planning, prediction, and clinical management, such as CAREX. Kamalakannan et al. (2022a; 2022b) describe the development of a mobile application for upper limb rehabilitation, entitled ReWin, and evaluate its feasibility and acceptability among target users in India. Their work demonstrates that such applications are generally met with positive feedback from patients and caregivers. Gokul Prasath et al. (2066) performed a survey among occupational therapists in India regarding their use of mobile applications for neurological rehabilitation. Their findings identified the general level of adoption among medical professionals as low due to a combination of factors, including lack of awareness and compatibility with the existing practices. Finally,

Badhal et al. (2026)'s work focuses on developing an ethical AI framework for neurological rehabilitation, postulating that AI technologies should be utilized to complement rather than replace the role of clinicians, which is in alignment with CAREX's approach to the doctor dashboard, which focuses on physician assessment rather than attempting to replace it.

2. Method

CAREX is structured with five interconnected elements namely: a patient application, a backend service layer, a rehab database, an artificial intelligence system, and a health professionals' dashboard. The platform is designed to be used by patients undergoing rehabilitation after surgery, fracture, an injury related to sports, or stroke, as well as other related musculoskeletal conditions. Unlike traditional patient care, where each new consultation is seen as a discrete event, CAREX uses a continuous

2.1. System Architecture

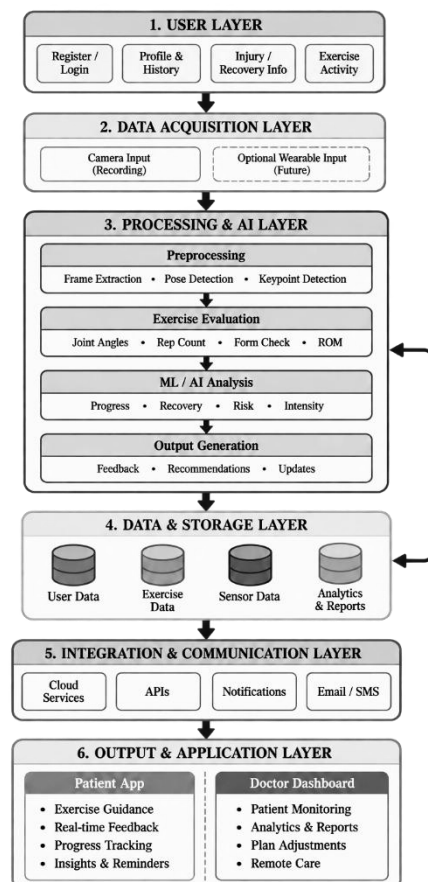


Figure 1 Architecture of the CAREX platform

The patient application collects information about the patient's status in addition to processing info and delivers them to CAREX backend which effectively manages data input and output to the signed database which provides data for the treatment and rehabilitation of patients. The backend user will get answers and information on their treatment in the AI system, including notifications about the possibilities of receiving the recommendation and predictions. The physician's console works parallel with this process and is receiving information from the backend and allows storing a new approach to treatment in the system[1 – 5].

2.2. Patient Data Preparation

A patient's state is treated as having two parts: relatively stable profile information and continuously changing recovery information. This can be written as

$$X = [X_p, X_r] \quad (1)$$

where X_p denotes profile attributes — medical condition, age, recovery stage, and treatment history — and X_r denotes rehabilitation information collected after treatment begins, such as exercise history and progress records. As the dataset contains both numerical and categorical features, it is preprocessed before it is executed in an AI engine. Specifically, categorical features are converted into a format compatible with computer systems while numeric ones get normalized to prevent dominance of any one feature in the model due to its specific scale. A value x is normalised as

$$x' = (x - x_{min}) / (x_{max} - x_{min}) \quad (2)$$

Historical rehabilitation records are also summarised into progress-related features that describe a patient's recent activity and recovery status, and it is this resulting feature vector that feeds into the profile-analysis and recovery-analysis stages that follow[6].

2.3. AI-Based Representation and Personalised Recommendation

The AI engine first builds an internal representation of the patient's profile, then a separate representation from the patient's rehabilitation history, and finally combines the two before generating any recommendation. This is expressed as

$$Z_p = f(X_p), \quad Z_r = g(R_t), \quad Z = F(Z_p, Z_r) \quad (3)$$

where R_t is the rehabilitation information accumulated up to time t . While Z_p identifies the

medical context of a patient, Z_r reflects the treatment response of the patient; this information can subsequently be processed by the downstream modules to reflect both aspects at once in their operation instead of viewing the diagnosis and the actual progress as independent occurrences. The recommendation engine then scores each candidate exercise e_i according to its fit with the current patient state [7 – 10]:

$$S(e_i) = w_1C_i + w_2R_i + w_3H_i + w_4P_i \quad (4)$$

where C_i , R_i , H_i , and P_i indicate, respectively, the appropriateness of the exercise according to the patient's condition, the appropriateness for the current recovery phase, the compatibility with treatment history, and the appropriateness of observed outcomes; and weights w_1 – w_4 show the relative importance of each criterion. Table 1 shows how each of these criteria is evaluated. The resulting scores give a ranking of exercises; only the highest ranked ones are selected to create the plan. The fact that the score is calculated in accordance with the features of the patient rather than only the diagnosis means that two patients diagnosed with the same condition receive different plans [11].

Table 1 Factors used in the exercise suitability score

Factor	What it captures
C_i	Compatibility with the patient's medical condition
R_i	Suitability for the current recovery stage
H_i	Consistency with treatment history
P_i	Fit with the patient's observed progress

2.4. Adaptive Feedback and Recovery Prediction

As the patient progresses through the recommended plan, new progress data flows back into the backend and into subsequent recovery analysis. The initial plan is never treated as fixed – later recommendations are generated from the updated patient state. A recovery prediction component estimates the likely path of recovery:

$$\hat{Y} = P(Z_p, Z_r) \quad (5)$$

This prediction should be used as an adjunct to monitoring and not as a sole basis for treatment. It is surfaced through the doctor dashboard where a clinician can accept, adjust or override the AI-generated plan based on their own judgment – a human-in-the-loop step of analysis, recommendation, professional review and an approved or modified plan. Supporting services, which are alongside this loop, aim to improve adherence and accessibility without replacing clinical supervision and include medication and appointment reminders, structured health reports and a conversational assistant for rehabilitation-related queries. [12]

3. Results And Discussion

3.1. Results

The results discussed in this section are the functional capabilities derived from the design specified in Section 2, and not measured clinical outcomes, since CAREX is presented here as a proposed system architecture and not a clinically deployed product. Structurally the design achieves three things that are usually only addressed individually in the literature reviewed. Finally, by separating profile information (X_p) from recovery information (X_r) and then recombining them before recommendation, the system can distinguish a patient's initial clinical context from their actual response to treatment instead of reducing both to a static diagnosis-to-exercise mapping. Second, the exercise score $S(e_i)$ is built on four independent factors, so the resulting plan changes in a traceable way when any of these factors changes. This is not the case for systems recommending only from diagnosis. Third, routing each plan and prediction generated by AI through the doctor dashboard before it reaches the patient keeps a clinician in the loop at each cycle, rather than only at scheduled visits—the same human-in-the-loop pattern that Badhal et al. (2026) argue for at a conceptual level. The resulting operating cycle is summarized in Figure 2: patient data is analyzed by the AI engine into a personalized plan, tracked through progress monitoring, fed back into recovery analysis and prediction, reviewed by a clinician, and finally fed back to the patient as an updated plan — at which point the cycle repeats using the newly observed progress. As shown in Figure 2 The

continuous feedback cycle underlying CAREX's operation [13]

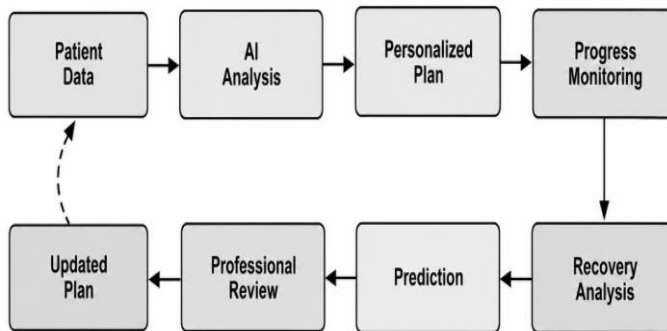


Figure 2 The continuous feedback cycle underlying CAREX's operation

3.2. Discussion

The main contribution of this design is not so much the single algorithm, but rather the way in which it integrates personalized recommendation, recovery prediction, clinician supervision and adherence support into a single profile per patient, separately addressed in Kim et al. (2021), Campagnini et al. (2022) and Nussbaum et al. (2019). But whether this actually improves outcomes in practice is a separate question from whether the architecture is coherent, and it can only be answered with real deployment.

This takes us directly to a couple of limitations. There the weights w_1 – w_4 in the recommendation score are treated as design parameters. In the absence of clinical data to fit or validate against, there is a real danger of a plan that looks reasonable on paper but is not actually well calibrated for a given condition, which echoes the validation concerns raised by Campagnini et al. (2022) about recovery-prediction models more generally. Technology literacy and user fatigue, as Sumner et al. (2023) also observe, limit the day-to-day use of AI-based rehabilitation tools, and CAREX is not immune to that: a patient who finds the application confusing or tiresome to use is unlikely to benefit from how well the recommendation engine performs behind the scenes. Gokul Prasath et al. (2026) describe a similar pattern among occupational therapists in India, where the uptake of mobile rehabilitation tools is heavily dependent on how well a tool fits into existing clinical workflow, which is as much a design and

change-management question as a technical one.

The present architecture makes the wearable part optional, and focuses on software and AI workflow. Extending [14] it to include continuous sensor data will narrow the recovery representation Z_r , but brings its own reliability and battery-life constraints, which is why it is not in the present scope. To summarise, the design can be considered a base, where certain parts – the recommendation weights, the prediction model, and the assistant's dialogue behaviour – would need to be individually clinically evaluated and validated before the platform could be used without supervision [15].

Conclusion

CAREX offers personalised exercise planning, continuous progress tracking, recovery forecasting and clinician oversight in a single platform, aiming to decrease the reliance of conventional rehabilitation on face-to-face visits and self-reported progress, while maintaining clinician control over every treatment decision. A review of the literature reveals that telerehabilitation, AI-based exercise recommendation, and machine-learning outcome prediction have been studied separately with promising, but methodologically limited results (Laver et al., 2020; Sumner et al., 2023; Campagnini et al., 2022). CAREX's contribution is to combine these components in a single adaptive environment, rather than proposing a new algorithm for any one of them. The architecture described here is a first step and not a finished product. The next steps are to fit and validate the recommendation weights and prediction model against real clinical data, run the platform through a real-world evaluation with patients and clinicians, and bolster the security and privacy protections that any system handling health data needs before it can be used at scale.

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