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Original Article

Social Network Analysis and Behavioral Insights to Enhance Patient Engagement in Chiropractic Care: A Quasi-Experimental Study Using Virtual Reality and Deep Learning

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ABSTRACT

Background: Chiropractic care is widely applied for pain relief and musculoskeletal improvement, yet limited emotional support and one-way communication may reduce trust and engagement. This quasi-experimental study aimed to examine the effect of a mobile Augmented Reality Application (ARA), combined with a Convolutional Neural Network (CNN) predictive model, on enhancing patient satisfaction, adherence, and clinical outcomes within chiropractic care.

Methods: A pre-test post-test quasi-experimental design was implemented from January to December 2022 in a private chiropractic clinic in Mashhad, Iran. Out of 73 eligible patients with musculoskeletal disorders, 51 completed the study, with low back pain and neck pain being the most common issues reported. Participants were randomly assigned to an intervention group (n=21; standard care + ARA app) or control group (n=30; standard care only). Outcomes included functional performance (mental health, vitality, social functioning, disability, and kinesiophobia), treatment satisfaction, and adherence. Assessments were conducted at baseline and weeks 3, 5, and 8 using validated tools, including the 12-item Short Form Health Survey Questionnaire (SF-12) and the Fear Avoidance and Belief Questionnaire (FABQ). The satisfaction rate was assessed at week 8 using a 10-item questionnaire developed by the research team, while treatment adherence was monitored by app usage in the intervention group or clinic attendance in the control group.

Results: By the eighth week, the intervention group reported higher satisfaction (91.6±6.5) compared to the control group (63.3±12.5; P<0.01). Significant improvements were observed in functional performance measures, including mental health, vitality, social functioning, and fear avoidance (P<0.01). A positive correlation was also found between adherence and satisfaction (r=0.402, P=0.003). The CNN model demonstrated moderate predictive accuracy with a Root Mean Squared Error (RMSE) of 0.1121 and a correlation coefficient of 0.1491 (P<0.01).

Conclusion: The ARA app significantly improved outcomes, suggesting a scalable, patient-centered digital strategy. However, further extensive and long-term trials are recommended to validate its scalability.

Keywords: Chiropractic, Mobile Applications, Neural Networks, Patient Satisfaction, Musculoskeletal Pain, Augmented Reality, Telemedicine

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Introduction

Musculoskeletal Disorders (MSDs) have become increasingly common due to the widespread use of electronic devices such as mobile phones and computers, along with sedentary lifestyles, physical inactivity, and obesity. A range of factors contribute to the development of these conditions, including physical, organizational, and social aspects of both the workplace and daily life, as well as individual physiological characteristics (1).

Work-related MSDs impose a significant economic burden on healthcare systems, with direct costs such as medical care and rehabilitation, and indirect costs including disability, lost wages, and reduced productivity (2, 3).

According to national surveys, lower limbs—particularly the lower back and knees—are most commonly affected, while neck-related injuries are most prevalent among upper limbs (4). Beyond physical pain, MSDs often contribute to psychological stress, exacerbating social isolation and emotional burden.

Chiropractic care, which emphasizes addressing the root causes of musculoskeletal problems through non-invasive methods, offers an alternative to conventional treatments. However, many patients still seek surgical interventions, often due to the expectation of rapid results. Evidence suggests that chiropractic care can significantly reduce the use of advanced imaging, surgical procedures, and hospitalizations for conditions such as low back and neck pain (5) Despite these benefits, chiropractic care remains underutilized, with only an estimated 5–10% of adults in North America seeking such services annually—a trend often attributed to limited public awareness, misinformation, and skepticism among both patients and healthcare providers (6).

Building trust and improving communication between chiropractors and patients is essential to increasing adherence to treatment plans. The COVID-19 pandemic highlighted these challenges, with reduced access to care, increased psychological distress, and sedentary lifestyles worsening existing pain conditions (7). With the rise of Mobile Health (mHealth) technologies and widespread smartphone usage (8), there is a growing opportunity to integrate digital interventions into chiropractic care. Social networks significantly influence health behaviors, with platforms enabling patients to exchange experiences and obtain support demonstrating potential to improve engagement and adherence (9). Additionally, social media acts as a valuable channel for disseminating both users' and healthcare providers' beliefs, attitudes, and experiences regarding Complementary and Alternative Medicine (CAM), while also providing an accessible, efficient, and practical way to deliver CAM therapies and related information. Leveraging this dynamic, we propose an innovative approach that integrates social network analysis into chiropractic care. By harnessing data from social interactions, patient communities, and online health forums, we aim to gain insights into patients' perceptions, concerns, and experiences related to chiropractic care. This information can guide healthcare providers in tailoring their communication strategies, addressing misconceptions, and building trust.

This study introduces an innovative model that combines Social Network Analysis (SNA) with an Augmented Reality (AR)–based mobile application to improve chiropractic care delivery. The SNA allows for the examination of peer interactions, influence patterns, and community behavior, enabling more tailored and effective patient engagement strategies.

To enhance the personalization of care, we integrated a Convolutional Neural Network (CNN) model into the application. The CNN uses patients' Magnetic Resonance Imaging (MRI) images to predict treatment outcomes, with attention maps identifying the anatomical areas most related to clinical improvement. These predictions are visualized through AR, allowing patients to see their likely treatment trajectory in an intuitive and motivating way.

The AR features allow patients to interact with educational content, track their exercise progress, and view predicted recovery paths. These tools foster a sense of control and transparency, thereby reducing anxiety and promoting consistent participation in care. Furthermore, virtual incentives, peer support features, and real-time feedback are embedded within the app to sustain long-term engagement.

By integrating deep learning, AR visualization, and social network engagement, we aimed to create a holistic digital framework that empowers patients, strengthens chiropractor-patient communication, and improves treatment outcomes. Incorporating social network analysis, AR-based patient visualization, and CNN-based prediction models into a chiropractic mobile application was proposed to enhance the patient satisfaction, adherence, and clinical improvement compared to standard chiropractic care. Accordingly, the main objective was to strengthen engagement and treatment adherence by visualizing predicted recovery pathways and facilitating peer support.

Methods

Study Design and Setting

This pre-test post-test quasi-experimental study was conducted at a private chiropractic clinic in Mashhad, Iran, from January to December 2022. The study aimed to evaluate the effectiveness of a mobile application—Augmented Reality Application (ARA)—that integrates CNN, AR, and social interaction to improve patient engagement, clinical outcomes, and satisfaction in chiropractic care.

Participants and Sampling

The study recruited 51 participants using consecutive sampling from a chiropractic clinic. Among the 73 eligible patients, 22 were excluded either because they were not interested or did not fulfill the inclusion criteria, leading to a final sample size of 51. Participants were allocated to two groups using simple randomization performed in SPSS v26 with random number generation and case sorting: the intervention group (n=21), which received standard chiropractic care enhanced with the ARA, and the control group (n=30), which received only standard chiropractic care. Allocation concealment was ensured using sequentially numbered, opaque, sealed envelopes prepared by a researcher who was not involved in participant enrollment. Due to the nature of the intervention, participants were aware of their group assignment, but data analysts and outcome assessors were blinded to reduce bias.

Inclusion criteria included adults aged 18–65 years with a diagnosed musculoskeletal condition (e.g., low back pain or neck pain), having undergone at least four weeks of chiropractic treatment prior to the study, willingness to provide informed consent, and ability to use mobile applications (for the intervention group). Exclusion criteria included acute trauma, neurological disorders, or severe cognitive/physical limitations preventing protocol adherence.

Due to recruitment constraints, the maximum feasible sample size was 51 participants. No prior studies with an identical design and intervention were available to justify this sample size a priori. Therefore, post hoc power analysis was conducted based on the observed effect size in patient satisfaction scores at week 8. The analysis yielded a statistical power of approximately 65%, which, despite being lower than the standard 80% threshold, was considered acceptable given the large observed effect size (Cohen's d=2.702). The overall patient recruitment process, including eligibility screening, randomization, allocation to intervention and control groups, and follow-up, is illustrated in the participants' recruitment flow diagram (Figure 1).

Procedures / Intervention

Patients meeting the eligibility criteria completed baseline (pre-test) questionnaires to assess their functional performance. Both groups were monitored for 12 weeks, with assessments conducted at baseline and at weeks 3, 5, and 8 (post-tests).

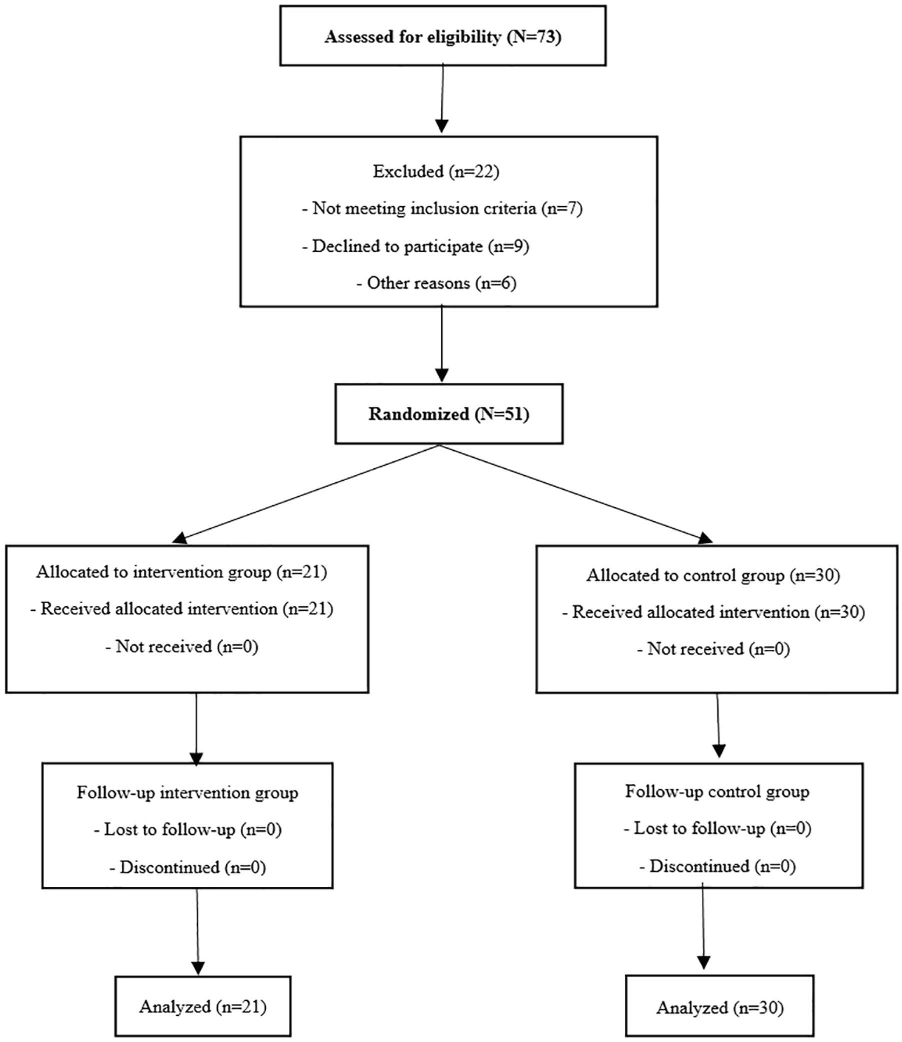

Figure 1: Participants recruitment flow diagram

The intervention and control groups received equivalent educational content over an 8-week program, covering identical topics (posture, rehabilitation, motivation) and instructional objectives (pain reduction, engagement, and self-care).

The intervention group received standard chiropractic care enhanced with ARA features, including guided exercises, educational materials, MRI-based predictive models, and AR visualization. Conversely, the control group received only the standard chiropractic care without the use of the app.

Intervention Group: The mobile application was primarily used as an intervention tool in the experimental group. It provided patients with personalized exercise recommendations, 3D augmented reality-based treatment visualization, predictive outcome estimates through CNN analysis of MRI scans, and peer engagement via a social support module. Upon first login, patients viewed a short welcome video explaining chiropractic concepts, study goals, and app navigation. Patients entered demographic and health-related data and uploaded their MRI scans via the app. These MRI images were processed by a CNN to predict treatment outcomes and satisfaction likelihood. Results were displayed through AR as a projected spinal image highlighting areas of concern (e.g., disc herniation) and estimated improvements. Saliency maps were generated to identify image regions most relevant for diagnosis and provided to the chiropractor to enhance diagnostic accuracy and treatment planning. The predicted satisfaction rate was displayed to patients in AR format to enhance motivation.

The ARA mobile app was created as an all-inclusive resource to improve patient education and involvement in chiropractic care. Its development was carried out by a multidisciplinary team comprising a PhD in biostatistics, a PhD in statistics, a Doctor of chiropractic with clinical neurology certification and over 15 years of experience, two orthopedic specialists with MSc degrees and more than a decade of clinical practice each, two MSc software engineers expert in health informatics and app development, and a medical educator with 12 years of expertise in adult education and instructional design. The educational materials were based on international chiropractic standards, evidence-based rehabilitation approaches—including WHO recommendations for musculoskeletal health—and authoritative references such as the National Institute for Health and Care Excellence (NICE) Guidelines for musculoskeletal disorders (10), World Federation of Chiropractic guidelines (11), and peer-reviewed research on digital rehabilitation, telehealth, and behavioral change models (12-14).

The ARA mobile app aimed to improve patients' self-management skills, functional literacy, and treatment adherence through several key objectives: enhancing understanding of chiropractic care mechanisms, promoting correct execution of home-based rehabilitation exercises, fostering motivation through feedback and community support, and building trust via transparent visualization of treatment effects. Upon first login, patients viewed a welcome video explaining chiropractic concepts, study goals, and app navigation. Users entered demographic and health-related data, and their MRI scans were uploaded for analysis by a CNN. The CNN processed MRI data to predict treatment response and satisfaction likelihood, displaying results through AR as a projected spinal image highlighting areas of concern and estimated improvements.

The ARA provided a range of features tailored to patients' needs. Personalized exercise modules, based on chiropractor input, included weekly sessions focused on spinal stabilization, core strength, posture training, joint mobility, and daily health tips delivered via text and video. Nutrition and lifestyle guidance provided individualized dietary plans and supplement recommendations (e.g., anti-inflammatory foods, vitamin D, and magnesium), with automated reminders for supplement intake and a tracking system to monitor adherence.

Patients were able to see anonymized progress data of their peers through social networking features, as well as like, comment, message, and directly pose questions to their chiropractor. Motivational elements involved tracking the completed sessions, awarding virtual badges, and providing weekly progress summaries with tailored behavioral nudges. Weekly push notifications summarized performance, with reminders sent within 24 hours for missed sessions. During in-person chiropractic sessions, clinicians reviewed app-generated weekly progress reports covering exercise completion, supplement adherence, and engagement with educational modules. Based on this, chiropractors assigned performance ratings within the app to enhance motivation. The app also displayed patients' performance scores to other users, along with the total points earned weekly and the name of the chiropractor providing feedback, accompanied by motivational messages based on the score.

The application's network connectivity was facilitated through a Representational State Transfer (REST) API model, implemented in an Android app built using Android Studio with Kotlin, Java, and the Vuforia AR Software Development Kit (SDK). Screenshots from the application pages are presented in Figure 2.

Control Group: The control group received all the related content verbally and through printed leaflets during clinic visits, delivered by the same chiropractic educator to ensure consistency. MRI images were gathered manually—either handed over in person or through physical storage devices—and then entered into the CNN for predicting treatment results and patient satisfaction

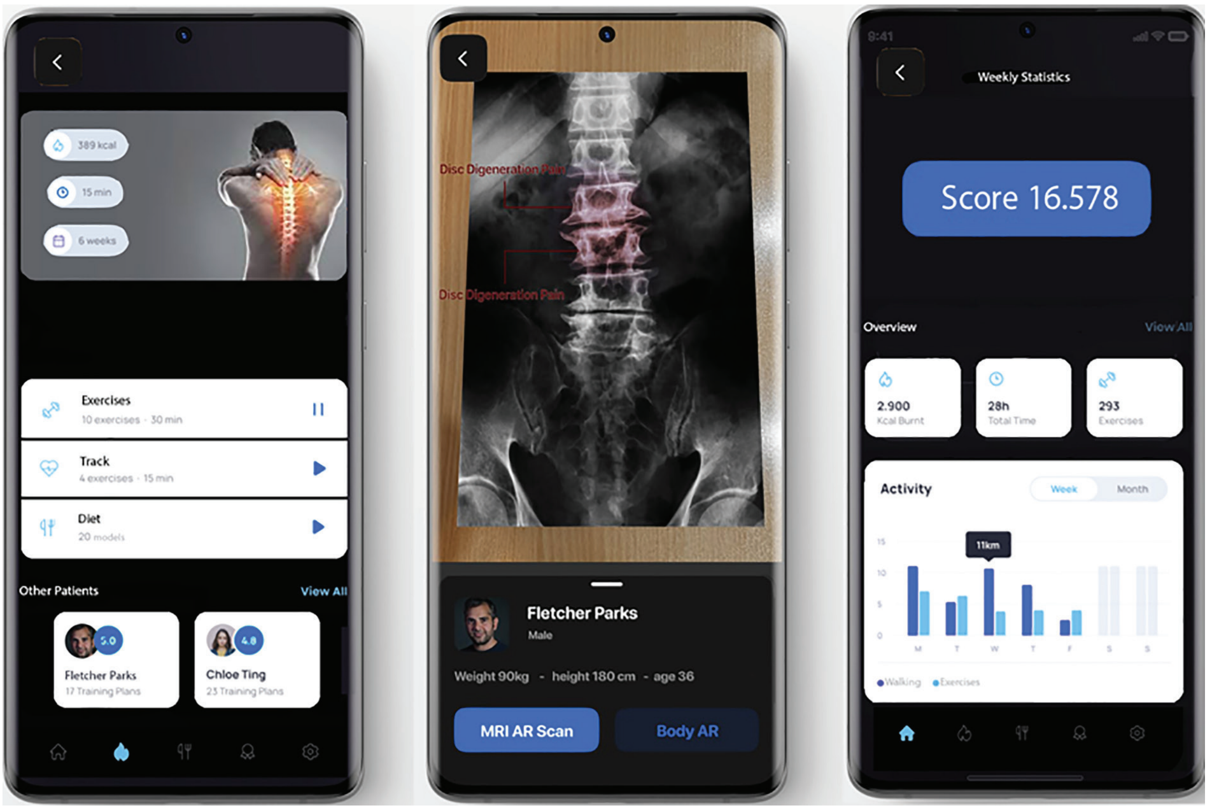

Figure 2: Screenshots from the Augmented Reality Application (ARA)

Tools/ Instruments

In this study, the functional performance was defined as physical and psychosocial outcomes measured through validated components of the functional assessment questionnaire, including “mental health/ social functioning”, “energy/vitality,” and “fear avoidance” domains.

Mental health **and** ***social functioning*** scores were derived from the 12-item Short Form Health Survey Questionnaire (SF-12), which included 2 items assessing psychological well-being (e.g., “Have you felt calm and peaceful?”). Items were rated on a 5-point Likert scale (1=all of the time, 5=none of the time). Scores were weighted and normalized to 0–100, with higher scores indicating better mental health (15).

Energy (vitality) was measured using the vitality subscale of the SF-12, which included 1–2 items assessing energy levels and fatigue (e.g., “Did you have a lot of energy?”). Items were rated on a 5-point Likert scale. Scores were normalized to 0–100, with higher scores indicating greater vitality.

Validity and Reliability - The SF-12 vitality subscale has shown good reliability, with Cronbach’s alpha values between 0.65 and 0.75 across various studies, indicating acceptable internal consistency. Test-retest reliability coefficients typically range from 0.70 to 0.80 over short intervals (e.g., 1-2 weeks). Construct validity is supported by strong correlations with the longer SF-36 vitality subscale (r>0.90) and moderate correlations with measures of fatigue and energy levels (e.g., r=0.60-0.70 with the Fatigue Severity Scale). Criterion validity is evidenced by its ability to discriminate between healthy populations and those with chronic conditions affecting vitality, such as depression or musculoskeletal disorders, with relative validity estimates for the mental component summary (including vitality) reaching a median of 0.97 in tests involving mental health criteria (16, 17).

Fear avoidance was measured using the Fear Avoidance Beliefs Questionnaire (FABQ), which included 16 items, with four items for the physical activity subscale (e.g., “Physical activity might harm my back”). Items were rated on a 7-point Likert scale

(0=completely disagree, 6=completely agree). Scores were normalized to 0–100, with lower scores indicating reduced fear-avoidance behaviors (18).

All domain scores were converted to a 0–100 scale, with higher scores representing better status for mental health, energy/vitality, and social functioning, and the lower scores indicating reduced fear avoidance. The questionnaire featured yes/no, multiple-choice, and Likert scale items (4- and 7-point formats). Data normality was confirmed using the Shapiro–Wilk test.

Validity and Reliability - The FABQ exhibits good reliability, with Cronbach's alpha for the Physical Activity Subscale (FABQ-PA) typically ranging from 0.77 to 0.88, indicating strong internal consistency. Test-retest reliability is high, with Intraclass Correlation Coefficients (ICC) of 0.74-0.95 over 1-2 weeks. Construct validity is well-established through correlations with measures of disability (e.g., r=0.50-0.70 with the Roland-Morris Disability Questionnaire) and pain intensity (e.g., r=0.40-0.60 with Quadruple Visual Analogue Scale scores). Criterion validity is supported by its predictive ability for work-related outcomes and chronic pain persistence, discriminating between patients with high vs. low fear-avoidance behaviors (P<0.01 in several previous studies). The questionnaire has been validated in diverse populations, including those with upper extremity injuries, with acceptable factor structure and no floor/ceiling effects (18, 19).

Satisfaction questionnaire: A 10-item satisfaction and adherence questionnaire, developed by the research team and validated by a panel of seven experts, was employed to measure patients' satisfaction following the 8-week intervention. Items were rated on a 5-point Likert scale (1=strongly disagree, 5=strongly agree), yielding a total score ranging from 10 to 50, with higher scores indicating greater satisfaction and adherence.

Validity and Reliability - Content validity was confirmed by a panel of experts, and the instrument demonstrated high internal consistency with a Cronbach's alpha of 0.88.

Clinical improvement and adherence tracking: Clinical improvement was assessed by analyzing changes in functional performance scores across four intervals: baseline (prior to intervention), and at weeks 3, 5, and 8 post-treatment commencement. Treatment satisfaction was assessed once at week 8 using the validated 10-item satisfaction and adherence questionnaire, developed by the research team, validated by a panel of seven experts, and rated on a 5-point Likert scale. The total satisfaction score was converted to a 0–100 scale, where higher values indicated greater satisfaction. Adherence was defined as the proportion of prescribed sessions and activities completed during the intervention period. For the intervention group, adherence was monitored by the ARA app logs (exercise completion, educational module viewing, supplement tracking), while for the control group was recorded based on clinic attendance.

Data Collection

Data collection took place between January 1 and December 31, 2022, at a chiropractic clinic in Mashhad, Iran, focusing on patients' satisfaction, functional performance (mental health, energy/vitality, social functioning, and fear avoidance), intervals between visits, total visit count, and MRI images.

Data were gathered using structured questionnaires and digital usage logs from the ARA mobile app. Clinical data (e.g., intervals between visits, total visit count) were extracted from electronic medical records, and adherence data were collected via ARA mobile app logs for the intervention group and clinic attendance records for the control group.

For the intervention group (n=21), questionnaires were distributed electronically via the ARA mobile app at all required intervals (baseline, weeks 3, 5, and 8 for functional performance; baseline and week 8 for satisfaction). Participants received a secure link within the app to complete the questionnaires, with a 48-hour window to respond. Automated reminders were sent via app notifications if questionnaires were not completed on time.

For the control group (n=30), questionnaires were administered manually during clinic visits using paper-based forms provided by a research assistant at the same time points (baseline, weeks 3, 5, and 8 for functional performance; baseline and week 8 for satisfaction). Participants were given a 24-hour window to complete the satisfaction questionnaire, with one phone call reminder if needed. Each questionnaire took approximately 5–20 minutes to complete, depending on the number of items.

Clinical photographs were obtained prior to chiropractic sessions for all participants to assess physical status (e.g., posture, spinal alignment). MRI images were collected from all patients for diagnostic and predictive purposes. Within the intervention group, patients viewed a short educational video via the ARA app explaining chiropractic methods and study goals upon the first login. These individuals subsequently uploaded their MRI images through the app, which were processed by a CNN to predict treatment outcomes and the probability of patient satisfaction. For those in the control group, MRI images were collected manually (delivered in person or through physical media), then digitized and processed using the same CNN predictive algorithm. Saliency maps were generated for both groups, highlighting significant image features such as disc herniation and spinal alignment anomalies, and these were supplied to the chiropractor to improve diagnostic precision and inform therapeutic strategies. In the intervention group, the predicted satisfaction and clinical outcomes were presented to patients using AR as a visual spinal model to boost motivation. By contrast, predicted outcomes were not visualized but were compared with actual satisfaction scores collected via questionnaires. All MRI images were securely archived within the clinic's electronic medical record system.

Participants were recruited consecutively from patients attending the chiropractic clinic, with a trained research assistant screening all entrants for eligibility during the study period. Those in the intervention group received a 10-minute training on app use during their first visit after enrollment, which covered how to watch the educational video and upload MRI images, alongside available technical support via phone or email.

For the intervention group, electronic questionnaire responses and MRI data were automatically recorded in the ARA app's database, with built-in validation ensuring responses fell within acceptable ranges. Control group questionnaire data, gathered on paper forms, were manually entered into a secure, password-protected Excel spreadsheet by a research assistant. Digitized MRIs from the control group were processed by the CNN to predict satisfaction, which was then compared with actual questionnaire responses. All entries were double-checked for accuracy, and random audits were conducted to verify data integrity. Any discrepancies, such as missing or invalid data, were addressed by contacting participants. A blinded statistician performed data cleaning and analysis using SPSS v26 to minimize bias. No participants were lost to follow-up, resulting in a 100% response rate for all questionnaires.

Data Analysis

All data were analyzed using SPSS version 26. The statistical tests included independent samples t-tests, Repeated Measures Analysis of Variances (ANOVA), chi-square tests, and Pearson correlation. A p-value of less than 0.05 was considered statistically significant.

Paired and independent-sample t-tests, Pearson correlation coefficients, and one-way repeated measures ANOVA were applied where appropriate to compare intra- and inter-group differences. The threshold for statistical significance was set at $P<0.05$.

Descriptive statistics including means, standard deviations, frequencies, and percentages were applied to summarize demographic variables and primary outcome measures, including satisfaction, clinical improvement, and treatment adherence. All questionnaire-based scores were normalized to a 0–100 scale for consistency. The Shapiro–Wilk test was used to verify the normal distribution of these scores.

Between-group comparisons were conducted using independent samples t-tests for continuous variables (e.g., satisfaction scores) and chi-square tests for categorical variables (e.g., gender), to compare groups at each of the four intervals: baseline (pre-intervention), and weeks 3, 5, and 8.

Within-group changes over time were evaluated using repeated measures ANOVA for normally distributed continuous variables. Post hoc pairwise comparisons with Bonferroni correction were applied when statistically significant effects were observed. For non-normal or ordinal data, Friedman's test was used.

Pearson correlation analysis was used to explore associations between continuous variables, including the correlation between app usage metrics (e.g., number of completed sessions) and satisfaction scores.

For Machine Learning (ML) evaluation, the predictive validity of the CNN model embedded in the ARA app was tested. Predicted satisfaction scores were compared to patient-reported satisfaction using Root Mean Square Error (RMSE) and Pearson correlation coefficient (r).

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{1}{n}\left(y_i - y_i\quad\right)^2}$$

Where y_i is the actual value, and $\hat{y}_i$ is the predicted value.
Accuracy: >85%

The CNN model demonstrated acceptable predictive performance with RMSE=0.1121 and a statistically significant correlation (r=0.1491, P<0.001).

A two-tailed P-value<0.05 was considered statistically significant. To ensure data reliability, all entries were double-checked and random accuracy audits were conducted during data processing.

Participants were assessed at the end of week 8 using a researcher-developed patient satisfaction questionnaire. Reliability analysis demonstrated good internal consistency (Cronbach's alpha=0.88). In addition, content validity was confirmed by expert review, supporting the appropriateness of the instrument for this study.

Their images were obtained prior to the chiropractic sessions. At the end of the sessions, the participants' satisfaction rates were calculated using the satisfaction rate formula:
w1×Patient satisfaction+w2×Chiropractor satisfaction rate

Here w1 is the weight for patient's satisfaction rate and w2 is chiropractor's opinion and w1+w2=1. In this paper, we considered w1=0.6 and w2=0.4. The satisfaction rate would be a number between 0 and 100.

Predictions Modeling

This section is divided in two parts. The first part involved training and prediction, which included three steps: data pre-processing, neural network learning, and testing out the learned model. MRI images from both the intervention and control groups were used as inputs for the CNN to predict treatment outcomes and patients satisfaction. For the intervention group, MRIs were uploaded via the ARA app, while for the control group were manually entered into the CNN.

Pre-processing is one of the easiest parts of model learning and yet one of the most important. Initially, the images were resized to 3×64×64 pixels to facilitate faster learning and normalization. Then, normalization was applied by scaling and centering the pixel values to a range between 0 and 1. This normalization step was essential for achieving more stable and accurate model performance (20).

$$\breve{X} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

In this Equation, X indicates the training values, X_{min} indicates the minimum values, and X_{max} indicates the maximum values.

The normalized data were integrated into a matrix for input into the learning model. This model was implemented using a CNN network (21). The CNN employs convolutional layers to generate feature maps, while pooling layers extract key features and enable regression via feedforward processes. The pooling layer decreases the spatial dimensions (width and height) of the input image, which reduces the number of parameters and computational load in the network, thereby helping to prevent overfitting. Pooling is applied independently to each deep slice of the input volume and spatially performs dimensionality reduction using the Excel MAX function (22).

Figure 3 shows the structure of this network. The dropout layer enhanced the model's resistant against noise. The dropout layer was another part of the defined artificial neuron and was selectively deactivated during training. This forces the network to reliably produce the same output, and it is consistently applied in CNNs to reduce overfitting (23).

The convolutional networks need massive amounts of data to learn from, and the 6-fold verification approach could make the model fit better.

The training of the network is by n samples, and the training and evaluating of the model is by the Leave One Out Cross Validation (LOOCV) approach. In the employed CNN model, n-1 samples were used to train the CNN model, while the remaining n^{th} sample served as the test case. This process was repeated n times, ensuring each sample was used once as a test set. Consequently, the model was only tested on data it had not been trained on. The quality of the prediction was evaluated using two factors: RMSE (the less R, the better) and Pearson correlation (the higher R, the better). The model's performance metrics are detailed in the results section.

The CNN model designed to predict patient improvement was trained on 73 patient records using an 80/20 train-test split. Specifically, the model's output represents a predicted percentage, $y_i \in [0,1]$, based on the input MRI defined by x_i. During the training phase, CNN determines the patterns in the training dataset. MRIs are presented to the network to produce an output $\hat{y}_i$. The output from the network was compared to the student output, and an objective function was defined as:

$$\sum_{i=1}^{\tilde{n}} \|y_i - \hat{y}_i\|$$

Where $\tilde{n}$ is the number of training samples.

Typically, large datasets are needed to train CNNs; however, our dataset was small. Similar to other works, we reinforced a series of data during each training session (24). Reinforced data from the training set was augmented into the dataset, and then network was trained with the augmented dataset. Furthermore, the network was pre-trained on the large ImageLet dataset (25) in order to reduce training data requirements.

The training and testing steps are detailed in Figures 4 (a) and (b), respectively. To discuss the results, we utilized saliency maps to explain trained CNN predictions. Saliency maps were built from the output gradients on the input that highlight the parts of the images associated with our predictions (Figure 4 (c)).

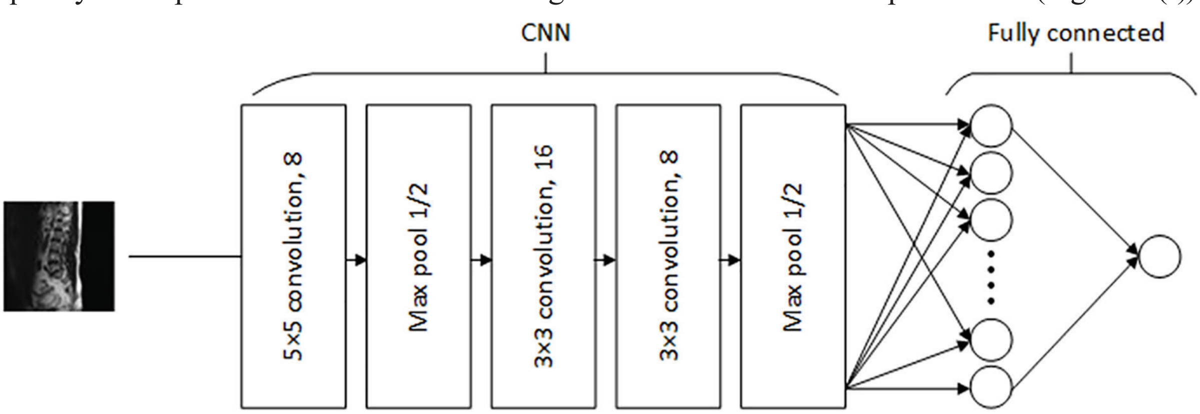

Figure 3: The study's CNN architecture; *CNN: Convolutional Neural Network

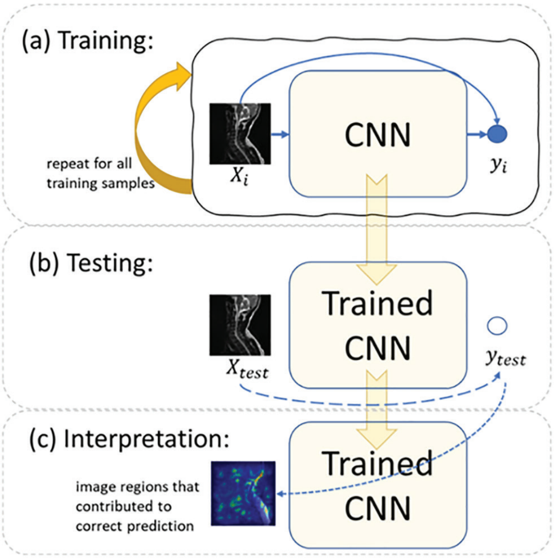

Figure 4: Training, testing, and interpretation of the CNN model used in this study. *CNN: Convolutional Neural Network

This approach enabled us to identify the pixels most responsible for inaccurate predictions of future satisfaction. For instance, in one case, the MRI region displaying substantial disc herniation indicated satisfaction following chiropractic treatment only to a limited degree. The saliency maps were produced using the Gradient-Weighted Class Activation Mapping (Grad-CAM) technique (26).

Besides using saliency maps, we analyzed the characteristics that the CNN model had acquired. The attributes obtained from the final convolutional layers are considered the features learned by the model. To illustrate the features in two-dimensional space, we utilized "t-distributed Stochastic Neighbor Embedding" (tSNE), commonly implemented to reduce the dimensionality of high-dimensional data. It is important to note that tSNE maintains the same neighbor structure with a lower dimension, making it particularly effective for visualization purposes.

In Figure 4, the learned feature space of our model is depicted. Each point represents a training instance, with its color reflecting the corresponding level of satisfaction. The plot clearly demonstrates that the model arranged the features such that individuals with lower satisfaction levels appear on the left, progressively increasing toward those with higher satisfaction on the right. This arrangement highlights that the algorithm successfully captured the underlying structure and constructed a meaningful feature space.

The saliency maps highlight the portions of the MRI imprints that contributed most significantly to the model's predictions. Several examples are presented in Figure 5. To validate these findings, a chiropractor was consulted to independently identify relevant regions on the MRIs, after which these were compared to the saliency maps. In most cases, there was a high degrees of agreement between the saliency maps and the areas suggested by the chiropractor. As an example, in Figure 6 (a), the saliency map identified mild compression of the right nerve root causing discomfort in the lumbar spinal surface and surrounding soft tissues—areas considered critical for predicting patient satisfaction. Likewise, in Figure 6 (c-d) the problem areas C4-5 to C6-7 are segmental surfaces relating to arm and hand pain, anterior and posterior regions of the neck, throat, voice box, and upper back. However, some cases demonstrated discrepancies: the saliency maps sometimes highlighted MRI regions not noted by the chiropractor. This suggests that the predictive model may consider additional or different features than those selected by the human expert, potentially providing more comprehensive diagnostic insights.

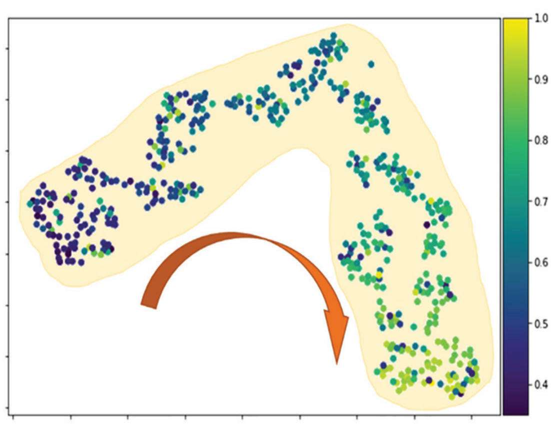

Figure 5: 2D tSNE visualization of the learned features by our CNN model. *CNN: Convolutional Neural Network; tSNE: t-distributed Stochastic Neighbor Embedding

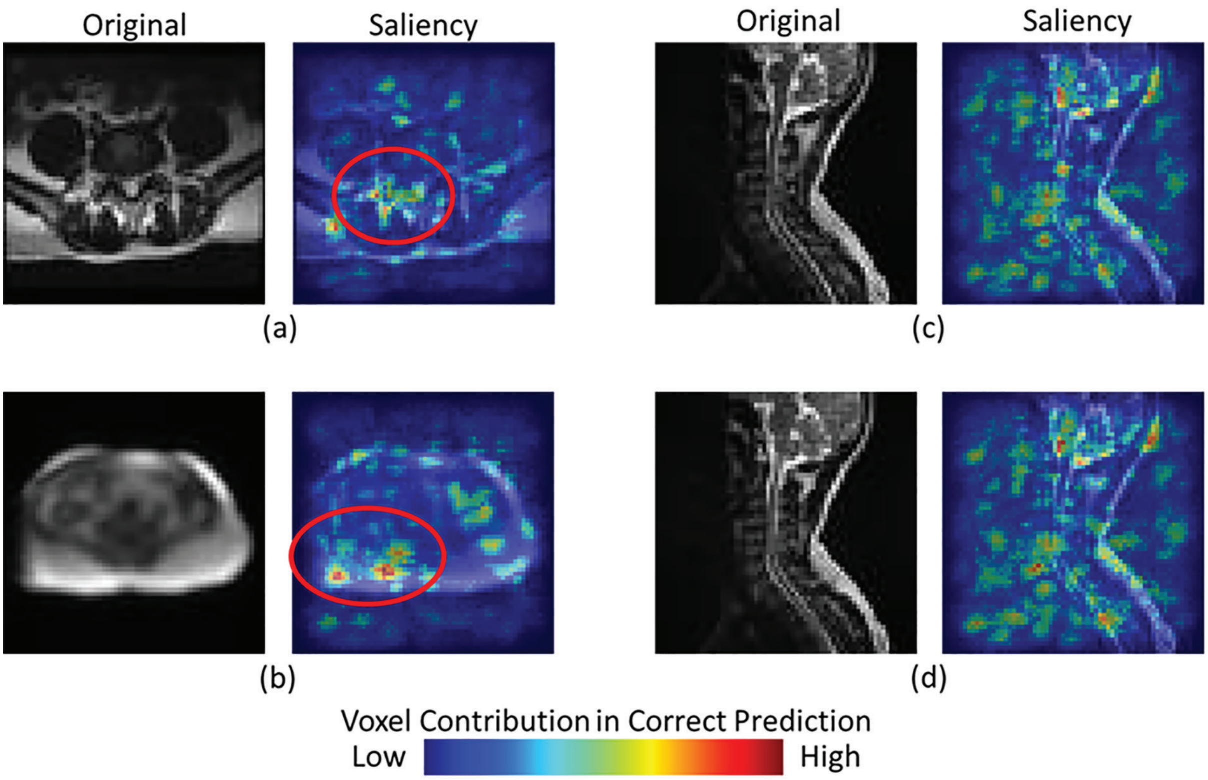

Figure 6: Left: Area of high impact in MRI identified by chiropractor. Right: Saliency Map generated using the proposed method; *MRI: Magnetic Resonance Imaging

Ethics - The present work was carried out in strict adherence to ethical principles of human research. Methodology of the research was approved by the Ethics Committee of Islamic Azad University, Mashhad Branch, Iran. Before registration, written informed consent was received from all of the participants. Each participant was explained in full detail about the purpose of the study, methods, potential harms, benefits, and their rights as research participants. This was explained verbally at clinical consultations by a professional research assistant as well as in writing in Persian in a written consent document. The consent form explicitly outlined the following issues:

Study Objectives: To evaluate the effectiveness of the ARA mobile app in enhancing patient engagement, satisfaction, and clinical outcomes in chiropractic care.

Nature of the Intervention: Use of the ARA mobile app (for the intervention group) or standard chiropractic care (for the control group), including the collection of functional performance data, MRI images, and satisfaction/adherence questionnaires.

Voluntarily Participation: Participants were informed that participation was entirely voluntary, and they could withdraw from the study at any time without any negative consequences.

Data Confidentiality: All collected data, including questionnaire responses, MRI images, and ARA app logs, were anonymized and stored securely in a password-protected database at the clinic. Access was restricted to authorized research team members only, ensuring compliance with data protection regulations.

Risks and Benefits: Potential risks (e.g., minor discomfort from completing questionnaires or using the app) and benefits (e.g., potential improvement in treatment outcomes and access to a digital health tool) were fully disclosed.

For the intervention group, additional explanations were provided regarding the use of the ARA app, including how to upload MRI images and interact with its social and AR features. Participants were informed that their MRI images would be processed by a CNN to predict treatment outcomes, with data handled anonymously and used solely for research and clinical purposes. For the control group, the process of manually collecting MRI images and their use in CNN predictions was similarly explained.

To ensure transparency, participants were assured that no identifiable information (e.g., names or numbers of identification) would be included in any report submitted for publication. For the MRI images used in article figures (e.g., Figures 5 and 6, showing saliency maps), separate consent was obtained for their anonymized publication, and participants were informed of being included in scientific publications.

A dedicated contact line (via email and phone) was provided for technical support and to address participants' queries. Participants were also informed of their right to access the study results upon publication, and data are available from the corresponding author upon reasonable request, subject to confidentiality constraints.

Results

Out of 73 patients initially eligible, 22 discontinued participation due to lack of cooperation or incomplete evaluations. The remaining 51 patients (24 males, 27 females) aged 18–65 years (Mean±SD: males 44.65±9.39 years; females 45.84±5.04 years). The average number of chiropractic visits was 7.96±2.96 for males and 10.48±3.10 for females, with no significant differences in age or visit interval between genders (P>0.05). The findings also showed that the average patient satisfaction score was 67.13.

As there were no other ways to forecast patient satisfaction after receiving chiropractic treatment with the MRI images, we set up baseline models employing commonly used traditional ML algorithms. We implemented a Support Vector Regression (SVR) approach with linear and Gaussian cores to achieve a forecast of satisfaction. Additionally we compared the outputs of our CNN performance with those from the Least Absolute Shrinkage and Selection Operator (LASSO) regression model, which implements sparse feature selection and subsequently regresses the output satisfaction values.

Table 1 shows the correlation between participants' characteristics and their reported satisfaction. The results indicated a significant positive correlation between the number of visits and satisfaction (r=0.402, P=0.003), while no significant relationships were found for age or the interval between visits (P>0.05). These findings imply that patient satisfaction with chiropractic care improves with an increased number of referral sessions.

Table 2 shows the average age, visit

Table 1: Correlation between participants' characteristics and their reported satisfaction

Satisfaction	Age		Visit intervals		Number of sessions	
	Correlation coefficient	P-value	Correlation coefficient	P-value	Correlation coefficient	P-value
	0.035	0.810	0.171	0.231	0.402	0.003*

*Correlation is significant at the 0.05 level (2-tailed).

Table 2: Comparison of patient satisfaction by gender across age, visit intervals, and number of sessions

Variables	Group	Mean±SD	n	t-statistic	df	P-value
Age (year)	Male	44.65±9.39	24	-0.325	46	0.747
	Female	45.84±15.04	27			
Visit intervals	Male	0.79±0.66	24	-0.318	47	0.752
	Female	0.84±0.37	27			
Number of sessions	Male	7.96±2.96	24	-2.913	47	0.005*
	Female	10.48±3.10	27			

*Significant p-values; SD: Standard Deviation, df: degrees of freedom.

intervals, and the number of sessions according to gender. The t-test analysis revealed a significant difference in the number of sessions attended by men and women ($P=0.005$), while no significant differences were observed in age or visit intervals between the two genders (Table 2).

Table 3 presents a comparative analysis of prediction models for estimating patient satisfaction based on MRI data. Among the models tested, the CNN outperformed all traditional approaches, achieving the lowest RMSE (0.1121) and a statistically significant correlation with actual satisfaction outcomes ($r=0.1491$, $P=0.0018$), highlighting its superior predictive validity of the CNN model for clinical use. In either model, the inputs are specified as the values from each of the MRIs. The SVR model utilized $C=10$ and $\sigma=2^{-3}$ and the LASSO uses $\lambda=0.1$. These hyperparameter values yielded the best network search results for the best hyperparameters. In the first phase, training and prediction were performed using a network with 6-fold cross-validation across six steps. In each step, one-sixth of the data was used for testing, and each of the resulting outputs was obtained. The outcomes from each group were then analyzed and compared using Fisher's test and the t-test.

To assess the patients' satisfaction levels, a questionnaire was designed and given to them prior to and following the treatment. The patients completed the questionnaire with assistance from their physician. The study revealed that patients' overall attitude towards their treatment contributed 91.55% effectiveness to their satisfaction.

Table 4 indicates correlation between the number of sessions and patient satisfaction with the ARA. There was significant positive correlation between numbers of sessions and patient satisfaction in both groups.

Table 5 indicates within-group comparisons of long-term outcomes over the four intervals (baseline, 3rd, 5th and 8th week) of the experimental study. Among participants in the normal group, comparisons between baseline and the third week revealed significant differences ($P<0.05$) in all outcome measures except Physical Functioning ($P=0.133$), while the ARA group demonstrated significant differences across all outcome parameters ($P<0.05$).

Comparisons between normal and ARA outcomes at the 3rd and 8th weeks indicate that energy/vitality and mental health improvements influence other indicators of health, including physical functioning and overall health status (Figure 7).

The intervention group had a higher average satisfaction score (91.55±6.48) and lower variability (CV=0.07) compared to the control group (63.30±12.52, CV=0.20). This suggests greater and more consistent

Table 3: Comparison of methods based on RMSE, correlation coefficient, and P-value

Model	RMSE	r	P-value
SVR (Linear)	0.4128	0.0315	0.4822
SVR (Gaussian)	0.3632	0.0513	0.2522
LASSO	0.3587	0.0665	0.1376
Ours (CNN)	0.1121*	0.1491*	0.0018*

*Significant P-values; r: Correlation Coefficient. RMSE: Root Mean Squared Error; CNN: Convolutional Neural Network.

Table 4: Correlation between patients' characteristics and their satisfaction with the ARA

Variables	Control Group		Intervention Group	
	P-value	Correlation coefficient	P-value	Correlation coefficient
Age (year)	0.715	0.035	0.810	-0.561
Number of sessions	0.021*	0.402	0.003*	0.293
Visit intervals	0.269	0.171	0.231	0.416

*Significant P-values; ARA: Augmented Reality Application.

Table 5: Comparison of participant treatment (Mean change) from baseline to week 8 by contextual variables

Variable	Normal method (n=30)	ARA (n=21)	Statistics	P-value
	Mean±SD	Mean±SD	t	
Baseline				
Bodily pain	75.57±3.674	77.62±3.788	1.939	0.058
General Health	46.03±4.460	43.24±5.915	1.229	0.255
Social functioning	34.57±4.083	38.57±4.854	3.189	0.002*
Mental Health	40.23±6.027	46.52±6.57	3.535	0.001*
Physical Functioning	29.27±5.439	31.14±3.825	1.361	0.180
Fear Physical	55.30±7.193	57.67±4.305	1.466	0.149
Vitality/energy	35.80±4.788	37.71±6.805	1.181	0.243
Week 3				
Bodily pain	64.7±7.724	58.714±6.657	-0.474	0.638
General Health	54.77±4.747	53.33±5.02	-1.036	0.305
Social Functioning	38.13±4.732	48.86±4.374	8.213	<0.001*
Mental Health	41.57±5.911	49.43±6.57	4.465	<0.001*
Physical Functioning	38.93±4.362	40.24±4.668	1.021	0.312
Fear Physical	53.53±4.584	53.43±5.723	-0.072	0.943
Energy/Vitality	40.47±6.548	59.71±4.921	11.393	<0.001*
Week 5				
Bodily pain	52.63±8.896	40.29±15.592	3.356	0.002*
General Health	69.33±5.967	83.38±5.869	-2.344	0.023*
Social Functioning	50.17±11.786	73.52±5.845	9.338	<0.001*
Mental Health	43.13±5.673	61.81±7.229	10.330	<0.001*
Physical Functioning	55.50±9.428	50.71±6.459	-2.016	0.049*
Fear Physical	49.67±4.270	44.24±8.654	-2.657	0.013*
Energy/Vitality	48.07±8.714	71.76±4.592	12.602	<0.001*
* Week 8				
Bodily pain	36.43±5.799	17.29±13.539	1.227	0.001*
General Health	78.30±3.344	89.95±7.318	-1.958	0.001*
Social Functioning	74.63±5.021	88.24±5.881	8.874	<0.001*
Mental Health	48.67±5.241	77.38±5.886	18.304	<0.001*
Physical Functioning	77.90±4.110	79.73±4.266	-1.529	0.133
Fear Physical	41.60±3.927	34.76±4.218	-5.937	<0.001*
Energy/Vitality	53.27±7.451	83.24±3.687	18.965	<0.001*

*Significant P-values; SD: Standard Deviation; ARA: Augmented Reality Application.

Table 6: The impact of the ARA in the intervention group

Groups	Coefficient of variation	Standard deviation	Average
Intervention groups	0.07	6.48	91.55
Control groups	0.20	12.52	63.30

ARA: Augmented Reality Application

satisfaction with chiropractic care in the intervention group. Additionally, 91.55% of participants reported that augmented reality positively influenced their treatment decisions and motivation to complete the program. Statistical significance tests were not performed (Table 6).

Discussion

This study aimed to evaluate the effectiveness of an AR enhanced mobile application integrated with a CNN model in improving patients' satisfaction, adherence, and clinical outcomes in chiropractic care. The findings indicated that the ARA app

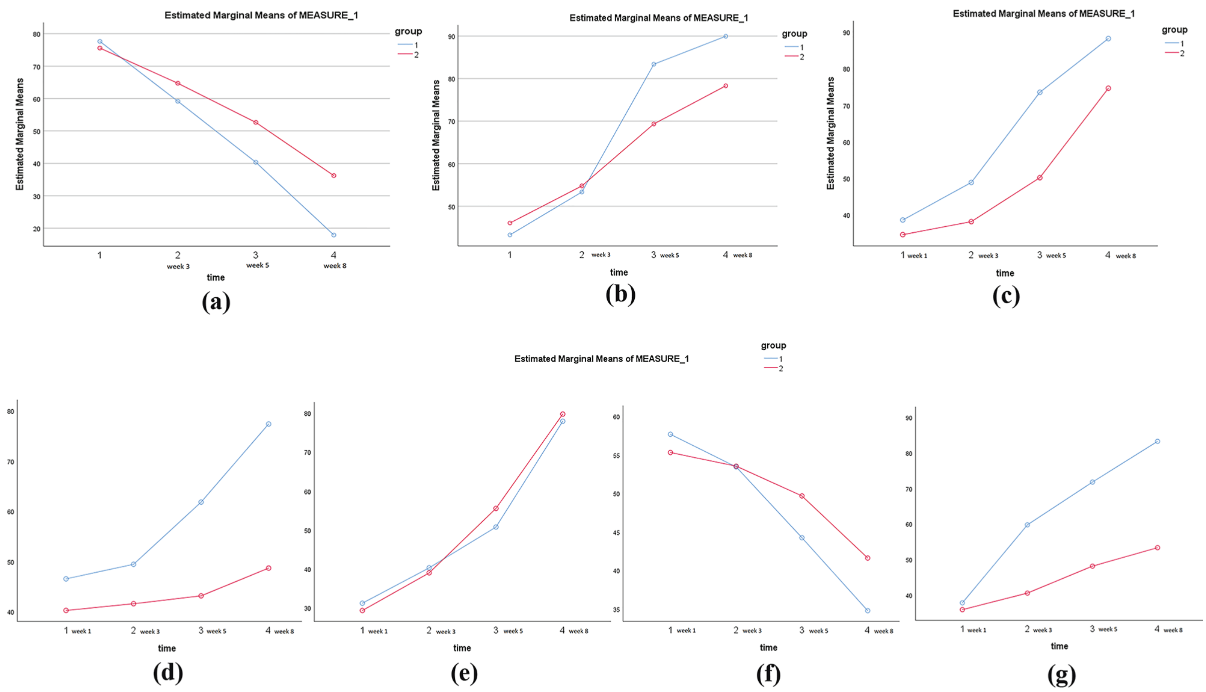

Figure 7: Comparison of treatment effects on health outcomes. Group 1: ARA vs. Group 2: Normal method. (a): Bodily pain, (b): General Health, (c): Social functioning, (d): Mental Health, (e): Physical functioning, (f): Fear Physical, (g): Energy/Vitality.

significantly improved patient satisfaction and clinical outcomes (e.g., mental health, social functioning) compared to standard care. The CNN model successfully predicted satisfaction, with saliency maps validating its alignment with clinically relevant MRI regions. These findings highlight the potential of integrating AI and social connectivity into chiropractic care.

One of the most notable findings was the predictive capacity of the CNN model. It achieved low RMSE and statistically significant correlations between predicted outcomes and patient-reported satisfaction, affirming its predictive validity. However, while the correlations were significant, the observed baseline characteristics was modest, suggesting that further model optimization and the use of larger, more diverse datasets are needed to enhance predictive accuracy. Despite this limitation, the use of saliency maps provided transparency and interpretability by highlighting MRI regions aligned with clinical relevance. These capabilities, when combined with AR visualization, empowered patients by offering a clearer understanding of their potential recovery trajectory, which contributed to increased trust and treatment adherence (27). Furthermore, mobile health (mHealth) technologies that incorporate patient feedback, predictive analytics, and social engagement features have demonstrated effectiveness in improving self-care and decision-making, as well as decreasing dropout rates (14, 28).

Nevertheless, the integration of CNN-based predictions and AR visualization proved to be a powerful patient-centered strategy. By allowing patients to visualize their recovery path and compare their outcomes with predicted expectations, the ARA app enhanced transparency and motivation. The app's ability to collect real-time behavioral data also adds value to patient monitoring and dynamic treatment adaptation.

This study may be the first to examine the integration of social networks, AR, VR, and ML in enhancing chiropractic care and patient adherence. The research results imply that ML-based predictive techniques that come with a combination of immersive digital visualization and a socially driven approach have the potential to not only increase treatment adherence but also patient satisfaction. They could lead to better clinical results. While the majority of previous studies had been conducted using X-ray or CT scans to create the musculoskeletal disorder treatment outcomes model (29), in our work, we utilized MRI imagery as the primary input. Not only is MRI more widespread and accessible in certain parts of the world, like Iran, but it also increases the accuracy of the prediction. Our method, in addition to the standard clinical data collection, encourages the implementation of local social features to enable real-time interaction between the patients and health workers. The sharing of recovery stories of other patients, getting encouragement, and sharing your own progress in social networks has been documented lately as helping to enhance self-efficacy and treatment adherence significantly in digital health platforms (30). Among the things that are important in the short-run, we can mention but single out the feature of peer influence through mobile health (mHealth) applications, which is the main and leading cause of patients' exercise adherence, following diet recommendations, and compliance with prescribed drug therapies (31).

Recent systematic reviews in the field of musculoskeletal care have shown the worth of mHealth instruments in giving people a better reach to healthcare, particularly through telehealth modalities (12). Nonetheless, it was noted that a large number of interventions were unable to maintain patient engagement over an extended period or enhance the patients' behavior (32). As a solution to this problem, our study employed social motivation tools like the comment threads, virtual rewards, and structured feedback loops, which are known to be efficient in keeping the users engaged (33).

Furthermore, studies have shown that mobile health (mHealth) applications, which involve community features, are more effective in patient retention and compliance with treatment compared to those who do not (30, 34, 35). Our platform, through peer-to-peer accountability and customized progress tracking, aligns with the concept of social accountability loops that are described in the literature and which are indispensable for behavior change (36-38).

This study also diverges from nonparallel research such as commercial health apps that rely solely on engagement indices without AR or predictive modeling (39), and telerehabilitation platforms limited to remote exercise delivery without real-time ML feedback (40). In contrast, our integration of CNN-based prediction, AR visualization, social networking, and clinician feedback within the ARA app offers a more comprehensive and engaging patient-centered approach.

Limitations and Suggestions

The findings of our study are encouraging; however, certain limitations must be acknowledged. The sample size and regional scope restrict the ability to generalize the results, and the follow-up duration was insufficient to assess the long-term durability of the effects. Besides, individual responses to peer-supported motivation differ, with some experiencing reduced motivation or heightened anxiety due to social comparison (41).

Although randomization was used, the results may only be generalizable to populations and care settings similar to those studied. While we assessed short-term engagement and satisfaction, the long-term maintenance of app use and clinical benefits remains unexamined. Previous research indicates that digital engagement can wane without continuous support, especially in groups with lower digital literacy (42).

Although post hoc power analysis based on the observed effect size yielded a power of approximately 65%, this falls short of the conventional 80% threshold typically recommended for robust inferential conclusions. As a result, the findings—while statistically significant and supported by a large effect size—should be interpreted with caution.

Future studies with larger and more diverse samples are warranted to validate these findings and enhance external validity. Subsequent research could incorporate more diverse datasets, including MRI and multiple imaging techniques, and tailor social interaction components to patient profiles and preferences through AI. Economic analyses should be undertaken to identify cost-effective approaches to reduce treatment dropout rates and avoid unnecessary surgical interventions (43). Furthermore, involving users in iterative co-design processes to refine message timing, frequency, and tone may enhance motivation while reducing unintended pressure (44).

Conclusion

This study highlights the significant value of integrating ML, immersive AR/VR technologies, and interactive mHealth features in chiropractic care using a synergistic approach. The findings contribute to a growing body of evidence indicating that digital therapy models—especially those promoting peer group formation and active engagement—have the potential to transform patient interactions with non-surgical musculoskeletal treatments. Future investigations should extend this framework to larger populations and assess its cost-effectiveness, scalability, and long-term effects on health outcomes.

Abbreviations

AI: Artificial Intelligence
AR: Augmented Reality
ARA: Augmented Reality Application
CAM: Complementary and Alternative Medicine
CNN: Convolutional Neural Network
Grad-CAM: Gradient-Weighted Class Activation Mapping
FABQ: Fear Avoidance Beliefs Questionnaire
LASSO: Least Absolute Shrinkage and Selection Operator
LOOCV: Leave One Out Cross-Validation
ML: Machine Learning
MRI: Magnetic Resonance Imaging
MSDs: Musculoskeletal Disorders
RMSE: Root Mean Squared Error
SVR: Support Vector Regression
tSNE: t-distributed Stochastic Neighbor Embedding
VR: Virtual Reality

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Authors' Contribution

NH was responsible for conceptualizing and designing the research, conducting the experimentation, acquiring data, performing statistical analysis (with statistical consultation), supervising app development, and preparing the manuscript. GV provided supervision as well as review and editing of the manuscript. Both authors approved the final manuscript.

Conflict of Interest

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The authors declare that there is no conflict of interest regarding the publication of this paper.

Ethical Considerations

The study strictly followed ethical guidelines approved by the Islamic Azad University Ethics Committee with the ethics code IR.IAU.MSHD.REC.1400.063. Written informed consent was obtained from all participants, who were fully informed about the study's purpose, methods, risks, benefits, and their rights. Data confidentiality was ensured by anonymizing all collected information and storing it securely. The intervention group received additional instructions on using the ARA mobile app and MRI image handling processed by CNN for outcome prediction, with similar explanations for the control group. Participants were assured their identities would remain confidential in publications, with separate consent obtained for MRI images used in figures. A support contact was provided, and participants were informed about their right to access study results after publication.

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Availability of Data and Materials

The datasets created during the current study are not publicly available to maintain patient confidentiality but can be obtained from the corresponding author upon reasonable request.

References

1 ILO. Recommendation concerning the list of occupational diseases and the recording and notification of occupational accidents and diseases (Recommendation R194). Geneva; 2002.

2 Parno A, Sayehmiri K, Parno M, Khandan M, Poursadeghiyan M, Maghsoudipour M, Ebrahimi MH. The prevalence of occupational musculoskeletal disorders in Iran: A meta-analysis study. Work. 2017;58(2):203-14. doi: 10.3233/WOR-172619. PubMed PMID: 29036866.

3 Waehrer G, Leigh JP, Miller TR. Costs of occupational injury and illness within the health services sector. Int J Health Serv. 2005;35(2):343-59. doi: 10.2190/RNQ3-0C13-U09M-TENP. PubMed PMID: 15934169.

4 Parno A, Sayehmiri K, Nabi Amjad R, H.Ahagh MM, Hosseini Foladi Sh, Khammar Ar, Poursadeqiyan M. Meta-analysis Study of Work-related Musculoskeletal Disorders in Iran. Rehabiliation. 2020;21(2):182-205. doi: 10.32598/RJ.21.2.2444.4.

5 5. Nelson CF, Metz RD, LaBrot T. Effects of a managed chiropractic benefit on the use of specific diagnostic and therapeutic procedures in the treatment of low back and neck pain. J Manipulative Physiol Ther. 2005;28(8):564-9. doi: 10.1016/j.jmpt.2005.08.010. PubMed PMID: 16226623.

6 Dagenais S. Why not everyone with low back pain chooses chiropractic care. J Can Chiropr Assoc. 2013;57(1):6-9. PubMed PMID: 23476079; PubMed Central PMCID: PMC3580998.

7 Gevers-Montoro C, Deldar Z, Conesa-Buendía FM, Lazar EA, Mahillo-Fernandez I, Khatibi A, Ortega de Mues A. Pain catastrophizing mediates rapid benefits of accessing in-person chiropractic care during the COVID-19 lockdown. Eur J Pain. 2022;26(2):463-479. doi: 10.1002/ejp.1872. PubMed PMID: 34618991; PubMed Central PMCID: PMC8653257.

8 Perrin A. Mobile technology and home broadband: Pew Research Center; 2021 June 3. [Cited 2024 October 12]. Available from: https://www.pewresearch.org/internet/2021/06/03/mobile-technology-and-home-broadband-2021/.

9 Ng JY, Verhoeff N, Steen J. What are the ways in which social media is used in the context of complementary and alternative medicine in the health and medical scholarly literature? a scoping review. BMC Complement Med Ther. 2023;23(1):32. doi: 10.1186/s12906-023-03856-6. PubMed PMID: 36732809; PubMed Central PMCID: PMC9893203.

10 National Guideline Centre (UK). Low Back Pain and Sciatica in Over 16s: Assessment and Management. London: National Institute for Health and Care Excellence (NICE); 2016 Nov. PubMed PMID: 27929617.

11 WFC. 20 Principles; Advancing awarness, utilization and integration of chiropractic internationally. Toronto, Canada: World Federation of Chiropractic 2023. Available from: https://www.wfc.org/website/documents/799_20-principles-2023.pdf.

12 Cottrell MA, Galea OA, O'Leary

SP, Hill AJ, Russell TG. Real-time telerehabilitation for the treatment of musculoskeletal conditions is effective and comparable to standard practice: a systematic review and meta-analysis. Clin Rehabil. 2017;31(5):625-38. doi: 10.1177/0269215516645148. PubMed PMID: 27141087.

13 Michie S, van Stralen MM, West R. The behaviour change wheel: a new method for characterising and designing behaviour change interventions. Implement Sci. 2011;6:42. doi: 10.1186/1748-5908-6-42. PubMed PMID: 21513547; PubMed Central PMCID: PMC3096582.

14 Free C, Phillips G, Watson L, Galli L, Felix L, Edwards P, Patel V, Haines A. The Effectiveness of Mobile-health Technologies to Improve Health Care Service Delivery Processes: A Systematic Review and Meta-analysis. PLoS Med. 2013;10(1):e1001363. doi: 10.1371/journal.pmed.1001363. PubMed PMID: 23458994; PubMed Central PMCID: PMC3566926.

15 RAND. 12-Item Short Form Survey (SF-12) 2020. [Cited 2024 Oct 22]. Available from: https://www.rand.org/health/surveys/mos/12-item-short-form.html.

16 Luo X, George ML, Kakouras I, Edwards CL, Pietrobon R, Richardson W, Hey L. Reliability, validity, and responsiveness of the short form 12-item survey (SF-12) in patients with back pain. Spine (Phila Pa 1976). 2003;28(15):1739-45. doi: 10.1097/01.BRS.0000083169.58671.96. PubMed PMID: 12897502.

17 Ware J Jr, Kosinski M, Keller SD. A 12-Item Short-Form Health Survey: construction of scales and preliminary tests of reliability and validity. Med Care. 1996;34(3):220-33. doi: 10.1097/00005650-199603000-00003. PubMed PMID: 8628042.

18 Waddell G, Newton M, Henderson I, Somerville D, Main CJ. A Fear-Avoidance Beliefs Questionnaire (FABQ) and the role of fear-avoidance beliefs in chronic low back pain and disability. Pain. 1993;52(2):157-168. doi: 10.1016/0304-3959(93)90127-B. PubMed PMID: 8455963.

19 Mintken PE, Cleland JA, Whitman JM, George SZ. Psychometric properties of the Fear-Avoidance Beliefs Questionnaire and Tampa Scale of Kinesiophobia in patients with shoulder pain. Arch Phys Med Rehabil. 2010;91(7):1128-36. doi: 10.1016/j.apmr.2010.04.009. PubMed PMID: 20599053.

20 LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015;521(7553):436-44. doi: 10.1038/nature14539. PubMed PMID: 26017442.

21 Lundervold AS, Lundervold A. An overview of deep learning in medical imaging focusing on MRI. Z Med Phys. 2019;29(2):102-27. doi: 10.1016/j.zemedi.2018.11.002. PubMed PMID: 30553609.

22 Dominik Scherer AMSB. Evaluation of pooling operations in convolutional architectures for object recognition. Artificial Neural Networks – ICANN 2010; Berlin: Springer; 2010. p. 99-101.

23 Y. LeCun BB, J. S. Denker, D. Henderson, R. E. Howard, W. Hubbard. Backpropagation Applied to Handwritten Zip Code Recognition. Neural Computation. 1989;1(4):541-51.

24 Hao R, Namdar K, Liu L, Haider MA, Khalvati F. A Comprehensive Study of Data Augmentation Strategies for Prostate Cancer Detection in Diffusion-Weighted MRI Using Convolutional Neural Networks. J Digit Imaging. 2021;34(4):862-76. doi: 10.1007/s10278-021-00478-7. PubMed PMID: 34254200; PubMed Central PMCID: PMC8455796.

25 Jia Deng WD, Richard Socher, Li-Jia Li, Kai Li, Li Fei-Fei. ImageNet: A large-scale hierarchical image database. Conference on Computer Vision and Pattern Recognition; 2009 June 20-25; Miami, FL, USA. USA: IEEE; 2009.P. 248-55, doi:10.1109/CVPR.2009.5206848.

26 Ramprasaath R.Selvaraju MC, Abhishek Das, Ramakrishna Vedantam, Devi

Parikh, and Dhruv Batra., editor Grad-CAM: Visual Explanations From Deep Networks via Gradient-Based Localization. Proceedings of the International Conference on Computer Vision (ICCV); 2017 Oct 22-29; Venice, Italy. USA: IEEE; 2017. doi: 10.1109/ICCV.2017.74.

27 Doyle C, Lennox L, Bell D. A systematic review of evidence on the links between patient experience and clinical safety and effectiveness. BMJ Open. 2013;3(1):e001570. doi: 10.1136/bmjopen-2012-001570. PubMed PMID: 23293244; PubMed Central PMCID: PMC3549241.

28 Luxton DD, McCann RA., Bush NE, Mishkind MC, Reger GM. mHealth for mental health: Integrating smartphone technology in behavioral healthcare. Prof Psychol Res Pr. 2011;42(6):505–12. doi:10.1037/a0024485.

29 Gitto S, Serpi F, Albano D, Risoleo G, Fusco S, Messina C, Sconfienza LM. AI applications in musculoskeletal imaging: a narrative review. Eur Radiol Exp. 2024;8(1):22. doi: 10.1186/s41747-024-00422-8. PubMed PMID: 38355767; PubMed Central PMCID: PMC10866817.

30 Yeo G, Fortuna KL, Lansford JE, Rudolph KD. The effects of digital peer support interventions on physical and mental health: a review and meta-analysis. Epidemiol Psychiatr Sci. 2025;34:e9. doi: 10.1017/S2045796024000854. PubMed PMID: 39945388; PubMed Central PMCID: PMC11886969.

31 Birrell L, Debenham J, Furneaux-Bate A, Prior K, Spallek S, Thornton L, Chapman C, Newton N. Evaluating a Peer-Support Mobile App for Mental Health and Substance Use Among Adolescents Over 12 Months During the COVID-19 Pandemic: Randomized Controlled Trial. J Med Internet Res. 2023;25:e45216. doi: 10.2196/45216. PubMed PMID: 37756116; PubMed Central PMCID: PMC10538359.

32 Paris Ferrer T, Masaracchio M, Kirker K, Madi Dewan B, Manthripragada M, Ojha H. Outcomes of direct access telehealth physical therapy for patients with musculoskeletal pain: a single cohort observational retrospective study. Physiother Theory Pract. 2024;40(10):2233-2240. doi: 10.1080/09593985.2023.2245032. PubMed PMID: 37585711.

33 Tran S, Smith L, Carter S. Understanding Patient Perspectives on the Use of Gamification and Incentives in mHealth Apps to Improve Medication Adherence: Qualitative Study. JMIR Mhealth Uhealth. 2024;12:e50851. doi: 10.2196/50851. PubMed PMID: 38743461; PubMed Central PMCID: PMC11134245.

34 Kruse CS, Mileski M, Moreno J. Mobile health solutions for the aging population: A systematic narrative analysis. J Telemed Telecare. 2017;23(4):439-51. doi: 10.1177/1357633X16649790. PubMed PMID: 27255207.

35 Amagai S, Pila S, Kaat AJ, Nowinski CJ, Gershon RC. Challenges in Participant Engagement and Retention Using Mobile Health Apps: Literature Review. J Med Internet Res. 2022;24(4):e35120. doi: 10.2196/35120. PubMed PMID: 35471414; PubMed Central PMCID: PMC9092233.

36 Naslund JA, Bondre A, Torous J, Aschbrenner KA. Social Media and Mental Health: Benefits, Risks, and Opportunities for Research and Practice. J Technol Behav Sci. 2020;5(3):245-257. doi: 10.1007/s41347-020-00134-x. PubMed PMID: 33415185; PubMed Central PMCID: PMC7785056.

37 Gabriela Villalobos-Zúñiga MC. Apps That Motivate: A Taxonomy of App Features Based on Self-Determination Theory. Int J Hum Comput Stud. 2020;140. doi: 10.1016/j.ijhcs.2020.102449.

38 Milne-Ives M, Homer SR, Andrade J, Meinert E. Potential associations between behavior change techniques and engagement with mobile health apps: a systematic review. Front Psychol. 2023;14:1227443. doi: 10.3389/fpsyg.2023.1227443. PubMed PMID: 37794916; PubMed Central PMCID:

PMC10545861.

39 Yae Won Tak JWL, Junetae Kim, Yura Lee Predicting Long-Term Engagement in mHealth Apps: Comparative Study of Engagement Indices.J Med Internet Res. 2024;26:e59444. doi: 10.2196/59444. PubMed PMID: 39250192. PubMed Central PMCID: 11420572.

40 Baroni MP, Jacob MFA, Rios WR, Fandim JV, Fernandes LG, Chaves PI, Fioratti I, Saragiotto BT. The state of the art in telerehabilitation for musculoskeletal conditions. Arch Physiother. 2023;13(1):1. doi: 10.1186/s40945-022-00155-0. PubMed PMID: 36597130; PubMed Central PMCID: PMC9810517.

41 Aschentrup L, Steimer PA, Dadaczynski K, Mc Call T, Fischer F, Wrona KJ. Effectiveness of gamified digital interventions in mental health prevention and health promotion among adults: a scoping review. BMC Public Health. 2024;24(1):69. doi: 10.1186/s12889-023-17517-3. PubMed PMID: 38167010; PubMed Central PMCID: PMC10763397.

42 Wang Y, Min J, Khuri J, Xue H, Xie B, A Kaminsky L, J Cheskin L. Effectiveness of Mobile Health Interventions on Diabetes and Obesity Treatment and Management: Systematic Review of Systematic Reviews. JMIR Mhealth Uhealth. 2020;8(4):e15400. doi: 10.2196/15400. PubMed PMID: 32343253; PubMed Central PMCID: PMC7218595.

43 Fatoye F, Gebrye T, Mbada C, Useh U. Economic Evaluations of Digital Health Interventions for the Management of Musculoskeletal Disorders: Systematic Review and Meta-Analysis. J Med Internet Res. 2023;25:e41113. doi: 10.2196/41113. PubMed PMID: 37410542; PubMed Central PMCID: PMC10359913.

44 Reimer LM, Nissen L, von Scheidt M, Perl B, Wiehler J, Najem SA, Limbourg FP, Tacke T, Müller A, Jonas S, Schunkert H, Starnecker F. User-centered development of an mHealth app for cardiovascular prevention. Digit Health. 2024;10:20552076241249269. doi: 10.1177/20552076241249269. PubMed PMID: 38774157; PubMed Central PMCID: PMC11107323.