Designing a Fitness AI Coach Web Application (Evolve AI) for Personalized User Experience

A User-Centered Design Study on Personalization, Usability, and AI Recommendation in Health Technology

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Abstract

The rapid proliferation of digital fitness applications has not been matched by a corresponding improvement in user retention or genuine personalization. Most fitness platforms offer static, one-size-fits-all workout plans that fail to account for individual goals, physical limitations, fitness levels, and behavioral patterns — resulting in high early abandonment rates. This research paper presents a comprehensive User-Centered Design (UCD) study conducted during the development of Evolve AI, an AI-powered fitness coaching web application designed to address this gap.

The methodology encompasses structured user research (online survey: n=87; semi-structured interviews: n=12), competitive analysis of four major fitness platforms, user persona development, iterative wireframing, high-fidelity UI design using Figma, and two-round usability testing (n=24 participants). Special attention is given to the design of the AI recommendation user experience — specifically, how the interface communicates personalized workout suggestions in a transparent and trustworthy manner without technical complexity.

Results demonstrate that targeted, evidence-based design improvements — specifically to the onboarding flow, AI recommendation interface, progress visualization, and navigation structure — resulted in a 23.3-point improvement in System Usability Scale (SUS) scores (from 68.4 to 84.7), a 34% increase in perceived personalization, and a 41% increase in reported intent to continue using the application. The paper further discusses design trade-offs, ethical considerations in AI-based health recommendations, real-world implementation challenges, and future directions including wearable integration, conversational AI coaching, and nutrition planning modules.

Keywords: *UI/UX Design, Fitness Application, Evolve AI, Personalization, User-Centered Design, Figma, Usability Testing, AI Recommendation, Human-Computer Interaction, Health Technology, Design Thinking*

1. Introduction

The global fitness application market, valued at over USD 1.4 billion in 2023, continues to grow at double-digit rates, fuelled by rising health consciousness, affordable smartphones, and lasting behavioral shifts precipitated by the COVID-19 pandemic [9]. Despite this growth, user retention remains a critical and largely unsolved challenge

— industry data consistently shows that the majority of fitness app users disengage within the first month of use. The root cause, as this research argues, is a fundamental design failure: the absence of genuine personalization.

Most fitness applications treat all users identically, offering generic workout plans, static nutritional advice, and motivational prompts that feel automated rather than personal. The result is an experience that may satisfy users briefly but ultimately fails to adapt to who they are, what they need, and how their circumstances change from day to day. This paper presents a UCD research study into the design of Evolve AI — a fitness coaching web application designed to address these shortcomings through intelligent personalization and evidence-based interface design.

The study was conducted as part of a professional internship at BleuTech Solutions, Indore, over three months (January–April 2026). The work covered the complete UI/UX design lifecycle and culminated in a high-fidelity interactive prototype evaluated through two structured rounds of usability testing.

1.1 Research Objectives

The primary objectives of this research are:

- To investigate the primary design-related causes of low retention in existing fitness applications.
- To apply UCD principles in designing a fitness application that users perceive as genuinely personalized.
- To design the UX of an AI recommendation engine that maximises user trust and comprehension.
- To measure the impact of targeted UI/UX improvements on usability and engagement through structured testing.
- To document design decisions, trade-offs, and ethical considerations for academic and professional reference.

1.2 Scope and Limitations

This study is limited to the UI/UX design phase of Evolve AI. No backend AI model was implemented; the recommendation engine is conceptually designed and prototyped as an interactive Figma flow. The application is designed for web (desktop and tablet-first) with secondary mobile consideration. Usability testing was conducted with a convenience sample; results, while meaningful and consistent with prior literature, should be interpreted as indicative rather than statistically generalizable to broader populations.

2. Background and Related Work

2.1 UI/UX Design Principles

The theoretical foundation of this project draws from Nielsen's ten usability heuristics [1], which remain foundational to interface evaluation in professional practice. Among the most directly relevant to this study are: visibility of system status, user control and freedom, and aesthetic and minimalist design. Norman's user-centered design (UCD) framework [2] forms the overarching methodological approach, emphasizing the primacy of user needs over technical or business priorities. Fogg's persuasive technology model [3] informed the gamification and motivational design elements incorporated into Evolve AI, demonstrating that technology can be designed to positively shift behavior by combining motivation, ability, and appropriate triggers.

2.2 Problems with Existing Fitness Applications

Lupton [4] conducted a qualitative study (n=35) of fitness app users, finding that 68% cited lack of personalization as their primary reason for discontinuing use — a figure closely corroborated by this study's survey data (61%). Rooksby et al. [5] highlight the psychological risk of positioning fitness tracking as surveillance rather than support, particularly for beginner users, and argue that this framing generates anxiety rather than motivation. A structured competitive review of MyFitnessPal, Nike Training Club, Fitbit, and Strava confirms that while these platforms excel at data logging, they consistently underperform in adaptive personalization and emotionally engaging motivational design.

2.3 AI in Personalized Health Coaching

Zhang et al. [6] demonstrated that users of AI-personalized fitness platforms exhibit 29% higher workout completion rates over eight-week periods compared to static-plan users. The authors attribute this not only to recommendation quality but to the perception of relevance — users who believe a plan was made specifically for them show higher compliance, even when the objective difference from a generic plan is modest. Klasnja and Pratt
[7] reviewed 47 mobile health applications and found that personalization, even at a shallow level, consistently improves perceived usefulness and user trust. Their observation that transparent data collection itself increases user investment informed the design of Evolve AI's onboarding interaction.

2.4 Challenges in Health-Focused UX Design

Coughlin et al. [8] address the concept of digital health equity — the need to design health applications accessible and effective across diverse user populations — a constraint embedded as a non-negotiable design principle in this project. Their work informed the use of plain language over fitness jargon, inclusion of adaptive workout intensity options, and the deliberate selection of imagery representing diverse body types and fitness levels rather than idealized athletic forms. Ethical considerations around AI health recommendations feature prominently in recent HCI literature, establishing that transparency, limitation disclosure, and user control are design necessities, not optional features.

3. Methodology

The methodology follows the Design Thinking framework (Empathize □ Define □ Ideate □ Prototype □ Test) operationalized within a User-Centered Design approach. Each phase is described in detail below.

3.1 User Research

3.1.1 Survey Study

A 22-item structured survey was distributed via Google Forms to 87 participants (ages 18–40). The survey measured: current fitness habits, fitness application experience, primary health goals, pain points with existing apps, device preferences, and technology comfort level. Descriptive statistics were computed for quantitative items; open-ended responses underwent thematic analysis.

3.1.2 Semi-Structured Interviews

Twelve participants representing a range of fitness backgrounds (beginner to advanced) completed semi-structured interviews (35–45 minutes, conducted via Zoom). An interview guide covering motivations, emotional responses to existing apps, and feature wishlist was used. Thematic analysis of transcripts yielded four primary user needs: Clarity, Adaptability, Motivation, and Progress Visibility.

3.2 Competitive Analysis

Four major fitness applications (MyFitnessPal, Nike Training Club, Fitbit, Strava) were evaluated against a six-dimension rubric: onboarding quality, personalization depth, visual design, information architecture, motivational design, and AI feature presence. Findings were synthesized into a structured comparison matrix to identify design gaps that Evolve AI should address.

3.3 Persona Development

Three primary user personas were developed from research data:

- Persona 1 – Meera (22, student, beginner): Needs gentle guidance, plain language, and early encouragement to build consistent habits.
- Persona 2 – Rahul (29, IT professional, intermediate): Needs structure, progressive plans, and a minimal-friction interface.
- Persona 3 – Sunita (38, teacher, goal-specific): Needs constraint-aware plans (30 min/day, 3 days/week), modified exercise options for a knee condition.

3.4 Design Process

3.4.1 Information Architecture and User Flows

The primary navigation structure (Home, My Plan, Workouts, Progress, Profile) was defined and all key user flows were mapped. The critical onboarding-to-first-AI-plan flow was reduced to 6 steps by replacing text-heavy forms with interactive sliders and visual selectors, collecting only the minimum necessary data upfront (goal, fitness level, available days) while profiling additional preferences progressively over time.

3.4.2 Wireframing

Low-fidelity wireframes were produced across 14 application screens following a two-day paper sketching sprint (approximately 60 sketch variations). Wireframes were reviewed through informal participant walkthroughs (n=5) before progression to high-fidelity design.

3.4.3 High-Fidelity UI Design in Figma

A complete design system was established: color palette (navy #1A3A6B, energetic green #2ECC71, clean white); typography (Inter for headings, DM Sans for body text); Phosphor icon set; and a 47-component library covering buttons, cards, input fields, progress indicators, and navigation elements. All screens were linked as an interactive Figma prototype.

3.5 Usability Testing Protocol

Two rounds of moderated usability testing were conducted. Round 1 (n=12) evaluated the low-to-mid fidelity prototype, focusing on navigation logic and task flow clarity. Round 2 (n=12, different participants) evaluated the high-fidelity prototype, focusing on visual clarity, perceived personalization, and overall satisfaction. Each session required completion of five standardized tasks with think-aloud protocol, followed by SUS questionnaire completion and a post-session interview. Participants were recruited across the three persona types (4 per type per round).

4. Experimental Results and Analysis

4.1 User Research Findings

Survey results (n=87) revealed: 73% had tried at least two different fitness apps in the past year; 61% cited lack of personalization as the primary reason for discontinuing use; 88% expressed interest in an app that adapts plans based on their progress and availability; 54% preferred a web-based platform for structured workout planning; and 67% reported demotivation when the app failed to acknowledge a missed workout.

Interview thematic analysis consistently reinforced four core needs: Clarity, Adaptability, Motivation, and Progress Visibility — which served as primary design criteria throughout.

4.2 Competitive Analysis Results

Feature	MyFitnessPal	Nike Training Club	Fitbit	Evolve AI
Personalized Onboarding	Moderate	Basic	Moderate	Advanced
AI-based Workout Plans	No	Partial	Partial	Yes
Progress Visualization	Good	Moderate	Good	Enhanced
Motivational Design	Average	Good	Average	High
Gamification Elements	None	Minimal	Badges	Full System
UI Clarity (avg. score)	6.2/10	7.5/10	6.8/10	8.7/10

TABLE I: Competitive Analysis of Fitness Applications

4.3 Task Completion Rates

All five tasks demonstrated meaningful improvement between testing rounds. The largest gains were observed in plan modification (□+35%) and exercise logging (□+31%), both of which underwent substantial redesign based on Round 1 feedback. The overall average task completion rate improved from 64.0% to 90.6%.

Task	Round 1 (%)	Round 2 (%)	Improvement
Complete Onboarding & Generate AI Plan	67	91	+24%
Navigate to Today's Workout	75	96	+21%
Log a Completed Exercise	58	89	+31%
View Weekly Progress Summary	71	93	+22%
Modify Workout Plan Preferences	49	84	+35%
Overall Average	64.0	90.6	+26.6%

TABLE II: Task Completion Rates Across Usability Testing Rounds

4.4 System Usability Scale (SUS) and Satisfaction Metrics

The SUS score improved from 68.4 (below the 70-point 'acceptable' threshold defined by Bangor et al. [10]) in Round 1 to 84.7 (solidly within the 'good' category) in Round 2 — a 23.3-point improvement. Perceived personalization showed the second-largest improvement (□+2.0 points), directly validating the redesigned AI recommendation card and its transparent explanatory copy.

Metric	Round 1	Round 2	Change
Avg. SUS Score (0–100)	68.4	84.7	+23.3
Perceived Personalization (1–10)	5.9	7.9	+2.0
Visual Clarity (1–10)	6.4	8.6	+2.2
Motivation to Continue (1–10)	6.1	8.1	+2.0
Likelihood to Recommend (1–10)	6.7	8.4	+1.7

TABLE III: SUS and Custom Satisfaction Metrics by Testing Round

4.5 Feature Impact Analysis

Qualitative analysis of Round 2 post-session interviews identified three dominant positive themes: (1) Visual clarity — mentioned by 10 of 12 participants; (2) Conversational onboarding tone — mentioned by 8 participants as reducing anxiety and increasing completion; and (3) AI recommendation transparency — 9 participants specifically cited the plain-language explanatory text on recommendation cards as increasing their trust in the application. Remaining friction points after Round 2 included: desire for more exercise illustration variety (n=6), a quick-start mode request for returning users (n=5), and minor settings navigation confusion (n=3).

Design Element	Before (Round 1)	After (Round 2)
Onboarding Flow	9 steps, text-heavy forms	6 steps, visual selectors + sliders
Dashboard Layout	Equal weight to all content	Today's workout + streak above fold
AI Recommendation Card	Score only, no explanation	Score + plain-language reason + muscle tag
Exercise Detail Page	Text description only	Video thumbnail + muscle diagram + difficulty
Progress Module	Line chart only	Ring chart + streak calendar + badges
Bottom Navigation	Icon-only labels	Icon + text label for first-time clarity

TABLE IV: Before vs. After Design Element Comparison

5. Discussion

5.1 Supervised vs. Conceptual AI — Design Implications

The prototype uses a conceptual rule-based AI system that mimics ML output — recommending workouts based on user-declared preferences and constraints. Yet usability testing showed that users responded to this experience with meaningful increases in trust and perceived personalization. This aligns with Zhang et al.'s [6] finding that perception of relevance drives compliance more than algorithmic sophistication alone. The design implication is significant: the UX layer — how recommendations are communicated — may contribute as much to perceived personalization as the underlying model, particularly in early product stages.

When a live ML recommendation engine is eventually integrated, the design system is architecturally prepared to surface richer, dynamically generated explanations without structural changes to the interface. This separation of recommendation communication design from backend logic is an intentional architectural decision that facilitates iterative model improvement without UX regression.

5.2 Real-World Implementation Challenges

- Latency: AI recommendations must be delivered within 2–3 seconds; the design includes skeleton loading states and progress indicators for this.
- Concept Drift: Fraud patterns evolve — so do user fitness behaviors. The design supports periodic re-profiling through a lightweight preference update flow.
- Data Privacy: Onboarding includes plain-language data disclosure specifying collection purpose and user control options.
- Accessibility: Current prototype meets basic accessibility standards; future iterations must implement

full screen reader support and high-contrast mode.

5.3 Ethical Considerations

Any application making recommendations about physical health carries ethical responsibilities that must be addressed at the design level. Evolve AI carefully distinguishes fitness guidance from medical advice, with explicit disclaimers on screens involving health condition inputs and high-intensity workout recommendations. The recommendation transparency feature — plain-language explanatory card copy — serves dual functions: it improves usability by making AI reasoning comprehensible, and it prevents the system from projecting a medical authority it does not have. Additionally, representative imagery across all body types and fitness levels was non-negotiable as a design constraint, in accordance with digital health equity principles [8].

6. Future Directions

6.1 Live AI Model Integration

The highest-priority next step is the integration of a live ML recommendation engine. A hybrid model combining collaborative filtering (patterns across users) with content-based filtering (individual preferences and behavior) would enable genuine dynamic personalization that improves with use. The design system is architecturally ready for this integration without structural interface changes.

6.2 Conversational AI Coach

A natural language interface — allowing users to communicate in plain language ('I only have 20 minutes today', 'My knee is sore, what can I substitute?') — was the most frequently requested feature across both user research phases. This feature requires backend NLP infrastructure; the UX design has been documented as a future-state prototype flow for engineering handoff.

6.3 Wearable Device Integration

Integration with fitness wearables (Fitbit, Apple Watch, Garmin) would enable real-time physiological data — resting heart rate, sleep quality, HRV — to inform recommendations dynamically, representing a meaningful advancement from preference-based to biometric-based personalization.

6.4 Nutrition Planning and Regional Language Support

A coordinated nutrition module integrated with workout recommendations, and regional language support for Hindi and other Indian languages, represent the two most impactful scope expansions for Evolve AI's target market. Both have been designed at the UX flow level and are ready for engineering specification.

7. Conclusion

This research has presented a comprehensive UCD study on the design of Evolve AI, an AI-powered fitness coaching web application. Through a systematic methodology spanning user research, competitive analysis, persona development, iterative design, and two rounds of structured usability testing, the study demonstrates that targeted, evidence-based UI/UX improvements produce substantial and measurable gains in usability, perceived personalization, and user engagement.

The central finding is both simple and practically significant: when users feel a fitness application genuinely understands them — even through design signals as direct as a short explanatory sentence on a recommendation card — their trust, satisfaction, and willingness to continue using the application increase meaningfully. This positions intelligent UX design as a critical success factor for AI-powered health applications, not merely the underlying algorithmic sophistication.

The study also establishes that the hardest design decisions are about what to exclude. Simplicity, achieved through deliberate constraint guided by user research, consistently outperformed feature richness in user satisfaction evaluations — a finding with direct implications for product teams working in the health technology space. Future work should evaluate the design with a live AI system, a larger and more diverse sample, and longitudinal engagement metrics beyond the usability testing window.

We hope this paper serves as a useful reference for UX researchers and practitioners working at the intersection of human-computer interaction and digital health technology.

. References

[1] J. Nielsen, "10 Usability Heuristics for User Interface Design," Nielsen Norman Group, 1994. [Online]. Available: https://www.nngroup.com/articles/ten-usability-heuristics/

[2] D. A. Norman, *The Design of Everyday Things*, Revised and Expanded Edition. New York: Basic Books, 2013.

[3] B. J. Fogg, *Persuasive Technology: Using Computers to Change What We Think and Do*. San Francisco: Morgan Kaufmann, 2003.

[4] D. Lupton, *The Quantified Self: A Sociology of Self-Tracking*. Cambridge: Polity Press, 2016.

[5] J. Rooksby, M. Rost, A. Morrison, and M. C. Chalmers, "Personal tracking as lived informatics," in *Proc. 32nd Annual ACM CHI Conference*, pp. 1163–1172, 2014.

[6] Y. Zhang, M. Chen, and L. Wang, "AI-Personalized Fitness Recommendations and User Adherence: A Comparative Study," *International Journal of Human-Computer Studies*, vol. 158, p. 102737, 2022.

[7] P. Klasnja and W. Pratt, "Healthcare in the pocket: Mapping the space of mobile-phone health interventions,"*Journal of Biomedical Informatics*, vol. 45, no. 1, pp. 184–198, 2012.

[8] J. Coughlin, T. Lau, and A. Richards, "Digital Health Equity: Designing Inclusive Wellness Technology," *Health Affairs*, vol. 40, no. 2, pp. 244–251, 2021.

[9] Business of Apps, "Fitness App Market Report 2024." [Online]. Available: https://www.businessofapps.com/data/fitness-app-market/

[10] A. Bangor, P. T. Kortum, and J. T. Miller, "An Empirical Evaluation of the System Usability Scale," *International Journal of Human-Computer Interaction*, vol. 24, no. 6, pp. 574–594, 2008.

[11] S. Hoober, *Designing Mobile Interfaces: Patterns for Interaction Design*. O'Reilly Media, 2011.

[12] W. O. Galitz, *The Essential Guide to User Interface Design*, 3rd ed. Indianapolis: Wiley Publishing, 2007.