

International Journal of Innovative Technologies in Social Science

e-ISSN: 2544-9435

Operating Publisher
SciFormat Publishing Inc.
ISNI: 0000 0005 1449 8214

2734 17 Avenue SW,
Calgary, Alberta, T3E0A7,
Canada
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ARTICLE TITLE	THE IMPACT OF ARTIFICIAL INTELLIGENCE ALGORITHMS AND ADAPTIVE COACHING ON BEHAVIORAL ADHERENCE AND COGNITIVE LOAD IN FITNESS APPLICATION USERS. A REVIEW
DOI	https://doi.org/10.31435/ijitss.4(52).2026.6867
RECEIVED	20 August 2026
ACCEPTED	27 October 2026
PUBLISHED	06 November 2026
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THE IMPACT OF ARTIFICIAL INTELLIGENCE ALGORITHMS AND ADAPTIVE COACHING ON BEHAVIORAL ADHERENCE AND COGNITIVE LOAD IN FITNESS APPLICATION USERS. A REVIEW

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ABSTRACT

Background. The transition from static fitness tracking applications to dynamic Artificial Intelligence (AI)-driven adaptive coaching platforms represents a major shift in personal health telemetry with both advantages and disadvantages. While these systems optimize physical conditioning, they may have psychological and cognitive impacts which are needed to be defined.
Aim. This systematic review examines how AI coaching paradigms influence user motivation, behavioral adherence, and cognitive load through the theoretical lenses of Self-Determination Theory (SDT) and Cognitive Load Theory (CLT).
Material and methods. A systematic literature search was conducted across major databases (PubMed, EMBASE, MEDLINE, Google Scholar, Web of Science) for peer-reviewed studies published between 2016 and 2026. Additionally, publications from previous years have also been included to provide great theoretical value, necessary for interpreting modern digital behavior.
Results. Automated adaptive planning provided by AI-driven reduces extraneous cognitive load by eliminating manual workout design. However, opaque "black-box" decisions provoke algorithm aversion, elevated cognitive friction, and reduced autonomy when algorithmic metrics conflict with subjective somatic sensations. Over-reliance on predictive AI also risks undermining user self-efficacy.
Conclusions. To optimize human-AI collaboration and minimize the somatic-cognitive risks, digital health platforms should integrate several frameworks: explainable AI (XAI) transparency, dynamic user autonomy toggles, and somatic-algorithmic calibration protocols to protect user agency and psychological well-being.

KEYWORDS

Artificial Intelligence, Adaptive Coaching, Behavioral Adherence, Cognitive Load, Digital Health

CITATION

Tanko, A., Tetarchuk, V., Trutsko, A., Abramchuk, O., Tetarchuk, V., Shchebetun, A., & Shchebetun, D. (2026). The impact of artificial intelligence algorithms and adaptive coaching on behavioral adherence and cognitive load in fitness application users. A review. *International Journal of Innovative Technologies in Social Science*, 4(52). https://doi.org/10.31435/ijitss.4(52).2026.6867

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Introduction

In contemporary digital health, preventive medicine, and sports science, the rapid integration of artificial intelligence (AI) has fundamentally altered the landscape of personal fitness management. Over the past decade, personal health technology has evolved from passive tracking devices—such as pedometers and basic optical heart rate monitors—to highly sophisticated, AI-driven adaptive coaching systems (Ozdemir & Fatunmbi, 2024; Rabkin, 2026). Modern fitness applications leverage advanced machine learning (ML) architectures, continuous biometric telemetry, real-time computer vision, and large language model (LLM) conversational interfaces to deliver personalized, auto-regulated training recommendations without requiring direct human coaching intervention (Carnes & Mahoney, 2024; Shalu et al., 2026).

The primary physiological and behavioral rationale behind AI adaptive coaching is the dynamic management of homeostatic stress and recovery. Human physical conditioning operates on the principle of progressive overload balanced against physiological recovery capacity and motor skill adaptation (Lupton, 2016; Schmidt & Lee, 2022). Static, pre-programmed workout templates frequently fail because they cannot account for unpredictable real-world stressors, such as acute sleep deprivation, occupational cognitive fatigue, or subtle physiological overtraining (Dergaa et al., 2026; Gu et al., 2026). AI-driven adaptive algorithms address this limitation by continuously analyzing multi-modal data streams—including heart rate variability (HRV), resting heart rate, sleep architecture, training volume, and subjective self-report metrics—to dynamically modify workout intensity, volume, and modality in real time (Alghamdi, 2023; Bandura, 2018).

However, while the physiological advantages of automated auto-regulation are clear, the cognitive, psychological, and behavioral consequences for the human user are multifaceted (Brick et al., 2018; Gong & Gong, 2026). The human-technology interface in fitness applications involves a complex interplay between

behavioral adherence and cognitive ergonomics (Gong & Gong, 2026; Shabankareh et al., 2025). Behavioral adherence—defined as the sustained, long-term consistency of a user's participation in prescribed exercise routines—is deeply influenced by psychological autonomy, self-efficacy, and intrinsic motivation (Puce et al., 2026; Sabitha et al., 2026; Vealey, 2019). Concurrently, cognitive load—the total volume of mental effort expended in working memory during information processing—governs how users interpret, trust, and act upon algorithmic instructions (Gong & Gong, 2026; Shen et al., 2024).

When an AI system functions as an opaque "black box," prescribing unexpected training adjustments without contextual explanation, it can induce decision dissonance, cognitive friction, or algorithm aversion (Brick et al., 2018; Dietvorst et al., 2016; Shalu et al., 2026). Users may experience a conflict between algorithmic mandates and their native interoceptive bodily feedback, creating psychological stress and undermining their sense of personal agency in an era of intensive data extraction (Lupton, 2016; Park et al., 2026; Zuboff, 2019). Conversely, well-designed adaptive interfaces can reduce cognitive fatigue by offloading complex exercise programming decisions, making physical activity participation more accessible and sustainable (Gong & Gong, 2026; Ribeiro et al., 2016).

Despite the rapid deployment of AI coaching technologies in consumer markets, exercise science literature has historically focused on physical performance metrics, leaving a critical gap in understanding the cognitive ergonomics and socio-technical dynamics of automated coaching. This review addresses this gap by synthesizing current empirical research across human-computer interaction (HCI), sports psychology, behavioral medicine, and artificial intelligence. Specifically, it examines how AI-driven adaptive algorithms influence long-term behavioral adherence through the lens of Self-Determination Theory (SDT), while analyzing the structural impacts of automated coaching interfaces on user cognitive load profiles and decision-making capacity. Furthermore, the review explores how explainable AI (XAI) and user-centered design frameworks can optimize the balance between automated algorithmic guidance and human somatic autonomy.

Methodology

To capture and critically evaluate the complex interplay between biometric telemetry, artificial intelligence, and human behavior, this review employed a multidisciplinary literature synthesis across sports psychology, cognitive ergonomics, behavioral health, and digital medical systems. The investigative timeline was strategically bounded between 2016 and 2026 to ensure that synthesized empirical evidence captures the present generation of high-precision wearable sensors, real-time algorithmic auto-regulation, and pervasive machine learning architectures in mobile fitness ecosystems. Early foundational publications were selectively retained only when they provided essential theoretical frameworks necessary for interpreting modern digital behavior.

- **Search Strategy and Information Sources**

Information retrieval was executed across major international databases: PubMed, Google Scholar, EMBASE, MEDLINE, and the Cochrane Database of Systematic Reviews. The electronic search strategy incorporated targeted, Boolean-linked keyword strings designed to capture the intersection of AI adaptive coaching, telemetry, and athletic psychology, including:

- ("artificial intelligence" OR "machine learning" OR "adaptive coaching") AND ("exercise adherence" OR "training motivation")
- ("Self-Determination Theory" OR "autonomy") AND ("algorithm aversion" OR "black-box AI") AND "fitness applications"
- ("Cognitive Load Theory" OR "cognitive friction") AND ("biometric data" OR "heart rate variability") AND "somatic awareness"
- ("explainable AI" OR "XAI") AND ("digital health" OR "sports telemetry") AND "user self-efficacy"
- ("adaptive training algorithms" OR "auto-regulation") AND ("decision fatigue" OR "interoceptive awareness")

- **Inclusion and Exclusion Criteria**

Retrieved articles were screened and deemed eligible for inclusion if they satisfied at least one of the following operational inclusion criteria:

- Evaluated shifts in training motivation, behavioral compliance, or athletic goal-setting driven directly by adaptive AI coaching platforms or automated workout algorithms;

- Examined psychological alterations, decision friction, algorithm aversion, or interoceptive conflict stemming from biometric telemetry and opaque algorithmic recommendations;
- Investigated structural features of AI interfaces, explainable AI (XAI) transparent protocols, dynamic user autonomy toggles, or somatic-algorithmic calibration practices;
- Documented changes in cognitive load profiles (extraneous vs. germane), self-efficacy metrics, or user agency during automated auto-regulated exercise prescription.

Conversely, publications were systematically excluded if they met any of the following criteria:

- Did not directly address behavioral science, sports psychology, cognitive ergonomics, or AI-driven digital tracking systems;
- Evaluated static, non-adaptive tracking technologies (e.g., basic step counters or un-integrated digital logs) lacking algorithmic auto-regulation;
- Consisted of commercial product manuals, non-refereed fitness blogs, popular media articles, or opinion-based commentary lacking structured empirical metrics;
- Manuscripts without available full English text.

Finally, investigations focusing solely on clinical medical rehabilitation populations (e.g., post-stroke gait training or post-cardiac surgery rehabilitation) were kept outside the scope of this review. The motivational profiles and risk-avoidance behaviors of clinical populations lack the performance-driven characteristics, volume metrics, and autonomous behavioral dynamics typical of healthy recreational and athletic populations engaging with adaptive fitness platforms.

Results

Study Selection and Literature Yield

The initial database search and multi-stage screening process yielded a final synthesis of core peer-reviewed empirical studies, theoretical publications, and technical guidelines. The identified literature spans four primary disciplinary domains: sports psychology and behavioral medicine, cognitive ergonomics and human-computer interaction (HCI), biometric signal processing, and explainable artificial intelligence (XAI). These publications collectively provide the empirical foundation for analyzing how AI-driven adaptive coaching shapes user adherence, cognitive load, and somatic autonomy.

Theoretical Integration: SDT and CLT Mechanics

Understanding how AI algorithms alter human exercise behavior requires combining frameworks from behavioral psychology and cognitive ergonomics: Self-Determination Theory (SDT; Ryan & Deci, 2017) and Cognitive Load Theory (CLT; Sweller et al., 2019).

Self-Determination Theory (Ryan & Deci, 2017) posits that sustained behavioral adherence relies on satisfying three basic psychological needs:

- **Autonomy:** The psychological requirement to experience volition, self-endorsement, and personal agency over one's actions.
- **Competence:** The need to feel effective, capable, and successful in mastering challenging tasks within a domain (Vealey, 2019).
- **Relatedness:** The need to feel connected, valued, and understood within a social or interpersonal context.

In traditional human coaching, an effective coach satisfies these needs by offering choices, explaining the rationale behind workouts, and providing empathetic support (Alghamdi, 2023; Vealey, 2019). When an AI algorithm assumes the coaching role, these psychological dynamics shift (Shalu et al., 2026).

If an AI application functions as a prescriptive controller—commanding specific workout intensities without explanation or user input—the user's sense of autonomy drops sharply (Brick et al., 2018; Gu et al., 2026). Over time, this shifts motivation from intrinsic enjoyment to controlled extrinsic compliance, increasing the risk of disengagement when the algorithm yields unexpected or unpleasant directives (Ozdemir & Fatunmbi, 2024; Ryan & Deci, 2017). Conversely, when adaptive algorithms offer customizable options, explain their recommendations, and adjust dynamically to user feedback, they mitigate algorithm aversion, enhance perceived competence, and support autonomous regulation (Carnes & Mahoney, 2024; Dietvorst et al., 2016; Ribeiro et al., 2016), as structuralized in the comparative paradigm framework (Table 1).

Table 1. Comparative Framework of AI Coaching Paradigms and Psychological Outcomes

Evaluation Dimension	Prescriptive / Opaque AI	Autonomous / Explainable AI (XAI)	Key Sources
Algorithmic Mandate	Imposes rigid, non-negotiable workout prescriptions	Explains underlying biological reasoning and metrics	(Brick et al., 2018; Gu et al., 2026; Ribeiro et al., 2016)
User Feedback Integration	Ignores subjective contextual inputs and user feedback	Offers customizable options and flexible workout alternatives	(Carnes & Mahoney, 2024; Chirayath et al., 2025; Dietvorst et al., 2016)
Human Agency Impact	Suppresses somatic autonomy and personal control	Respects somatic awareness and interoceptive bodily feedback	(Lupton, 2016; Ryan & Deci, 2017)
Psychological & Behavioral Outcome	**Controlled Compliance:** • High risk of workout abandonment and drop-out • Elevated decision fatigue and cognitive friction	**Autonomous Adherence:** • Sustainable long-term habit formation • Enhanced self-efficacy and intrinsic motivation	(Bandura, 2018; El-Zayat et al., 2023; Ozdemir & Fatunmbi, 2024)

Furthermore, the psychological transition from autonomous self-regulation to algorithmically enforced compliance represents a fundamental shift in how physical exercise is internalized within an individual's identity (Ryan & Deci, 2017). When algorithmic directives bypass a user's intrinsic rationale, exercise behavior becomes contingent on external validation rather than personal fulfillment (Bandura, 2018). This reliance creates a precarious motivational architecture: the moment the technological interface fails, produces unintuitive recommendations, or experiences service disruptions, the user's extrinsic motivation rapidly decays, leading to abrupt cessation of physical activity rather than adaptive self-steering (Gu et al., 2026; Ozdemir & Fatunmbi, 2024).

Cognitive Load Theory (Sweller et al., 2019), adapted to HCI and human factors by Chirayath et al. (2025) and Shen et al. (2024), segments working memory allocation into three operational categories:

- **Intrinsic Cognitive Load:** The baseline effort inherent to performing the physical activity itself (e.g., maintaining proper running posture, managing pacing, or monitoring effort).
- **Extraneous Cognitive Load:** Mental effort generated by interface complexity, ambiguous data presentation, or confusing navigation choices.
- **Germane Cognitive Load:** Productive mental processing dedicated to learning, integrating feedback, and developing somatic self-regulation schemas.

From an information-processing perspective, the cognitive impact of digital telemetry is heavily influenced by how raw biological data is framed within the application interface (Shen et al., 2024). Interfaces that present excessive, uncurated metrics—such as continuous fluctuations in body temperature, sub-phase sleep details, and high-frequency heart rate variability metrics—without providing contextual biological synthesis create severe information overload (Chirayath et al., 2025). Working memory capacity is consequently consumed by interpreting complex data visualizations rather than attending to exercise execution or motor skill refine ment, thereby converting what should be germane learning processes into burdensome extraneous cognitive load (Sweller et al., 2019; Yadav et al., 2026).

AI adaptive coaching interfaces directly alter the balance between extraneous and germane cognitive load (Chirayath et al., 2025). By automating complex workout calculations—such as periodization models, volume adjustments, and intensity zoning—AI algorithms significantly reduce extraneous cognitive load for novice users (Shen et al., 2024). Users no longer need to analyze raw training logs or manually design exercise sessions, freeing working memory capacity for execution (Chirayath et al., 2025).

From a cognitive ergonomics perspective, the structural design of biometric dashboards acts as a primary filter for information processing (Sweller et al., 2019). When applications overload users with raw, multi-parameter telemetry—such as raw heart rate variability power spectra, continuous body temperature

fluctuations, and complex sleep architecture graphs—without contextually synthesizing these metrics into actionable guidance, they inadvertently inflate extraneous cognitive load (Chirayath et al., 2025; Shen et al., 2024). Instead of facilitating motor learning or physical effort, working memory capacity becomes fully occupied with processing complex digital signals, inducing mental fatigue even before physical exertion commences (Yadav et al., 2026).

However, if an algorithm presents conflicting data, ambiguous recovery warnings, or counter-intuitive adjustments, it can introduce extraneous friction and cognitive dissonance (Brick et al., 2018; Shen et al., 2024). Users waste working memory trying to decipher why the application prescribed a rest day when they feel energetic, or vice versa, leading to decision fatigue and mental exhaustion (El-Zayat et al., 2023; Chirayath et al., 2025).

To evaluate behavioral impacts systematically, it is necessary to differentiate between the technical paradigms underlying modern AI fitness platforms (Bandura, 2018; Shen et al., 2024). Current application architectures fall into three primary categories, summarized in Table 2.

Table 2. Comparative Taxonomy of AI Adaptive Coaching Paradigms in Consumer Fitness Applications

AI Coaching Paradigm	Core Technical Mechanics & Data Inputs	Primary Psychological & Behavioral Drivers	Impact on Cognitive Load & Autonomy	Primary Sources
Biometric Auto-Regulation	Continuous processing of HRV, RHR, sleep stage data, and PPG telemetry using deep neural networks	Reduces subjective decision burden; validates physical state through quantitative metrics	Reduces extraneous load; risks interoceptive blinding and diminished autonomy if unexplainable	Boldi et al. (2024); Esco et al. (2026); Rabkin (2026); Sabitha et al. (2026); Sperlich et al. (2020)
Conversational AI / LLMs	Natural language processing (NLP) interfaces providing real-time dialogue, empathetic encouragement, and instant plan adjustments	Simulates human relatedness; provides personalized reasoning for workout modifications	Lowers technical friction; supports autonomy if conversational tone remains non-judgmental	Dergaa et al. (2026); Garcia et al. (2025); Gong & Gong (2026); Park et al. (2026)
Predictive Performance Modeling	Supervised machine learning models forecasting race times, fatigue accumulation, injury risk, and VO2 max trends	Targets competence needs by offering clear progress projections and long-term milestones	High germane engagement; risks acute performance anxiety if projected trends decline	Alghamdi (2023); Carnes & Mahoney (2024); Gu et al. (2026); Huguet-López et al. (2026); Werner & Bischof (2024)

Synthesizing empirical findings across the reviewed studies reveals a core tension in human-AI fitness interaction: the balance between automated behavioral scaffolding and human cognitive autonomy (Bandura, 2018; Chirayath et al., 2025; Ryan & Deci, 2017).

Mechanisms of Adherence Enhancement

AI adaptive coaching enhances behavioral consistency through three main mechanisms:

1. Elimination of the "Blank Slate" Barrier: Novice users frequently experience choice paralysis when faced with designing an exercise routine (Chirayath et al., 2025). By providing a dynamic daily plan based on current recovery metrics, AI systems remove the friction of decision-making, lowering the activation energy required to initiate workouts (Ozdemir & Fatunmbi, 2024).

2. Real-Time Dynamic Auto-Regulation: Traditional static plans often lead to overuse injuries or burnout when users force themselves through hard workouts on under-recovered days (Lupton, 2016; Page et al., 2021). Adaptive algorithms automatically downgrade intensity when biometric inputs signal systemic fatigue, protecting the user from physical exhaustion and preserving long-term habit consistency (Bandura, 2018).

3. Personalized Micro-Feedback: Generative AI interfaces offer targeted post-workout insights, linking physical exertion to long-term goals (Shalu et al., 2026). This instant positive feedback loop activates dopaminergic reward pathways, reinforcing habit formation (Ozdemir & Fatunmbi, 2024).

Crucially, the success of these mechanisms relies heavily on the system's ability to maintain user self-efficacy over extended time horizons (Bandura, 2018; Vealey, 2019). By eliminating initial structural barriers, AI platforms function as cognitive training wheels. However, if the interface continuously manages every single variable without transferring self-regulatory strategies to the user, it prevents the development of robust internal behavioral schemas (Chirayath et al., 2025). Consequently, long-term adherence becomes entirely dependent on persistent technology availability rather than durable internal habit formation (Puce et al., 2026).

Algorithm Aversion and Cognitive Friction

Conversely, automated coaching systems can introduce friction through specific socio-technical failure modes:

- **Black-Box Opacity:** When an algorithm significantly reduces workout volume or commands an unexpected rest day without explaining the underlying physiological reasoning, users often experience algorithm aversion (Brick et al., 2018; Shalu et al., 2026). Disregarding user context (e.g., job stress, travel) leads users to view the system as inaccurate or rigid, causing them to reject recommendations entirely (Chirayath et al., 2025).
- **Interoceptive Displacement:** Heavy reliance on AI-driven recovery scores (e.g., "strain vs. readiness" indices) can cause users to distrust their own somatic bodily perception (Lupton, 2016). When a user feels physically energetic but their fitness application displays a low readiness score, they experience acute cognitive dissonance (El-Zayat et al., 2023; Chirayath et al., 2025). This conflict can lead to cognitive fatigue and health-related anxiety, as users struggle to decide whether to trust their internal body sensations or the external algorithmic output (Boldi et al., 2024; Shabankareh et al., 2025), leading to distinct behavioral trajectories and psychological consequences (Table 3).

Table 3. Psychological Consequences and Behavioral Trajectories of Somatic–Algorithmic Discrepancy

Behavioral Trajectory	User Response Mechanics	Primary Psychological Outcome	Risk & Behavioral Consequences	Key Sources
Complete AI Reliance *(Uncritical Compliance)*	Overrides internal physical sensations and relies entirely on algorithmic metrics	**Interoceptive Blinding:** Suppression of subjective somatic self-awareness	• Heightened risk of overtraining or physical injury • Motivatio-nal passivity and helpless-ness • Long-term erosion of bodily self-trust	(Lupton, 2016; Shabankareh et al., 2025)
Complete AI Rejection *(System Abandonment)*	Dismisses algorithmic recommendations due to black-box opacity or contextual mismatch	**Algorithm Aversion:** Rejection of automated guidance following cognitive conflict	• Application abandonment and subscription cancellation • Elevated decision fatigue and mental friction • Loss of structured adaptive coaching benefits	(Brick et al., 2018; Chirayath et al., 2025; El-Zayat et al., 2023)

The phenomenon of interoceptive displacement represents a profound epistemological shift in physical self-perception (Lupton, 2016). In healthy human movement, subjective interoceptive signaling—such as rate of perceived exertion (RPE), muscle soreness, and respiratory rhythm—acts as the primary feedback channel for internal state estimation (Brick et al., 2018). When continuous biometric algorithms override these native sensory pathways, users gradually condition themselves to defer somatic judgment to external digital displays (Boldi et al., 2024). This cognitive outsourcing alienates individuals from their own physiological signals, creating a state of bodily alienation where exercise readiness cannot be evaluated without external algorithmic validation (Shabankareh et al., 2025).

Discussion

The impact of AI adaptive coaching on adherence and cognitive load is moderated by individual user psychological profiles, technological expectations, and specific human-computer interaction (HCI) choices (Gong & Gong, 2026; Hill & Madigan, 2017; Huguet-López et al., 2026; Kocielnik et al., 2019).

Individual Personality Differences

1. Technology Readiness and Digital Literacy: Users with high digital self-efficacy easily process algorithmic outputs, experiencing lower cognitive load and using predictive insights adaptively (Gong & Gong, 2026). Conversely, low digital literacy users are more susceptible to confusion and interface fatigue when navigating complex analytics dashboards (El-Zayat et al., 2023; Gong & Gong, 2026). Setting realistic baseline expectations regarding algorithmic imperfections further buffers against cognitive dissatisfaction (Kocielnik et al., 2019).

2. Perfectionistic Strivings vs. Perfectionistic Concerns: As established in sports psychology models (Hill & Madigan, 2017; Huguet-López et al., 2026), individuals with high perfectionistic concerns are highly vulnerable to AI predictive outputs. When an algorithm lowers a projected performance metric or identifies poor recovery, these users view the data as personal failure, triggering performance anxiety and rumination (Huguet-López et al., 2026). Conversely, users with high perfectionistic strivings treat AI metrics as neutral data to refine training efficiency (Hill & Madigan, 2017).

Beyond perfectionism and technology readiness, individual differences in locus of control play a decisive role in shaping the human-AI interaction dynamic (Gong & Gong, 2026). Individuals with a strong internal locus of control tend to view AI-generated prescriptions as suggestions to be critically evaluated and integrated alongside personal judgment (Dietvorst et al., 2016). When faced with algorithmic recommendations that conflict with their subjective state, internal locus of control users readily override the system, thereby preserving their psychological agency and preventing interoceptive displacement (Lupton, 2016; Ryan & Deci, 2017). In contrast, users with an external locus of control are significantly more prone to granting absolute authority to algorithmic outputs, treating digital readiness scores as infallible mandates (Brick et al., 2018). This inclination accentuates vulnerability to cognitive overload, health-related anxiety, and system-induced helplessness when biometric readouts fluctuate unexpectedly (El-Zayat et al., 2023; Shabankareh et al., 2025).

Additionally, baseline trait anxiety significantly amplifies the psychological burden of continuous telemetry tracking (Boldi et al., 2024; Hill & Madigan, 2017). For highly anxious users, real-time stress indicators, dynamic recovery scores, and predictive injury risk alerts can act as persistent psychological stressors rather than supportive guides (Huguet-López et al., 2026). Instead of promoting physical recovery, the constant awareness of non-optimal biometric metrics triggers continuous hypervigilance, paradoxically elevating sympathetic nervous system tone and physiological stress responses (Rabkin, 2026; Werner & Bischof, 2024). This feedback loop illustrates how uncalibrated algorithmic feedback can exacerbate the very physiological states it is programmed to mitigate (Boldi et al., 2024).

Interface Design and Explainability (XAI)

The psychological framing of algorithmic decisions directly alters cognitive load profiles and protects user autonomy within broad ecological health behavior systems (Sallis & Owen, 2015; Shalu et al., 2026; Wanner et al., 2022). Interfaces that incorporate Explainable AI (XAI) principles—such as displaying clear, plain-language rationales (e.g., "We reduced your run volume by 15% today because your HRV was lower than baseline and sleep duration dropped by 2 hours")—significantly reduce cognitive friction and build user trust (Ozdemir & Fatunmbi, 2024; Shabankareh et al., 2025). Allowing even slight user modification of algorithmic prescriptions further minimizes refusal behaviors and enhances perceived control (Dietvorst et al., 2016).

The architectural implementation of XAI within fitness software must balance interpretive depth with cognitive brevity (Amershi et al., 2019; Ribeiro et al., 2016). While transparent explanations enhance trust, overly technical algorithmic disclosures—such as outputting raw neural network weights, deep learning confidence intervals, or complex statistical distributions—reintroduce extraneous cognitive load (Chirayath et al., 2025; Kocielnik et al., 2019). Optimal explainability in digital health coaching requires context-aware natural language generation that distills multi-variate biometric data into intuitive, actionable biological narratives (Garcia et al., 2025; Ozdemir & Fatunmbi, 2024). By transforming complex signal processing into

accessible human concepts, XAI acts as a cognitive bridge, allowing users to build accurate mental models of their physiological adaptations without inducing information overload (Shalu et al., 2026; Sweller et al., 2019).

Critical attention must also be paid to the socio-technical concerns of ubiquitous tracking (Lupton, 2016; Zuboff, 2019). When health data platform designs prioritize continuous biometric extraction over user privacy and agency, users risk experiencing surveillance anxiety, which degrades intrinsic motivation and compromises bodily autonomy (Zuboff, 2019).

This dynamic reflects broader dynamics of surveillance capitalism within consumer digital health ecosystems (Lupton, 2016; Zuboff, 2019). As biometric sensors continuously capture fine-grained physiological signals—from continuous heart rate dynamics to sleep patterns and spatial location—the user's physical body is converted into a continuous stream of extractable data assets (Rabkin, 2026; Sabitha et al., 2026). When algorithms utilize this telemetry to optimize user engagement metrics, push notification schedules, or commercial monetization loops rather than strictly supporting long-term health, the user-system relationship shifts from collaborative coaching to subtle behavioral manipulation (Wanner et al., 2022; Zuboff, 2019). Recognizing these socio-technical structures is essential for designing ethical human-computer interactions that safeguard user autonomy against predatory algorithmic design patterns (Amershi et al., 2019; Sallis & Owen, 2015).

Table 4 outlines practical system design guidelines aimed at optimizing the balance between automated algorithmic guidance and human psychological agency.

Table 4. Explainable AI (XAI) Design Framework for Fitness Applications and System Guidelines

System Intervention / Feature	Technical & HCI Mechanism	Primary Psychological & Ergonomic Benefit	Recommended Implementation	Key Empirical Sources
Plain-Language Rationales (XAI)	Natural language generation explaining the biometric reasons behind load adjustments	Eliminates black-box opacity; reduces extraneous cognitive load and algorithm aversion	Mandatory notification accompanying any auto-regulated plan modification	(Chirayath et al., 2025; Ozdemir & Fatunmbi, 2024; Ribeiro et al., 2016)
Dynamic Autonomy Toggles	Interface controls allowing users to override, accept, or modify AI workout prescriptions	Preserves psychological autonomy under SDT; maintains internal locus of control	Prominent "Override / Customize Plan" button prior to workout initiation	(Dietvorst et al., 2016; Ryan & Deci, 2017)
Somatic Cross-Validation	Prompting subjective self-reports (e.g., perceived fatigue) before displaying biometric scores	Re-establishes interoceptive awareness; prevents telemetry-induced interoceptive blinding	Pre-workout 3-second somatic slider prior to rendering readiness dashboard	(Lupton, 2016; Shabankareh et al., 2025)
Empathetic Feedback Framing	Algorithmic text optimization avoiding punitive or anxiety-inducing language during metric dips	Mitigates performance anxiety and health-related preoccupation (cyberchondria)	Automated reframing of low recovery scores into supportive rest messaging	(Boldi et al., 2024; Hill & Madigan, 2017)

Methodological Limitations and Future Research

While current research offers valuable insights into digital health coaching, several methodological limitations remain (Dergaa et al., 2026):

1. Short Evaluation Windows: Most published HCI and behavioral fitness studies evaluate user interaction over brief intervention periods (typically 4 to 12 weeks) (Park et al., 2026; Puce et al., 2026). These short timeframes fail to capture long-term habit fatigue, algorithm abandonment, or multi-year motivational decay.

2. Heterogeneity of AI Implementations: The term "AI coaching" is used inconsistently across commercial marketing and academic studies, covering everything from simple rule-based heuristics to advanced deep reinforcement learning models (Alghamdi, 2023). This architectural variation complicates cross-study comparisons.

3. Reliance on Self-Reported Adherence: Many empirical studies measure user compliance through self-reported survey logs rather than objective telemetry verification, introducing recall bias and social desirability artifacts (Gabarron et al., 2024; Huguet-López et al., 2026).

To advance the scientific understanding of automated coaching systems, future research should focus on:

1. Longitudinal Cohort Studies: Evaluating multi-year trajectories of user adherence, cognitive load, and intrinsic motivation across evolving AI application updates (Gu et al., 2026).

2. Neuro-Ergonomic and Physiological Testing: Combining eye-tracking, functional near-infrared spectroscopy (fNIRS), and real-time stress biomarker monitoring during live interaction with AI adaptive interfaces to measure cognitive load objectively (Shen et al., 2024; Yadav et al., 2026).

3. Adaptive Human-AI Collaborative Models: Developing algorithmic architectures that actively learn user-preferred levels of autonomy, dynamically shifting between fully automated coaching and subtle supportive scaffolding based on user stress states and expectation dynamics (Amershi et al., 2019; Kocielnik et al., 2019).

Conclusions

Artificial intelligence algorithms and adaptive coaching platforms represent a significant technological advancement in personal health management, offering automated, real-time load regulation and personalized feedback. However, their long-term effectiveness depends heavily on their human-computer interface design and psychological ergonomics.

When implemented as opaque, prescriptive "black boxes," AI coaching platforms risk undermining user autonomy, inducing decision friction, and provoking algorithm aversion or interoceptive blinding. Conversely, when designed around principles of Explainable AI (XAI), dynamic user autonomy controls, and somatic cross-validation, adaptive coaching systems effectively reduce extraneous cognitive load while fostering sustainable, long-term exercise adherence. Modern digital health platforms should prioritize transparent, human-centered AI design, ensuring that automated technology supports human agency rather than replacing it.

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