BEYOND THE APP: A FUNCTIONAL TAXONOMY OF ARTIFICIAL INTELLIGENCE TOOLS FOR PHYSICAL ACTIVITY PROMOTION

Mariasole Antonietta Guerriero
Pegaso Telematic University
mariasole.guerriero@unipegaso.it

Angelo Basta
eCampus University
angelo.basta@uniecampus.it

Fiorenzo Moscatelli
Pegaso Telematic University
fiorenzo.moscatelli@unipegaso.it

Francesco Paolo Colecchia
University of Campania "Luigi Vanvitelli"
francescopaolocolecchia@gmail.com

Double Blind Peer Review

Citation
Guerriero, M. A., Basta, A., Moscatelli, F., & Colecchia, F. P. (2026). Beyond the app: A functional taxonomy of artificial intelligence tools for physical activity promotion. *Italian Journal of Health Education, Sport and Inclusive Didactics*, *10*(4). https://doi.org/10.32043/gsd.v10i4.1900

Doi: https://doi.org/10.32043/gsd.v10i4.1900

Copyright notice:
© 2026 The Author(s). This is an open access, peer-reviewed article published by Cares S.r.l. – REN Press and distributed under the terms of the Creative Commons Attribution 4.0 International License (CC BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

renpress.it/index.php/gsdj
ISSN: 3103-5744

ABSTRACT
Physical inactivity represents a major global health concern. This study maps AI-based tools for physical activity promotion using an exploratory functional classification approach. A purposive sample was identified through There's an AI for That and web searches. Six functional categories emerged inductively: adaptive real-time coaching, adaptive workout planning, monitoring and tracking, promotion of daily movement, motivation and engagement, and conversational coaching and behaviour change. The framework provides a conceptual basis for understanding how AI mediates physical activity practices.

KEYWORDS
artificial intelligence; physical activity; fitness technology; behaviour change; digital health.

Received 2026-07-10
Accepted 2026-10-27
Published 2026-10-30

1. Introduction

Physical inactivity and sedentary behaviour represent one of the most pressing global health challenges of the twenty-first century. According to the World Health Organization 2020 guidelines on physical activity and sedentary behaviour, insufficient physical activity is causally associated with increased risk of non-communicable diseases including cardiovascular disease, type 2 diabetes, and several cancers, as well as with mental health disorders and premature mortality (Bull et al., 2020). Despite decades of public health investment in physical activity promotion, global levels of inactivity have not declined, and sedentary behaviour continues to increase across all age groups and world regions (WHO, 2022). Previous research has further highlighted the relationship between sedentary lifestyle, physical activity levels, and stress, particularly among young adult populations such as university students (Guerriero et al., 2025).

In this context, digital health technologies and artificial intelligence (AI) have emerged as promising tools for supporting physical activity promotion at scale (Guerriero et al., 2026). The proliferation of smartphones — with approximately 6.92 billion users worldwide as of 2023 (He et al., 2024) has created unprecedented opportunities for delivering personalised, accessible, and low-cost physical activity interventions directly to individuals in their everyday environments. AI-powered applications can provide personalised feedback, adaptive coaching, real-time monitoring, and behavioural nudges in ways that traditional interventions cannot replicate in terms of reach, scalability,

and cost-effectiveness. A growing body of evidence suggests that mobile health (mHealth) app-based interventions can produce modest but significant improvements in physical activity outcomes (He et al., 2024; Daryabeygi-Khotbehsara et al., 2021), and that AI-driven interventions — including mobile apps, recommendation systems, and chatbots — can improve physical activity outcomes compared to traditional approaches (An et al., 2024)).

However, the landscape of AI tools for physical activity is rapidly expanding and highly heterogeneous. Research remains fragmented across disciplinary domains — computer science, exercise science, public health, and behavioural science — with limited understanding of how these systems concretely shape user engagement and adherence to physical activity. Existing reviews have tended to focus on specific typologies of AI intervention, such as chatbots and conversational agents (Laranjo et al., 2018; Oh et al., 2021; Luo et al., 2021; Montelaghi et al., 2025), or gamification in mHealth (Xu et al., 2022; Mazeas et al., 2022), without providing a comprehensive functional mapping of the full spectrum of AI tools currently available. Furthermore, the rapidly expanding AI tool market — in which new applications are released daily — means that the available landscape far exceeds what has been studied in controlled trials, and a mapping of what currently exists is a prerequisite to future effectiveness research.

Unlike previous reviews primarily examining digital and AI-supported physical activity interventions from research, technological, or effectiveness perspective, the present study adopts an end-user perspective. Rather than restricting the analysis to tools evaluated in

scientific literature, it considers AI-based tools that are publicly accessible to users and examines the functions they are publicly described as providing. This approach is intended to reflect the digital landscape encountered by individuals seeking AI-supported solutions for physical activity, including tools that may not yet have been subject to empirical evaluation. Accordingly, this study aims to provide an exploratory functional mapping of AI-based tools currently accessible to end users for physical activity promotion. Specifically, it seeks to answer the question: What functional roles are publicly accessible AI-based tools designed and described as providing in support of physical activity-related behaviours? By examining the functions these tools are publicly described as providing — rather than directly testing their features or evaluating their efficacy — this study aims to contribute a conceptual framework that can inform future research and the design of AI-mediated physical activity interventions.

2. Methodology

This study adopted an exploratory digital landscape mapping design from an end-user perspective. The aim was not to conduct a formal scoping review of the scientific literature, but to identify and functionally classify AI-based tools that were publicly accessible to users at the time of the search. The mapping followed a structured process of tool identification, eligibility assessment, data extraction, and inductive functional classification to enhance transparency and reproducibility.

RQ: What functional roles are publicly accessible AI-based tools designed and described as providing in support of physical activity-related behaviours?

2.1 Source and Search Strategy

The primary source was There's an AI for That (TAAFT; theresanaiforthat.com), a specialised online directory that systematically indexes and categorises AI tools across application domains, with over 50,000 tools catalogued at the time of the search. TAAFT was selected as the primary source due to its systematic categorisation, consistent update frequency, broad coverage of AI application domains, and its established use as a reference resource in AI market landscape analyses. The following thematic categories were systematically navigated in their entirety: Fitness (146 tools at time of access), Fitness Coaching (71 tools), Running (14 tools), Strength Training (6 tools), and Physiotherapy (5 tools). All category pages were accessed and fully reviewed in June 2026.

The TAAFT category search was complemented by targeted Google searches restricted to the TAAFT domain, using thematic keywords derived from the research question: “physical activity”, “workout”, “running”, “movement”, “walking”, “sedentary”, “wellness”, and “wearable”. These searches were used to identify potentially relevant TAAFT-indexed tools that might not have been retrieved through direct navigation of the selected categories. Additional broader web searches were conducted to identify well-established user-facing platforms relevant to the functional landscape of physical activity promotion, including platforms such as Strava and Zombies, Run!. This integration

aimed to capture tools not surfacing through direct category navigation, and to incorporate tools identified in broader web searches for well-established platforms (e.g., Strava, Zombies Run!) that, while not exclusively indexed on TAAFT, represent significant phenomena in the AI fitness tool landscape. Searches were conducted in June 2026. No geographical restrictions were applied. No explicit language restriction was imposed; however, the primary source (TAAFT) and the search terms used for complementary searches were in English. Records identified across TAAFT categories and complementary searches were consolidated into a single dataset, and duplicate entries referring to the same tool were removed before eligibility assessment. The 53 tools reported in the Results therefore represent unique tools after duplicate removal. Tool selection and eligibility assessment were conducted by two authors using the predefined inclusion and exclusion criteria. Cases in which eligibility was uncertain were discussed with the other co-authors, who also reviewed and confirmed the final set of included tools. Verification was based on publicly accessible information, prioritising official developer or provider sources where available.

2.2 Inclusion and Exclusion Criteria

Tools were included if they: (a) presented a direct user-facing interface accessible to the end user without the need for professional intermediaries; (b) had an explicit primary or secondary function related to the promotion, support, or monitoring of physical activity or movement-related behaviours; and (c) were active and publicly accessible at the time of the search (June 2026); (d) the use of AI was

explicitly declared by the developer or platform in publicly accessible documentation, such as the official website, application description, or technical/product documentation. Tools were not classified as AI-based solely on the basis of the authors' inference from their functionality.

For the purposes of this study, an AI-based tool was operationally defined as a publicly accessible digital tool whose developer or provider explicitly described its functionality as involving artificial intelligence or a specific AI-related technology (e.g., machine learning, large language models, computer vision, or AI-based recommendation/personalisation). This classification reflects publicly available developer claims and was not based on independent technical verification of the underlying algorithms.

Tools were excluded if they: (a) were exclusively business-to-business (B2B) solutions without a direct user interface for the person engaging in physical activity; (b) required the purchase of dedicated hardware devices (wearables, smart rings, exoskeletons, dedicated cameras) as a prerequisite for use, since the study focused on software applications; (c) were sport-specific tools targeting competitive athletic performance in a single sport (e.g., basketball skill training, tennis analytics) without broader physical activity promotion relevance; (d) were not publicly verifiable through accessible online sources at the time of the search; or (e) functionally redundant tools presenting substantially overlapping user-facing functions.

During the exploratory search phase, more than 60 GPT-based tools related to fitness and physical activity were encountered. Because many of these tools presented substantially overlapping user-facing functions

and highly similar descriptions, they were not all entered individually into the screening dataset. Instead, two representative GPT-based tools were retained to capture this recurring functional profile without disproportionately weighting the subsequent classification toward highly similar tools. Accordingly, these additional GPT-based tools are not included in the count of 53 unique tools assessed for eligibility. This purposive reduction was applied for functional mapping purposes and should not be interpreted as theoretical saturation or as an exhaustive enumeration of all GPT-based tools available at the time of the search.

2.3 Analytical Approach

Each included tool was analysed using a structured coding grid developed specifically for this study, comprising two analytical layers. The first descriptive layer captured: tool name, source URL, platform, pricing model, functional description written in the researcher's own words (not copied from source material), target behaviour, modality of user interaction, degree of adaptivity over time, and declared AI technology. The second, inductive coding layer — completed after reviewing all tools comparatively — assigned: a primary functional code, a secondary functional code where applicable, the primary phase of the behaviour targeted (pre-activity / during activity / post-activity / cross-cutting), and the locus of action (cognitive, motivational, behavioural, physiological).

Consistent with an inductive thematic approach (Braun & Clarke, 2006), categories were not predefined prior to data collection. They emerged from iterative comparison of the functional descriptions across all

included tools. The analytical process involved: (1) a first-pass reading of all functional descriptions without coding; (2) generation of provisional labels for each tool; (3) comparative analysis to identify clusters of functionally similar tools; (4) refinement and naming of emerging categories; and (5) verification that each tool's assignment was consistent with the category definition. Tool identification and eligibility assessment were conducted by two authors. Initial functional coding was conducted by the lead author. Category definitions, potentially ambiguous assignments, and cases presenting overlapping functions were subsequently reviewed and discussed with the co-authors. Disagreements or uncertainties were resolved through discussion until consensus was reached, and category definitions were refined where necessary to improve consistency across assignments. No formal inter-rater agreement statistic was calculated, as the classification process followed a consensus-based rather than an independent double-coding procedure. The six categories were defined according to the primary user-facing function of each tool rather than as mutually exclusive technological classes. When a tool supported multiple functions, classification was based on the function that appeared most central to its publicly described purpose, while secondary functions and interaction modalities were considered as additional descriptive characteristics. The resulting categories may therefore partially overlap, reflecting the multifunctional nature of contemporary AI-based tools.

3. Results

A total of 53 tools were initially identified through TAAFT category navigation and complementary web searches. Following the application of inclusion and exclusion criteria, 33 of the 53 identified tools were retained for analysis and 20 were excluded. Reasons for exclusion included an exclusively B2B focus, dependence on dedicated hardware, sport-specific applications, lack of publicly verifiable information or discontinuation, and functional redundancy among GPT-based tools.

Inductive analysis of the 33 included tools yielded six functional categories. These are described below and summarised in Table 1. The categories are presented in order of temporal proximity to the act of movement, from tools that intervene during the activity itself to those that operate at a distance from it.

3.1 Adaptive Real-Time Coaching

Tools in this category provide immediate, personalised guidance during or immediately after the physical activity session. Feedback is delivered in real time (during movement) or in near-real time (asynchronously following video upload), targeting execution quality, intensity management, and technique correction. Representative examples include Arvo, which guides users set-by-set through resistance training sessions adjusting loads and recovery times based on declared effort and historical performance data; Broccoli AI, which delivers adaptive audio coaching during running sessions responding to real-time heart rate data; and Forma Run, which analyses user-uploaded running videos and

provides biomechanical feedback asynchronously. The distinguishing characteristic of this category is the temporal proximity of the AI intervention to the physical act of movement — the system is present, in some form, while the body is in motion. This category differs from monitoring and tracking tools in that data are not merely recorded or summarised but are used to provide immediate or near-real-time feedback intended to modify the user's ongoing activity or performance.

3.2 Adaptive Workout Planning

This was the most populated category, encompassing tools that generate and continuously update personalised training programmes based on user data collected over time. Unlike real-time coaching, these tools operate primarily before the session, delivering a structured plan that evolves with the user's progress, recovery status, goals, and available equipment. Tools range from beginner-oriented platforms such as Planfit to advanced periodisation systems such as Pelaris, which employs a five-layer large language model (LLM) pipeline for programme generation across multiple sports. Common mechanisms include progressive overload optimisation based on historical session data (Fitbod, FitnessAI), body composition analysis from photographs to inform programme design (Zing Coach, FlexToast), and integrated workout-nutrition planning (MikeAI, Freeletics). The convergence of a large number of tools on this functional category reflects the current technological emphasis on personalisation as the primary value proposition of AI in the fitness domain, consistent with broader trends in AI recommendation systems. Tools were assigned to this category when

publicly available descriptions indicated that workout plans could be dynamically adjusted or personalised in response to user characteristics, goals, progress, or performance data, rather than simply providing a predefined or static personalised programme.

3.3 Monitoring and Tracking

Tools in this category focus on recording and interpreting physical activity and physiological data, providing users with insights that inform — but do not directly prescribe — training decisions. This category includes both passive monitoring tools and active logging tools. Welltory measures heart rate variability (HRV) via smartphone camera to produce daily readiness scores that guide the decision of whether and how intensely to train. Train Fitness automatically detects and records exercises via smartwatch motion sensors, removing the administrative burden of manual logging. LiftLog supports manual workout logging with AI-assisted progression analysis. Gyroscope represents a further variant: a health data aggregation platform that centralises inputs from multiple wearables and applications into a unified personalised dashboard. The common thread across these tools is the transformation of raw activity and physiological data into actionable insights, without directly prescribing movement content or intensity.

3.4 Promotion of Daily Movement

This category groups tools that do not target athletic performance or structured exercise, but instead address sedentary behaviour in

everyday contexts, consistent with the public health framing of physical activity as including all movement, not only structured exercise (Bull et al., 2020). These tools are particularly relevant for populations with low baseline physical activity levels, for whom structured workout planning may represent an inappropriate or inaccessible first intervention (Ueno et al., 2022). NeckFit provides AI-based postural analysis and corrective exercise routines for desk workers experiencing neck and cervical pain, targeting micro-movement integration into sedentary work routines. AI Steps promotes daily walking through personalised goal-setting and motivational nudges calibrated to individual activity patterns. Posture Reminder AI uses on-device computer vision to detect postural deviation during computer use and trigger real-time alerts, supporting postural behaviour change in the workplace. The locus of action in this category is the routine daily environment — the desk, the commute, the domestic space — rather than the gym or the running track.

3.5 Motivation and Engagement

Two distinct motivational mechanisms were identified within this category, reflecting different theoretical accounts of why people engage in physical activity. Zombies, Run! exemplifies narrative gamification: users engage in a post-apocalyptic audio story that unfolds during real-world running sessions, with physical movement advancing the narrative and unlocking resources. The physical activity is instrumentalised as gameplay, transforming what might otherwise be experienced as effortful exercise into a meaningful narrative act. This approach aligns with research demonstrating that gamification mechanisms can improve

physical activity participation and adherence, particularly through narrative elements that foster intrinsic motivation (Xu et al., 2022; Mazeas et al., 2022). Strava, by contrast, leverages social competition and community: users track outdoor activities via GPS, share results with a network of followers, and compete on virtual segments (crowdsourced timed sections of road or trail). The motivational mechanism is social comparison, public accountability, and the pursuit of community recognition — a form of what Self-Determination Theory identifies as relatedness need satisfaction (Ryan & Deci, 2017). Both tools promote physical activity without prescribing its content, relying instead on engagement architectures to sustain adherence.

3.6 Conversational Coaching and Behaviour Change

Tools in this category use conversational AI agents — either on dedicated messaging platforms (Telegram, WhatsApp) or within LLM interfaces (ChatGPT) to deliver personalised coaching and behaviour change support through natural language dialogue. Delta Driven operates as a Telegram bot providing proactive daily check-ins, personalised workout and nutrition advice, and motivational follow-ups, exploiting a communication channel that users already habitually engage with. FitGPT and Stretch GPT are ChatGPT-based agents offering on-demand fitness and flexibility coaching through conversational interaction. Running Habit Architect is specifically designed to build the habit of running through progressive plans and psychological behaviour change strategies, targeting users who have previously failed to sustain a running routine. The defining characteristic of this category is the

conversational modality of the AI-user interaction — a modality that connects these tools to a growing body of literature on conversational agents for health behaviour change (Laranjo et al., 2018; Oh et al., 2021; Luo et al., 2021; Montelaghi et al., 2025). The use of existing messaging platforms (Telegram, WhatsApp) as delivery channels represents a notable design strategy: rather than requiring users to adopt a new application, these tools embed within communication environments already present in users' daily digital routines. Conversational interaction alone was not sufficient for assignment to this category. Tools were classified here when natural-language dialogue represented the primary user-facing mechanism through which ongoing coaching, guidance, or behaviour-change support was delivered. Tools using conversational interfaces primarily to deliver another dominant function, such as workout planning, were classified according to that primary function.

Table 1: Functional classification of AI tools for physical activity promotion

Functional Category	Representative Tools	Primary Function	AI Technology	Platform	Phase
1. Adaptive Real-Time Coaching	Arvo; Broccoli AI; Forma Run	Provides immediate personalised guidance during or immediately after the session, targeting execution quality, intensity, and technique	LLM + multi-agent AI; GPS + audio AI; computer vision for biomechanical analysis	App (iOS/Android); Web	During activity / post-session
2. Adaptive Workout Planning	Fitbod; Pelaris; Planfit; Zing Coach; FitnessAI; Freeletics; FlexToast	Generates and continuously updates personalised training programmes based on user history, recovery, goals, and available equipment	Proprietary ML; LLM pipeline (up to 5 layers); progressive overload algorithms; body scan from photos	App (iOS/Android); Web	Pre-activity
3. Monitoring and Tracking	Welltory; Gyroscope; Train Fitness; LiftLog; WorkHard Fitness	Records and interprets physiological and activity data to produce insights that inform training decisions without directly prescribing movement	ML on HRV/biometric data; motion recognition via smartwatch; data aggregation AI	App (iOS/Android); Web; Smartwatch	Cross-cutting (pre/post)
4. Promotion of Daily Movement	NeckFit; AI Steps; Posture Reminder AI	Addresses sedentary behaviour in everyday contexts by promoting micro-movements and postural correction, targeting low-activity populations	Computer vision for posture detection; AI for step pattern analysis and personalised nudging	App (iOS/Android/macOS)	Cross-cutting (daily life)
5. Motivation and Engagement	Zombies, Run!; Strava	Leverages gamification or social competition to sustain motivation and adherence without prescribing specific workout content	GPS tracking; narrative AI and gamification engine; social algorithms for leaderboards and segment ranking	App (iOS/Android); Web	During activity / cross-cutting
6. Conversational Coaching and Behaviour Change	Delta Driven (Telegram); FitGPT (ChatGPT); Running Habit Architect; Stretch GPT	Uses conversational AI via messaging platforms or LLM interfaces to support coaching and behaviour change through natural language dialogue.	LLM (GPT-4/4o); chatbot frameworks on Telegram / WhatsApp / ChatGPT	Messaging platforms; ChatGPT; Web	Pre-activity / cross-cutting

The six functional categories differed in behavioural targets, interaction modalities, and patterns of adaptation, while retaining overlapping functions. Coaching tools addressed exercise execution through set-by-set guidance, audio instructions, or video-based feedback, whereas planning tools organised workouts using goals, training histories, and user feedback. Monitoring combined sensor-based recording, manual

logs, and dashboards, sometimes also informing subsequent workout prescriptions. Daily-movement tools addressed walking, posture, and movement breaks through prompts and corrective feedback. Motivation-oriented tools used narrative or social interaction, while conversational tools provided advice and habit-related guidance through dialogue. Support occurred before activity through planning, during activity through guidance and recording, and afterwards through analysis and feedback; everyday movement and conversational support extended across these phases. The descriptions indicated behavioural, cognitive, motivational, and physiological areas of intervention, with physiological information primarily informing readiness and training adjustments. Adaptation varied within categories: session-responsive adjustments and longitudinal updates coexisted with initial personalisation and independent, on-demand outputs.

These functional patterns describe how the included tools are publicly presented and classified within the present mapping; they should not be interpreted as evidence of effectiveness, clinical validity, or demonstrated behaviour-change mechanisms.

4. Discussion

This study provides an exploratory functional classification of AI tools for physical activity promotion, identifying six categories based on the role these systems play in mediating movement-related behaviours. The mapping reveals a heterogeneous and rapidly evolving landscape, in which AI intervenes across the full spectrum of the physical activity experience: before movement (planning), during movement (coaching,

tracking), after movement (analysis, recovery guidance), and transversally across daily life (sedentary behaviour interruption, habit formation, social engagement).

The predominance of adaptive workout planning as the most populated category reflects the current state of AI fitness technology, in which personalisation of training content has become the dominant commercial and technological paradigm. This finding is consistent with the broader AI market trend toward recommendation and optimisation systems, and with consumer demand for fitness solutions that feel tailored rather than generic. However, the functional convergence of a large number of tools on this single category — with varying degrees of genuine adaptivity and scientific grounding — raises important questions about what distinguishes effective from ineffective personalisation, and how the quality of AI-driven planning can be evaluated beyond commercial claims.

The emergence of the promotion of daily movement as a distinct category is theoretically significant. Public health guidelines define physical activity as any bodily movement produced by skeletal muscles that requires energy expenditure, and explicitly identify the reduction of sedentary time as an independent health target (Bull et al., 2020). Yet most AI fitness tools — and most research in this space — focus on structured exercise rather than overall movement behaviour. Tools such as NeckFit, AI Steps, and Posture Reminder AI occupy a different niche: they target populations who may not consider themselves as exercisers, and they intervene in the daily environments (workstations, domestic spaces) where sedentary behaviour actually occurs. This aligns with

public health calls for interventions that meet people where they are (Ueno et al., 2022; Daryabeygi-Khotbehsara et al., 2021), and represents an underexplored area in the research literature on AI and physical activity.

The conversational coaching and behaviour change category connects AI fitness tools to a substantial existing literature on conversational agents in health. Laranjo et al. (2018) identified conversational agents as a promising modality for health behaviour change, noting their potential to provide personalised, scalable support at low cost. Subsequent reviews have shown that AI chatbots can produce positive effects on physical activity, though effect sizes remain modest and evidence quality is variable (Oh et al., 2021; Luo et al., 2021; Montelaghi et al., 2025). A notable finding of the present mapping is the deployment of AI coaches on existing messaging platforms (Telegram, WhatsApp) rather than standalone applications — a design strategy that reduces adoption barriers by embedding the intervention within communication tools already integrated into users' daily digital behaviour. This design approach has not been systematically studied in the physical activity literature and represents a promising avenue for future research.

The motivation and engagement category reveals an important theoretical distinction between tools that prescribe physical activity (what to do, when, and how) and tools that create the conditions for movement without prescribing its content. Strava and Zombies, Run! do not generate training plans or coach technique; they create motivational architectures — social accountability, narrative immersion, competitive dynamics, gamified progress — that generate the desire or the

contextual conditions to move. From a theoretical perspective, these features can be interpreted through the lens of Self-Determination Theory. For example, the social and community-oriented features of Strava may be interpreted as targeting relatedness, while the gamified features of Zombies, Run! may be interpreted as supporting intrinsic forms of motivation. These interpretations are theoretical and are based on the publicly described functions of the tools rather than on empirical assessment within the present study. Accordingly, the classification does not establish whether these mechanisms actually produce changes in physical activity, motivation, or related behavioural outcomes.

This study has several limitations that must be acknowledged. The mapping was conducted at a single point in time (June 2026), in a sector characterised by extremely rapid evolution; tools identified may have since changed their functions, been discontinued, or been superseded by new entrants. The purposive sampling approach, while appropriate for an exploratory digital landscape mapping, does not support claims about the exhaustiveness or statistical representativeness of the identified tool landscape. Functional descriptions were based on publicly available information — platform descriptions, official websites, user reviews, and directory entries — rather than direct testing of the tools or controlled observation of user behaviour, which may introduce inaccuracies in the characterisation of some tools. Although initial functional coding was conducted by the lead author, category definitions and ambiguous or overlapping assignments were subsequently reviewed through a consensus-based process involving the co-authors. No formal inter-rater agreement statistic was calculated, which limits the assessment of

coding reliability through quantitative measures. Additional limitations concern the broader characteristics of the digital AI landscape. Publicly available information may provide limited insight into data governance, algorithmic opacity, potential bias, and the actual operation of proprietary AI systems. Moreover, access to and use of these tools may be influenced by digital inequalities, including differences in digital literacy, device and internet access, language, and accessibility for users with disabilities. Finally, AI-supported physical activity tools used without professional supervision may raise safety concerns, particularly when recommendations are generated without adequate consideration of individual health status, functional limitations, or exercise-related risks. The present framework should therefore be regarded as preliminary, exploratory, and non-exhaustive, reflecting the publicly accessible digital landscape at the time of the search rather than a validated assessment of tool quality, safety, or effectiveness.

5. Conclusions

This study provides an exploratory functional classification of AI tools for physical activity promotion, identifying six partially overlapping functional categories — adaptive real-time coaching, adaptive workout planning, monitoring and tracking, promotion of daily movement, motivation and engagement, and conversational coaching and behaviour change — based on the role each type of tool plays in mediating movement-related behaviours. The proposed taxonomy should be regarded as a preliminary and exploratory framework for describing the primary user-facing functions of AI-based tools for physical activity

promotion. The framework proposed here offers a conceptual organiser for researchers and practitioners seeking to describe and compare the functional roles of AI-based tools across different physical activity contexts.

Several directions for future research emerge from this mapping. First, effectiveness research is needed within each identified category to determine which functional approaches produce the most robust and sustained improvements in physical activity behaviour. Second, the promotion of daily movement category warrants particular attention as a distinct intervention target for sedentary populations, for whom tools designed for structured exercise may be inappropriate or inaccessible. Third, the design strategy of embedding AI coaching within existing messaging platforms (Telegram, WhatsApp) — identified in the conversational coaching category — represents a novel approach that merits study in terms of adoption, engagement, and behaviour change outcomes. Fourth, the equity implications of the current AI fitness tool landscape require examination: the majority of tools identified assume smartphone access, digital literacy, and a degree of pre-existing motivation to exercise — conditions that may systematically exclude the populations who stand to benefit most from physical activity promotion. The integration of AI fitness tools with established behaviour change frameworks — such as Self-Determination Theory (Ryan & Deci, 2017), the Transtheoretical Model, or the COM-B system — represents a further promising direction for advancing both the science and the practice of AI-mediated physical activity promotion. Given the rapidly evolving nature of the AI landscape and the reliance on publicly available

information, the framework is not intended to be exhaustive or definitive. Future research should validate and refine the proposed categories, examine tools through direct assessment, and investigate their effectiveness, safety, accessibility, and applicability across different populations and contexts.

References

An, R., Shen, J., Wang, J., & Yang, Y. (2024). A scoping review of methodologies for applying artificial intelligence to physical activity interventions. Journal of Sport and Health Science, 13(3), 428–441. https://doi.org/10.1016/j.jshs.2023.09.010

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Bull, F. C., Al-Ansari, S. S., Biddle, S., Borodulin, K., Buman, M. P., Cardon, G., Carty, C., Chaput, J. P., Chastin, S., Chou, R., Dempsey, P. C., DiPietro, L., Ekelund, U., Firth, J., Friedenreich, C. M., Garcia, L., Gichu, M., Jago, R., Katzmarzyk, P. T., … Willumsen, J. F. (2020). World Health Organization 2020 guidelines on physical activity and sedentary behaviour. *British Journal of Sports Medicine, 54*(24), 1451–1462. https://doi.org/10.1136/bjsports-2020-102955

Daryabeygi-Khotbehsara, R., Shariful Islam, S. M., Dunstan, D., McVicar, J., Abdelrazek, M., & Maddison, R. (2021). Smartphone-based interventions to reduce sedentary behavior and promote physical activity using integrated dynamic models: Systematic review. *Journal of Medical Internet Research, 23*(9), Article e26315. https://doi.org/10.2196/26315

Guerriero, M. A., Dipace, A., Monda, A., De Maria, A., Polito, R., Messina, G., Monda, M., di Padova, M., Basta, A., Ruberto, M., Capasso, E., Moscatelli, F.,

& Limone, P. (2025). Relationship between sedentary lifestyle, physical activity and stress in university students and their life habits: A scoping review with PRISMA checklist (PRISMA-ScR). *Brain Sciences, 15*(1), Article 78. https://doi.org/10.3390/brainsci15010078

Guerriero, M. A., di Padova, M., Basta, A., Polito, R., Messina, G., Casillo, M., Dipace, A., & Moscatelli, F. (2026). Relationship between artificial intelligence and physical activity. *Sport Sciences for Health, 22*(1), Article 97. https://doi.org/10.1007/s11332-026-01685-x

He, Z., Hassan, M. A., Saiz-González, P., Ryu, S., Wang, R., & Gao, Z. (2024). Smartphone app-based interventions on physical activity behaviors and psychological correlates in healthy young adults: A systematic review. *PLOS ONE, 19*(4), Article e0301088. https://doi.org/10.1371/journal.pone.0301088

Laranjo, L., Dunn, A. G., Tong, H. L., Kocaballi, A. B., Chen, J., Bashir, R., Surian, D., Gallego, B., Magrabi, F., Lau, A. Y., & Coiera, E. (2018). Conversational agents in healthcare: A systematic review. *Journal of the American Medical Informatics Association, 25*(9), 1248–1258. https://doi.org/10.1093/jamia/ocy072

Luo, T. C., Aguilera, A., Lyles, C. R., & Figueroa, C. A. (2021). Promoting physical activity through conversational agents: Mixed methods systematic review. *Journal of Medical Internet Research, 23*(9), Article e25486. https://doi.org/10.2196/25486

Mazeas, A., Duclos, M., Pereira, B., & Chalabaev, A. (2022). Evaluating the effectiveness of gamification on physical activity: Systematic review and meta-analysis of randomized controlled trials. *Journal of Medical Internet Research, 24*(1), Article e26779. https://doi.org/10.2196/26779

Montelaghi, A., Ciorciari, A., Roklicer, R., Jurak, G., & Carraro, A. (2025). AI in motion: A systematic review of artificial intelligence-driven virtual assistants for physical activity promotion and their comparison with traditional strategies. *Artificial Intelligence Review, 58*, Article 367. https://doi.org/10.1007/s10462-025-11361-0

Oh, Y. J., Zhang, J., Fang, M. L., & Fukuoka, Y. (2021). A systematic review of artificial intelligence chatbots for promoting physical activity, healthy diet, and weight loss. *International Journal of Behavioral Nutrition and Physical Activity, 18*(1), Article 160. https://doi.org/10.1186/s12966-021-01224-6

Ryan, R. M., & Deci, E. L. (2017). *Self-determination theory: Basic psychological needs in motivation, development, and wellness*. The Guilford Press. https://doi.org/10.1521/978.14625/28806

Ueno, D. T., Guerra, P. H., Christofoletti, A. E. M., Bonolo, A., Nakamura, P. M., & Kokubun, E. (2022). Mobile health apps to reduce sedentary behavior: A scoping review. *Health Promotion International, 37*(2), Article daab124. https://doi.org/10.1093/heapro/daab124

World Health Organization. (2022). *Global status report on physical activity 2022*. https://www.who.int/publications/i/item/9789240059153

Xu, L., Shi, H., Shen, M., Ni, Y., Zhang, X., Pang, Y., Yu, T., Lian, X., Yu, T., Yang, X., & Li, F. (2022). The effects of mHealth-based gamification interventions on participation in physical activity: Systematic review. *JMIR mHealth and uHealth, 10*(2), Article e27794. https://doi.org/10.2196/27794