Received: 23 September 2024 | Accepted: 19 March 2025

DOI: 10.1111/inr.70019

International Nursing Review | ICN International Council of Nurses | WILEY

SYSTEMATIC REVIEW

The impact of machine learning on physical activity–related health outcomes: A systematic review and meta-analysis

Ezgi Hasret Kozan Cikirikci PhD(c) | **Melek Nihal Esin PhD, Professor**

Florence Nightingale Faculty of Nursing, Department of Public Health Nursing, Istanbul University-Cerrahpasa, Istanbul, Turkey

Correspondence
Ezgi Hasret Kozan Cikirikci, Florence Nightingale Faculty of Nursing, Department of Public Health Nursing, Istanbul University-Cerrahpasa, Istanbul, Turkey.
Email: e.h.kozan@gmail.com

Abstract

Aim: To analyze randomized controlled trials evaluating the effectiveness of machine learning (ML)–based interventions in promoting physical activity.

Background: Evidence on the effectiveness of ML-based interventions to increase physical activity from randomized controlled trials is limited. Synthesizing existing evidence is crucial for nurses to integrate such advancements into their care and implement health-promoting interventions.

Methods: Randomized controlled trials from 2013 to 2024 have been accessed by PubMed, EBSCO, Cochrane, and Turkish national databases. The study was conducted and reported in accordance with the PRISMA statement. The methodological quality was assessed using the Cochrane Risk of Bias 1 (RoB 1) tool. Ten studies with a total sample size of 2269 individuals were included.

Results: Analysis of studies showed that ML-based lifestyle interventions are effective in detecting physical activity levels, increasing daily step count and moderate to vigorous physical activity, predicting adherence to physical activity levels goals, and tailoring recommendations and feedback. Meta-analysis revealed that ML interventions significantly increased daily step count (Hedge's $g = 0.402$, 95% CI: 0.231–0.573, $p<0.000$).

Discussion: The studies involving ML-based physical activity promotion initiatives led by nurses were limited. The inclusion of studies published only in English and Turkish may have excluded potentially valuable data.

Conclusion: ML can effectively support public health initiatives by enabling self-monitoring, personalized recommendations, adaptive interventions, and predicting future physical activity behavior.

Implications for Nursing Practice and Policy: Nurses can leverage ML algorithms to provide timely, tailored, and cost-effective care to promote physical activity. To integrate ML into public health initiatives, and develop programs aligned with care models, it is essential to create opportunities and policies that support collaboration between nurses and software developers with nurses leading the process.

KEYWORDS
community care, community-based health promotion, health service management, nursing, public health nursing, primary care

INTRODUCTION

Physical activity is a crucial aspect of public health, essential in preventing and managing various chronic conditions, including cardiovascular disease, type 2 diabetes, and obesity (Apovian, 2016; Carbone et al., 2020; Zhang et al., 2020). It is particularly vital in health promotion strategies to maintain a healthy weight and prevent long-term weight gain (Bourdier et al., 2023; Hernández-Reyes et al., 2019). Additionally, regular participation in physical activity is linked to enhanced physical and mental health, reduced morbidity, and improved quality of life (da Silva et al., 2023; Mahindru et al., 2023). Despite these well-established benefits, a significant portion of the population remains inactive (World Health Organization, 2024). Guthold et al. (2018) stated that 27.5% of adults globally fail to achieve the physical activity levels recommended by public health guidelines. Furthermore, the World Health Organization (2022) specified in a global status report on physical activity that insufficient physical activity affects 16.2% of adults in low-income countries, 26% in middle-income countries, and 36.8% in high-income countries.

Developing and implementing effective interventions to promote physical activity is crucial for reducing the substantial health risks associated with inactivity (Dhuli et al., 2022; Singh et al., 2024). These interventions are key in preventing chronic diseases and enhancing overall quality of life (Anderson & Durstin, 2019). While strategies can range from public health campaigns to individualized approaches, research consistently shows that tailored interventions are generally more effective in changing health behaviors than standardized ones (Tong et al., 2021). Personalization is essential, as it allows interventions to be tailored to an individual's unique characteristics and delivered through the most appropriate channels at the optimal time (Bol et al., 2020; Gaysynsky et al., 2022). Recent advancements in mobile and wearable sensor technologies, coupled with artificial intelligence (AI) and machine learning (ML), have transformed the way these personalized interventions are both designed and delivered (Junaid et al., 2022; Li et al., 2024; Olyanasab & Annabestani, 2024).

ML, a subset of AI, enables the analysis of large and complex data sets to provide users with customized programs (Chakraborty et al., 2024). These technologies are particularly effective in tailoring physical activity recommendations, generating adaptive motivational messages, and designing recommender systems to promote active lifestyles (An et al., 2024).

For public health professionals, such as nurses, these tools enable the prediction of outcomes, recognition of behavior patterns, and improvements in physical activity levels through personalized feedback, coaching, and motivation delivered via websites or mobile applications (Chaudhari et al., 2022; Ghanvatkar et al., 2019). However, despite the theoretical advantages of ML-driven interventions, empirical evidence on their impact is mixed. While some studies report significant improvements in physical activity levels and associated health outcomes, others show limited or no effect (An et al., 2024; Singh et al., 2024). This inconsistency highlights the need for a systematic examination of the effectiveness of ML-based interventions in promoting physical activity. This systematic review and meta-analysis aimed to evaluate the current evidence on the impact of ML-based interventions on physical activity–related health outcomes. By synthesizing findings from diverse studies, this research aims to clarify the role of ML in physical activity promotion and provide guidance for future intervention design and implementation.

METHODS

Design

This systematic review and meta-analysis aimed to analyze randomized controlled trials (RCTs) evaluating the effectiveness of ML-based interventions in promoting physical activity compared with non-ML-based interventions. The study was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement (Page et al., 2021). The review protocol (CRD42023461189) was registered prior to data extraction on September 17, 2023, and is available at PROSPERO.

Search Methods

The data were searched in five electronic databases—PubMed, EBSCO (MEDLINE, CINAHL, Scopus, Springer Nature Journals, Science Citation Index Expanded), Cochrane, and Turkish national databases (DergiPark, TR Index)—from October 1, 2023, to December 20, 2024. We included studies published between 2013 and 2024, a period during which significant advancements in learning algorithms and the availability of online data occurred (Goh et al., 2022). The keywords used included (physical activity OR exercise OR fitness) AND (machine learning OR AI). The Population, Intervention, Comparison, Outcomes and Study (PICOS) framework was employed to develop the search strategy. The references of included studies and systematic reviews on the subject were also reviewed for additional studies.

Inclusion and Exclusion Criteria

The selection of studies for our analysis was guided by a set of inclusion and exclusion criteria based on the PICOS framework (Eriksen & Frandsen, 2018). The inclusion criteria for this review required studies to involve adults aged 18 years or older without severe mobility impairments and to focus on ML-based interventions designed to increase physical activity. Eligible applications of ML included intervention delivery, data collection, behavior prediction, or personalized feedback. Additionally, studies needed to report measurable physical activity–related health outcomes, such as daily step count, moderate to vigorous physical activity (MVPA), or adherence to physical activity goals, and adopt an RCT design with a comparator group receiving standard or non–ML-based interventions. Studies were excluded if they did not report physical activity–related health outcomes, were nonrandomized trials, qualitative studies, systematic reviews, meta-analyses, conference abstracts, dissertations, or editorials, were published in languages other than English or Turkish, or if full-text articles were unavailable for review.

Data Selection

EndNote software, version 20.1, was used to scrutinize and de-duplicate citations across five databases. Two independent researchers (EHKC and MNE) engaged in selecting and extracting studies via Covidence systematic review software, maintaining confidentiality regarding each other's judgments

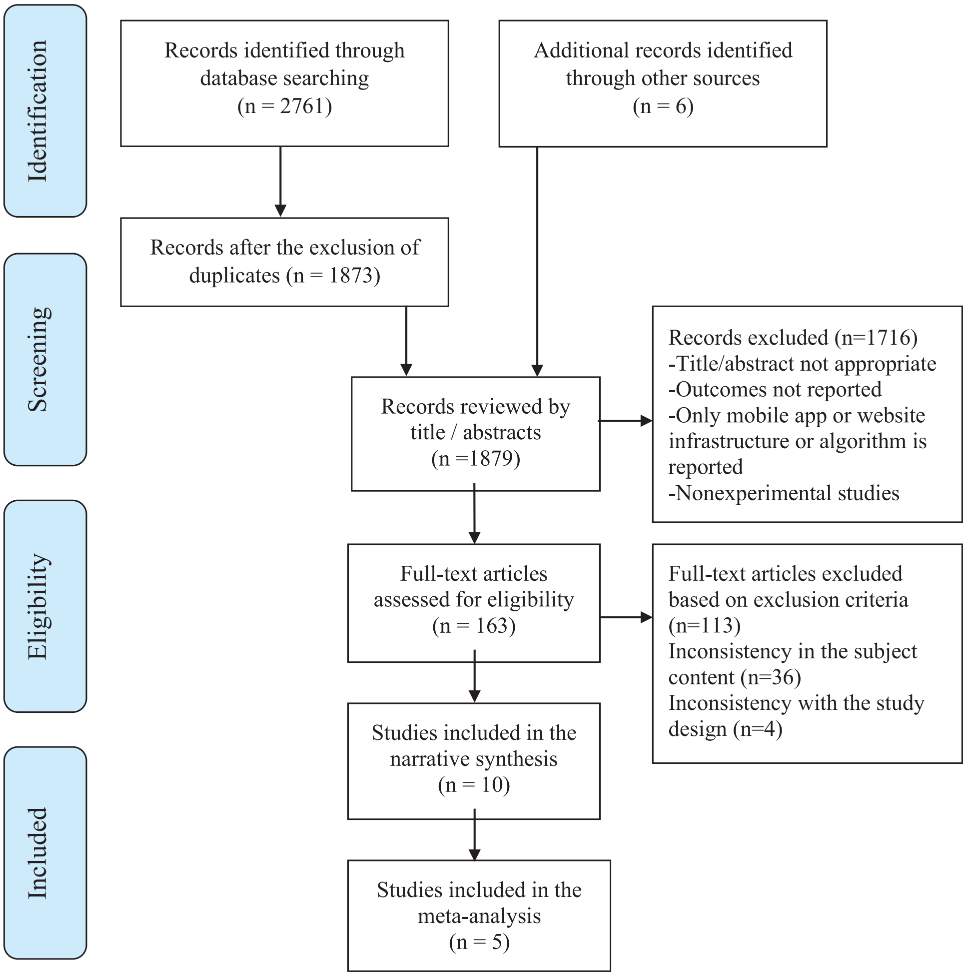

FIGURE 1 PRISMA flowchart for the study screening and selection

while being informed of the journal titles, authors, and institutional affiliations. The studies were evaluated based on predefined inclusion and exclusion criteria to ascertain their appropriateness for the study, with any arising discrepancies resolved through consensus discussions. The results of this screening process are systematically documented and depicted in the PRISMA flowchart (Figure 1).

Data Extraction

A structured format was used to extract study characteristics, including author information, publication year, study setting, population, intervention, inclusion and exclusion criteria, data collection method, and physical activity–related outcomes. Data extraction was independently performed by EHKC and MNE, and disagreements were resolved through discussion until a consensus was reached.

Quality Appraisal

Two researchers (EHKC and MNE) independently assessed the included studies selected for review using the Cochrane risk of bias (RoB) framework, aiming to reevaluate the findings and reach a consensus in cases of divergence (Sterne et al., 2019). The RoB 1.0 instrument was deployed for the appraisal of RCTs, scrutinizing each piece of research across five specific domains: the process of randomization, any deviations from the specified interventions, the absence of outcome data, the method of outcome measurement, and the choice of results reported, as well as an overall assessment of bias. The quality of the evidence was evaluated using the Grading of Recommendations, Assessment, Development, and Evaluations (GRADE) method (Schumemann et al., 2013). The assessment was completed by EHKC for each domain of risk of bias, indirectness of evidence, inconsistency, imprecision, and other considerations, including publication bias.

Data Synthesis

All analysis was conducted using Comprehensive Meta-Analysis software, incorporating variables such as the studies' means, standard deviations, sample sizes, post-test scores, and p values (Borenstein, 2022). The effect size, specifically

Hedge's g, along with 95% confidence intervals (CI), was calculated to quantify the magnitude of the difference between the intervention and control groups' means, normalized by the pooled standard deviation (Higgins et al., 2023). Hedge's g, to Cohen's d but adjusted for bias in small sample sizes, allows for interpretation to be interpreted following Cohen's guidelines, wherein effect sizes of 0.2, 0.5, and 0.8 indicate small, medium, and large effect sizes, respectively. Statistical heterogeneity between studies was assessed using Cochran's Q test ($p < 0.05$) and I^2 (0%–40 %, 30%–60%, 50%–90%, and 75%–100%) statistics (Higgins et al., 2023; Higgins & Green, 2011). An I^2 value exceeding 50% was considered indicative of significant heterogeneity. Additionally, publication bias was examined using Egger's regression test, and Tau coefficient and Begg's adjusted rank correlation test for meta-analysis included more than two studies (Begg & Mazumdar, 1994; Egger et al., 1997). The robustness of the analysis was determined by examining effect sizes within the original 95% CI (Higgins et al., 2023).

RESULTS

The database search yielded 2761 records. After eliminating duplicates, 1879 studies were screened by title and abstract. Of these, 163 studies were assessed for full-text eligibility. The references of the screened studies and systematic reviews on the subject were also reviewed for additional studies. The search resulted in ten studies included for data extraction and qualitative synthesis and five studies included in the meta-analysis (Figure 1).

Study Characteristics

The ten included studies were RCTs conducted between 2013 and 2024 (Aguilera et al., 2024; Bizhanova et al., 2023; Fukuoka et al., 2019; Gonze et al., 2020; Meng et al., 2022; Nelson et al., 2019; Patel et al., 2019; Schoeppe et al., 2022; Zhou et al., 2018a, 2018b). Seven studies were conducted in the United States (Aguilera et al., 2024; Fukuoka et al., 2019; Nelson et al., 2019; Patel et al., 2019; Zhou et al., 2018a, 2018b), one in China (Meng et al., 2022), one in Australia (Schoppe et al., 2022) and one in Brazil (Gonze et al., 2020). The total sample size across studies was 2269 participants ($n_{\text{intervention}}$: 1349; n_{control}: 920). Participants included adults aged over 18 (Aguilera et al., 2024; Bizhanova et al., 2023; Fukuoka et al., 2019; Gonze et al., 2020; Meng et al., 2022; Nelson et al., 2019; Patel et al., 2019; Schoeppe et al., 2022; Zhou et al., 2018a, 2018b) with one study targeting individuals over 65 (Meng et al., 2022) and another targeting college students (Zhou et al., 2018a). Two studies focused on individuals with overweight and obesity (Bizhanova et al., 2023; Patel et al., 2019), while two studies included individuals with minimal physical activity (Fukuoka et al., 2019; Schoeppe et al., 2022).

Intervention Characteristics

ML was utilized in various capacities: six studies used it for delivering the physical activity intervention (Aguilera et al., 2024; Fukuoka et al., 2019; Gonze et al., 2020; Schoeppe et al., 2022; Zhou et al., 2018a, 2018b), two for both intervention delivery and data collection (Bizhanova et al., 2023; Patel et al., 2019), one for data collection (Nelson et al., 2019), and one for predicting post-interventional frailty (Meng et al., 2022). Social cognitive theory was the most frequently used behavioral change model (Schoeppe et al., 2022; Zhou et al., 2018a, 2018b), followed by the theory of goal setting (Zhou et al., 2018a, 2018b), theory of planned behavior (Schoeppe et al., 2022), prospect theory (Patel et al., 2019), self-determination theory (Schoeppe et al., 2022), transtheoretical model (Gonze et al., 2020), and the COM-B Model of Behavior (Aguilera et al., 2024). Interventions in the included studies were applied in-person in two studies (Meng et al., 2022; Zhou et al., 2018a), through mobile application in six studies (Aguilera et al., 2024; Bizhanova et al., 2023;Fukuoka et al., 2019; Gonze et al., 2020; Patel et al., 2019; Zhou et al., 2018b), phone calls in one study (Nelson et al., 2019), and a web site in one study (Schoeppe et al., 2021). Study characteristics are detailed in Supporting Information Table S1.

Risk of Bias

The overall risk assessment revealed a low risk of bias in the majority of studies (Supporting Information Figure S1). Some studies exhibited unclear or high risk of selection bias due to unspecified (Bizhanova et al., 2023; Meng et al., 2022) or not having (Fukuoka et al., 2019) allocation concealment, performance bias due to lack of information (Meng et al., 2022; Nelson et al., 2019) or not having (Aguilera et al., 2024; Fukuoka et al., 2019) blinded participants or personnel and detection bias due to not having blinded outcome assessors (Fukuoka et al., 2019; Nelson et al., 2019; Zhou et al., 2018a, 2018b).

The evidence quality was rated high using the GRADE method (Supporting Information Table S2). The risk of bias was in the assessment evaluated and estimated to be low. The results were generally consistent showing the same direction of effect.

Physical Activity–Related Health Outcomes

Daily Step Count

Six studies (Aguilera et al., 2024; Fukuoka et al., 2019; Gonze et al., 2020; Patel et al., 2019; Zhou et al., 2018a, 2018b) reported results on the effect of ML-based PA interventions on daily step count, involving 499 participants. In one study (Fukuoka et al., 2019), it was found that regular and plus groups had an increase in daily total steps per day compared with con-

International Nursing Review ICN International Council of Nurses

Model	Study name	Outcome	Hedges's g	Standard error	Variance	Lower limit	Upper limit	Z-Value	p-Value
	Fukuoka et al 2019	Daily step counts	0,401	0,170	0,029	0,068	0,734	2,362	0,018
	Gonze et al 2020	Daily step counts	-0,075	0,541	0,292	-1,135	0,985	-0,139	0,889
	Patel et al 2019	Daily step counts	0,418	0,116	0,014	0,190	0,645	3,593	0,000
	Zhou et al 2018a	Daily step counts	0,419	0,524	0,275	-0,608	1,446	0,800	0,424
	Zhou et al 2018b	Daily step counts	0,431	0,250	0,063	-0,059	0,922	1,723	0,085
Fixed			0,402	0,087	0,008	0,231	0,573	4,616	0,000
Random			0,402	0,087	0,008	0,231	0,573	4,616	0,000

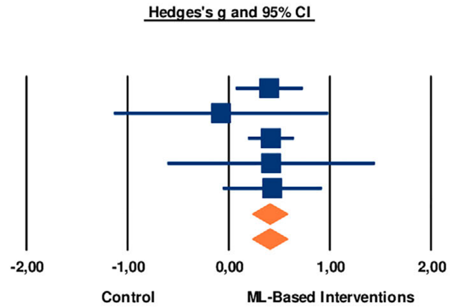

FIGURE 2 Forest plot of daily step counts

trols. In another study (Gonze et al., 2020), there was no significant difference in the average number of steps per day between the intervention and control groups. In one study (Patel et al., 2019), compared with controls, participants had a greater increase in mean daily step count from baseline during the intervention in the competition group, support group, and collaboration group. One study (Zhou et al., 2018a) found that the control group had a decrease in daily step count whereas the intervention group showed an increase between baseline and 10 weeks. In another study (Zhou et al., 2018b), it was found that the intervention led to a difference in daily steps in the intervention group compared with the control over 10 weeks. One study demonstrated that the intervention group that received algorithm-driven personalization showed a higher increase in step count compared with the random text group and control group (Aguilera et al., 2024).

Meta-analysis on Daily Step Count

The meta-analysis of five studies (Fukuoka et al., 2019; Gonze et al., 2020; Patel et al., 2019; Zhou et al., 2018a, 2018b) for daily step count revealed that ML-based interventions increased the mean daily step count compared with control groups (Hedge's $g = 0.402$, [95% CI: 0.231–0.573], $p < 0.00001$) (Figure 2). Homogeneity was observed across these studies ($I^2 = 0.000\%$, $Q = 0.726$, $p = 0.948$) (Supporting Information Table S3). Egger's regression analysis yielded a β value of -0.488 and a t-value of 1.313 ($p = 0.280$), while Kendall's tau test result was -0.600 ($p = 0.141$), indicating no evidence of publication bias.

Moderate to Vigorous Physical Activity (MVPA)

Three studies (Bizhanova et al., 2023; Fukuoka et al., 2019; Nelson et al., 2019) reported results on the effect of ML-based PA interventions on MVPA. One study (Nelson et al., 2019) found that the intervention group showed an increase in MVPA minutes/day compared with a decrease in the control group. Bizhanova et al. (2023) indicated that greater adherence to the MVPA goal was associated with factors such as gender, education level, marital status, and absence of obstructive sleep apnea. Another study (Fukuoka et al., 2019) reported an increase in MVPA in both regular and plus groups compared with controls.

Other Physical Activity–Related Outcomes

Three studies reported findings on ten-meter maximum walking speed (10 m MWS), grip strength (GS), timed up and go test (TUGT), six-minute walk test (6 min WT), prediction of frailty (Meng et al., 2022), website usage, acceptability, usability and perceived usefulness of the PA improvement website (Schoeppe et al., 2022), and self-reported physical activity (kcal/kg/day) (Fukuoka et al., 2019). One study found no significant differences in overall usage, acceptability, usability, and satisfaction of tailored PA websites between video-tailored and text-tailored groups. The perceived usefulness of the website was rated higher in intervention groups compared with the control group (Schoeppe et al., 2022). Another study reported increased self-reported physical activity in intervention groups using the mPED app (Fukuoka et al., 2019). In one study, it was found that the stacking model outperformed other algorithms in predicting whether an elderly will reverse frailty following an exercise program, with significant improvements observed in walking speed and six-minute walk test outcomes in TaiChi, Strength and Endurance group (Meng et al., 2022).

DISCUSSION

ML can be an effective tool in public health services to implement physical activity promotion initials at a societal level. It can be used in self-monitoring the progress, tailoring the recommendations and motivational messages, adapting the intervention, and predicting the future patterns of physical activity behavior. The heterogeneity observed in the included studies reflects the nature of ML as an approach rather than a standalone intervention. ML serves as a versatile tool that can be applied across various stages of health promotion strategies, including intervention delivery, data collection, evaluation, and behavior prediction. This adaptability allows

ML to be tailored to specific needs and contexts, offering diverse pathways for enhancing physical activity promotion. While this variability introduces challenges in comparing outcomes, it highlights the extensive potential of ML in designing comprehensive and dynamic health promotion programs.

This systematic review and meta-analysis aimed to investigate the impact of ML-based lifestyle interventions on improving PA among adult individuals. The narrative synthesis of the ten studies (Aguilera et al., 2024; Bizhanova et al., 2023; Fukuoka et al., 2019; Gonze et al., 2020; Meng et al., 2022; Nelson et al., 2019; Patel et al., 2019; Schoeppe et al., 2022; Zhou et al., 2018a, 2018b) included PA-related health outcomes such as daily step count, MVPA, and other PA outcomes. The meta-analysis of five studies confirmed that interventions employing ML are effective in increasing daily step counts.

In this review and meta-analysis, we found that lifestyle interventions aimed at increasing PA and involving ML were generally effective in increasing daily step counts (Aguilera et al., 2024; Fukuoka et al., 2019; Patel et al., 2019; Zhou et al., 2018a, 2018b) with one exception (Gonze et al., 2020). A recent scoping review revealed that AI-powered interventions effectively modified daily steps (An et al., 2024). An umbrella review assessed the impact of e- and m-Health interventions on 24-hour movement behaviors and revealed that interventions resulted in increased steps per day (Singh et al., 2024). Literature suggests that mobile app-based lifestyle interventions alone may not be sufficient to increase daily step counts (Schoeppe et al., 2016; Stuckey et al., 2017). However, there is evidence that indicates tailored and adaptive physical activity goals, recommendations, and feedback facilitated by technologies such as AI and ML, can enhance daily step counts (Singh et al., 2024).

The results revealed that ML is an effective tool for detecting MVPA (Nelson et al., 2019), increasing MVPA levels (Fukuoka et al., 2019; Nelson et al., 2019), and predicting adherence to MVPA goals (Bizhanova et al., 2023) when used in lifestyle interventions. Another systematic review and meta-analysis revealed that chatbot-based interventions incorporating AI similarly have a significant effect on increasing MVPA (Singh et al., 2023).

There are several ways public health nurses can utilize ML in planning and delivering lifestyle interventions. AI technologies, such as ML, have the potential to analyze large-scale data, providing meaningful insights. This capability allows for continuous monitoring and precise prediction of adherence to physical activity programs, using data from phone step trackers or wearable devices (Farrahi & Rostami, 2024). Recent studies highlight the benefits of integrating ML in healthcare, particularly in enhancing data-driven decision-making and personalized care (Mauco et al., 2020; Xiao et al., 2024).

To achieve the required levels of PA, goal attainment and self-efficacy are crucial factors that contribute to goal commitment (An et al., 2024; Gonze et al., 2020). Enhancing self-efficacy in PA promoting lifestyle interventions through setting achievable, realistic, and adaptive goals is possible with ML algorithms (Zhou et al., 2018b). Mobile technologies with AI have the potential to automate and individualize the process, thereby increasing daily step counts (An et al., 2024). Tailoring PA programs for each individual is key to success. However, it is almost impossible to individualize PA promotion programs for every person due to the significant time, number of public health nurses, and expertise required. ML can bridge this gap by providing the most suitable recommendations and setting goals based on previous data or individual preferences and expectations. Recent studies have demonstrated that ML-based interventions are effective in promoting physical activity by personalizing and optimizing recommendations (Xiao et al., 2024).

The Global Action Plan on Physical Activity (GAPPA) 2030 emphasizes integrating physical activity into daily life across all ages (Sharma et al., 2023). Mobile physical activity applications incorporating AI or ML have significant potential to assist public health nurses in achieving this goal by adapting and individualizing physical activity recommendations, setting realistic goals, providing personal feedback, and enhancing self-efficacy. Despite the widespread use of mobile phones, access to these technologies can be challenging for certain populations, such as the elderly, individuals with limited digital literacy, or those living in low-income areas (Singh et al., 2023). When broadly implemented, ML-based interventions have the potential to promote health, ease the workload of public health nurses, and help in the prevention of noncommunicable diseases such as obesity and diabetes.

Although many physical activity promotion websites and mobile applications are in use, it is crucial for public health nurses to integrate these technologies into nursing care to build evidence-based and holistic models that can respond to individuals' care needs and support lifelong maintenance of the changed behavior. Public health nurses are encouraged to develop a lifestyle intervention model that is easy to implement, accessible, personalized, adaptive, and ideally based on health promotion theories and models. Conducting feasibility studies to assess the effects of such models is recommended. Given that technologies like ML and AI are relatively new, their application in health promotion remains limited. Therefore, interdisciplinary, RCTs involving public health nurses, software engineers, and other health professionals are needed to evaluate the impact of these interventions on physical activity.

Study Limitations

To our knowledge, this is the first systematic review and meta-analysis examining the effects of machine learning-based lifestyle interventions on physical activity. All included studies were RCTs, used similar measurement tools, and had moderate to good quality assessment scores. Despite the meta-analysis showing homogeneity, there were variations in the age groups and characteristics of the participants. This study has several limitations. Some studies had small sample sizes and limited diversity in their sample populations. Lifestyle interventions to increase PA should be applicable to all age groups, genders, cultures, and health characteristics. Therefore, the effects of the interventions presented in this study are limited to specific groups. As ML is relatively a recent development, the number of studies involving health promotion initiatives led by nurses was also limited. Additionally, the inclusion of studies published only in English and Turkish may have excluded potentially valuable data.

Implications for Nursing Practice and Policy

This study underscores the significance of ML-based lifestyle interventions in enhancing PA, a key factor in preventing non-communicable diseases. Despite existing knowledge, awareness, urban infrastructure, and health policies aimed at increasing PA levels, these factors alone are insufficient to foster a more active lifestyle. As emphasized in many health promotion models, an individual's decision to become more physically active is closely linked to self-efficacy, motivation, and personal characteristics. Customizing and adapting interventions to individual needs are crucial for enhancing self-efficacy and motivation during the behavior change process. However, public health nurses often face challenges in designing and implementing these complex and time-consuming programs for each person consistently.

ML or AI offers significant potential by providing personalized PA recommendations, feedback, and goals based on individual characteristics. Developing tailored PA programs that incorporate ML, designed by public health nurses and physicians, can offer new perspectives on obesity and overweight prevention. Such programs empower individuals to take an active role in their health promotion efforts, enabling them to participate more fully and make informed decisions about lifestyle and behavior changes.

Policymakers should foster interdisciplinary collaboration where public health nurses can work alongside software developers to exchange knowledge and skills. This collaboration can help develop theory-based and evidence-based health promotion programs using ML, enabling nurses to plan and deliver nursing care effectively at the societal level. Nurses should be supported and encouraged to lead or participate in technology-based care initiatives.

CONCLUSION

This systematic review and meta-analysis explores the effects of machine learning-based lifestyle interventions on physical activity–related health outcomes. These interventions have demonstrated effectiveness in enhancing MVPA, daily step counts, ten-meter maximum walking speed, GS, TUGT performance, six-minute walk test results, frailty prediction, the usefulness of PA improvement websites, and self-reported PA levels. While these outcomes are crucial for assessing PA, they are limited in providing a holistic evaluation that incorporates psychosocial, cultural, and individualistic factors. Feasibility studies are critical to bridging this gap by identifying ways to expand these interventions into more comprehensive models that address the complex interplay of factors influencing physical activity. We encourage public health nurses to develop tailored, ML- and theory-based lifestyle interventions that integrate these refined factors to promote PA effectively across diverse populations.

The findings of this study highlight the benefits of ML in promoting PA and emphasize the necessity of integrating adaptive and deep learning technologies, such as ML into nursing care at a societal level. Moreover, the study underscores the need for further evidence and ML-based lifestyle interventions developed and led by nurses.

AUTHOR CONTRIBUTIONS

Study design: Ezgi Hasret Kozan Cikirikci and Melek Nihal Esin. *Data collection*: Ezgi Hasret Kozan Cikirikci and Melek Nihal Esin. *Data analysis*: Ezgi Hasret Kozan Cikirikci and Melek Nihal Esin. *Study supervision*: Melek Nihal Esin. *Manuscript writing*: Ezgi Hasret Kozan Cikirikci. *Critical revisions for important intellectual content*: Ezgi Hasret Kozan Cikirikci and Melek Nihal Esin.

ACKNOWLEDGMENTS

We would like to thank Maide Nur Tumkaya for providing biostatistical assistance and consultancy in this systematic review and meta-analysis.

CONFLICTS OF INTEREST STATEMENT

No conflict of interest has been declared by the authors.

FUNDING INFORMATION

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

ORCID

Ezgi Hasret Kozan Cikirikci PhD(c) https://orcid.org/0000-0002-7840-1635
Melek Nihal Esin PhD https://orcid.org/0000-0002-5476-9419

REFERENCES

Aguilera, A. *et al.* (2024) Effectiveness of a digital health intervention leveraging reinforcement learning: results From the Diabetes and Mental Health Adaptive Notification Tracking and Evaluation (DIAMANTE) Randomized Clinical Trial. *Journal of Medical Internet Research*, 26, e60834. https://doi.org/10.2196/60834

An, R. *et al.* (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.

Anderson, E. & Durstine, J.L. (2019) Physical activity, exercise, and chronic diseases: a brief review. *Sports Medicine and Health Science*, 1(1), 3–10. https://doi.org/10.1016/j.smhs.2019.08.006.

Apovian, C.M. (2016) Obesity: definition, comorbidities, causes, and burden. *The American Journal of Managed Care*, 22(7 Suppl), s176-185.

Begg, C. B., & Mazumdar, M. (1994). Operating characteristics of a rank correlation test for publication bias. *Biometrics* 50(4), 1088–1101.

Bizhanova, Z. *et al.* (2023) Identifying predictors of adherence to the physical activity goal: a secondary analysis of the SMARTER weight loss trial.

Medicine and Science in Sports and Exercise, 55(5), 856–864. https://doi.org/10.1249/MSS.0000000000003114.
Bol, N., Smit, E.S. & Lustria, M.L.A. (2020) Tailored health communication: opportunities and challenges in the digital era. *Digital Health*, 6, 2055207620958913. https://doi.org/10.1177/2055207620958913.
Borenstein, M. (2022) Comprehensive meta-analysis software. In *Systematic reviews in health research*. John Wiley & Sons, Ltd, 535–548. https://doi.org/10.1002/9781119099369.ch27.
Bourdier, P. *et al.* (2023) The role of physical activity in the regulation of body weight: the overlooked contribution of light physical activity and sedentary behaviors. *Obesity Reviews*, 24(2), e13528. https://doi.org/10.1111/obr.13528.
Carbone, S., Ozemek, C. & Lavie, C.J. (2020) Sedentary behaviors, physical inactivity, and cardiovascular health: we better start moving!. *Mayo Clinic Proceedings: Innovations, Quality & Outcomes*, 4(6), 627–629. https://doi.org/10.1016/j.mayocpiqo.2020.09.013.
Chakraborty, C. *et al.* (2024) From machine learning to deep learning: advances of the recent data-driven paradigm shift in medicine and healthcare. *Current Research in Biotechnology*, 7, 100164. https://doi.org/10.1016/j.crbiot.2023.100164.
Chaudhari, S., Ghanvatkar, S. & Kankanhalli, A. (2022) Personalization of intervention timing for physical activity: scoping review. *JMIR mHealth and uHealth*, 10(2), e31327. https://doi.org/10.2196/31327.
Cochrane handbook for systematic reviews of interventions (2011). [Accessed 24th August 2024]. https://handbook-5-1.cochrane.org/
da Silva, A.S. *et al.* (2023) Correlates of physical activity in Brazilian older adults: the National Health Survey 2019. *International Journal of Environmental Research and Public Health*, 20(3), 2463. https://doi.org/10.3390/ijerph20032463.
Dhuli, K. *et al.* (2022) Physical activity for health. *Journal of Preventive Medicine and Hygiene*, 63(2 Suppl 3), E150–E159. https://doi.org/10.15167/2421-4248/jpmh2022.63.2S3.2756.
Egger, M. *et al.* (1997) Bias in meta-analysis detected by a simple, graphical test, *BMJ*, 315(7109), 629–634. https://doi.org/10.1136/bmj.315.7109.629.
Eriksen, M.B. & Frandsen, T.F. (2018) The impact of patient, intervention, comparison, outcome (PICO) as a search strategy tool on literature search quality: a systematic review, *Journal of the Medical Library Association*, 106(4), 420–431. https://doi.org/10.5195/jmla.2018.345.
Farrahi, V. & Rostami, M. (2024) Machine learning in physical activity, sedentary, and sleep behavior research, *Journal of Activity, Sedentary and Sleep Behaviors*, 3(1), 5. https://doi.org/10.1186/s44167-024-00045-9.
Fukuoka, Y. *et al.* (2019) Short- and long-term effects of a mobile phone app in conjunction with brief in-person counseling on physical activity among physically inactive women: the mPED randomized clinical trial. *JAMA Network Open*, 2(5), e194281. https://doi.org/10.1001/jamanetworkopen.2019.4281.
Gaysynsky, A., Heley, K. & Chou, W.Y.S. (2022) An overview of innovative approaches to support timely and agile health communication research and practice. *International Journal of Environmental Research and Public Health*, 19(22), 15073. https://doi.org/10.3390/ijerph192215073.
Ghanvatkar, S., Kankanhalli, A. & Rajan, V. (2019) User models for personalized physical activity interventions: scoping review. *JMIR mHealth and uHealth*, 7(1), e11098. https://doi.org/10.2196/11098.
Goh, Y.S. *et al.* (2022) Machine learning in health promotion and behavioral change: scoping review. *Journal of Medical Internet Research*, 24(6), e35831. https://doi.org/10.2196/35831.
Gonze, B.D.B. *et al.* (2020) Use of a smartphone app to increase physical activity levels in insufficiently active adults: feasibility sequential multiple assignment randomized trial (SMART). *JMIR research protocols*, 9(10), e14322. https://doi.org/10.2196/14322.
Guthold, R. *et al.* (2018) Worldwide trends in insufficient physical activity from 2001 to 2016: a pooled analysis of 358 population-based surveys with 1·9 million participants. *The Lancet Global Health*, 6(10), e1077–e1086. https://doi.org/10.1016/S2214-109X(18)30357-7.
Hernández-Reyes, A. *et al.* (2019) Changes in body composition with a hypocaloric diet combined with sedentary, moderate and high-intense physical activity: a randomized controlled trial, *BMC womens health*, 19(1), 167. https://doi.org/10.1186/s12905-019-0864-5.
Higgins, J.P. & Green, S. (2011) Cochrane handbook for systematic reviews of interventions : Cochrane book series. https://10.1002/9780470712184
Higgins, J.P.T. *et al.* (2023). *Cochrane handbook for systematic reviews of interventions*. Chapter 10: Analysing data and undertaking meta-analyses. [Accessed 24th August 2024]. https://training.cochrane.org/handbook/current/chapter-10
Junaid, S.B. *et al.* (2022) Recent advances in artificial intelligence and wearable sensors in healthcare delivery. *Applied Sciences*, 12(20), 10271. https://doi.org/10.3390/app122010271.
Li, Y.-H. *et al.* (2024) Innovation and challenges of artificial intelligence technology in personalized healthcare. *Scientific Reports*, 14(1), 18994. https://doi.org/10.1038/s41598-024-70073-7.
Mahindru, A., Patil, P. & Agrawal, V. (2023) Role of physical activity on mental health and well-being: a review. *Cureus*, 15(1), e33475. https://doi.org/10.7759/cureus.33475.
Mauco, K.L., Scott, R.E. & Mars, M. (2020) Validation of an e-health readiness assessment framework for developing countries. *BMC Health Services Research*, 20(1), 575. https://doi.org/10.1186/s12913-020-05448-3.
Meng, D. *et al.* (2022) Effectiveness of a hybrid exercise program on the physical abilities of frail elderly and explainable artificial-intelligence-based clinical assistance. *International Journal of Environmental Research and Public Health*, 19(12), 6988. https://doi.org/10.3390/ijerph19126988.
Nelson, S.H. *et al.* (2019) Physical activity change in an RCT: comparison of measurement methods. *American Journal of Health Behavior*, 43(3), 543–555. https://doi.org/10.5993/AJHB.43.3.9.
Olyanasab, A. & Annabestani, M. (2024) Leveraging machine learning for personalized wearable biomedical devices: a review. *Journal of Personalized Medicine*, 14(2), 203. https://doi.org/10.3390/jpm14020203.
Page, M.J. *et al.* (2021) The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ*, 372, n71. https://doi.org/10.1136/bmj.n71.
Patel, M.S. *et al.* (2019) Effectiveness of behaviorally designed gamification interventions with social incentives for increasing physical activity among overweight and obese adults across the United States. *JAMA Internal Medicine*, 179(12), 1624. https://doi.org/10.1001/jamainternmed.2019.3505.
Schoeppe, S. *et al.* (2016) Efficacy of interventions that use apps to improve diet, physical activity and sedentary behaviour: a systematic review. *International Journal of Behavioral Nutrition and Physical Activity*, 13(1), 127. https://doi.org/10.1186/s12966-016-0454-y.
Schoeppe, S. *et al.* (2022) Acceptability, usefulness, and satisfaction with a web-based video-tailored physical activity intervention: the TaylorActive randomized controlled trial. *Journal of Sport and Health Science*, 11(2), 133–144. https://doi.org/10.1016/j.jshs.2021.09.001.
Schumemann H., Brożek J., Guyatt G., Oxman A. (2013). *GRADE handbook for grading of recommendations assessment, development and evaluation*. Grade Working Group. [Accessed 24th August 2024]. https://gdt.gradepro.org/app/handbook/handbook.html
Sharma, C. *et al.* (2023) Life course research in physical activity: pathway to Global Action Plan 2030. *Obesity Reviews*, 24(5), e13554. https://doi.org/10.1111/obr.13554.
Singh, B. *et al.* (2023) Systematic review and meta-analysis of the effectiveness of chatbots on lifestyle behaviours. *npj Digital Medicine*, 6(1), 1–10. https://doi.org/10.1038/s41746-023-00856-1.
Singh, B. *et al.* (2024) A systematic umbrella review and meta-meta-analysis of eHealth and mHealth interventions for improving lifestyle behaviours. *npj Digital Medicine*, 7(1), 1–9. https://doi.org/10.1038/s41746-024-01172-y.
Sterne, J.A.C. *et al.* (2019) RoB 2: a revised tool for assessing risk of bias in randomised trials. *BMJ*, 366, l4898. https://doi.org/10.1136/bmj.l4898.
Stuckey, M.I., Carter, S.W. & Knight, E. (2017) The role of smartphones in encouraging physical activity in adults, *International Journal of General Medicine*, 10, 293–303. https://doi.org/10.2147/IJGM.S134095.
Tong, H.L. *et al.* (2021) Personalized mobile technologies for lifestyle behavior change: a systematic review, meta-analysis, and meta-regression, *Preventive Medicine*, 148, 106532. https://doi.org/10.1016/j.ypmed.2021.106532.
WHO (2022) Prevalence of insufficient physical activity among adults: data by World Bank income groups. [Accessed 24th August 2024]. https://apps.who.int/gho/data/view.main.2487?lang=en

International Nursing Review ICN International Council of Nurses The global voice of nursing WILEY

World Health Organization (2024). *Physical activity*. [Accessed 24th August 2024]. https://www.who.int/health-topics/physical-activity

Xiao, K. *et al.* (2024) The effectiveness of E-health interventions promoting physical activity in cancer survivors: a systematic review and meta-analysis of randomized controlled trials. *Journal of Cancer Research and Clinical Oncology*, 150(2), 72. https://doi.org/10.1007/s00432-023-05546-9.

Zhang, Y. *et al.* (2020) Mental health problems during the COVID-19 pandemics and the mitigation effects of exercise: a longitudinal study of college students in China. *International Journal of Environmental Research and Public Health*, 17(10), 3722. https://doi.org/10.3390/ijerph17103722.

Zhou, M. *et al.* (2018a) Evaluating machine learning-based automated personalized daily step goals delivered through a mobile phone app: randomized controlled trial. *JMIR mHealth and uHealth*, 6(1), e28. https://doi.org/10.2196/mhealth.9117.

Zhou, M. *et al.* (2018b) Personalizing mobile fitness apps using reinforcement learning. *CEUR workshop proceedings*, 2068, http://ceur-ws.org/Vol-2068/humanize7.pdf.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Kozan Cikirikci, E.H. & Esin, M.N. (2025) The Impact of Machine Learning on Physical Activity–Related Health Outcomes: a Systematic Review and Meta-Analysis. *International Nursing Review*, 72, e70019. https://doi.org/10.1111/inr.70019