AI-Driven Decision Support Systems for Lifestyle Modification in Cancer Prevention: Personalisation, Technologies and Ethical Challenges*

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Abstract
The incidence of cancer continues to rise worldwide, although it is estimated that up to 40% of cancer cases could be prevented by lifestyle changes (World Cancer Research Fund/American Institute for Cancer Research) [1], which means that traditional health promotion methods often fail to fully achieve lasting behavioural changes and thus primary prevention of disease development. In this review article, we explore the role of artificial intelligence-based decision support systems in enabling personalised, real-time interventions that potentially better modify risky lifestyles to reduce cancer risk. The review includes current literature on AI coaching, integration of data from wearable devices, advanced nutritional analysis, and the synergy of these approaches. It addresses critical ethical challenges such as data privacy, algorithm bias, and transparency. I will also provide guidance for future research and implementation in clinical and public health systems.
Keywords: cancer, prevention, artificial intelligence, lifestyle, personalised health, behavioural change.

I. INTRODUCTION

A. Background and issues

Cancer remains one of the leading causes of death worldwide. Global data show that the annual incidence of cancer is expected to increase by more than 60% by 2040 [2]. Nevertheless, there is strong evidence that a large proportion of cases could be prevented by optimising lifestyle, primarily through changes in diet, increased physical activity and cessation of smoking and alcohol consumption [1]. Traditional health promotion programmes – such as general advice from doctors or one-off educational sessions – often fail to bring about long-term change due to poor adaptation to the individual and a lack of ongoing support and monitoring [3].

B. Personalised AI systems and devices

Systems and devices based on artificial intelligence (AI) represent a new generation of intervention tools to support lifestyle changes and primary prevention. Their key advantage is their ability to process large amounts of heterogeneous data, dynamically personalise recommendations and implement interventions in real time, which significantly exceeds traditional static models of health promotion [4]. Personalisation is therefore the central mechanism through which AI systems increase the effectiveness of behavioural interventions compared to traditional healthy lifestyle promotion. Instead of generic recommendations, they enable individualized strategies that take into account: an individual's behavioral patterns, physiological data, demographic characteristics, psychological profile, and the environment in which the person lives.

Meta-analyses of digital behavioural interventions show that personalised interventions achieve higher levels of engagement and better long-term results than general approaches [5], [6]. In the context of primary cancer prevention, this means better support for quitting smoking, improving dietary habits and increasing physical activity, which are key determinants of cancer risk [1]. AI systems can adapt recommendations in real time based on user response. This approach is in line with the concept of "just-in-time adaptive interventions" (JITAI), which enable intervention at the moment of greatest likelihood of behavioural change [7].

C. Review methodology

This paper is based on a structured scoping review approach aimed at identifying and synthesizing current evidence on digital interventions designed to promote lifestyle changes related to primary cancer prevention among adolescents and young adults aged 15–25 years. A scoping review methodology was selected because the field is interdisciplinary, rapidly evolving, and includes heterogeneous intervention types and study designs.

The literature search was conducted using several major scientific databases, including PubMed, Web of Science, and Google Scholar. The search focused primarily on studies published between 2013 and 2025 in order to capture recent developments in mobile health (mHealth), digital behavioral interventions, and artificial intelligence-supported health promotion.

The search strategy combined keywords related to digital technologies and cancer prevention behaviors, including terms such as "digital intervention", "mHealth", "mobile applications", "SMS interventions", "wearable devices", "e-

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learning", "photo-aging", "adolescents", "young adults", "lifestyle change", "physical activity", "smoking cessation", "healthy diet", and "cancer prevention".

Studies were included if they:

• focused on adolescents or young adults aged approximately 15–25 years,

• investigated digital or technology-supported interventions,

• addressed behavioural risk factors associated with cancer prevention,

• and reported behavioural, psychological, or engagement-related outcomes.

Both randomized controlled trials and systematic reviews/meta-analyses were included due to the exploratory nature of the review. Studies not available in English, studies focused exclusively on clinical cancer treatment, and interventions unrelated to behavioural prevention were excluded.

Particular attention was given to behavioral mechanisms, engagement strategies, effectiveness, limitations, and implications for future intervention design.

II. Literature review: AI in the service of lifestyle change

A. Epidemiological basis for digital intervention

Primary cancer prevention is based on modifying behavioural risk factors, the most important of which are smoking, diet, physical inactivity, obesity and alcohol consumption. It is estimated that approximately 40% of all cancers could be prevented by optimising lifestyle (World Cancer Research Fund/American Institute for Cancer Research [1]. Meta-analyses of online and mobile behavioural interventions show that personalised digital interventions are statistically more effective than generic programmes [6]. Further research confirms that the use of mobile health applications correlates with a higher likelihood of changing health behaviour, especially when the system includes tailored feedback [5].

AI systems enable the upgrading of classic digital interventions through the use of supervised and unsupervised learning for user segmentation, as well as predictive models for assessing the likelihood of goal abandonment. The concept of Just-in-Time Adaptive Interventions (JITAI) represents an important theoretical framework that enables context- and psychophysiological state-optimised intervention [7]. This approach is particularly relevant for cancer-related behaviours such as smoking or a sedentary lifestyle, where decisions are often situationally conditioned.

B. AI and Physical Activity as a Protective Factor

Physical activity is associated with a reduced risk of several types of cancer, including colorectal, breast and endometrial cancer [8]. Wearable devices and AI analytics enable continuous monitoring of movement and automatic generation of personalised recommendations.

Research in the field of deep learning for activity recognition shows high accuracy in the classification of behavioural patterns [9]. When such models are combined with reinforcement learning, the system can optimise messages and goals based on individual responses, leading to increased physical activity [10].

Randomised studies using wearable devices have shown a moderate but statistically significant increase in daily step count and a reduction in sedentary behaviour [11]. However, it should be noted that a direct link between AI systems and cancer incidence has not yet been confirmed in longitudinal studies.

C. AI in smoking cessation

Smoking remains the leading preventable risk factor for cancer. Digital interventions for smoking cessation have shown positive effects, especially when they include personalised communication [12]. AI systems can analyse usage patterns, emotional responses and contextual data to predict the risk of relapse.

Reinforcement learning enables dynamic adaptation of strategies based on user response, increasing abstinence rates compared to static programmes [10]. Such systems can detect critical moments (e.g. stressful situations) and trigger a supportive intervention.

D. Diet and obesity

Excess weight and dietary patterns rich in red meat, processed foods and sugars are associated with an increased risk of certain cancers [1]. One of the biggest methodological limitations in dietary interventions is inaccurate self-reporting.

Photo-based meal analysis technologies enable automated meal analysis and improve the objectivity of dietary monitoring [13]. Integrating this data into AI models enables real-time analysis of energy intake and identification of unhealthy patterns and personalised adjustment of dietary recommendations. Such systems can have a long-term impact on reducing obesity, which is a significant oncological risk factor.

E. Taxonomy of AI-supported preventive interventions

AI-supported interventions can be classified according to: AI method (machine learning, deep learning, reinforcement learning, conversational AI), intervention type (coaching systems, adaptive messaging, dietary analysis, activity monitoring, smoking cessation support), input data sources (wearables, electronic health records, self-reported data, mobile applications), outcome measures (behavioural, biological and epidemiological outcomes), and level of evidence (pilot studies, randomized trials, longitudinal studies). This taxonomy improves comparison between studies and clarifies the current limitations of evidence.

III. Technological framework of AI in the role of primary cancer prevention

The effectiveness of artificial intelligence in primary cancer prevention does not depend solely on a single algorithm, but on an integrated multi-layered system that combines data collection, predictive modelling, personalised communication and adaptive optimisation of interventions. Below, we present the key components of such a technological framework.

A. Data collection and integration

The foundation of successful primary prevention is based on continuous monitoring of behavioural and physiological risk determinants. AI systems must therefore enable secure and standardised data collection from multiple sources, such as: wearable devices (physical activity, heart rate, sleep), mobile applications (diet, smoking, self-reported data), electronic health records (medical history, laboratory parameters) and environmental data (location, air quality, socio-economic context). In the context of cancer prevention, the following types of data are particularly relevant: physical activity patterns, dietary patterns, changes in body weight, indicators of chronic stress and sleep, and behavioural markers (smoking, alcohol) [20].

B. Core for analysis and modelling

The core of the AI system acts as a predictive and decision-making mechanism. Its functions can be divided into three levels.

C. Individual risk assessment

Such models enable the transition from population-based epidemiological assessments to individualised risk assessment. In primary prevention, this means that the system does not merely assess general risk, but dynamically adjusts the assessment based on the individual's current behaviour [14].

D. Prediction of behavioural patterns

In addition to the classic risk of disease, AI models also predict the likelihood of behavioural deviations (e.g. reduced activity, smoking relapse, dietary slip). Time series models and recurrent neural networks enable the detection of trends and the prediction of imminent behavioural changes. Such a predictive mechanism is crucial for primary prevention, as it enables proactive intervention before risky behaviour becomes entrenched.

E. Generating personalized recommendations

Based on risk assessment and behavioural predictions, the AI system generates recommendations. These may include adjusting daily activity goals, personalised dietary guidelines, supportive messages and suggestions for other behavioural changes. They also contain learning elements, which allow these recommendations to be optimised based on user response, making the system more effective over time [10].

F. How AI actually works in primary cancer prevention – a mechanistic view

In summary, AI works in primary prevention through three mechanistic pathways: early risk identification, dynamic assessment of behavioural and physiological indicators enables early detection of adverse trends, optimisation of behavioural decisions and stabilisation of long-term habits.

It is important to emphasise that AI does not directly prevent cancer, but rather influences behavioural and biological risk mediators (e.g. obesity, insulin resistance, inflammation, hormonal profile) that are epidemiologically linked to the development of malignant diseases.

G. Distinction between conventional digital health tools and AI-driven systems

Conventional digital health tools usually provide static recommendations, reminders or educational content. In contrast, AI-driven systems continuously analyses incoming data, adapt recommendations dynamically and learn from user behavior over time. This adaptive decision-making capability represents the core difference between standard mobile health applications and genuine AI-supported decision support systems.

IV. Ethical Challenges and Limitations

The use of artificial intelligence in primary cancer prevention raises important ethical, legal and social issues. Since AI systems interfere with individual behaviour, process sensitive health data and can influence health decisions, their legitimacy depends on the appropriate management of risks related to privacy, fairness, transparency and accountability.

A. Privacy protection and data security

AI systems for primary cancer prevention collect extensive personal data, including: an individual's physiological condition, behavioural data (exercise, diet, smoking), potential clinical data (laboratory results, medical history) and location data. This combination creates a highly sensitive digital profile of the individual. Even if the data is anonymised, combining multiple sources makes it possible to re-identify the user, which poses a significant risk [15]. In the EU context, the use of these systems is subject to the requirements of the General Data Protection Regulation (GDPR), which establishes the principle of data minimisation, the right of access and erasure, and the requirement for informed consent.

B. The professionalism of AI applications, regulation and the boundary between "wellness" and medicine

One of the most complex challenges is the distinction between wellness applications (e.g. fitness applications) and medical AI systems. AI that provides personalised cancer risk assessments or guides healthcare decisions may fall under the regulatory framework for medical devices. In the EU, this area is regulated by the MDR (Medical Device Regulation), which requires clinical validation, proof of safety and effectiveness, and systematic monitoring after market introduction. The question of liability becomes crucial in the event of incorrect recommendations or harmful consequences [16]. Is the algorithm developer or the user responsible?

C. Limitations of current research

Most existing studies focus on short-term behavioural outcomes (e.g. increase in number of steps), while direct evidence of the long-term impact of AI systems on reducing cancer incidence is still lacking. There is a risk of excessive technological optimism without adequate epidemiological confirmation. Furthermore, models are often not validated on limited populations, long-term prospective studies are lacking, and standardised performance indicators have not yet been uniformly defined.

V. Discussion and Future Directions

A. Effectiveness assessment

Although preliminary studies of digital and AI-supported interventions show statistically significant improvements in behavioural indicators (e.g., physical activity, weight loss, smoking cessation), direct evidence of an impact on cancer incidence remains limited. Most studies measure short-term outcomes (3–12 months), whereas cancer development is a long-term process that requires longitudinal follow-up over several years. The effectiveness of AI systems in cancer prevention should be evaluated at several levels:

- behavioural indicators (increased activity, improved diet, smoking abstinence),
- biological markers (BMI, CRP, insulin resistance, hormone profile),
- indirect epidemiological outcomes (reduction in relative risk),
- long-term clinical outcomes (incidence of malignant diseases).

Since primary prevention is a population-based approach, even small individual changes can have a significant public health impact. Therefore, the use of population impact modelling is essential. Technological effectiveness alone is not sufficient. The implementation of AI requires systemic integration into existing healthcare structures, which is why AI systems themselves must not operate in isolation from public healthcare systems and the profession. Without this connection, there is a serious risk that the AI system will remain at the pilot project stage without wider application [21], [22].

B. Critical interpretation of current evidence

Although many studies report statistically significant behavioural improvements, important methodological limitations remain. Existing evidence is often based on small samples, short intervention periods and indirect outcome measures rather than direct reductions in cancer incidence. Moreover, higher engagement with digital tools does not necessarily translate into long-term behavioural maintenance. Therefore, the current evidence should be interpreted cautiously, and future studies must include longitudinal epidemiological validation.

C. Table 1: Critical interpretation of current evidence

Study focus	AI method	Data source	Outcome	Evidence level
Physical activity	Reinforcement learning	Wearables	Increased activity	Randomized trials
Smoking cessation	Predictive analytics	Mobile applications	Abstinence rates	Systematic reviews
Diet monitoring	Deep learning/image analysis	Meal photographs	Dietary adherence	Pilot studies
AI coaching	Conversational AI	User interaction data	User engagement	Experimental studies

VI. Research agenda

Despite the rapid development of artificial intelligence, key questions remain open regarding the long-term clinical effectiveness, regulatory adequacy and professional integration of AI solutions in primary cancer prevention. Technological progress alone is not enough; future development must be based on an interdisciplinary research framework that systematically links data science, oncology, epidemiology, public health, behavioural psychology and bioethics. One of the key research gaps is the lack of long-term data on the impact of AI interventions on the actual incidence of malignant diseases. Most existing studies focus on short-term behavioural changes (e.g. physical activity, dietary habits, smoking cessation), whereas cancer development is a process that takes years or decades.

To scientifically substantiate the effectiveness of AI systems in primary prevention, the following are necessary: multi-year longitudinal studies, linking data with national cancer registries, collaboration with public health institutions, and the use of population-based epidemiological models to assess absolute risk reduction. Without such integration, the impact of AI systems on primary cancer prevention remains merely indirect and hypothetical. Unfortunately, there is currently no uniform standard for evaluating AI systems in cancer prevention. Future research should define a minimum set of performance indicators, reporting standards (transparency of models, data sources), and a framework for comparison between systems. Independent validation tests need to be developed, and all AI systems that aim to influence behavioural change should be linked to the professional community [17], [23].

VII. Conclusion

Artificial intelligence is one of the most promising technological tools for transforming primary cancer prevention. The ability to process large amounts of heterogeneous data, recognise risk patterns and generate personalised interventions enables a shift from generic recommendations to individually tailored lifestyle change strategies.

Nevertheless, technological potential alone does not guarantee a public health impact. The effectiveness of AI systems will depend on: collaboration with experts, scientific validation in longitudinal studies, successful integration into healthcare systems and ensuring accessibility, and ethical responsibility.

AI in cancer prevention should not become merely a technological innovation, but must become a clinically proven, ethically designed and socially responsible tool that supports individuals in maintaining healthy lifestyles throughout their lives.

An important step toward large-scale validation and implementation of AI-supported primary cancer prevention is represented by ongoing European research initiatives. One notable example is the Horizon Europe project SUNRISE (Grant Agreement No. 101136829), which investigates the usability, clinical relevance and public health impact of AI-based applications in the context of primary cancer prevention. The project aims to integrate advanced digital technologies with evidence-based oncological and public health frameworks, thereby strengthening the scientific and regulatory foundation for AI-driven preventive strategies [17]. Such initiatives demonstrate that AI in cancer prevention is transitioning from conceptual exploration to structured, collaborative and policy-aligned research at the European level.

If future research focuses on interdisciplinary collaboration, standardisation of methodology and long-term epidemiological validation, AI could become an important factor in reducing the burden of cancer and improving population health in the 21st century.

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