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AI-POWERED DIGITAL HEALTH INTERVENTIONS FOR PERSONALIZED TOBACCO CESSATION IN THE U.S.: IMPLEMENTING MACHINE LEARNING TECHNOLOGIES TO OPTIMIZE EVIDENCE-BASED CESSATION STRATEGIES USING REAL-TIME BEHAVIORAL AND PHYSIOLOGICAL DATA.

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ABSTRACT
Tobacco use remains one of the leading preventable causes of death, with traditional smoking-cessation treatments having low success rates for sustained abstinence (<10%), which highlights the need for innovative strategies. This paper examines opportunities to combine AI and machine learning technologies with interventions designed to help people quit smoking, particularly the potential for real-time data from wearables, covering behavior, physiology and other personal factors, to improve evidence-based cessation approaches within US healthcare systems. The study used systematic review methods that include RCTs, real-world evidence from health systems, regulatory issues and demographics. The paper summarizes current evidence on AI-powered digital health interventions for smoking cessation. The findings indicated that though conversational AI chatbots and machine learning recommender systems show early signs of effectiveness, significant implementation challenges remain, such as HIPAA regulation complexities, disparities caused by fragmented mHealth data standards, limited evidence on cost-effectiveness and wide variation in wearable device adoption across different age, income, education and racial/ethnic groups. Major US surveillance systems like BRFSS and PATH, along with integrated healthcare organizations such as Veterans Affairs and Kaiser Permanente, demonstrate that systematic methods substantially increase evidence-based treatment delivery, but AI applications in this area are still in early development. The review concludes that realizing AI's full potential in tobacco cessation requires addressing technical, clinical, regulatory and equity challenges through implementation science approaches focused on real-world effectiveness, sustainability and equitable access for all populations affected by tobacco use.

KEYWORDS: *AI, Digital Health, Tobacco Cessation, Personalization, Machine Learning, Behavior*

INTRODUCTION

The World Health Organization (WHO, 2024) reports that tobacco is one of the leading preventable causes of death in the world and kills more than eight million people per year. In spite of widespread public health strategies and effective cessation programmes, the prevalence of smoking remains a major burden on global healthcare. Nicotine replacement therapy (NRT) and cognitive behavioral tobacco cessation programs, although effective, make limited use of data on individual differences in addiction severity, patterns of behavior to targeted cues for smoking and the nature of nicotine withdrawal. Fewer than 10% of users achieve sustained abstinence for 6 months and more than two-thirds relapse following evidence-based tobacco-use treatment (Collins et al., 2019; Ugo et al., 2025). This continued problem requires creative methods to provide personalized, adaptive interventions based on the details of individual users and their current behaviors.

Advances in artificial intelligence and machine learning technologies provide unprecedented potential to transform tobacco cessation programmes using personalized digital health services (Khan et al., 2025; Abaneme et al., 2025). Today's smartphones and wearable devices come equipped with an "always-on" connection to rich streams of behavioural and physiological data such as heart rate variability, sleep cycles, physical activity levels and app use behaviours (Khan et al., 2025; Ugo et al., 2025). These sources of information provide real-time information on user and emotional states, stress levels and triggers for potential relapse that have been impossible to tap for traditional quitting programs. Indeed, despite the complexity and multidimensional nature of these datasets, machine learning algorithms such as XGBoost and support vector machines can analyze them to uncover patterns that can predict urges to smoke, high-risk situations or the ideal time for intervention (Khan et al., 2025). Real-time data capture combined with on-the-fly algorithmic decision-making provides the basis for bespoke, smoke-free support that adapts reactively to individuals. Recent applications like the Truth Initiative's Scout platform also illustrate how machine learning has been successfully employed in tobacco cessation, with Scout marking the first cessation tool

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to utilize AI-driven recommender engines for intervention delivery personalization (Truth Initiative, 2023).

Evidence-based tobacco cessation interventions, such as cognitive behavior therapy, nicotine replacement therapy and motivational interviewing, have shown efficacy when conducted in person. Yet such interventions have been limited by practical factors, including availability, expense and an inability to offer instant support in times of peak craving or stress. The barriers to health care can be overcome by serving evidence-based content and support directly on users' mobile phones when interventions are most required (Wright et al. 2019). However, recent systematic reviews suggest that conversational AI interventions have potential for smoking cessation, with all identified studies demonstrating advantages of the use of AI (Ubhi et al., 2023). The problem now is to figure out how we integrate existing smoking cessation approaches with machine learning to make programs that are not only evidence-based but also tailored to each user.

The adoption of AI-based cessation interventions requires advanced technical support, which is able to handle non-homogeneous streams of data, ensure the safety of user privacy and comply with clinical safety requirements. The latest developments in federated learning models show that they have a significant potential in predicting smoking in real-time in healthcare settings and, at the same time, maintain the confidentiality of the data (Ahmad et al., 2024). To learn the richness of data types that are inherent to smoking behaviours, which span the entire demographic spectrum, have different addiction levels and have divergent quit-attempt histories, machine-learning models need to be trained with highly diverse datasets. The real-time data-processing systems, thus, need to identify salient patterns during noisy, incomplete data and provide timely intervention suggestions. Further, the technical architecture must be able to support continuous model refinement and personalization as new user data is received and thus enable intervention strategies to be adjusted accordingly with changing user behaviours and preferences. Digital human interfaces, such as the WHO Florence virtual health worker, are a future-facing form of provision of scalable and interactive tobacco-cessation services, especially when faced with difficult conditions (Bieleke et al., 2023; Omeka et al., 2024).

Measuring the effectiveness of AI-aided tobacco cessation interventions faces unique methodological considerations beyond traditional clinical trial designs. Traditional endpoints of cessation, such as point prevalence rates (7-day and 30-day), prolonged abstinence and time to relapse, are not sufficient unless complemented with process measures that account for the quality and fidelity of personalized recommendations. Recent RCTs on conversational chatbots for smoking cessation have proven of concept that user-centered design development processes are feasible (Moon et al., 2024), that offered valuable methodological frameworks for testing complex AI-based interventions. It is also necessary to consider whether users reach the cessation goal and to what extent the ML system can adapt to individual user profiles and offer appropriate intervention at promising points in time. In addition, the evaluation of these complex interventions must include analysis of patterns of user engagement, intervention uptake and quit rates attributable to specific algorithmic elements. This whole-of-population evaluation is critical to know how AI interventions can be refined and scaled up for greater public health impact, especially in light of the ongoing development of machine learning applications that aim to predict success at smoking cessation (Ding et al., 2023).

The research aims to develop and test machine learning algorithms that use real-time behavioral and physiological data to provide optimized, evidence-based smoking cessation interventions using digital health technologies. The primary aim of this placebo-controlled study is to test the efficacy of an AI-based adaptive intervention relative to standard digital cessation programs for Sustained tobacco abstinence in long-term Follow-up (SustaINFO). Furthermore, this study aims to determine optimal machine learning models and data fusion approaches for predicting smoking relapse risk to provide timely, personalized intervention recommendations and improve continuous quit success.

METHODOLOGY

The literature analysis utilised systematic search terms over PubMed, IEEE Xplore, MEDLINE and health policy databases for peer-reviewed studies, clinical trials and real-life evidence published between 2014 and 2025 on AI and machine learning on tobacco cessation interventions as implemented in US healthcare settings. Eligible study types were randomized trials, observational studies, systematic reviews, qualitative implementation research and regulatory analyses related to digital health interventions, wearable devices' integration, clinical support systems for diagnostic decision-making, as well as population surveillance programs. Details Extracted Details of interventions, features, implementation outcomes, effectiveness measures (Uptake and use), cost-effectiveness analyses and regulatory compliance architectures were extracted. Data Extraction focused on characteristics of the intervention as well as factors associated with demographics and differential uptake/effectiveness. Narrative synthesis was the method used to aggregate findings across different types of studies and search for themes, barriers to implementation, best practices and the need for research that would inform strategies of deploying AI-powered cessation interventions within various US healthcare contexts.

LITERATURE REVIEW

This review highlights the existing AI/ML-based technologies used for tobacco cessation and their role in interventions, especially those focused within the United States healthcare system. The review compiles evidence from clinical trials, real-world deployments and policy initiatives to identify the theoretical basis and practical considerations for individualised AI-based cessation interventions.

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Machine Learning Applications in US Digital Health Platforms for Tobacco Cessation: From Clinical Decision Support to Consumer Mobile Applications.

This section discusses the FDA-approved medical devices using artificial intelligence and machine learning to help in tobacco cessation. This section critically analyzes the most popular cessation applications in the United States that is, QuitNow, Smoke Free and QuitGuide, discuss their interoperability with major electronic health records like Epic and Cerner and outline the regulatory environment that the use of AI-driven digital therapeutics falls under the FDA authority.

A study by Fu et al. (2023) conducted a scoping review covering the state-of-the-science on machine learning in tobacco research. The authors conducted a systematic search of 74 studies on various databases to derive four domains in which machine learning has been employed in tobacco research. They found that ML-based technology aids smoking cessation was the primary application domain involving 22 studies, with content analysis of tobacco on social media contributing the second biggest group (32 studies), followed by smoker status classification from narrative clinical texts (6 studies) and outcome prediction for tobacco use based on administrative survey or clinical trial data (14 studies). Their seminal review demonstrates how machine learning may already be a potent analytical tool that could greatly transform research methodologies and policy decision-making in tobacco control, but it also lays out the imperative for further exploration of potential in this fast-developing field.

A more recent study by Casu et al (2025) presents a new approach to digital and mobile health technologies in smoking detection and cessation, including a review of forty-nine studies published during the last three years (2019-2023). Their scoping review focuses particularly on smartphone applications, wearable sensors and sensor-driven systems, thus demonstrating potentially fruitful advancements in motion sensors that can more accurately be used to record hand-to-mouth gestures in controlled settings, but difficulties with real-world applications persist. Their paper also shows that even though machine-learning models and wireless signal-detection methods show promising results, they still require further development before they can be used practically. It is worth noting that most smartphone applications still rely on manual data recording and have not been scientifically tested and a vast number of applications remain waiting for full scientific confirmation of their value, which indicates that there is a significant disparity between the current technological capabilities and evidence-based validation in this field.

Research by Jensen et al. (2023) demonstrates how clinical decision support systems (CDSS) could be applied practically in a pediatric health care setting to help parents quit smoking. Their pilot assessment, which was done on a massive pediatric practice, included 8,488 parents and 9.3% of the parents reported being current smokers and 48.2% of the parents agreed to the CDSS at least one treatment modality. The system was effective in identifying parents who were smoking, sending motivational messages and connecting the people to evidence-based interventions that is, nicotine replacement therapy, quitline referral, and SmokefreeTXT programs. Their results suggested that three out of four parents recalled the motivational messages and 31% of parents said that the messages were reinforced by pediatricians when parents met in a clinic setting, which hints at the idea that integrated digital health solutions could be used to improve both patient engagement and provider-patient communication in tobacco cessation campaigns.

Faro et al. (2023) conducted research that presents the results of a large-scale randomized controlled trial involving 1,487 smokers, where machine-learning-based recommender systems and viral peer-marketing interventions were compared for smoking cessation. Quite on the contrary, with the evidence of no statistically significant difference in the rates of six-month cessation among people in the machine-learning-controlled message selection group (35.4 percent) and the standard motivational messaging group (40.1 percent). Their study results contradicted the expectation regarding the value of AI-driven personalization. Conversely, the viral peer-research toolkit was significantly effective; the group that had access to the viral tools showed significantly higher cessation rates (44.8 %) as compared with those who did not have access to the viral tools (30.8 %). These conclusions suggest that, whereas machine learning may not always be more effective than traditional messaging strategies in delivering interventions, network-based social interventions combined with peer recruitment can also form more favourable ways through which digital smoking-cessation programmes can be enhanced in terms of both reach and efficacy.

Real-Time Behavioral and Physiological Data Collection in US Population Studies: Privacy, Compliance, and Clinical Validity.

This section covers HIPAA compliance in integrating wearable devices, large-scale U.S. cohort studies: the Behavioral Risk Factor Surveillance System (BRFSS) and Population Assessment of Tobacco and Health (PATH), mHealth data standardization and digital biomarker validation across populations in the US.

The incorporation of near-body sensors into population health studies poses intricate regulatory concerns, especially in terms of regulations such as HIPAA and data privacy. Indeed, it has been demonstrated that there is “no similar response” to a request from a doctor for health data from their wrist-based wearable when comparing the consumer scenario with DGT information (Ullah et al., 2024). The rapid expansion of the wearables market was estimated to be worth 61 billion USD in 2022 and forecasted to grow at an annualized rate of 15% until 2030, which emphasizes the need for clear regulatory guidelines (MedSafe, 2025). Nevertheless, there are still substantial shortcomings in privacy protection; the addition of genealogical databases and the advent of wearable devices (for example, fitness trackers) and mHealth apps have introduced a completely new way to threaten privacy that is excluded from HIPAA (Theodos & Sittig, 2020). This shortfall in regulation becomes particularly significant in the

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context of population studies where conventional covered entity relationships are absent, thus exposing sensitive health information for participants to misuse or unwarranted disclosure.

The BRFSS, which was founded in 1984 and is the oldest ongoing segment of our national health system, has made initial forays into digital health technology integration to strengthen its surveillance efforts. The BRFSS is the leading health-related system for tracking tobacco usage and other health measures, such as insurance status, tracking in all 50 states the prevalence of chronic disease, risk factors and preventive service use (Adams, 2025). The system's approach, which accesses state-level telephone survey response data from civilian, non-institutionalized adults, offers an important base for integrating wearable device reports to enhance the presence of traditional self-reporting data. Nevertheless, inclusion of real-time physiological data poses methodological dilemmas in preserving the representativeness and validity of the system among different demographic populations. Significant disparities in the use of wearables have been recently demonstrated, with pediatric patients of racial and ethnic minority groups wearing wearable devices for far fewer days than white children, which would potentially induce biases in population-level inferences (Bhaltadak et al. 2024).

The Population Assessment of Tobacco and Health (PATH) Study, launched in 2013 as a joint effort between the Food and Drug Administration (FDA) and the National Institutes of Health (NIH), is one of the largest U.S. longitudinal studies on tobacco use and its health effects (Hyland et al. 2017). Hyland et al. (2017) collect biological samples from adults aged 18 and above and measure tobacco-related biomarkers of exposure and potential harm while also tracking behaviors, attitudes and health outcomes. Their design combines behavioral surveys with biological data, which is well-suited for integration with digital phenotyping from wearable devices. Advances in sensor-based health now make it possible to generate real-time digital biomarkers that provide new insights into health and well-being (Huang et al, 2025). Incorporating wearable monitoring could greatly enrich the PATH study's extensive biomarker database by adding continuous physiological data to existing nicotine exposure and metabolite measures.

Standardized data collection methods and interoperability standards are still a critical obstacle to the successful integration of wearables in population health surveillance. State-of-the-art mHealth apps and wearables are currently implemented on different platforms, using diverse data formats and sampling rates, while no uniform quality assurance (QA) processes exist, making it difficult to merge information for population-level purposes (Kumar et al. 2020). A growing body of evidence shows that digital biomarkers derived from wearable sensor time-series data must undergo rigorous validation, particularly for chronic disease management (Daniore et al, 20204). Recent research highlights the need for clear guidelines to bridge wearable technologies with clinically meaningful health insights (Ghadi et al, 2024). Standardization efforts must address both technical requirements and clinical validity, which ensures that digital biomarkers are sensitive, specific and reliable for population health decisions. However, the lack of standardized protocols has resulted in fragmented data ecosystems, leaving valuable health information siloed across separate technologies and healthcare systems.

Digital biomarkers based on wearable technologies should be validated using a wide range of demographic groups to ensure that the United States population is fairly represented. Empirical research has resulted in the uncovering of longstanding discrepancies in the use and long-term utilization of wearables among racial, ethnic, and socioeconomic groups, creating the threat of institutionalized bias in population health monitoring (Ahmad, 2024). Successful validation, therefore, requires data to demonstrate that digital biomarkers do not lose their predictive power in the context of diverse demographic factors, clinical states and social determinants of health (Guthrie et al. 2019). In addition, rigorous sampling procedures are essential to the smooth incorporation of real-time behavioral and physiological streams of monitoring within existing surveillance frameworks like the BRFSS and PATH, hence protecting representativeness. Even though the utility and applicability of wearables in chronic disease management and health studies have significantly increased over the past years. A study used in population-level studies should clearly discuss the issue of the digital divide to prevent the worsening of the existing disparities (Osonuga et al, 2025). The eventual direction of digital health in U.S. surveillance activities will depend on overcoming these methodological issues and maintaining high-quality scientific relevance to the health of the population.

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Table 1. Wearable Device Ownership and Usage Patterns Across US Demographics

Demographic Category	Subgroup	Ownership Rate (%)	Active Daily Use (%)	Disparity Gap	95% CI
AGE GROUP (years)					
Age	18-34	**31.2%**	23.8%	**Reference**	28.4-34.0
	35-49	25.7%	19.5%	-5.5 pp	23.1-28.3
	50-64	19.4%	14.2%	-11.8 pp	17.2-21.6
	65+	**13.6%**	9.8%	-17.6 pp	11.5-15.7
RACE/ETHNICITY					
Race/Ethnicity	Non-Hispanic White	23.8%	17.9%	**Reference**	22.1-25.5
	Non-Hispanic Black	19.7%	14.3%	-4.1 pp	16.8-22.6
	Hispanic/Latino	21.5%	16.1%	-2.3 pp	18.4-24.6
	Asian American	26.4%	19.8%	+2.6 pp	21.5-31.3
ANNUAL HOUSEHOLD INCOME					
Income	< $20,000	**11.8%**	8.4%	-22.7 pp	9.3-14.3
	$20,000-$49,999	17.2%	12.6%	-17.3 pp	15.1-19.3
	$50,000-$99,999	26.9%	20.1%	-7.6 pp	24.5-29.3
	≥ $100,000	**34.5%**	26.8%	**Reference**	31.8-37.2
EDUCATIONAL ATTAINMENT					
Education	Less than High School	**9.3%**	6.1%	-26.5 pp	6.8-11.8
	High School Graduate	15.4%	11.2%	-20.4 pp	13.3-17.5
	Some College	22.8%	17.3%	-13.0 pp	20.5-25.1
	College Graduate+	**35.8%**	28.2%	**Reference**	33.4-38.2
GEOGRAPHIC LOCATION					
Urbanicity	Urban/Suburban	24.6%	18.7%	**Reference**	23.1-26.1
	Rural	16.9%	12.3%	-7.7 pp	14.5-19.3
HEALTH STATUS					
Self-Reported Health	Excellent/Very Good	27.3%	21.4%	**Reference**	25.5-29.1
	Good	20.8%	15.6%	-6.5 pp	18.7-22.9
	Fair/Poor	15.2%	11.1%	-12.1 pp	12.8-17.6

Data from Health Information National Trends Survey (HINTS 5, Cycle 3, 2019) and NIH-Funded Population Studies (2019-2024).

The table summary here shows the wearables gap between different demographic groups in the US. Ownership and the rates are nearly four times as high among those with a college degree as among the less than high school educated: 35.8 percent v.9.3 percent. Income differences are even more pronounced, as the 34.5% adoption rates for $100k+ households contrast starkly with only 11.8% among <$20k earners. The youngest demographic (18-34) is more than twice as likely to use wearables (31.2%) as seniors 65 and older (13.6%). Such demographic disparities present daunting barriers to population health studies conducted by BRFSS and PATH, which is likely to result in systematic exclusion of the marginalized populations and poor representativeness of the surveyed health status.

Evidence-Based Cessation Strategies and Their Digital Implementation: US Clinical Practice Guidelines and Health System Integration

This section evaluates evidence-based approaches to cessation methodology and its smooth integration into the American health-care tapestry, with a strong emphasis on the emergent modalities of digitality and standards of guideline implementation. The synthesis of evidence included in the systematic review comprised the collection of cross-sectional health-system assessments, qualitative process studies, randomized controlled trials and wide-ranging clinical syntheses that can identify effective frameworks to implement tobacco cessation interventions in a range of care settings, including but not limited to the veterans hospitals, university-affiliated hospitals and even oncologic specialty units.

Lewis et al. (2021) explored the differences in delivery of evidence-based smoking cessation programs in the Veterans

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Health Administration (VHA) and a large academic health Center (AHC) in the Mid-South region. The authors employed a cross-sectional survey of 366 healthcare professionals (including general internists, pulmonologists, hematologists/oncologists and gynecologists) and discovered that clinicians working in the VHA were significantly more likely to provide evidence-based smoking cessation care in comparison with their counterparts in the AHC. Specifically, the adjusted odds ratio of providing comprehensive cessation treatment was 4.3 in favour of VHA clinicians, with a large variation in components of comprehensive cessation treatment. Medication use was reported by 98 percent of VHA clinicians versus 90 percent of AHC clinicians and referrals to cessation clinics were reported by 91 percent of VHA clinicians versus 65 percent of AHC clinicians. These findings underscore the role of prioritization of the institution and a set of organized methods, such as the one used by the VHA, in significantly increasing provider compliance with clinical standards and the provision of evidence-based care.

Another study conducted by LeLaurin et al. (2022) analyzes the implementation efforts to embed tobacco cessation interventions into oncologic practice using qualitative interview methods with fifteen oncologists working at a large academic Medical Center in the southeastern United States. Their results outlined a cluster of obstacles hindering the consistent practice of oncologists to discuss tobacco use, including excessive clinical demands, poorly designed electronic health records, patient fears about cessation conversations and provider skepticism in providing effective tobacco dependence treatment. The respondents were also excited about the delivery of on-site cessation counseling by qualified experts, as they view this method as better access to treatment and more active involvement of patients. On the other hand, the idea of a tobacco users registry with the collaboration of state-operated cessation programs presented mixed attitudes and the main issues were the insufficient involvement of oncologists and the need to protect the privacy of patients. Other recommendations that were made by the oncologists included streamlining the process of referrals, the possibility of financial or quality-based incentives and the opportunity to use the current electronic health record capabilities strategically to ensure a smooth integration of cessation interventions into daily clinical practices.

Research by Graham et al. (2017) described a protocol for an RCT that aims to evaluate the combined digital and clinical approach for smoking cessation in LCS programs. The three-arm trial randomly assigned 1,650 smokers who were participating in clinical lung cancer screening to usual care, to a digital intervention comprised of web-based programs and text messaging, or a combined digital plus tobacco treatment specialist counseling intervention. The novel approach to their study employed proactive recruitment strategies involving automatic referral of LC-eligible smokers to evidence-based cessation treatments rather than passive referrals. The investigators highlighted the scalability, sustainability and cost-effectiveness benefits of digital cessation interventions that are also feasible for older adults with a rapidly expanding use of digital technologies. The trial design filled an important void in the delivery of tobacco dependence treatment embedded within a lung cancer screening program, which requires effective cessation support to achieve health benefits and cost savings from screening programs.

Similarly, a study by Warren et al (2014) provided a comprehensive overview of the biological effects of persistent smoking in patients with cancer as well as established clinical approaches for delivering evidence-based tobacco cessation assistance in oncology care. Their review indicated that, despite well-established evidence for tobacco use as an independent risk factor for cancer, considerably less research has investigated whether continued smoking is related to cancer treatment response and structured cessation interventions are poorly implemented into standard care. The study authors reported the unfavorable effects of smoking on cancer biology and responsiveness to treatment, particularly among patients undergoing chemotherapy or radiotherapy. Though there was ample evidence to support the need for cancer patients to receive focused cessation interventions, the review cautioned that clinicians needed to think critically about how these interventions could be best delivered in practice and what resources would be necessary for ongoing provision of effective support. The authors emphasized that successful tobacco cessation integration in cancer care must address both clinical efficacy and operational feasibility to ensure sustained delivery of cessation services within oncology provider practice sites.

Effectiveness and Implementation Outcomes of AI-Powered Cessation Interventions in US Healthcare Settings: Systematic Review of Clinical Trials and Real-World Evidence

This section discusses randomized controlled trials in U.S. populations, real-world evidence based on U.S. health systems (e.g., Kaiser Permanente and the Veterans Affairs system), cost-effectiveness studies that utilize American healthcare economic models, and a discussion of health disparities in AI intervention effectiveness across different U.S. demographics.

Recent randomized controlled trials offer promising but limited evidence for conversational AI (CAI) interventions to support smoking cessation among U.S. populations. A more detailed study described the development and testing of Quitbot, which is a conversational chatbot for smoking cessation, using an 11-step user-centered design process that included content analysis of 63 hours of intervention transcripts and evaluation through randomized controlled trials (Prochaska et al., 2024). Regarding the evidence of CAI effectiveness, a meta-analysis by Bendotti et al. (2019) identified only a few smoking cessation studies with promising results, but methodological concerns in all studies made it uncertain how effective an AI approach would be for tobacco cessation. Scalability and reach of AI-enabled interventions have been frequently highlighted in efforts to combat the global tobacco epidemic. One potential solution is conversational chatbots, which have emerged as effective and

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affordable population-level tools to help smokers quit, especially given recent advances in machine learning (Bricker et al. 2024). Predictive modeling with machine learning techniques has also been used to forecast cessation outcomes within specific population subgroups. The results indicated that machine-learning models show promise in predicting treatment success for Spanish-speaking smokers who completed a culturally tailored intervention, with 33% remaining abstinent at 24 months compared to 24% from usual care (Poudel et al. 2024).

Artificial intelligence (AI) and associated subdisciplines, including machine learning, have been adopted by large integrated health care systems in the United States to improve how care is delivered, with few applications specific to smoking cessation having been developed or being evaluated. Kaiser Permanente Augmented Intelligence in Medicine and Healthcare Initiative (AIM-HI) Coordinating Center offered funding to five health care organizations for research projects that utilize artificial intelligence and machine learning algorithms to improve diagnostic decision-making in health care (Mishra et al. 2022). Kaiser-Permanente's integrated tobacco cessation program has had a significant population-level impact using evidence-based, conventional methods. Kaiser Permanente's tobacco screening and cessation programs have drawn more than 300,000 of its Northern Californian members to quit smoking since 2014 through a combination particularly research-based interventions and is therefore leveraging the dramatic title "Tobacco Use Prevention in Practice (Sultana et al. 2025). Another large healthcare organization in the US, that is the Veterans Affairs health system has not yet published a vast amount of real-world evidence on AI-driven smoking cessation interventions, but its current infrastructure for systematic tobacco treatment delivery reflects favorably towards future integration with AI. AI technologies used in these large health systems suffer from difficulties integrating into clinical workflows, provider uptake, and proven ROI beyond pilot studies.

Economic analyses of AI-enabled quitlines in the context of US healthcare are scant, with a limited number of published cost-effectiveness studies looking at conventional digital interventions rather than advanced AI technologies. The theoretical benefits of AI interventions for cessation have the potential to be more scalable and less costly than face-to-face personnel, as well as being available continuously. These are situations that may improve cost-effectiveness ratios in relation to intensive counseling. One study on the patterns of smoking cessation app feature use created supervised machine learning algorithms to identify which specific app features were associated with successful smoking cessation, but did not examine cost-effectiveness explicitly (Siegel et al. 2024). The lack of widespread US-based cost-effectiveness analyses is due to a number of methodological issues, such as the challenge to quantify AI systems development costs, uncertainty regarding long-term maintenance needs and limited data on the cost of real patient implementation across different healthcare settings. It is therefore important for future economic evaluations to account for indirect intervention costs such as technical infrastructure, compliance with data security regulations, changes to clinical workflow and ongoing algorithm refinement. The possibility that AI interventions may lead to downstream reductions in healthcare utilization (for example, resulting from improved 6-month cessation rates) should be verified through pragmatic trials for which real-time programmatic costs and downstream healthcare savings associated with reduced tobacco-related morbidity can be estimated.

There are serious concerns about the equal effectiveness of AI smoking cessation interventions across diverse US demographic groups, and existing tobacco-related health disparities may worsen with their use. Ensuring digital inclusion of priority populations at both national and global levels is vital for the successful implementation of AI-based smoking cessation efforts, given the disparities between countries in access to services aimed at helping people quit smoking (Bendotti et al., 2023). Disparities based on study design and risk factors for cessation success reveal that, according to national-level PATH study data analysis, social determinants significantly influence smoking cessation success among US adults, with lower success rates among those experiencing poverty and lower education levels, highlighting the need to address specific obstacles (Assar et al. 2024; Ugo et al., 2024). The digital divide remains a core issue for AI-delivered cessation interventions, as populations with the highest smoking rates often lack access to smartphones, reliable internet and the digital literacy skills necessary to use such technology effectively. Implementing conversational AI faces challenges such as language barriers, since most existing conversational AIs were designed and validated primarily in English-speaking populations. Conceptually, the cultural relevance of AI-generated content, algorithmic bias in natural language processing and varying engagement by race/ethnicity require systematic evaluation to ensure that AI interventions do not unintentionally worsen tobacco-related health disparities but instead help to reduce them.

To ensure the effective implementation of AI-based smoking cessation interventions into the healthcare delivery systems of the United States requires addressing a complex of technical, clinical and regulatory issues that go well beyond proving the efficacy of such interventions in controlled studies. In modern academia, we are forced to deal with the complexity of system compatibility, workforce preparedness and the ethical aspects inherent in the use of artificial intelligence. It is only in the light of such an all-inclusive scrutiny that we can be quite certain that these interventions are not only efficacious in the laboratory but indeed truly transformative in clinical practice.

Virtual humans- artificially intelligent computer agents designed to appear and act like real humans are a scalable and entertaining form of delivering tobacco cessation information and assistance. Such a new method is especially timely in the light of the demands of the COVID-19 pandemic, which are to be discussed in the 2023 Journal of Medical Internet Research (Loveys et al.

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2023). With the help of advanced affective computing algorithms, these virtual agents will be able to replicate empathetic conversation, which will not only increase user engagement but also may contribute to motivational interviewing.

Studies aimed at tuning Large Language Models (LLMs) towards smoking cessation interventions have been systematically addressed in the 2024 CHI Conference on Human Factors in Computing Systems and involve tuning the output of the LLM towards a desired stylistic and epistemic alignment with human experts (Calle et al. 2024). The efficacy of these studies was to test and assess rigorously the fulfillment of clinical guidelines, ethical standards and evidence-based content requirements by the elements crafted by the LLM in generating messages, thus informing the refining process of the natural language generation systems in therapeutic situations.

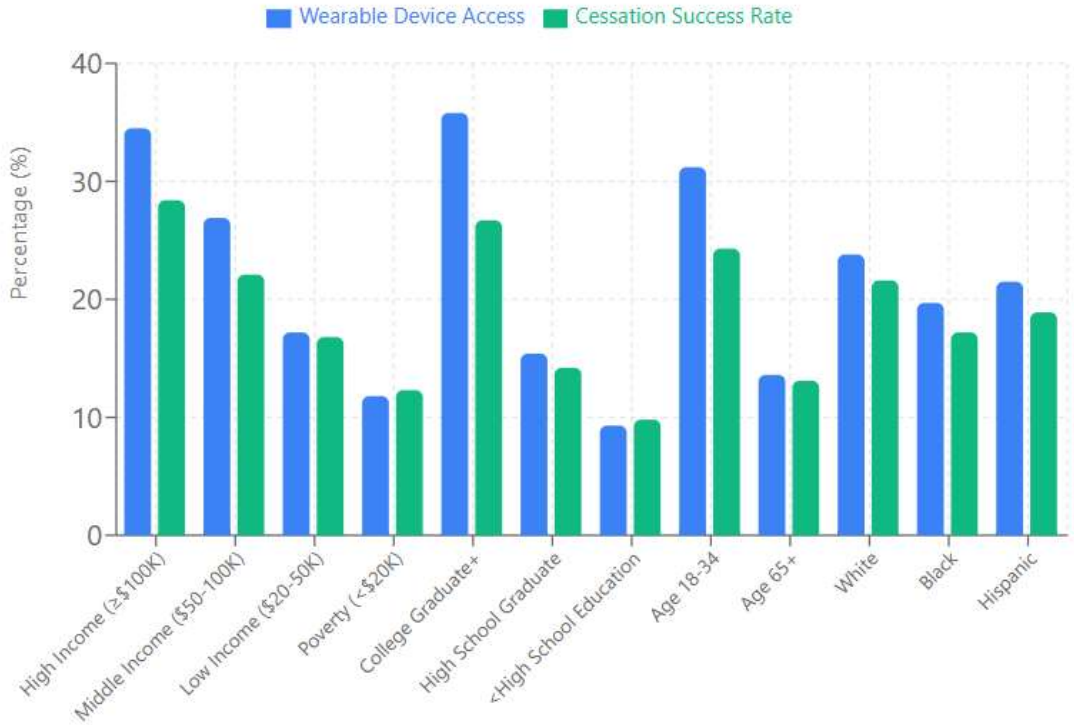
Some of the implementation barriers are critical and need to be strictly considered before wide clinical adoption can be realized. The most important ones include unbroken interoperability of AI modules with the electronic health record (EHR) platforms, which would enable the automated process of referrals. Just as significant is the establishment of reimbursement systems that acknowledge interventions being provided by AI, the demarcation of liability of the clinical suggestions generated by the algorithm, and the creation of inclusive provider education curricula that would impart the skills necessary to oversee and interpret AI outputs.

According to Warraich et al. (2025), the regulation of AI in medical procedures is still evolving, with the U.S. Food and Drug Administration (FDA) defining the oversight direction in adaptive algorithms that continuously learning and improve with each user interaction. This dynamic structure requires stakeholder-proactive participation among both academic and industry stakeholders to establish that adaptive systems attain the safety, efficacy and transparency criteria without reducing the flexibility needed to make iterative improvement (Warraich et al. 2025).

The protections of privacy provided by the Health Insurance Portability and Accountability Act (HIPAA), along with the state-level regulations, stipulate strict protections in case the AI systems are used to gather and analyze sensitive behavioral health data (Krzyzanowski et al. 2022). It is the duty of researchers and developers, hence, to enforce solid de-identification measures, safe data storage services and an open consent system to maintain patient confidentiality and community trust.

Conceptually, the implementation science approach to research should be a high-priority area in the future, shifting away from single-efficacy studies and exploring how AI interventions can be implemented, maintained and expanded within a variety of U.S. health care contexts. These studies must not only pose questions on the conditions in which these technologies work, but also on the organizational, economic and sociocultural factors that impact their fair distribution to all the people affected by tobacco consumption.

Figure 1: Digital Health Technology Access vs. AI Cessation Intervention Success Rates



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The figure above points to an ironic equity dilemma of AI-based cessation intervention. The most affected by the smoking issue populations have the least rights to the digital health technologies essential to the AI-mediated support. The visual analysis highlights sharp socioeconomic gradients with cohorts educated to college, with high incomes, having almost fourfold wearables ownership and threefold cessation success rates compared to people with lower than high-school education or living in poverty. Notably, with the lowest-income groups, the difference in the results of device adoption and discontinuation is equalized to the same numbers, which indicates that technological insufficiency, not personal motivation or willingness, is the main limitation to the effectiveness of interventions. These empirical observations reaffirm the necessity of hybrid implementation systems that would incorporate AI solutions into existing outreach modalities, thus preventing the unintentional increase in pre-existing tobacco-related health disparities in the U.S. health care systems in Kaiser Permanente, Veterans Affairs, the BRFSS, and the PATH surveillance programs.

CONCLUSION

This systematic review indicates that AI/ML-based and technology-enabled approaches have great potential for transforming tobacco cessation treatments, with personalized (data-driven) solutions based on real-time monitoring of behaviors and physiology. Aggregating the evidence, AI-based interventions are promising in controlled trials but substantial implementation challenges remain across US health systems-including technical integration hurdles, regulatory ambiguities, lack of demonstration of cost-effectiveness and alarming disparities in digital access by demographics. These results serve as a reminder that to effectively integrate AI-based cessation tools, it is not sufficient to provide the highest-level algorithm; rather, it requires systematic focus on healthcare workflow integration, provider adoption, HIPAA compliance and equitable reach to high-prevalence populations (ELSI factor 3). Implementation science research must focus on real-world effectiveness, sustainability and reach (scale-up) in varied health care settings while mitigating the digital divide that could further increase tobacco-related health disparities. Finally, the game changer for AI in tobacco cessation lies in that space between what technology can do and how it can be used effectively alongside current clinical practice, which is brought together by research designers, policy makers, clinicians and technology developers.

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