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Review article

Artificial intelligence in tobacco control: A systematic scoping review of applications, challenges, and ethical implications

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ABSTRACT

Background: Tobacco use remains a significant global health challenge, contributing substantially to preventable morbidity and mortality. Despite established interventions, outcomes vary due to scalability issues, resource constraints, and limited reach.
Objective: To systematically explore current artificial intelligence (AI) applications within tobacco control, highlighting their usefulness, benefits, limitations, and ethical implications.
Method: This scoping review followed the Arksey and O'Malley framework and PRISMA-ScR guidelines. Five major databases (PubMed, Scopus, Web of Science, IEEE Xplore, and PsycINFO) were searched for articles published between January 2010 and March 2025. From 1,172 initial records, 57 studies met inclusion criteria after screening.
Results: AI-driven tools, including machine learning and natural language processing, effectively monitor social media for emerging tobacco trends and personalize smoking cessation interventions. Applications were predominantly focused on predictive modelling (using algorithms like XGBoost and SVM to predict e-cigarette use and relapse risk), cessation support (employing chatbots and reinforcement learning to improve accessibility), and social media surveillance (detecting synthetic nicotine promotions and analysing vaping trends). Approximately 22% of studies aligned with WHO FCTC Article 13 (tobacco advertising regulation), while 45% supported Article 14 (cessation services). However, tobacco industry interference remains a critical challenge, with AI technologies exploited to undermine public health initiatives, target vulnerable populations, and manipulate policy discussions. Critical issues including algorithmic bias, privacy concerns, interpretability challenges, and data quality must be addressed to ensure positive impact.
Conclusion: AI holds considerable promise for extending tobacco control if implemented ethically, transparently, and collaboratively. Future directions emphasize explainable AI development, integration of real-time intervention systems, global data inclusion, and robust cross-sector collaboration. While the current landscape shows a laudable start, it reflects the need for more diverse skill sets to fully harness AI's extensive prospects for tobacco control and achieving tobacco endgame goals.

1. Introduction

The World Health Organization Framework Convention for Tobacco Control (WHO FCTC) describes tobacco control as "a range of supply, demand, and harm reduction strategies that aim to improve the health of a population by eliminating or reducing their consumption of tobacco products and exposure to tobacco smoke" [1]. These strategies seek to decrease tobacco use and mitigate its significant health risks through policies, legislation, and educational initiatives [2]. Implementation is facilitated primarily through the WHO FCTC and MPOWER strategies (Monitor tobacco use, Protect people from smoke, Offer help to quit, Warn about dangers, Enforce bans, and Raise taxes), which serve as vital

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tools for tracking global progress and facilitating tobacco use reduction [3–5].

Tobacco use causes 8 million annual deaths globally, with 7 million attributable to direct use and 1.2 million to secondhand smoke [6]. Despite MPOWER strategies, progress remains uneven, particularly in low- and middle-income countries (LMICs) [5,7]. As highlighted in the 2024 Lancet Global Health commentary on tobacco endgame goals, the persistent challenges of inconsistent implementation across countries and unequal policy maintenance continue to hinder global health systems [8,9]. Traditional tobacco control methods, although effective to varying degrees, frequently encounter limitations related to scalability, cost-efficiency, reach, and sustained effectiveness. For instance, pharmacological treatments may present side effects or compliance issues, behavioural therapies require intensive resources, and health campaigns may fail to effectively engage high-risk populations.

In response to these persistent challenges, Artificial Intelligence (AI) has emerged as an innovative and powerful tool with the potential to revolutionize approaches to tobacco control. AI encompasses computational technologies capable of analysing large-scale datasets, learning from complex patterns, making predictive decisions, and facilitating personalized interventions [10]. Its capabilities extend across various domains with specific applications to tobacco control: Machine learning (ML) enables predictive modelling of relapse risk and tobacco initiation patterns; Natural language processing (NLP) automates surveillance of illicit tobacco promotions on social media and analyses public sentiment toward tobacco policies; Deep learning (DL) identifies tobacco imagery in digital content and classifies smoking behaviors from multimodal data sources; and Reinforcement learning optimizes personalized cessation interventions based on user engagement patterns.

There has been widespread application of AI across the tobacco control spectrum. Numerous studies have utilized AI for analysing hospital records to detect and categorize smoking history [11–18], predict effects of smoking after cancer diagnosis [19–24], measure smoke exposure metrics [25], predict cardiovascular disease risk [26,27], detect tobacco-related cancers [28–30], and identify tobacco plant diseases [31]. Within healthcare and social services, AI has supported tobacco control by predicting smoking relapse and tobacco dependence [32–35], classifying social smoking behaviours [36], detecting smoking environments to prevent cravings [37], characterizing e-cigarette emissions [38], and assessing secondhand and third-hand smoke exposure [39].

While several narrowly-focused reviews have examined AI applications in specific tobacco control domains such as smoking detection [25,37] or cessation interventions [40,41], there exists a notable gap in comprehensive assessments that systematically evaluate AI across the full spectrum of tobacco control efforts. Previous studies have typically addressed isolated applications without examining alignment with global tobacco control frameworks or addressing ethical implications and industry interference. This lack of synthesis limits our understanding of how AI technologies can be strategically integrated within comprehensive tobacco control programs and policy frameworks.

This review systematically synthesizes evidence on AI applications in tobacco control, evaluates their alignment with WHO FCTC articles, and identifies ethical risks and industry exploitation concerns. By comprehensively mapping the current landscape, we address the urgent need to understand how emerging technologies can support tobacco endgame strategies, particularly in resource-constrained settings where traditional approaches face significant implementation barriers. The review covers AI-based surveillance and detection methods, predictive modeling for risk assessment, personalized intervention techniques, and evaluation methods of policy effectiveness. Furthermore, we examine industry interference, highlighting how tobacco companies leverage AI to circumvent public health measures and influence public opinion.

Ultimately, this paper contributes to ongoing discussions around best practices, ethical considerations, and policy recommendations by providing evidence-based insights on the transformative role AI can play in enhancing tobacco control strategies. By identifying existing challenges, implementation gaps, and future research opportunities, we aim to inform strategic integration of AI within global tobacco control efforts and accelerate progress toward achieving the WHO's tobacco reduction targets.

2. Method

This scoping review was conducted to systematically map the existing literature on the application of artificial intelligence (AI) in tobacco control and identify key themes, research gaps, and opportunities for future study. The review followed the methodological framework proposed by [42] and further refined by [43] incorporating the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) guidelines.

2.1. Search strategy

A comprehensive search was conducted across five major electronic databases: PubMed, Scopus, Web of Science, IEEE Xplore, and Google Scholar. The search strategy employed precise Boolean operators and keywords: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "natural language processing" OR "predictive modelling") AND ("tobacco control" OR "smoking cessation" OR "vaping" OR "e-cigarettes" OR "tobacco policy") AND ("public health" OR "intervention" OR "surveillance" OR "prevention"). Studies published between January 2010 and March 2025 were included to capture the evolution of AI applications in tobacco research. Language was restricted to English-language publications.

2.2. Eligibility criteria

Studies were selected based on a structured framework addressing Population, Intervention, Comparison, and Outcomes (PICO):

Population: – Tobacco and nicotine users (including cigarettes, e-cigarettes, heated tobacco products) – General population targeted by tobacco control measures – Industry actors and regulatory bodies involved in tobacco control.

Intervention: – AI tools including but not limited to machine learning algorithms, deep learning models, natural language processing systems, and predictive analytics – AI-enabled platforms such as chatbots, mobile applications, and decision support systems for tobacco control.

Comparison: – Traditional tobacco control interventions (when available) – No intervention (in observational studies) – Different AI approaches compared within the same study.

Outcomes: – Cessation rates and behavioural changes – Surveillance accuracy and efficiency – Policy impact assessment – Public health outcomes – FCTC alignment and implementation effectiveness.

For this review, "tobacco control" was operationalized as any systematic approach to reducing tobacco consumption, preventing initiation, promoting cessation, protecting non-smokers, or regulating tobacco products through policy, education, or direct intervention.

Inclusion criteria:

- Empirical research or systematic reviews focusing on AI applications in tobacco control interventions, surveillance, policy evaluation, or cessation support
- Use of AI methods such as machine learning, deep learning, natural language processing, or predictive modelling
- Published in peer-reviewed journals, conference proceedings, or technical reports in English
- Explicit relevance to tobacco/nicotine products or smoking behaviours

Exclusion criteria:

- Opinion pieces, editorials, or news articles without empirical data
- Studies that did not describe an AI component or failed to focus on tobacco-related issues
- Research focused exclusively on genomic or molecular-level AI applications without direct behavioural relevance
- Studies where tobacco was only mentioned peripherally and not central to the research question

2.3. Study selection and data extraction

Initial search results were imported into EndNote X9 reference management software, where duplicates were removed. Titles and abstracts were independently screened for relevance, followed by full-text review of potentially eligible articles. Discrepancies were resolved through discussion with a third reviewer. A standardized data extraction form was developed in Microsoft Excel and used to chart information from each included study, capturing:

1 Study characteristics (author, year, country, study design) 2. Study aim and research questions 3. AI method and algorithm specifications 4. Data sources and sample size 5. Main findings and conclusions 6. Reported limitations 7. AI application area (surveillance, cessation, etc.) 8. Alignment with WHO FCTC article(s) 9. Ethical considerations addressed 10. Industry involvement or conflict of interest.

An initial total of 1,172 records was identified through systematic database searches. After eliminating 347 duplicate entries, 825 unique studies were subjected to preliminary screening based on their titles and abstracts. This screening step focused on identifying relevance to the scope and objectives of the review. From this pool, 288 articles were shortlisted for full-text assessment according to the predefined inclusion and exclusion criteria. Upon detailed evaluation, 57 studies were deemed eligible and included in the final synthesis.

The 231 studies excluded after full-text review were categorized by reason for exclusion: no AI component (n = 83), insufficient focus on tobacco control (n = 65), opinion/editorial without empirical data (n = 29), focus limited to genomic applications (n = 38), and unavailable full text (n = 16). The entire selection process spanning identification, screening, eligibility assessment, and final inclusion is illustrated in the PRISMA flow diagram (Fig. 1), ensuring a clear and systematic overview of the review methodology.

2.4. Data synthesis

Given the heterogeneity of study designs, methodologies, and AI techniques, a narrative synthesis approach was employed. Findings were organized thematically under surveillance and monitoring, cessation support, risk prediction, policy evaluation, and industry interference. We further categorized studies by their alignment with specific WHO FCTC articles (as shown in Fig. 2) to evaluate how AI applications support global tobacco control frameworks. The WHO FCTC is an evidence-based treaty that reaffirms the right of all people to the highest

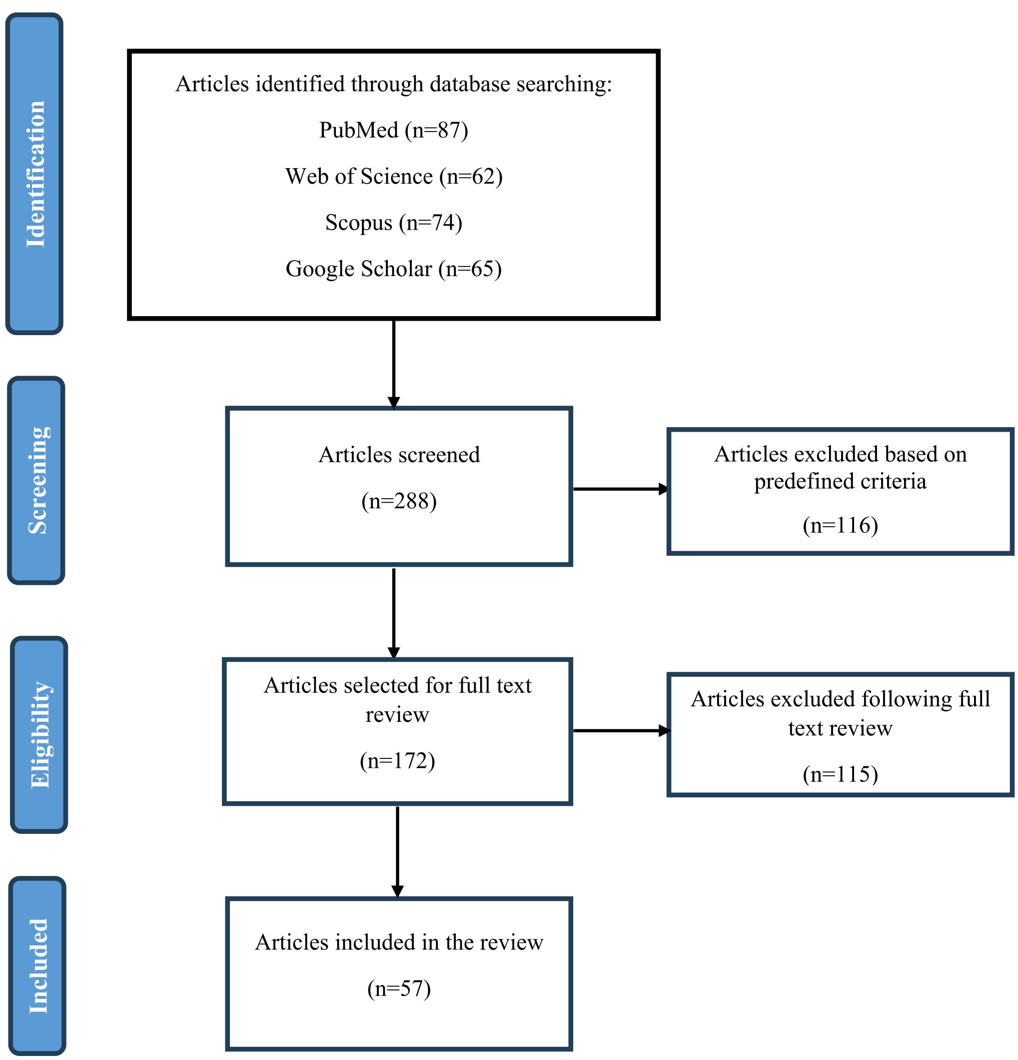

Fig. 1. PRISMA flow diagram of the article selection process.

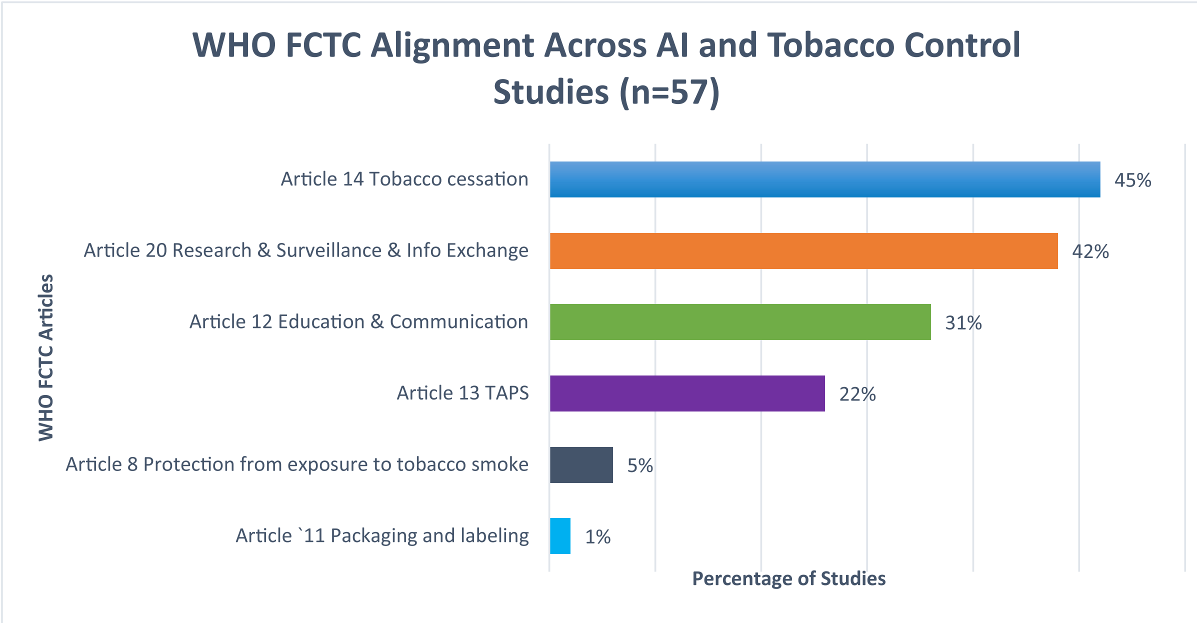

Fig. 2. WHO FCTC Articles addressed Using AI. *Note: Percentages exceed 100% as some studies aligned with more than one FCTC Article.*

standard of health and provides legal dimensions for international health cooperation. Key articles relevant to this review include:

- Article 8: Protection from exposure to tobacco smoke
- Article 11: Packaging and labelling of tobacco products
- Article 12: Education, communication, and public awareness
- Article 13: Tobacco advertising, promotion, and sponsorship
- Article 14: Demand reduction measures concerning tobacco dependence and cessation
- Article 20: Research, surveillance, and exchange of information

This approach facilitated an integrative summary of how AI is currently leveraged in tobacco control and identified both strengths and limitations of existing approaches.

2.5. Quality appraisal

As per scoping review methodological guidelines [44,45], a formal risk of bias assessment was not conducted, as the primary aim was to map the available evidence rather than assess the effectiveness of interventions. However, studies were informally appraised for methodological clarity, transparency in AI application, and relevance to public health outcomes. We evaluated whether studies provided sufficient information on:

I1 AI algorithm selection and specification
II1 Dataset characteristics, including size and representativeness
III1 Evaluation metrics and validation approach
IV1 Limitations and potential biases in the AI implementation

Studies with inadequate methodological detail or unclear AI implementations were contextualised accordingly during synthesis to maintain the integrity and reliability of the review's conclusions **but were not excluded on this basis alone**.

3. Results

The detailed characteristics and data extraction table provides a concise summary of 57 recent studies exploring artificial intelligence applications in tobacco control. Table 1 captures essential study details, including aims, methodologies, AI algorithms, data sources, primary outcomes, and noted limitations. The table highlights the diversity of AI techniques such as machine learning, large language models, and topic modelling across various data sources like social media, clinical trials, and online interventions. This structured synthesis allows for easy comparison of findings, methodologies, and potential gaps or biases, facilitating a clearer understanding of current research trends and future directions in AI-driven public health interventions.

3.1. AI in tobacco control

Artificial intelligence (AI) has significantly transformed traditional approaches to tobacco control by enhancing capabilities in surveillance, prevention, intervention, and policy evaluation. Leveraging sophisticated techniques such as Natural Language Processing (NLP), machine learning (ML), predictive analytics, and conversational AI, these technological innovations enable precise monitoring of tobacco-related behaviours, facilitate personalised cessation interventions, enhance predictive risk assessment, and optimise policy impact assessments [45,47,93]. AI-driven strategies offer scalable, real-time insights and interventions, empowering public health authorities to proactively respond to emerging trends and challenges associated with tobacco use, thereby advancing global tobacco control efforts.

Table 2 summarises the primary artificial intelligence (AI) technologies, algorithms, and data types utilised within tobacco control. The table standardizes AI technologies used in tobacco control research, showing the relationship between specific algorithms, data sources, application areas, alignment with WHO Framework Convention on Tobacco Control (FCTC) articles, and representative studies from the literature review. Each technology is detailed alongside specific algorithms, relevant data types, common data sources, and typical application areas. For instance, natural language processing leverages sentiment analysis to evaluate social media data [72], while deep learning uses convolutional neural networks (CNN) to analyse image data [61]. This table underscores the interdisciplinary nature of AI, illustrating how different data streams and analytical methods combine effectively to support targeted public health responses.

Several key themes emerged from the reviewed literature, which indicates the evolving role of artificial intelligence in tobacco control. These themes inform both current practice and future potential in public

Table 1
Characteristics and Data Extraction of Included Studies on AI Applications in Tobacco Control.

Reference	Study Aim/Purpose	AI Method/ Algorithm	Data Sources / Sample Size	Main Findings/ Conclusions	Limitations Reported/ Comments	Relevant WHO FCTC Articles
[44]	Evaluate adherence of ChatGPT-generated responses to smoking cessation guidelines	Content analysis of LLM (ChatGPT-3.5) outputs	100 cessation-related prompts analyzed	ChatGPT responses aligned moderately well with CDC guidelines; varied by prompt specificity	AI's consistency and safety require further testing for clinical reliability	Article 14, Article 12
[45]	Evaluate ChatGPT's effectiveness in providing vaping cessation support.	Generative AI (ChatGPT)	10 Reddit vaping questions evaluated by expert panel (n = 5).	ChatGPT provided highly accurate and empathetic responses suitable for cessation interventions.	Limited to small query set; unclear real-world applicability.	Article 14
[46]	Identify factors predicting e-cigarette use in never-smokers	ML models (e.g., logistic regression, decision trees)	U.S. adult population survey data	Peer influence, age, media exposure were top predictors	Cross-sectional design limits causal inference	Article 20
[47]	To identify predictors of electronic nicotine delivery system (ENDS) initiation among tobacco-naive young adults using machine learning	Machine learning classification algorithms (e.g., logistic regression, decision trees, etc.)	PATH study data; N = 2,944 tobacco-naive young adults	Susceptibility to ENDS, cigarette use, marijuana use, and social media exposure were top predictors	Model interpretability and generalizability may be limited; cross-sectional variables used for prospective prediction	Article 20
[48]	Evaluate conversational AI interventions' effectiveness for smoking cessation.	Meta-analysis	Systematic review of RCTs from 6 databases (since 2005).	Conversational AI significantly improved cessation rates at 6-month follow-up.	High heterogeneity among studies included.	Article 14
[49]	Analyze adolescent attitudes toward JUUL using Twitter data	Topic modeling and sentiment analysis	Public tweets mentioning JUUL	Found majority expressed curiosity or usage; health concerns secondary	Age verification of users not possible; informal language challenged classification	Article 12, Article 13
[50]	Explore AI potential in improving anti-smoking campaign effectiveness.	Conceptual overview (predictive analytics, personalized interventions, social network analysis)	N/A (Perspective article, no empirical study conducted).	AI can enhance campaign effectiveness through personalised and predictive interventions.	No empirical validation provided; theoretical recommendations only.	Article 12
[51]	To systematically review ML-based predictors of smoking cessation across experimental studies.	Systematic Review, Multiple Machine Learning Techniques	Review of prior smoking cessation ML studies; N = varies	Common predictive features: motivation, nicotine dependence, app use patterns, craving levels.	Heterogeneity of datasets and ML methods limited *meta*-analysis.	Article 14, Article 20
[52]	Examine regional variations in tobacco-related tweets	Topic modeling (LDA), sentiment analysis	Geotagged Twitter data	Found differing themes and sentiment trends across regions; informed place-based policy	Data sparsity in less active areas	Article 20, Article 12
[53]	Characterization of e-cigarette aerosols using a field-portable holographic microscope	Image analysis and classification via AI-enhanced microscopy	Vape shop aerosol samples	Provided real-time aerosol particle analysis; useful for public exposure risk assessment	Lab validation required; limited to one vape shop context	Article 8, Article 20
[54]	To explore how AI and LLMs, particularly ChatGPT, can assist in the management of tobacco dependence and cessation.	Review and expert commentary on LLMs like ChatGPT in cessation support	Not a primary study; discusses application contexts and existing capabilities	AI, especially ChatGPT, shows promise in enhancing accessibility to cessation support, especially in underserved populations	Need for rigorous evaluation, regulation, and integration with health systems; risks of misinformation	Article 14
[55]	Identify target audiences for hookah prevention campaigns	Supervised Machine Learning (Gradient Boosting, Random Forest)	Multinational Adult Tobacco Survey + focus group feedback	ML predicted demographics most receptive to campaign messages	Limited generalizability across cultures/regions; focus on hookah only	Article 12
[56]	To analyze the content and themes of e-cigarette-related conversations on Twitter using social listening methods	Natural Language Processing (NLP), content analysis	Tweets related to e-cigarettes; 87,963 tweets collected over 2 months	Promotional content dominated discussions; user conversations revealed themes around quitting, flavors, and perceptions of safety	Limited to publicly available tweets; potential sampling bias; did not analyze sentiment in depth	Article 12, Article 13
[57]	Predict individual outcomes of smoking cessation treatments	Machine Learning (Logistic regression, decision trees, SVM)	Cessation trial data from 757 individuals	ML models predicted successful quitters based on early behavioral and psychological data	Lacks external validation; limited demographic diversity in training data	Article 14
[58]	To explore the role of chatbots and virtual assistants in improving tobacco cessation services, especially post-pandemic.	Conversational AI, Virtual Assistants	Review of case studies and applications (qualitative evidence)	Chatbots increase accessibility and user engagement; shown useful during public health emergencies like COVID-19.	Conceptual overview; lacks quantitative analysis and empirical validation.	Article 14, Article 12
[59]	Predict tobacco-related tweet topics around COP9.	LDA, Random Forest, sentiment analysis	Tweets captured via DMI-TCAT around COP9 event.	Achieved 91.87 % accuracy in topic prediction; sentiment correlated with retweet frequency.	Study limited to specific event (COP9); short-term insights only.	Article 20
[60]	Enhance sentiment and intent analysis in public health using fine-tuned	Fine-tuned Large Language Models (e.g., BERT, RoBERTa)	Tobacco and e-cigarette-related tweets (size not explicitly stated)	Fine-tuned LLMs significantly improved accuracy in detecting	Generalizability limited by training data; challenges with sarcasm and	Article 12, 20

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Table 1 (*continued*)

Reference	Study Aim/Purpose	AI Method/ Algorithm	Data Sources / Sample Size	Main Findings/ Conclusions	Limitations Reported/ Comments	Relevant WHO FCTC Articles
	LLMs on tobacco-related tweets			nuanced sentiment and intent; valuable for public health surveillance	ambiguous language in tweets	
[37]	Identifying smoking environments from images of daily life using deep learning	Deep learning (CNNs for image classification)	Photographs from smoking participants' daily environments	Model accurately detected smoking-related cues in personal environments; implications for relapse prevention	Contextual factors in image interpretation not explored in depth	Article 8, Article 14
[61]	Use ML for detecting tobacco point-of-sale advertising in retailer photographs.	Image classification (Inception V3), Object detection (YOLO V3)	Large dataset of tobacco retailer photographs (West Virginia & Washington, DC).	Successfully classified and located tobacco advertising in photographs using deep learning.	Geographic limitation; effectiveness in diverse settings unclear.	Article 13
[62]	Assess ML-based recommender system's effect on cessation	Recommender system integrated with viral peer referral model	RCT with 1747 adult smokers	Cessation rates improved with combined ML + peer network design	Not all peer-referrals reached intended targets; sample bias possible	Article 14
[36]	Examination of social smoking classifications using a machine learning approach	Machine Learning classification models	Survey data on smoking behavior; n = unspecified	ML revealed nuanced social smoking typologies; potential to inform tailored interventions	Did not assess long-term cessation outcomes; sample size not detailed	Article 14, Article 20
[41]	Review machine learning applications in tobacco research.	Scoping review	Literature search of 74 ML studies across multiple databases.	Rapid growth of ML use in tobacco research since 2018; common in cessation tech and social media analysis.	English-language restriction; potential publication bias.	Article 20
[63]	Discuss AI applications for smoking cessation in pregnancy	AI-assisted behavioral interventions (conceptual)	Review-based; no primary data	AI can personalize pregnancy-safe cessation programs; emphasizes ethical frameworks and risk stratification	Perspective only; lacks empirical validation or technical implementation	Article 14
[64]	Identify nicotine gum-related topics using Twitter data.	Top2Vec topic modelling	Twitter API collected tweets; validation with 1000 tweets.	Smoking/vaping cessation most common topic; minor themes included branding, health concerns, COVID-19 relief.	Twitter data limitations; possible selection bias.	Article 12
[32]	To predict the first smoking lapse during a quit attempt using real-time data and machine learning	Machine Learning (Gradient Boosting Machine, Elastic Net, Random Forest, etc.)	Data from a mobile app used by 209 socioeconomically disadvantaged adults during cessation	ML models accurately predicted first lapse within first 3 days of quit attempt; real-time factors like urge to smoke and stress were strong predictors	Generalizability to other populations unclear; mobile app data may not capture all contextual factors	Article 14, Article 20
[65]	Identify predictors of response to digital smoking cessation intervention using machine learning.	LASSO regression	National sample; adult smokers with depressive symptoms; randomised controlled trial (RCT).	Time spent on app predicted smoking reduction; educational attainment moderated depressive outcomes.	Limited to smokers with depressive symptoms; generalizability unknown.	Article 14
[66]	Explore vaping risk perceptions on Twitter during EVALI	Mixed methods (topic modeling + qualitative coding)	Twitter data (EVALI timeline)	Identified shifts in user sentiment and misconceptions during crisis	Difficult to isolate tweet authors' demographics	Article 12
[67]	Track compliance with e-cigarette warning labels on Instagram	Deep Learning (CNN for object detection, YOLO for image annotation)	Instagram posts related to e-cigarettes (exact sample not specified)	Deep learning accurately identified label violations; many posts lacked visible warnings	Focus on images only; no content/contextual interpretation of posts	Article 11
[68]	Characterize vaping content on Instagram	Unsupervised ML (clustering, image recognition)	Vaping-related Instagram posts	Identified promotional themes, youth appeal elements; aided in policy-targeted content tracking	Image-focused only; limited textual metadata	Article 13
[69]	Evaluate LLM accuracy in sentiment analysis of social media on heated tobacco products (HTPs).	GPT-3.5 & GPT-4 Turbo	1000 social media messages (Facebook & Twitter).	GPT-4 Turbo achieved higher accuracy than GPT-3.5 in sentiment evaluation.	Limited platforms; unclear broader generalisability.	Article 20
[70]	Classify e-cigarette content on YouTube via machine learning.	NLP, supervised ML (embedding, BLSTM)	YouTube videos identified through specific search terms.	Videos often featured product reviews and promotional offers (43.2 %).	Limited analysis to YouTube platform only.	Article 13
[71]	Explore generative AI use in tobacco control via social media.	Generative AI (theoretical insights and practical examples)	N/A (Perspective article).	Generative AI useful for social media analysis, misinformation detection; potential industry misuse noted.	Theoretical and commentary-based; no specific methodology reported.	Article 12, Article 20
[72]	Develop AI to identify tobacco-promoting content on Turkish Twitter.	BERT-based model	177,684 tweets (quantitative); qualitative analysis of 200 tweets.	BERT model identified tobacco-promoting content accurately; 39.9 % of tweets promoted tobacco.	Limited to Turkish language tweets; cultural specificity.	Article 13
[73]	To build a deep learning model for detecting smoking	Multimodal Deep Learning (CNN + RNN architecture)	Custom small-scale dataset: biosignals, user logs, image features	Model accurately detects smoking events with high	Performance may not generalize; tested on limited	Article 20

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Table 1 (*continued*)

Reference	Study Aim/Purpose	AI Method/ Algorithm	Data Sources / Sample Size	Main Findings/ Conclusions	Limitations Reported/ Comments	Relevant WHO FCTC Articles
	behavior from multimodal small-scale datasets.			precision, even from small datasets.	population with controlled inputs.	
[74]	Identify e-cigarette content on TikTok using topic modeling	BERTopic (transformer-based topic modeling)	2347 TikTok videos with e-cigarette hashtags	Most content focused on product promotion and vape tricks; minority on health effects or warnings	Lacks cross-platform comparison; sample drawn from specific keywords	Article 13
[75]	Classify image content in e-cigarette-related TikTok videos	Unsupervised Machine Learning (Image Clustering with CNN embeddings + K-means)	1220 TikTok video frames (image dataset)	Clustered images into promotional, social, and neutral content types; promotional content dominated	No audio/text analysis; visual focus limits content understanding	Article 13
[76]	Analyze anti-tobacco campaign message engagement on Facebook using ML	Machine Learning Classification (Support Vector Machine, Naïve Bayes, Decision Trees)	Facebook posts from CDC Tips campaign (n = 3,835 posts)	Identified which post features (tone, visual content, themes) influenced engagement; positive tone and visual posts had higher interaction	Limited to Facebook; engagement does not directly translate to behavior change	Article 12
[77]	To analyze public response to e-cigarette regulations using NLP and topic modeling	NLP, Latent Dirichlet Allocation (LDA) topic modeling, sentiment analysis	Twitter data; exact size not reported	Identified dominant topics and sentiments following policy changes; highlighted negative sentiment spikes during regulation announcements	Challenges with filtering bots, sarcasm, and non-English content; difficulty interpreting unsupervised topics	Article 20
[78]	Assess user experience of virtual human (Florence) for tobacco cessation during COVID-19.	AI conversational agent	Web-based survey of 115 global users (49 countries).	Positive user experience, increased intent to pursue recommended cessation services.	Convenience sample; potential self-selection bias.	Article 14
[79]	Test feasibility of AI conversational agent for medication adherence	Conversational AI prototype with ML behavior tracking	Mixed methods trial on varenicline users	Promising user engagement and intent to adhere; informed digital health tool refinement	Still in feasibility phase; outcome data pending	Article 14
[39]	Assessing secondhand and thirdhand smoke exposure in infants using ML and biomarkers	Machine learning integration of questionnaire and biomarker data	Canadian infant cohort; survey and biomarker data	ML identified key exposure predictors; potential for environmental health monitoring	Generalizability may be limited by cohort composition	Article 8, Article 20
[80]	To assess whether Reddit discussions could detect early signals of vaping-associated lung injury (EVALI)	Qualitative NLP methods, trend analysis	Reddit posts mentioning vitamin E acetate and Dank Vapes	Increase in mentions of vitamin E acetate preceded CDC alert; Reddit can serve as early surveillance tool	Retrospective study; cannot infer causality; potential sampling bias from subreddit selection	Article 20
[81]	Detect vaping-related tweets during 2019 EVALI outbreak	Supervised ML classifiers (e.g., logistic regression, random forest)	Vaping-related tweets during EVALI (Twitter API)	ML detected vaping discourse spikes during health alerts; potential for early warning	Limited to public tweets; lacked location tagging	Article 20
[82]	Apply predictive analytics to tobacco cessation	Data mining techniques (association rules, classification)	Survey/interview data from tobacco users	Predicted relapse risk and intervention timing	Exploratory study; lacked clinical integration	Article 14
[83]	Identify and analyze synthetic nicotine promotions on Instagram	Natural Language Processing (NLP), supervised text classification	Instagram posts related to synthetic nicotine products	Promotional content often lacked warning labels and used youth-targeted language	Instagram's evolving API access limits repeatability; focus on English-language content	Article 13
[84]	Evaluate AI and ML tools for screening public health-relevant content on social media	Generative AI (e.g., ChatGPT), ML classifiers (e.g., logistic regression)	Diverse social media content; specific sample details not provided	Highlighted utility of AI for automating content moderation and screening; proposed framework for integrating generative models with traditional ML	Data privacy and ethical concerns in deployment; model performance depends on prompt quality and training data bias	Article 12
[85]	Simulate adolescent responses to vaping-prevention messaging via AI.	AI simulation model (LLM) trained on adolescent ratings	Adolescents rated vaping prevention messages (46 text-only; 220 text/image combined).	AI accurately predicted adolescent effectiveness ratings; visual information significantly enhanced model predictions.	Sample diversity limited; controlled study conditions.	Article 12
[86]	To discuss the role of AI in supporting tobacco cessation strategies during the COVID-19 pandemic	Artificial Intelligence (general applications), including digital health platforms and chatbots	Not based on original dataset; perspective piece referencing global trends and technologies	AI tools such as chatbots and digital interventions can aid cessation efforts by offering scalable, accessible support during health system strain	Perspective article; lacks empirical data or specific algorithmic evaluation; conceptual overview only	Article 14
[87]	Predict e-cigarette use and dependence in youth	Supervised ML (e.g., XGBoost, logistic regression)	Survey data from Ontario high school students	Accurate risk stratification model; top predictors included peer use and depression	Self-report bias; lack of biological markers	Article 20

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Table 1 (*continued*)

Reference	Study Aim/Purpose	AI Method/ Algorithm	Data Sources / Sample Size	Main Findings/ Conclusions	Limitations Reported/ Comments	Relevant WHO FCTC Articles
[88]	Explore link between media coverage and support for Tobacco 21 policies	Supervised and unsupervised ML on media content	News articles and online commentary	Identified correlation between news frequency and policy awareness	Causality not confirmed; time-lag effects not fully explored	Article 12
[89]	To identify which features in cessation apps correlate with successful quitting using ML.	Supervised Machine Learning Models	Experimental dataset from cessation app users (sample size not stated)	Goal-setting, reminders, and coaching tools positively associated with quitting success.	Potential selection bias; feature usage self-reported; secondary analysis limits causal inference.	Article 14
[90]	To review how machine learning has been integrated into various aspects of tobacco control research.	Machine Learning (general overview of techniques)	Tobacco-related ML studies and databases (review)	ML has improved disease prediction, biomarker identification, and cessation support; future potential noted.	Non-systematic review; no original data analysis performed.	Article 20
[91]	Evaluate GPT-4o in detecting vaping themes in social media.	GPT-4o multimodal AI	102 Instagram/TikTok micro-influencer videos.	GPT-4o accurately detected vaping and related promotional contexts (87 %-99 %).	Small, niche sample; generalisability limited.	Article 13
[92]	Examine early adolescent vaping through ML risk modeling	Machine Learning (decision tree, random forest)	Cross-sectional adolescent survey data	Predicted initiation likelihood; social influences key predictors	Model may not generalize outside studied region	Article 20
[93]	To identify Reddit users contemplating vaping cessation for targeted digital interventions	Large Language Models (LLMs), classification with prompt-based tuning	Reddit posts from vaping-related subreddits	LLMs successfully identified users likely to engage with cessation content; provides a pipeline for digital health outreach	Ethical concerns over user consent and potential intervention biases	Article 14
[94]	Explore targeted marketing toward marginalized groups via cigar tweets	Computational content analysis with NLP and engagement prediction models	Public & protected cigar-related tweets; user-level metadata (sample not specified)	Targeted tweets had higher engagement among minority groups; suggested intentional marketing bias	Cannot confirm industry intent; access to protected tweets limited verification	Article 13
[95]	Automated detection of hookah imagery on Instagram	CNN + SVM hybrid model	Instagram posts with hookah-related hashtags	High accuracy in hookah image recognition; supported surveillance and trend tracking	Focused on visual data only; lacked behavioral context	Article 13

Table 2
AI Technologies, Algorithms, and Data Types Used in Tobacco Control.

AI Technology	Algorithms	Datasets	Applications	WHO FCTC Article	Representative References
Machine Learning (ML)	Random Forest, Support Vector Machine (SVM), Gradient Boosting, Logistic Regression, XGBoost	Electronic Health Records (EHRs), Survey data, Social media data, Public health databases	Risk prediction, User behavior classification, Relapse forecasting, Population screening	Article 14 (Cessation), Article 20 (Research)	[47,57,65,87,92]
Natural Language Processing (NLP)	Sentiment Analysis, Topic Modeling (LDA), BERT, Named Entity Recognition, Text classification	Twitter/Reddit posts, Clinical text notes, Tobacco policy documents, Health forum discussions	Trend monitoring, Public sentiment analysis, Marketing detection, Policy text analysis	Article 13 (Advertising), Article 20 (Research)	[44,59,72,80]
Deep Learning	Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Transformer models	Image/video data, Physiological sensor streams, Multimodal social media content	Content analysis, Facial recognition, Emotion detection, Warning label compliance	Article 11 (Packaging), Article 13 (Advertising)	[25,37,61,67,73]
Reinforcement Learning	Q-learning, Deep Reinforcement Learning	User interaction logs, Mobile app engagement data, Behavioral patterns	Personalized interventions, User engagement optimization, Adaptive messaging	Article 14 (Cessation)	[57,62,79,89]
Large Language Models	GPT-3.5/4, ChatGPT, BERT	Conversational data, Health information databases, Clinical guidelines	Cessation chatbots, Health communication, Content analysis, Education	Article 12 (Education), Article 14 (Cessation)	[44,45,54,69,93]

health policy and intervention design.

3.1.1. *Social media surveillance and sentiment analysis*

By leveraging AI for social media surveillance and sentiment analysis, public sentiment, misinformation, and marketing trends can be tracked to facilitate faster regulatory response, and media campaign adjustments. Artificial intelligence models, particularly Natural Language Processing (NLP) and machine learning (ML) algorithms, have significantly improved the surveillance of tobacco use patterns. By systematically analysing large datasets derived from social media platforms such as Twitter, Reddit, Instagram, and various online forums, these AI-driven tools provide timely identification of emerging tobacco-related trends, such as the rapid uptake of e-cigarettes and vaping devices [56,80,91]. NLP algorithms, for example, can extract critical insights by identifying recurring themes, phrases, or keywords indicative of tobacco-related behaviours and public sentiments.

AI-driven analysis of Twitter and other social media platforms has demonstrated substantial promise for tobacco control surveillance and policymaking [56,60,64]. Using natural language processing (NLP), sentiment analysis, and machine learning classifiers, researchers systematically evaluate public reactions to tobacco control measures such as anti-smoking legislation, and public health campaigns [77,85]. For example, AI techniques have been instrumental in tracking responses to smoke-free laws, identifying public sentiment shifts, and detecting covert promotional strategies deployed by e-cigarette companies [67,72,77]. These analyses offer public health authorities actionable insights, enabling timely interventions to counteract misinformation, evaluate the effectiveness of messaging, and enhance regulatory measures against aggressive tobacco product marketing, particularly toward vulnerable groups and youth.

Sentiment analysis, a subset of NLP, has become particularly valuable for understanding public attitudes and reactions toward tobacco control measures and new tobacco products. By assessing sentiment in real-time, policymakers and public health practitioners can respond swiftly and effectively to public concerns, misinformation, or promotional content. Studies have successfully utilised sentiment analysis to gauge public response toward tobacco legislation, taxation, health warnings, and the introduction of novel tobacco products [64,69,77] thereby assisting regulatory bodies in making informed, data-driven decisions.

3.1.2. *Conversational AI and digital cessation support*

AI technology has been instrumental in developing innovative, personalised tools for smoking cessation. Mobile health applications powered by AI—such as Quit Genius and SmokeFree—use advanced reinforcement learning algorithms and predictive analytics to customise interventions according to individual user profiles, behaviours, and risk factors [48,58,78]. These apps monitor user progress and behavioural patterns in real-time, offering tailored motivational messages, coping strategies, and rewards, significantly enhancing user engagement and quit rates.

Furthermore, conversational AI, in the form of chatbots and virtual health assistants, has emerged as an effective approach to deliver immediate, continuous support for individuals attempting to quit tobacco [48,78]. Virtual assistants utilise sophisticated dialogue systems to simulate empathetic and personalised interactions, provide immediate responses to user queries, track moods and cravings, and proactively offer relapse prevention strategies. Such technologies not only improve accessibility and scalability of cessation services but also provide vital support during high-risk relapse periods.

3.1.3. *Predictive risk modelling and personalized interventions*

Predictive modelling, another crucial AI application, has demonstrated substantial promise in identifying individuals at high risk for tobacco initiation and those who require cessation support [47,51,65]. AI-driven predictive models leverage extensive datasets from electronic health records (EHRs), genetic markers, behavioural assessments, and socio-demographic variables to create comprehensive risk profiles. By analysing complex patterns within these datasets, machine learning algorithms can accurately forecast individual vulnerability to tobacco initiation, and those needing needed cessation support based on behavioural, demographic, and psychosocial inputs.

The use of predictive risk modelling aligns closely with precision medicine, enabling healthcare providers to deliver highly personalised and targeted preventive measures or interventions tailored specifically to the individual's risk profile. For instance, healthcare systems have implemented these predictive tools to proactively identify patients who may benefit from early cessation counselling, pharmacotherapy, or other supportive services, thereby optimising resource allocation and enhancing overall effectiveness [48,51,63].

3.1.4. *Policy surveillance, evaluation and public health messaging*

Studies revealed AI could be used in policy surveillance and compliance monitoring. This could be done by assessing media coverage's influence on policy support [77,88], automating the tracking of tobacco-related regulations or policy impacts [88] and evaluating platform-level visual warning compliance [61,67]. These applications offer a scalable method for real-time policy surveillance, though challenges persist in understanding intent and context solely from visual or textual data.

AI techniques have also advanced the evaluation of tobacco control policies and the delivery of adaptive public health messaging [50,71,96]. Through sophisticated modelling and simulation, AI systems can predict the potential impacts of various tobacco control measures—such as advertising restrictions, smoke-free laws, and packaging regulations on different population groups. These models help policymakers anticipate behavioural and economic outcomes, refine policy implementation strategies, and preempt potential unintended consequences.

Moreover, AI's ability to continuously analyse real-time engagement and behavioural data facilitates highly dynamic and adaptive public health messaging campaigns [71,96]. AI algorithms can optimise communication strategies by rapidly assessing message performance across various demographics, social platforms, or geographic areas. This capability allows health campaigns to promptly adjust messaging content, timing, and delivery methods to maximise public impact, ensuring messages are resonant, culturally sensitive, and effectively targeted to high-risk groups or communities that may otherwise be difficult to engage through traditional methods.

3.2. *Distribution of AI methodologies across tobacco control applications*

Machine learning emerged as the most widely used AI technology, employed in 68 % (n = 39) of included studies. These applications typically focused on classification tasks, risk prediction models, and pattern recognition within diverse datasets. Natural language processing (NLP) was utilized in 35 % (n = 20) of studies, primarily for social media surveillance, sentiment analysis, and content evaluation of tobacco-related messaging. Deep learning approaches featured in 21 % (n = 12) of studies, with convolutional neural networks (CNNs) being the most common architecture for image analysis applications such as detecting tobacco imagery in social media and compliance monitoring of warning labels.

Less frequently utilized methodologies included reinforcement learning (12 %, n = 7), which was predominantly applied in personalized cessation interventions and adaptive health messaging, and large language models (LLMs) (9 %, n = 5), which represented the newest technological wave focused on conversational agents for cessation support and comprehensive content analysis. Table 3 provides a detailed breakdown of the AI methodologies and their distributions across the

Table 3
Distribution of AI Methodologies Across Included Studies.

AI Technology	Number of Studies (%)	Primary Algorithms	Major Application Areas
Machine Learning	39 (68 %)	Random Forest, Support Vector Machine, Gradient Boosting, Logistic Regression	Risk prediction, user behavior classification, policy impact assessment
Natural Language Processing	20 (35 %)	Sentiment Analysis, Topic Modeling, BERT, Named Entity Recognition	Social media surveillance, public sentiment analysis, marketing detection
Deep Learning	12 (21 %)	Convolutional Neural Networks, Recurrent Neural Networks, Transformer models	Image analysis, multimodal data integration, behavioral pattern recognition
Reinforcement Learning	7 (12 %)	Q-learning, Deep Reinforcement Learning	Personalized cessation interventions, adaptive health messaging
Large Language Models	5 (9 %)	GPT-3.5, GPT-4, ChatGPT, BERT	Cessation support chatbots, content analysis, health communication

Note: Percentages exceed 100% as many studies employed multiple AI technologies.

included studies.

3.2.1. Temporal trends in AI adoption

Fig. 3 illustrates the temporal evolution of AI applications in tobacco control from 2010 to 2025. A notable inflection point occurred around 2018, with a significant acceleration in publications employing AI for tobacco control purposes. The most substantial growth was observed in machine learning applications, which showed a 320 % increase between 2018–2022 compared to 2013–2017. Studies utilizing deep learning methodologies began appearing predominantly after 2019, while large language models represent the newest technological wave, with all identified applications emerging after 2022.

A significant finding was the growing trend toward methodological integration, with 42 % (n = 24) of studies employing multiple AI technologies within the same application. The most common integration pattern combined machine learning with NLP (19 %, n = 11), particularly for social media surveillance applications that required both content classification and sentiment analysis.

Our analysis revealed substantial diversity in data sources utilized across studies. Social media platforms served as the primary data source for 46 % (n = 26) of studies, with Twitter/X being the most frequently utilized platform (28 %, n = 16), followed by Instagram (12 %, n = 7) and Reddit (9 %, n = 5). Electronic health records provided data for 25 % (n = 14) of studies, primarily those focused on risk prediction and personalized interventions. Survey data, mobile application usage data, and image/video datasets were also commonly utilized.

Computational infrastructure requirements varied considerably, with most machine learning studies utilizing standard statistical packages, while deep learning applications typically required more sophisticated GPU-based computing environments. Notably, only 5 studies (9 %) reported the computational resources required for model development and deployment, highlighting a significant gap in methodological reporting that could impact reproducibility and practical implementation.

3.2.2. Thematic mapping of AI applications in tobacco control

Beyond methodological classification, our review identified four primary thematic domains where AI is being applied across the tobacco control landscape. These domains represent distinct intervention targets, stakeholder groups, and implementation contexts that shape how AI technologies are being leveraged to advance tobacco control objectives.

It's important to note that the thematic categorization presented here differs from the WHO FCTC article alignment shown in Fig. 2. While Fig. 2 presents the distribution of all 57 studies by their alignment with specific FCTC articles (with some studies aligning with multiple articles), our thematic analysis categorizes each study into one primary application domain based on its main focus. Therefore, the numbers and percentages in this section represent the primary thematic classification of each study, whereas Fig. 2 shows all.

3.2.2.1. Surveillance and monitoring (n = 24, 42 %). The largest thematic cluster focused on surveillance and monitoring applications, where AI technologies enable automated, large-scale analysis of tobacco-related behaviours, marketing activities, and public discourse. Key applications within this domain included:

- Social media monitoring of emerging products and trends (n = 14)
- Sentiment analysis toward tobacco control policies (n = 9)
- Detection of illicit or non-compliant marketing content (n = 7)
- Geographic and demographic pattern identification (n = 5)

Machine learning classifiers and NLP techniques dominated this domain, with a growing integration of computer vision approaches for image and video content analysis. These surveillance applications primarily aligned with WHO FCTC Articles 13 (tobacco advertising, promotion, and sponsorship) and 20 (research, surveillance, and exchange of information), while some also supported Article 12 (education, communication, and public awareness) as a secondary alignment.

3.2.2.2. Cessation support and intervention (n = 19, 33 %). The second-largest thematic cluster encompassed cessation support and intervention applications, where AI enables personalized, scalable approaches to smoking cessation. Key applications included:

- Digital cessation chatbots and virtual assistants (n = 8)

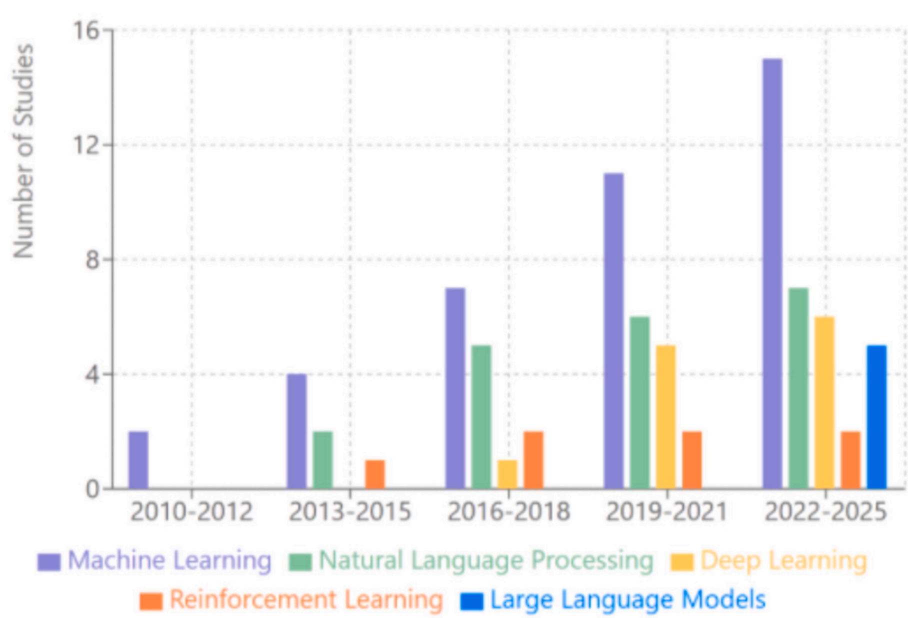

Fig. 3. Temporal Evolution of AI Technologies in Tobacco Control (2010–2025). This figure illustrates the temporal evolution of AI applications in tobacco control from 2010 to 2025. A notable inflection point occurred around 2018, with significant acceleration in publications employing AI for tobacco control purposes, particularly in machine learning applications. Deep learning methodologies began appearing predominantly after 2019, while large language models represent the newest technological wave, with all identified applications emerging after 2022.

- Predictive modelling of relapse risk (n = 7)
- Personalized intervention matching (n = 6)
- Real-time craving and trigger detection (n = 4)

Reinforcement learning and predictive analytics were prominently featured within this domain, alongside conversational AI applications utilizing large language models in more recent studies. These applications primarily aligned with WHO FCTC Article 14 (demand reduction measures concerning tobacco dependence and cessation). While Fig. 2 shows 26 studies (45 %) with Article 14 alignment, only 19 studies had cessation support as their primary focus. The remaining 7 studies had cessation as a secondary application while primarily focusing on surveillance (n = 4), policy support (n = 2), or education (n = 1).

3.2.2.3. Policy and regulatory support (n = 9, 16 %). A smaller but significant cluster focused on policy and regulatory applications, where AI tools assist in policy development, implementation, and evaluation. Key applications included:

- Impact assessment of proposed regulations (n = 5)
- Compliance monitoring with existing policies (n = 4)
- Policy effectiveness modelling (n = 3)
- Regulatory text analysis and comparison (n = 2)

This domain featured diverse methodological approaches, with machine learning and NLP being most common. These applications aligned with multiple WHO FCTC articles including Articles 8 (protection from exposure to tobacco smoke), 11 (packaging and labelling of tobacco products), and 13 (tobacco advertising, promotion, and sponsorship).

3.2.2.4. Education and communication (n = 5, 9 %). The smallest thematic cluster focused on education and communication applications, where AI enhances the development and delivery of anti-tobacco messaging. Key applications included:

- Message tailoring and optimization (n = 3)
- Audience segmentation for targeted campaigns (n = 2)
- Educational content personalization (n = 2)

Machine learning and NLP dominated this domain, with emerging applications of large language models for content generation. These applications primarily aligned with WHO FCTC Article 12 (education, communication, and public awareness). Fig. 2 shows 13 studies (22 %) with Article 12 alignment, but only 5 studies had education and communication as their primary focus. The remaining 8 studies included Article 12 as a secondary alignment while primarily focusing on surveillance (n = 5) or cessation support (n = 3).

Our thematic analysis reveals that AI applications in tobacco control remain unevenly distributed across potential domains, with surveillance and cessation support receiving the most attention, while policy support and education applications represent emerging areas with significant growth potential.

The synthesis of methodological approaches and thematic domains provides a comprehensive landscape view of how AI is transforming tobacco control across multiple dimensions. This integrated perspective highlights both the current state of development and critical gaps that require further research and implementation attention.

3.3. Case studies and applications

The integration of Artificial Intelligence (AI) into tobacco control is exemplified by several innovative case studies and real-world applications. These cases illustrate how advanced AI technologies, including facial recognition, machine learning (ML), and natural language processing (NLP), are actively transforming public health practices by enabling comprehensive surveillance of tobacco-related attitudes and behaviours. The following case studies highlight the practicality, effectiveness, and potential of AI-driven approaches in addressing the complexities of tobacco use.

3.3.1. AI applications in tobacco industry interference

Tobacco industry interference (TII) represents a significant and persistent barrier to effective global tobacco control. Historically, tobacco corporations have employed diverse strategies, including influencing research outcomes, manipulating data, infiltrating regulatory processes, and shaping public perceptions to maintain market dominance [97,98]. Understanding and addressing these tactics are essential for ensuring AI-driven tobacco control measures remain unbiased, effective, and ethically aligned with public health goals.

Table 4 integrates essential information on key organisations, AI-based tools, and ethical and regulatory frameworks guiding AI applications in tobacco control. It provides a clear overview of organisations

Table 4
AI-based Tools, Key Organisations, and Ethical Frameworks in Tobacco Control.

Organisation/ Initiative	Country/ Region	AI-based Tools and Projects	Key AI Features	Relevant Ethical or Regulatory Guidelines
Truth Initiative	USA	Digital cessation tools and chatbot interventions	Predictive analytics, conversational AI	WHO Framework Convention on Tobacco Control (FCTC), FDA Digital Health Plan
Quit Sense	UK	Personalised smoking cessation application	Reinforcement learning, behavioural analytics	GDPR, WHO Ethics and Governance of AI
WHO Digital Health Initiative	Global	Florence: Artificial Intelligence bot to support smoking cessation	Advanced neural network-based cognitive architecture with real-time emotional responsiveness	WHO Ethics and Governance of AI for Health, Article 5.3 of WHO FCTC
SmokeFree App Ltd	Global	SmokeFree cessation mobile app	Real-time analytics, predictive relapse alerts	GDPR, IEEE Ethical Framework
National Cancer Institute (NCI) — Smokefree.gov	USA	Text-based quit programs and SmokefreeTXT	Predictive messaging algorithms, user behavior tracking	HIPAA, U.S. Health IT regulations, FDA guidance
Health Promotion Board (HPB)	Singapore	“I Quit” Programme with digital support tools	Behavior-based AI tracking, progress analytics	Singapore PDPA, WHO FCTC
Canadian Cancer Society	Canada	“Break It Off Cessation Campaign” and “Quit Coach” apps	Gamified interventions, push-based behavioral reminders	PIPEDA, Canadian Centre for Ethics in AI (Montreal Declaration)
My Life My Quit (National Jewish Health)	USA	MyQuit app and integrated telehealth coaching	Machine learning for quit plan personalization	HIPAA, FDA Digital Health Framework
Be He@lthy, Be Mobile (WHO-ITU)	Global	mCessation initiative (SMS and app-based)	Scalable AI-based messaging systems	WHO Ethics and Governance of AI, WHO FCTC

such as the Truth Initiative, the UK NIHR (Quit Sense), and the WHO Digital Health Initiative, each actively deploying AI technologies for prevention, intervention, and monitoring efforts. The table identifies distinct AI features like conversational AI, facial recognition, predictive modelling, and real-time analytics used in these tools. Additionally, it aligns each initiative with pertinent ethical standards and regulatory frameworks, such as the WHO Framework Convention on Tobacco Control (FCTC), FDA Digital Health Innovation Action Plan, and the European Union's General Data Protection Regulation (GDPR). Thus, this comprehensive summary underscores the critical interplay between technological innovation, organisational efforts, and ethical compliance essential for responsible and effective public health interventions.

3.3.2. Corporate rebranding and digital innovation

In response to global shifts toward harm reduction and smoke-free alternatives, tobacco companies have strategically leveraged AI technologies to promote alternative nicotine delivery systems such as heated tobacco products and e-cigarettes [99]. For example, Altria utilizes machine learning algorithms to analyse consumer behaviour and purchasing patterns, enabling more personalized and targeted marketing strategies [100]. British American Tobacco (BAT) has also expanded its product range to include synthetic nicotine pouches, leveraging digital insights to inform product development and marketing approaches [101]. These technological advancements are part of a broader industry-wide strategy wherein tobacco companies reposition themselves as stakeholders in tobacco harm reduction, while continuing to market and expand their portfolio of novel nicotine products [102]. Such repositioning efforts allow tobacco firms to gain access to regulatory conversations and influence tobacco control policy under the guise of innovation and risk reduction. These approaches allow tobacco companies to present their products as innovative, technologically advanced, and potentially less harmful, thus reinforcing nicotine addiction under a veneer of modernity and safety [103,104]. Such AI-driven tactics pose ethical and regulatory challenges, raising serious concerns regarding youth exposure, product normalisation, and perpetuation of addiction cycles.

3.3.3. Data manipulation and research influence

Tobacco corporations have historically sought to influence research agendas and outcomes [104,106], a pattern now extending into AI-focused research. Companies frequently fund studies emphasising the purported reduced harm of their newer products [103,104] deliberately minimising associated health risks. AI-based simulations and predictive models financed by industry sources risk producing biased or misleading results, which can distort evidence-based policymaking and compromise public health efforts. Additionally, proprietary datasets owned by tobacco companies, utilised in their AI research, are typically inaccessible to independent investigators or regulatory agencies, further limiting transparency and rigorous independent assessment.

3.3.4. Algorithmic targeting of vulnerable groups

A critical ethical concern associated with tobacco industry-driven AI technology is the targeted exploitation of vulnerable populations. AI algorithms, employing extensive behavioural data analytics, enable the precise targeting of demographic groups at greater susceptibility to nicotine addiction—such as adolescents, low-income communities, or individuals with mental health disorders. By algorithmically profiling these populations and delivering personalised, compelling messaging, tobacco companies can exacerbate health disparities and undermine global public health efforts aimed at reducing tobacco use and its related harms.

3.3.5. Undermining AI-Based tobacco control measures

AI-enabled tobacco control strategies such as real-time social media monitoring, sentiment analysis, and trend prediction have themselves become targets for industry interference. Tobacco companies can employ bots, coordinated misinformation campaigns, and automated promotional content dissemination to flood digital platforms, skewing data analysed by public health AI systems. Such tactics deliberately distort public opinion metrics and undermine the credibility of AI surveillance tools designed to inform policy decisions, thus reducing their effectiveness and reliability as instruments for tobacco control.

3.3.6. Regulatory evasion and lobbying

The tobacco industry can expand its use of AI into sophisticated lobbying and regulatory evasion practices. AI tools can assist tobacco corporations in monitoring legislative developments, analysing policy trends, and framing strategic lobbying communications designed to influence legislators and undermine public health initiatives [105,106]. Additionally, advanced AI-driven opinion-mining and content optimisation technologies enable the targeted discrediting of tobacco control advocates and health organisations, strategically diminishing their influence and credibility. This undermines public trust in health authorities and contributes significantly to delays in the adoption and enforcement of AI-supported tobacco control policies.

3.4. Safeguarding AI for public health

Given the substantial risks posed by tobacco industry interference, safeguarding the integrity and effectiveness of AI applications in tobacco control has become increasingly important. A critical component of this safeguarding involves maintaining strict transparency and independence in AI research. Researchers and public health institutions must ensure that their studies and interventions remain entirely free from tobacco industry funding or influence (WHO FCTC Article 5.3 – Implementing public health policies devoid of tobacco industry influence), clearly disclosing funding sources and methodologies to avoid conflicts of interest and preserve scientific credibility.

Public health organisations should also prioritise developing and utilising open-source AI tools, which promote transparency, accessibility, and independent verification. Open-source systems reduce the risk of manipulation by commercial interests, allowing independent researchers and regulators to verify findings, methods, and outcomes, thereby enhancing public trust and scientific robustness. Robust data governance policies and regulatory frameworks are essential for protecting AI-driven public health initiatives. Such policies must clearly define data collection standards, secure data handling procedures, and rigorous auditing processes. Effective data governance prevents industry manipulation of AI datasets, ensures unbiased analyses, and safeguards sensitive health data against misuse or exploitation.

Moreover, international collaboration plays a pivotal role in establishing ethical standards for AI in tobacco control in line with vital health policies such as the WHO FCTC Article 22 which encourages parties to share technical, scientific and legal knowledge towards achieving the WHO FCTC objectives and SDG 17- which emphasizes the importance of collaboration between developed and developing nations to achieve the Sustainable Development Goals.

Global partnerships and consistent regulatory alignment with the WHO Framework Convention on Tobacco Control (FCTC) particularly Article 5.3, which explicitly calls for protecting public health policies from tobacco industry interference are essential. Coordinated global actions can help standardise ethical AI practices, enhance surveillance capabilities, and promote equitable and effective tobacco control interventions worldwide. By proactively adopting these comprehensive protective strategies, public health systems can leverage the immense potential of AI technologies effectively, ensuring that such innovations remain ethically sound, unbiased, and optimally beneficial to global tobacco control efforts.

3.4.1. Applying AI to extend the WHO FCTC

Cessation (Article 14) and Research (Article 20) dominate due to the data-driven nature of AI and machine learning. Education and

Communication (Article 12) using AI-powered message targeting, user education, and campaign enhancement is also addressed. Also, Promotion and Advertising (Article 13) is a strong area where AI is used to monitor and counteract digital tobacco marketing, particularly among youth. On the other hand, underexplored areas such as labeling, tax policies, or secondhand and thirdhand smoke protections present potential for future AI-focused research.

The use of varied artificial intelligence models was noticeably skewed towards predictive modelling, cessation support and social media surveillance. While this is a laudable start, it reflects the need for more divergent skill set to fully harness the extensive prospects that AI offers for tobacco control. For example, the available literature did not address how AI could facilitate WHO FCTC 22 to foster stronger government policy, collaboration and automated knowledge sharing towards achieving tobacco endgame [8,9] especially as Article 20 was strongly addressed.

4. Discussion

4.1. Critical analysis of AI in tobacco control: innovation versus ethical risks

The findings of this review reveal a complex landscape where AI technologies simultaneously offer unprecedented opportunities for tobacco control while introducing significant ethical and implementation challenges. Our analysis highlights the need for nuanced consideration of both innovation potential and associated risks within specific application contexts.

4.1.1. Innovation potential

The integration of multimodal AI approaches represents one of the most promising innovations identified in this review. Studies like Engelhard et al. [37] demonstrate how deep learning algorithms can identify smoking environments from images of daily life with high accuracy, potentially enabling just-in-time interventions during high-risk moments for relapse. This capability to process and integrate diverse data streams (visual, textual, and behavioral) enables a more comprehensive understanding of tobacco use contexts than previously possible with traditional surveillance methods.

Similarly, conversational AI applications are transforming cessation support through personalized, scalable interventions. The emergence of large language models, though still in early application stages, shows particular promise for addressing accessibility barriers. Chow et al. [54] emphasize AI's potential to reduce disparities in accessing quality cessation services, particularly benefiting regions with limited healthcare resources. This ability to provide continuous, adaptive support through digital interfaces addresses a critical gap in traditional cessation programs, which often struggle with engagement sustainability and personalization at scale. The ability to provide continuous, adaptive support through digital interfaces addresses a critical gap in traditional cessation programs, which often struggle with engagement sustainability and personalization at scale.

Predictive modelling applications have demonstrated impressive capabilities in identifying at-risk populations before tobacco initiation. For instance, Atuegwu et al. [47] achieved high accuracy in predicting electronic nicotine delivery system initiation among tobacco-naive young adults, potentially enabling targeted prevention efforts. This proactive capability represents a significant shift from reactive approaches that intervene only after tobacco use has begun.

4.1.2. Ethical risks and challenges

Despite these promising innovations, our findings also reveal substantial ethical concerns and implementation challenges. A particularly troubling pattern is the potential for corporate misuse of AI technologies. Wu et al. [94] documented how machine learning algorithms have been employed to enable targeted marketing of cigar products toward historically marginalized communities, with higher engagement rates among minority groups suggesting intentional bias in marketing algorithms. This finding aligns with tobacco industry's historical targeting of vulnerable populations, now amplified through AI's precision targeting capabilities.

The emergence of generative AI tools like ChatGPT presents a double-edged sword for tobacco control. While these systems can provide personalized cessation advice and enhance health communication, they also risk amplifying misinformation if not integrated with evidence-based frameworks. Abroms et al. [44] found that ChatGPT-generated responses to cessation queries aligned only moderately well with CDC guidelines, with accuracy varying substantially based on prompt specificity. This inconsistency raises concerns about the potential for AI systems to disseminate inaccurate health information at scale if not properly validated against clinical guidelines.

Privacy concerns represent another significant ethical challenge. Many AI applications in tobacco control rely on continuous monitoring of user behaviour through smartphones, social media, or wearable devices. While this enables personalized interventions, it also creates risks of surveillance overreach and data misuse. Few studies explicitly addressed user consent processes or data governance frameworks, suggesting a concerning gap in ethical implementation.

Perhaps most problematic is the persistent issue of algorithmic bias. Our review found limited consideration of how AI systems might perform differently across diverse populations. Given documented disparities in tobacco use across racial, socioeconomic, and geographic dimensions, AI systems trained on non-representative datasets risk exacerbating existing inequities rather than reducing them. Sharp et al. [84] highlight this concern, noting that social media screening tools with algorithmic bias could disproportionately flag content from minority communities, potentially leading to discriminatory outcomes.

4.2. Policy implications and governance recommendations

Our findings point to several critical policy implications and governance recommendations to maximize AI's benefits while mitigating associated risks.

4.2.1. Transparency and accountability frameworks

Regulators must mandate transparency in AI-driven marketing surveillance and detection systems. We recommend establishing comprehensive transparency requirements that include regular algorithmic audits, particularly for systems that monitor or analyse tobacco-related content on social media and digital platforms. These audits should assess potential biases in detection algorithms and ensure equal enforcement across different population groups and tobacco product categories. Public health authorities should establish clear guidelines for validating AI-driven cessation tools against established clinical standards before deployment. This would address the inconsistency in quality noted across digital cessation applications and ensure alignment with evidence-based practices. Such validation frameworks should include minimum performance standards across diverse user populations to ensure equitable effectiveness.

4.2.2. Ethical data governance

Our findings suggest an urgent need for ethical frameworks governing data collection and use in AI-driven tobacco surveillance. We recommend WHO-compliant data governance standards that protect individual privacy while enabling public health monitoring. These standards should include explicit informed consent processes, clear limitations on data use, and appropriate anonymization techniques to prevent re-identification of individuals. Given the significant privacy implications of continuous behavioural monitoring, regulatory bodies should establish specific guidelines for AI applications that track individual tobacco use behaviours. These guidelines should address data minimization principles, storage limitations, and user control over personal data, while facilitating legitimate public health surveillance.

4.2.3. Equity and access considerations

To address potential disparities in access to AI-driven cessation tools, policymakers should ensure equity in digital cessation tool development and distribution. This includes incentivizing the development of low-bandwidth applications suitable for regions with limited internet connectivity and supporting the adaptation of AI tools for diverse linguistic and cultural contexts. Resource allocation for AI implementation should prioritize underserved communities with high tobacco burden. This could include dedicated funding for community-based organizations to adapt and implement AI tools in partnership with local stakeholders, ensuring culturally appropriate implementation.

4.3. Future research directions

Our review identifies several critical gaps in the current literature that future research should address to advance the field of AI in tobacco control.

4.3.1. Methodological Priorities

Longitudinal studies of AI intervention effectiveness represent an urgent research need. Most current studies employ cross-sectional designs or short follow-up periods, limiting understanding of sustained impact. Future research should employ robust experimental designs with extended follow-up periods to assess long-term outcomes of AI-driven interventions. Greater methodological transparency in AI implementation is essential. Future studies should provide detailed reporting of algorithm selection rationales, training data characteristics, validation procedures, and performance metrics across demographic subgroups to facilitate reproducibility and comparative evaluation.

4.3.2. Context-specific research

Research in low- and middle-income countries (LMICs) should be prioritized, given the disproportionate tobacco burden these regions face. Current applications are heavily concentrated in high-income settings despite 80 % of tobacco users residing in LMICs [6]. Future research should explore context-appropriate AI implementations that address unique challenges in these settings, including limited digital infrastructure and different tobacco use patterns. Industry interference patterns require more systematic investigation. Given evidence of tobacco industry exploitation of AI technologies, future research should specifically examine how industry actors leverage AI for marketing, product development, and policy interference to inform targeted regulatory responses.

4.3.3. Emerging technology applications

Explainable AI approaches represent a promising direction for enhancing transparency and trust. Future research should focus on developing interpretable AI models that can provide clear explanations for their predictions and recommendations, particularly in clinical and policy decision support contexts. Real-time intervention systems that integrate multiple data streams warrant further investigation. Building on promising work in just-in-time adaptive interventions, researchers should explore systems that combine physiological, environmental, and behavioural data to deliver precisely timed cessation support. Generative AI applications for health communication and education deserve careful evaluation. As large language models continue to evolve, research should assess their effectiveness for tobacco education and behaviour change communication while establishing guardrails against misinformation.

5. Challenges and limitations

While Artificial Intelligence (AI) offers significant promise for tobacco control, several critical challenges and limitations must be acknowledged and addressed to ensure effective, ethical, and equitable applications. These challenges include inherent biases and disparities, privacy concerns and ethical dilemmas related to data usage, issues surrounding interpretability and transparency, and complexities in data quality and integration.

5.1. Bias and disparity

One of the most significant limitations of AI applications in healthcare, including tobacco control, is the potential for bias and disparity. AI models depend heavily on the quality, diversity, and representativeness of their training datasets. When datasets disproportionately represent certain populations or exclude minority or vulnerable groups, AI systems can inadvertently perpetuate or exacerbate existing health disparities [94]. This can lead to unequal access to or effectiveness of interventions, potentially disadvantaging populations already facing social or health inequities. Addressing these biases requires careful dataset selection, inclusive representation, and continuous monitoring of AI-driven outcomes across diverse demographic groups.

5.2. Privacy and ethical concerns

AI-driven tobacco control tools frequently rely on sensitive personal data obtained from electronic health records, social media platforms, wearable devices, and clinical interactions [18,49,56]. The utilisation of this data raises substantial privacy and ethical concerns. Without robust governance structures, there is a risk of data misuse, unauthorised surveillance, or breaches that could compromise patient confidentiality and trust. Additionally, ethical questions arise regarding informed consent and the boundaries of personal privacy in the context of predictive analytics, behavioural monitoring, and targeted interventions. Ensuring ethical data management practices, stringent privacy protections, and clear consent processes are vital to addressing these concerns effectively.

5.3. Interpretability

Many advanced AI models, particularly deep learning algorithms, function as “black boxes,” making it challenging for healthcare providers, policymakers, and stakeholders to understand precisely how predictive decisions or recommendations are derived. The lack of transparency and interpretability can hinder trust and acceptance among clinicians, patients, and public health officials, potentially limiting the adoption and practical application of AI tools. Addressing interpretability challenges requires advancements in explainable AI methodologies, fostering clearer, understandable models, and providing transparency about the data inputs, analytical processes, and decision-making criteria underlying AI outputs.

5.4. Data quality and integration

The effectiveness and reliability of AI systems are significantly dependent on the quality, completeness, and consistency of input datasets. Incomplete, inaccurate, or inconsistent data can severely undermine AI performance, leading to erroneous predictions, inappropriate recommendations, or compromised outcomes. Additionally, integration challenges arise when combining diverse data types from multiple sources, such as healthcare systems, social media, wearable devices, or other digital platforms. Effective AI application necessitates robust data governance frameworks, consistent data standards, rigorous data cleaning procedures, and advanced methods for harmonising and integrating heterogeneous data sources to maintain AI reliability and generalisability.

6. Limitations of the review

While this scoping review provides a comprehensive synthesis of the current landscape of artificial intelligence (AI) applications in tobacco control, several limitations should be acknowledged. First, as a scoping review, the primary aim was to map the breadth and nature of the existing literature rather than to assess the quality of evidence or perform a *meta*-analysis. Consequently, although informal appraisals of methodological rigour were undertaken, no formal critical appraisal tool was applied across studies, and findings should be interpreted accordingly.

Second, the rapid pace of technological advancement in AI means that relevant studies may have emerged after the final literature search was conducted. Despite efforts to include the most up-to-date and relevant sources, some emerging applications or tools may not have been captured, particularly those in the grey literature or recently published but not yet indexed. This is particularly relevant in the rapidly evolving field of generative AI and large language models, where applications specific to tobacco control are emerging at an accelerating rate.

Third, this review included only English-language publications, which may have led to language bias and the exclusion of potentially important studies published in other languages. Given the global burden of tobacco use, the exclusion of non-English sources may underrepresent contributions from low- and middle-income countries (LMICs) where innovative applications of AI may be underreported in the English literature. This limitation is particularly significant since LMICs bear approximately 80 % of the global tobacco burden and may benefit most from cost-effective AI solutions.

Fourth, heterogeneity in study designs, AI methodologies, outcome measures, and reporting formats made it difficult to standardise comparisons or draw definitive conclusions about effectiveness, scalability, or ethical implementation. Many studies used exploratory or theoretical approaches rather than real-world evaluations, which limits generalisability and applicability to policy and practice. This is reflected in the predominance of proof-of-concept studies and prototype implementations rather than rigorously evaluated interventions with clearly reported outcomes.

Fifth, the interdisciplinary nature of AI applications in tobacco control created challenges in comprehensive literature identification. Studies bridging computer science, public health, psychology, and policy domains may use varied terminology and be published in diverse journals, potentially leading to incomplete coverage despite our systematic search strategy. Additionally, commercial AI applications in tobacco control may not be publicly documented in academic literature, creating a potential gap between research and practice.

Finally, our review focused primarily on the beneficial applications of AI for tobacco control but may not have captured the full extent of AI misuse by the tobacco industry due to limited transparency in industry practices. The tobacco industry's use of AI for marketing, product development, and policy interference likely exceeds what is documented in accessible literature, presenting an area for further investigation through alternative research methodologies such as investigative reporting and whistleblower accounts.

Despite these limitations, this scoping review represents an important first step in systematically documenting the current state of AI applications in tobacco control and identifying critical gaps in the literature. Future research should address these limitations through multi-language reviews, primary research in underrepresented regions, standardized reporting frameworks for AI interventions in tobacco control, and innovative approaches to investigating industry use of these technologies.

7. Conclusion

AI has transformative potential in tobacco control but requires rigorous ethical oversight. This scoping review has identified diverse AI applications across surveillance, cessation support, and policy domains, with substantial promise for extending global tobacco control efforts. AI has emerged as a transformative force with substantial potential to revolutionise global efforts in tobacco control. Through innovative applications, including enhanced surveillance, personalised cessation support, real-time monitoring, and strategic policy evaluation, AI technologies provide unprecedented opportunities to proactively address the complexities associated with addiction and tobacco-related health issues. AI's capabilities to rapidly process extensive datasets, identify critical patterns, and predict behavioural risks enable healthcare systems and public health organisations to design highly targeted, efficient, and adaptable interventions that align with WHO FCTC implementation goals.

However, realising the full potential of AI in this critical area of public health is contingent upon addressing significant challenges and ethical considerations. Ensuring transparency through explainable AI models is essential for gaining trust among clinicians, policymakers, and the public, facilitating widespread adoption and effective implementation. Moreover, ethical design principles, stringent data privacy measures, and rigorous governance frameworks must underpin AI applications to protect vulnerable populations and prevent exacerbation of existing health disparities. Particular attention must be paid to algorithmic bias, data sovereignty, and protection against industry exploitation of these technologies.

The future success of AI-driven tobacco control strategies also hinges critically upon effective cross-sector collaboration and global inclusivity. Partnerships between technology developers, healthcare providers, public health authorities, community stakeholders, and policymakers are essential to ensuring that AI tools address real-world needs equitably and ethically. Additionally, efforts must prioritise data diversity and representation, particularly from low- and middle-income countries disproportionately affected by rising tobacco use and emerging tobacco products. Stakeholders must develop capacity-building initiatives to empower LMIC researchers to develop contextually appropriate AI solutions while ensuring accessibility beyond high-resource settings.

Overall, AI offers unprecedented opportunities to enhance the effectiveness, scalability, and responsiveness of tobacco control interventions. Yet, its sustainable and equitable integration into public health requires careful consideration of ethical standards, comprehensive data representation, transparent methodologies, and collaborative global efforts. By addressing these critical factors, AI technologies can significantly contribute to reducing the global burden of tobacco use, ultimately improving health outcomes and promoting health equity worldwide. As the tobacco endgame approaches in many countries, strategic integration of AI within comprehensive tobacco control programs will be essential for countering industry innovation and achieving public health goals.

Policymakers and technologists must collaborate to ensure transparency, equity, and alignment with WHO FCTC goals. Funding bodies should prioritize research that addresses identified gaps, particularly in LMIC contexts, real-world implementation studies, and frameworks for ethical AI governance in tobacco control. Through thoughtful development and responsible deployment, AI can become a powerful ally in achieving the WHO's target of a 30 % reduction in tobacco use by 2025.

CRediT authorship contribution statement

David B. Olawade: Writing – original draft, Writing – review & editing, Methodology, Project administration, Investigation, Data curation, Formal analysis, Conceptualization. **Charity A. Aienobe-Asekharen:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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