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Systematic Review

Keywords:

Posted Date: July 8th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10117247/v1>

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Additional Declarations: No competing interests reported.

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Study Identifiers

Review Short Title: AI-assisted interventions to reduce alcohol consumption and smoking: a systematic review

Version: 1.0

Registration: PROSPERO CRD42025642317 and CRD42025642334.

Disclosure of Interests: None declared

Acknowledgements and funding: Jenny Lowe provided professional services support for the review. National Institute for Health and Care Research Public Health Research Programme (NIHR175419). This research was supported by the National Institute for Health and Care Research Applied Research Collaboration South West Peninsula. Prof G.J. Melendez-Torres is an NIHR Senior Investigator. Prof JS Chandan is an NIHR Research Professor (NIHR306365). The views expressed in this publication are those of the author(s) and not necessarily those of the National Institute for Health and Care Research. This work was supported by DECIPHer, funded by Welsh Government through Health and Care Research Wales. We are grateful to the following advisory groups for their support during this review: the NIHR Health Determinants Research Collaborations (HDRCs) in England and Wales (including Zoe Lancelott, Sophia Looney, Sarah Markham, Sarah McGarrol, and Francis McKay); the Health Foundation; the Faculty of Public Health “AI and Digital Public Health” Special Interest Group (including Elliott Roy-Highley); the Local Government Association AI Network; and public contributors (including Sian Harding).

Abstract

Background: Prevalence of alcohol consumption and smoking is high across high-income countries, and interventions to decrease either can include behaviour change delivered digitally. Artificial intelligence (AI) is a broad field encompassing various techniques, which include algorithms that learn from data to perform automated tasks without explicit human programming, and could potentially increase the effectiveness of digital behaviour change interventions through personalisation and reducing barriers to engagement. This review summarises the evidence for the effectiveness of AI-assisted interventions to reduce alcohol consumption and smoking.

Methods: We conducted a systematic review to identify and summarise evidence from randomised controlled trials (RCTs) of AI-assisted interventions for reducing alcohol consumption or smoking. Eligible trials were RCTs that reported results of an AI-assisted public health intervention for reducing engagement with alcohol consumption or smoking in a high-income country. We searched Medline (Ovid), Embase (Ovid), Web of Science (Core collection), and Scopus for relevant trials published between 2010 and 14 January 2025. We also searched for reviews of public health interventions for alcohol consumption or smoking published between 2023 and 14 January 2025, and extracted all references from relevant reviews for screening. We conducted forward and backward citation searching on all included trials (dates of searches: July to September 2025). Screening for trials was conducted independently by two reviewers. Two reviewers independently assessed risk of bias using the Cochrane Risk of Bias 2 tool. As the included trials were heterogeneous in terms of interventions, outcomes, and timepoints, we synthesised the results narratively.

Results: We included 4 trials for reducing alcohol consumption (comprising 16 reports and 4,718 randomised participants): 3 trials used apps with chatbots and reported mixed evidence, and one trial, which was effective, used a rules-based AI that tailored website content. We included 12 trials for stopping smoking (comprising 31 reports and 68,659 randomised participants): 8 trials of apps or messenger chatbots and 4 trials of

recommender systems, all of which had mixed evidence. For many trials, the interventions had multiple components, of which AI-assistance was only one, meaning the effectiveness of AI-assistance specifically could not be determined. Additionally, high risks of bias across almost all trials reduced confidence in the results. There were no trials using large language models (LLMs).

Discussion: There is no strong evidence of a beneficial effect of AI-assistance in public health interventions for reducing alcohol consumption or smoking in high-income countries. Future research should better describe public health interventions that use AI and embed equity considerations into their design and analysis to ensure already disadvantaged groups are not harmed further by the adoption of AI-assisted interventions in public health.

Background

The age-standardised prevalence of alcohol use disorders in high sociodemographic index countries in 2021 was estimated to be 1,848 per 100,000 people aged 15 years and older (1), and alcohol consumption causes a number of communicable and non-communicable diseases, including cancer, with an estimated 494,700 cancer deaths and 13,000,000 cancer disability-adjusted life years globally in 2019 (2). In 2020, around 9.0% of men and 5.2% of women were daily smokers in high sociodemographic index countries, and smoking caused 15% to 19% of deaths in people aged 30 years and older in the UK, US, Canada, and most of Western Europe (3). While alcohol use and smoking have decreased over time (2, 3), prevalence remains high, and both stand as leading causes of preventable deaths worldwide. Public health interventions are necessary to reduce the burden of disease and number of deaths even further.

Artificial intelligence (AI) is a broad field encompassing various techniques, including machine learning, natural language processing, and generative AI (4). AI learns from data to perform automated tasks without explicit human programming, using algorithms integrated into systems and tools (5-7). While the theoretical groundwork for machine learning was laid in the 1980s, recent advancements in computing power and the development of large language models (LLMs) like OpenAI's ChatGPT and Google's Gemini have sparked renewed interest in AI (8). These models, with more user-friendly interfaces and general-purpose applications, offer the potential to tackle a wide range of problems (9).

Interventions to reduce or stop alcohol consumption and smoking can include behaviour change techniques (10, 11), which can be delivered digitally (11, 12). AI-assisted interventions could be effective in reducing alcohol use and smoking, for example by personalising interventions, or reducing barriers to engaging with behavioural interventions (such as stigma and accessibility) (13). For instance, chatbots, autonomous conversational agents that could be rules-based (where responses are governed by rules, like a flowchart) or generative (where responses are generated de novo, potentially using

LLMs), have been used to provide an interface to information about reducing or stopping alcohol consumption (14), smoking (15, 16), or both (17, 18). Similarly, recommender systems, which learn over time which information or messages could be most likely to influence a person, also try to encourage people to stop smoking (19, 20). The rapid pace of development in AI generally, and in LLMs specifically, means new evidence assessing the effectiveness of AI-assisted interventions is constantly required, as newer versions of these tools may have differential effectiveness.

The purpose of this review is to identify and synthesise trials of AI-assisted public health interventions for reducing or stopping alcohol consumption or smoking, and to determine whether current evidence suggests these interventions are effective.

Methods

This systematic review searched for and synthesised evidence from randomised controlled trials (RCTs) from high-income countries to answer the following review questions:

1. Are AI-assisted interventions effective for reducing alcohol consumption?
2. Are AI-assisted interventions effective for reducing smoking?

This review formed part of a broader programme of work evaluating the past, current, and potential uses of AI in public health (21-23). The protocols for these reviews were registered on PROSPERO: CRD42025642317 (24) and CRD42025642334 (25). This review was conducted with reference to the Cochrane Handbook for Systematic Reviews of Interventions (26) and reported with reference to the 2020 PRISMA statement (27). All data produced in this review are contained in the manuscript and its supplementary information files. We did not use AI in any part of the review process or when writing this article.

Stakeholder Engagement

We conducted stakeholder engagement across our broader programme of work across two phases of activity. The first phase involved protocol refinement and confirmation, with the aim of defining concepts related to AI and understanding comprehension of different models and platforms. The second phase gained feedback on initial synthesis findings, with consideration of how public health systems may support diffusion and delivery of AI-based interventions.

We conducted consultation meetings with two UK-based communities of practice at each phase. One community comprised nine practitioners from the NIHR funded Health Determinants Research Collaborations (HDFCs), with experience of public health service delivery. HDFCs are Local Government funded infrastructures intended to develop

research capacity and capability to improve evidence-based decision-making. The second community, also comprising nine people, included strategic directors with significant leadership roles for AI in public health across data science institutes, public health agencies, and national Local Government networks.

Eligibility Criteria

The eligibility criteria are listed in **Table 1**. Briefly, interventions must have been assisted by AI (broadly defined as algorithms integrated into systems and tools that can learn from data to be able to perform automated tasks without explicit human programming), set in a public health context, and target alcohol consumption or smoking. AI-assisted interventions could be of any modality (for example, text, audio, images) and technology (for example wearables, social media, sensors), and could be part of a wider intervention. We defined public health contexts as those where the primary aim was to improve public health, typically involving local and national Government-funded public health organisations delivering interventions or making policy decisions. We excluded clinical settings, for instance reports where reports only considered interventions that used NHS resources, although trials that recruited from healthcare contexts were included so long as the intervention itself did not use healthcare resources beyond usual care (for example, participants with coronary heart disease recruited from secondary care where the intervention was a self-guided phone app). Included studies must have been set in high-income countries, as defined by the World Bank (28). Included studies must also have been written in the English language. We included relevant trial protocols and reported these as ongoing trials if we found no associated trial report.

In the sole post-hoc change to the protocol, we excluded interventions where expert systems or computer-tailoring were the sole AI-assistance, as we wanted to focus on more modern uses of AI in this review.

Table 1: Inclusion and Exclusion Criteria

	Included	Excluded
Population	Any	
Setting	High-income countries, as defined by the World Bank	Middle- and lower-income countries
Context	Public health	Healthcare, clinical, and other contexts
Intervention	<p>AI-assisted interventions aiming to reduce engagement with alcohol consumption or smoking. AI is broadly defined as algorithms integrated into systems and tools that can learn from data to be able to perform automated tasks without explicit human programming.</p> <p>Interventions can be delivered through any technology including wearable, sensors, and computers. Can be delivered through any modalities, including text, images, videos, sensory data, and audio.</p> <p>AI delivery may be supported by a third-party individual (for example, a health professional) or organisation or directly accessed by the participant.</p>	Other interventions
Comparator	Usual care or an active comparator	
Outcomes	<p>Any outcome directly associated with alcohol consumption or smoking, including engagement with risk behaviour (initiation, cessation, amount of engagement).</p> <p>Additionally, satisfaction with and acceptability of the intervention, cost-effectiveness, and side effects.</p>	Other outcomes
Language	English	Other languages
Date of publication	<p>For RCTs: From 01 January 2010 to 03 February 2025 (to September 2025 for citation searching)</p> <p>For reviews: From 01 January 2023 to 03 February 2025</p>	
Study design	<p>Randomised controlled trials, including crossover and cluster randomised controlled trials, and any equity-specific moderation analyses linked to these trials.</p> <p>Sibling studies from included trials will also be searched for and included.</p>	Other study designs, including all observational study designs, editorials, commentaries, and reviews (although reviews will be searched for primary studies)
Publication type	Published or preprint, although conference abstracts of trials will only be included if there is sufficient information for data extraction and risk of bias appraisal	

Information Sources

We conducted searches for alcohol and smoking separately, but each followed the same protocol, comprising three elements to maximise sensitivity. We conducted all searches in Medline (Ovid), Embase (Ovid), Web of Science (Core collection), and Scopus.

First, we searched for relevant RCTs directly. These searches combined an AI facet with terms for alcohol consumption or smoking, as well as the Cochrane Highly Sensitive Search Strategy for identifying randomized trials in MEDLINE (29). The AI facet drew upon an unpublished filter created by members of the InterTASC (Technology Appraisal Support Collaboration) Information Specialists' Sub-Group (ISSG), as well as filters hosted on the associated ISSG Search Filter Resource (30). We applied a date limit from 01 January 2010 onwards for the direct RCT search (dates of searches: 13 to 15 January 2025).

Second, we searched for reviews (systematic, rapid, or other) of public health interventions (of any kind, AI-assisted or otherwise) for alcohol consumption or smoking, and extracted all references from relevant reviews for screening along with the references found in the direct RCT search. We included no AI terms in this search, instead only including terms for alcohol consumption or smoking, terms for public health and “prevention”, and a systematic review filter (31). Our supposition was that although RCTs of an AI-assisted intervention may have been missed in our direct RCT search (as AI use in an intervention is not always included in searchable article metadata or abstracts), they may have been included in previous reviews of interventions for alcohol consumption or smoking, thereby increasing the sensitivity of this review. We excluded reviews that were conducted in non-high-income countries or healthcare settings, reviews of drug interventions only, and reviews of study designs other than RCTs. We applied a date limit from 01 January 2023 onwards for the review search (dates of searches: 13 to 15 January 2025). We searched any relevant umbrella reviews and subsequently extracted references from relevant reviews as necessary. We extracted the reference lists of eligible reviews using Citationchaser (32) or manually, depending on the number of included

studies in the review and whether the reference list of the review contained the included studies.

Third, we conducted forward and backward citation searching on included trials using Citationchaser (32), both to identify trials missed in the direct RCT and review searches, and to find all published studies that used data from included trials (sibling studies; dates of searches: 17 July to 08 September 2025). We conducted additional citation searching using Citationchaser (32) on any trials and sibling studies identified from previous rounds of citation searching.

All search strategies for all databases are presented in **Supplementary Information A**.

Selection Process

For RCTs, two reviewers (SH with AD, JK, or CT) independently screened titles and abstracts in Rayyan (33) and full texts in a standardised Excel sheet. Titles and abstracts included by at least one reviewer on eligibility assessment progressed to full-text screening. Conflicts in assessment of full texts were resolved through discussion, with no necessity to involve a third party.

For reviews, one reviewer (SH) screened titles and abstracts and full texts of relevant reviews, and extracted the reference lists of relevant reviews for screening as above.

Data Collection Process and Items

One reviewer (SH) completed all data extraction, which was checked by a second reviewer (CT). For each included RCT, we extracted information into standardised Excel sheets concerning study identification, methods, population, intervention, baseline data, and outcome data. We extracted outcome data from all relevant outcome and effect measures at all timepoints.

Study Risk of Bias Assessment

Two reviewers (SH and CT) independently used the Cochrane RoB2 tool to assess the quality of the effect of assignment to the intervention on the primary outcome (34). For each trial, we selected the most objective outcome (for example, carbon monoxide [CO] validated cigarette abstinence over self-reported cigarette abstinence) at the longest timepoint as the outcome for risk of bias assessment, if multiple outcomes were reported.

Synthesis Method and Certainty Assessment

Meta-analysis was not possible due to the low number of RCTs reporting similar interventions and comparators with similar outcomes at similar timepoints. We therefore reported narrative summaries for each trial, along with a broad overall synthesis. We stated in the protocol that we would conduct intervention component analysis to characterise how AI was used in included interventions (35), but there were insufficient trials to do so. We also stated we would assess certainty of evidence using GRADE (36-38), though there was insufficient evidence for any particular outcome and timepoint to do so. We considered health equity where possible, reporting subgroup or interaction analyses when the subgroups of interest were relevant to PROGRESS-Plus characteristics (39).

Ethics

Ethical approval for this review was not required. We conducted consultations with stakeholder groups in accordance with any ethical requirements stipulated by the organisations and research studies that recruited participating members.

Results

Figure 1 shows the PRISMA diagrams for the flow of references. Briefly, from all information sources for alcohol consumption, we screened 4,775 titles and abstracts, 650 full texts, and included 16 reports from four trials (two RCTs and two cluster RCTs) (14, 17, 18, 40-52). For smoking, we screened 7,165 titles and abstracts, 910 full texts, and included 31 reports from 12 trials (10 RCTs and 2 cluster RCTs) (15-20, 43-48, 53-71), and one RCT protocol (72).

Supplementary Information B.1 and B.2 contain full text screening results for primary studies and reviews, and full data extractions and risk of bias assessments for all included trials. **Supplementary Information C** contains narrative summaries for included trials.

Figure 1a. PRISMA diagram for alcohol consumption

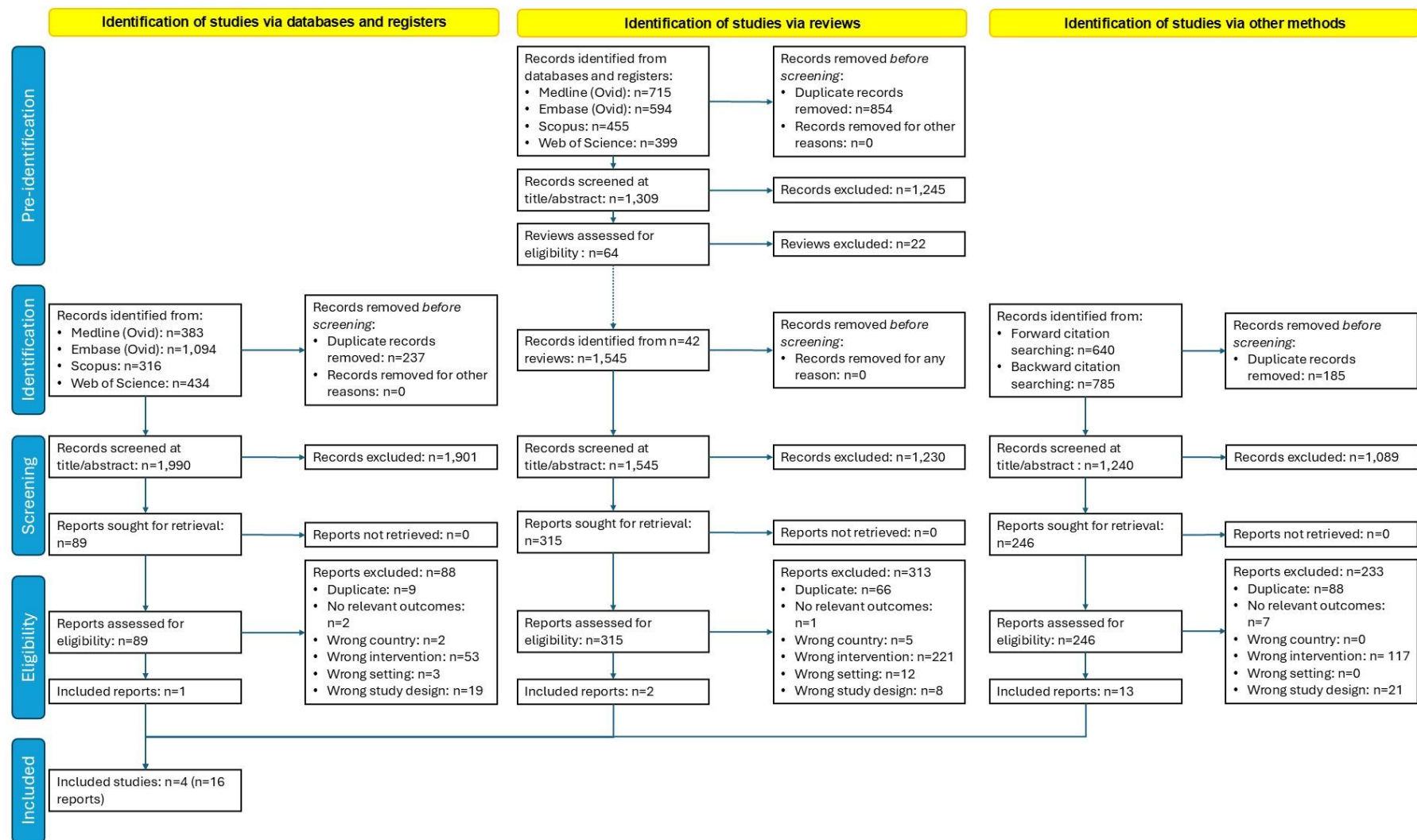
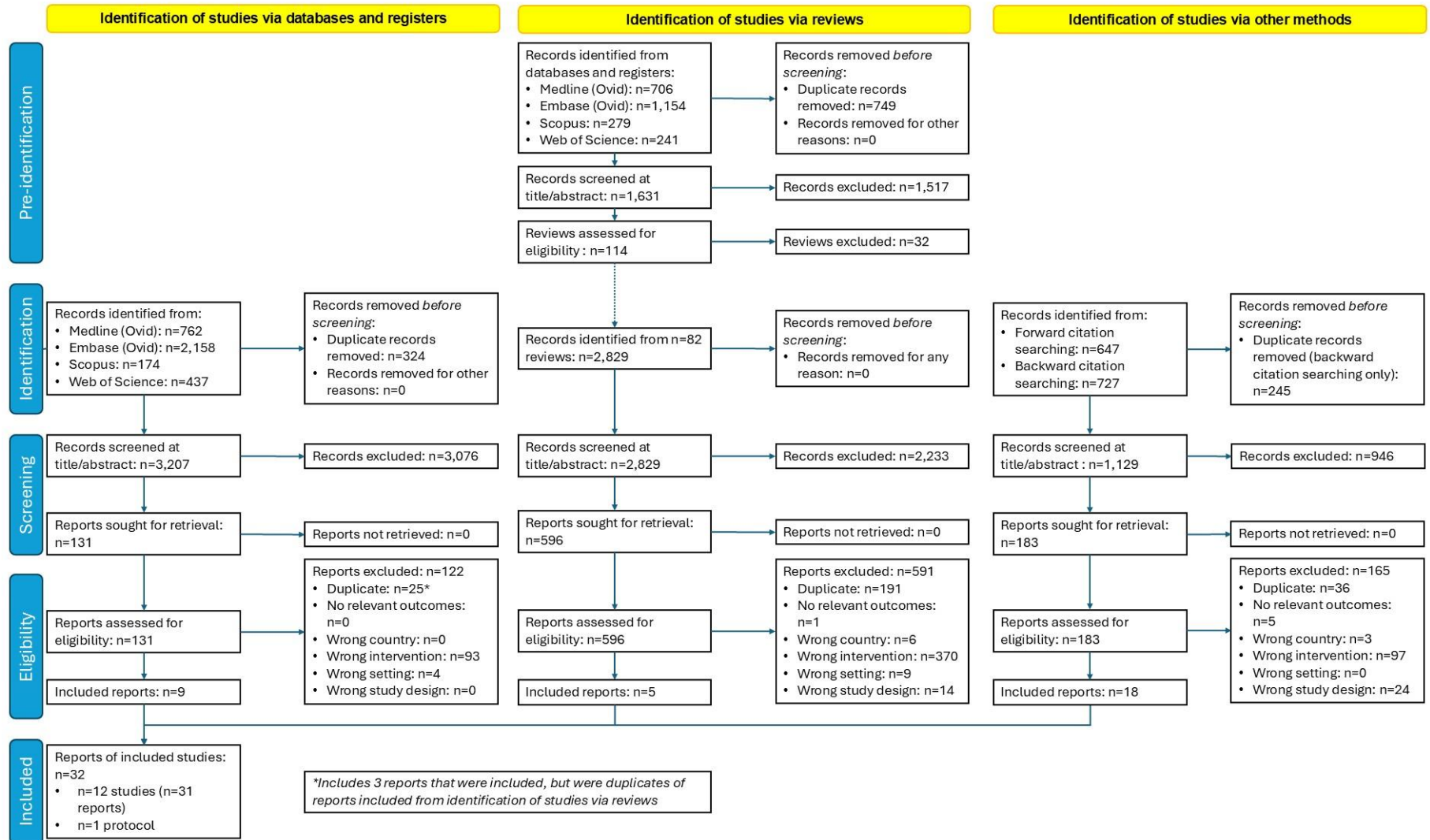


Figure 1b. PRISMA diagram for smoking



Alcohol Consumption

For alcohol consumption, three trials estimated the effectiveness of apps with chatbots (14, 17, 18), and one trial of a rules-based AI that tailored website content (49). Three trials compared AI-assisted interventions with usual practice (17, 18, 49), so for these trials there is no way to discern the effectiveness of chatbots or AI-tailoring alone. The remaining trial compared an app with a chatbot against both the app without a chatbot, and assessment only (14). Two trials were conducted in Germany (17, 49), one in Switzerland (18), and one in the US (14). All trials were conducted between 2015 and 2023. The trials randomised between 191 and 2,568 participants, and collectively randomised 4,718 participants. See **Table 2a** for trial characteristics and **Table 3a** for intervention characteristics.

Overall, there was mixed evidence that chatbot-assisted apps reduced alcohol consumption: two trials suggested no difference in alcohol consumption among both adult and student populations (14, 17), and one trial suggested reduced alcohol consumption among students (18). The evidence was mixed even for trials that used the same app in similar populations (17, 18). There was evidence the website with AI-tailoring was more effective at reducing alcohol consumption than usual care (49). See **Table 4a** for the primary results of all trials.

We assessed the primary results of all trials as having high risks of bias, as all studies had high risks of bias for missing outcome data (high attrition in all trials) and outcome measurement (self-report without blinding in all trials), see **Table 5a** for risk of bias assessment summaries.

Smoking

For smoking, eight trials estimated the effectiveness for reducing smoking of apps or messenger chatbots (15-18, 60, 64, 66, 70) and four trials of recommender systems (19, 20, 58, 71). Three trials were conducted in the US (15, 20, 71), two in Spain (19, 66), one in Germany (17), one in Switzerland (18), one in Hong Kong (16), one in Japan (64), one in Taiwan (58), and two were potentially worldwide (60, 70). All trials were conducted between 2014 and 2023. The trials randomised between 120 and 57,214 participants, and collectively randomised 68,659 participants. See **Table 2b** for trial characteristics and **Table 3b** for intervention characteristics.

There was mixed evidence for the 3 trials comparing chatbot-assisted apps to apps without chatbots, with 2 trials suggesting the interventions increased smoking cessation at one month (70) and between 3 and 12 months (64), and one trial suggesting no change at 3 months (15). There was also mixed evidence for the 5 trials comparing chatbot-assisted apps to usual practice, with 2 trials suggesting some evidence for increased smoking cessation at 6 months (18, 66), one trial showing evidence of slightly increased cessation at 12 months but not 6 months (17), and 2 trials with little evidence for any change in smoking cessation at 4 and 7 months (60) and 6 and 12 months (16).

There was mixed evidence for moderation of the effectiveness of chatbot-assisted apps when compared with usual practice by equity characteristics: one trial suggested the intervention was more effective in women compared with men, and younger compared with older participants, with no moderation by education (16), but 2 trials saw no differential effects of age or sex (18), or age, gender, education, or financial situation (60).

The three trials comparing recommender systems to similar rules-based systems suggested recommender systems did not change smoking cessation outcomes at one month (71) or six months (20, 58). The single trial comparing a recommender system-assisted app to usual practice suggested the app was substantially more effective for smoking cessation at 12 months (19). See **Table 4b** for the primary results of all trials.

We assessed the primary results of two trials as having some concerns of bias (15, 64), and 10 trials as having a high risk of bias (16-20, 58, 60, 66, 70, 71), see **Table 5b** for risk of bias assessment summaries.

Ongoing trials

We identified one ongoing trial looking at a recommender system to reduce smoking (72). Full details are presented in **Supplementary Information C**.

Table 2: Trial characteristics

Acronyms: AUDIT = Alcohol Use Disorders Identification Test, CO = carbon monoxide, SMS = short message service, US = United States

Table 2a: Alcohol consumption trials

Reference	Participants recruited	Country, trial dates	Outcome measurement	Inclusion and exclusion criteria
Dulin, 2022 (14, 40-42)	191	US June 2021 to December 2021	Self-report (web-based survey)	Inclusion criteria: Facebook users who: (1) were aged at least 18 years; (2) had either an iPhone or an Android phone; (3) resided in the US; (4) were not in another form of alcohol treatment or using another mobile health alcohol intervention, (5) were an active drinker, (6) were proficient in English language, and (7) had a USAUDIT score between 8 and 24 inclusive for males aged up to and including 65 years and a score between 7 and 24 inclusive for females and males aged at least 65 years Exclusion criteria: None
Gurtler, 2025 (17, 43-47)	2,568 students from 376 vocational school classes	Germany October 2020 to April 2023	Self-report (app-based survey)	Inclusion criteria: Vocational students who were aged at least 16 years, had a smartphone, and provided informed consent Exclusion criteria: None
Haug, 2022 (18, 48)	1,351 students from 153 vocational school classes	Switzerland 2021 to 2022	Self-report (computer-assisted assessment)	Inclusion criteria: None Exclusion criteria: None
Zill, 2019 (49-52)	608	Germany March 2015 to March 2017	Self-report (method not stated)	Inclusion criteria: (1) Aged at least 18 years; (2) an average consumption of more than 12g (women) or 24g (men) of pure alcohol per day, or an AUDIT-C score at least 3 (indicating unhealthy alcohol use); and (3) informed consent Exclusion criteria: People with suicidal ideation or intent, technical reasons (for example, email address not reachable)

Table 2b: Smoking trials

Reference	Number recruited	Country, trial dates	Outcome measures	Inclusion and exclusion criteria
Chatbots				
Bricker, 2024 (15, 53)	404	US September 2018 to June 2019	Self-report (web-based survey)	<p>Inclusion criteria: (1) age at least 18 years; (2) having smoked at least 1 cigarette a day for at least the past 12 months; (3) wanting to quit cigarette smoking within the next 14 days; (4) if concurrently using any other nicotine or tobacco products, wanting to quit using them within the next 14 days; (5) being interested in learning skills to quit smoking; (6) being willing to be randomly assigned to either condition; (7) residing in the United States; (8) having daily access to their own smartphone; (9) having both SMS text messaging and Facebook Messenger on their smartphone (criteria 8 and 9 were required to receive each interventions' content); (10) being willing and able to read in English; and (11) not using other smoking cessation interventions.</p> <p>Exclusion criteria: None</p>
Guertler, 2025 (17, 43-47)	2,568 students from 376 vocational school classes	Germany October 2020 to April 2023	Self-report (app-based survey)	<p>Inclusion criteria: Vocational students who were aged at least 16 years, had a smartphone, and provided informed consent</p> <p>Exclusion criteria: None</p>
Guo, 2023 (16)	664	Hong Kong August 2019 to May 2021	Self-report, objective (CO test for those reporting quitting, if they were willing)	<p>Inclusion criteria: Hong Kong residents (1) aged at least 18 years who were able to read and communicate in Chinese; (2) currently smoked at least one cigarette daily, validated by an exhaled carbon monoxide level of at least 4 parts per million; and (3) owned a smartphone and were willing to install an instant messaging app (if not already installed).</p> <p>Exclusion criteria: Smokers who had (1) psychiatric or psychological diseases or were on regular psychotropic medications; (2) were using smoking cessation medication, nicotine replacement therapy, other smoking cessation services; or (3) had contraindication for nicotine replacement therapy use</p>
Haug, 2022 (18, 48)	1,351 students from 153 vocational school classes	Switzerland 2021 to 2022	Self-report (computer-assisted assessment)	<p>Inclusion criteria: None</p> <p>Exclusion criteria: None</p>
Jackson, 2024 (60-63)	3,143	Potentially worldwide August 2020 to December 2021	Self-report (online questionnaire)	<p>Inclusion criteria: Current cigarette smokers: (1) aged at least 18 years, (2) English speaker, (3) owns a smartphone, (4) provided a valid email address not previously used by another participant, (5) interested in making a quit attempt within the next month, and (6) willing to be followed up by email and complete online questionnaires.</p> <p>Exclusion criteria: None</p>
Masaki, 2020 (64, 65)	584	Japan October 2017 to January 2019	CO test (in person), self-report (continuous abstinence)	<p>Inclusion criteria: Adult current smokers who (1) were diagnosed with nicotine dependence (tobacco Dependence Screener score of at least 5 points); (2) had a smoking history of at least 10 pack-years; (3) intended to quit smoking immediately; (4) agreed to participate in a smoking cessation treatment program with written informed consent; and (5) could use a smartphone without difficulty (self-report)</p> <p>Exclusion criteria: (1) had severe mental illness; (2) could not come to the follow-up clinic visits during the trial period; (3) started taking a smoking cessation medication less than a year before registration; or (4) planned to use any smoking cessation aids and/or to participate in any kind of smoking cessation activities (not limited to smoking cessation therapy) outside of the trial.</p>

Reference	Number recruited	Country, trial dates	Outcome measures	Inclusion and exclusion criteria
Olano-Espinosa, 2022 (66-69)	513	Spain October 2018 to October 2019	Self-report with CO test confirmation (in person)	Inclusion criteria: (1) smokers aged over 18 years who visited their doctor or nurse for consultation for any reason; (2) smoked at least one cigarette over the previous month; (3) accept professional help for quitting in the following month; (4) own a smartphone in which a messaging app (Telegram) could be installed; (5) confirm their availability to be reached for 6 months following the intervention; and (6) provide informed written consent. Exclusion criteria: (1) showing significant communication barriers, and (2) participation in another dishabituaton program or clinical trial
Perski, 2019 (70)	57,214	Potentially worldwide September 2018 to January 2019	Self-report (in app)	Inclusion criteria: (1) owned an iPhone; (2) purchased the 'pro' version of the Smoke Free app between 1 September 2018 and 18 December 2018; (3) had their phone set to English language; (4) were aged at least 18 years; (5) reported being a daily or non-daily smoker at the time of registration; and (6) set a quit date less than 2 days before and less than 14 days after their date of registration. Exclusion criteria: None
Recommender systems				
Carrasco-Hernandez, 2020 (19)	240	Spain October 2016 to October 2018	CO and urine cotinine tests (in person)	Inclusion criteria: (1) age over 18 years and desire to stop smoking; (2) own an Android smartphone; and (3) ability to interact with the smartphone Exclusion criteria: Any previous adverse effect related to the present pharmacological treatment
Faro, 2023 (20, 54-57)	1,487	US July 2017 to September 2019	Self-report with non-mandatory nicotine saliva test confirmation	Inclusion criteria: Current smokers aged 18 years and older who spoke English Exclusion criteria: None
Hors-Fraile, 2022 (58, 59)	371	Taiwan November 2017 to January 2020	Self-report (in app)	Inclusion criteria: Smokers who (1) were over 20 years of age, (2) were willing to quit, (3) owned a compatible smartphone and downloaded the "Quit and Return" app, (4) registered on 15 July 2019 or earlier, (5) accepted the terms and conditions of the mobile app, (6) made a valid quitting attempt (not cancelled in the first 24 hours, not set in the past, and set within 90 days of the app registration date), and (7) were able to understand Mandarin Chinese or English. Exclusion criteria: None
Sadasivam, 2016 (71)	120	US October 2014 to January 2015	Self-report (unclear if in person)	Inclusion criteria: Current smokers who were (1) aged 18 years or older; (2) English speaking; and (3) had Internet access Exclusion criteria: None

Table 3: Intervention characteristics

Acronyms: AI = artificial intelligence, AUDIT = Alcohol Use Disorders Identification Test, CASC = CureApp Smoking Cessation, CO = carbon monoxide, CTHC = computer-tailored health communication, IQR = interquartile range, OR = odds ratio, PERSPeCT = Patient Experience Recommender System for Persuasive Communication Tailoring, QFI = Quantity-Frequency-Index (amount of alcohol in grams over the past 30 days), SD = standard deviation, So-Lo-Mo = Social-Local-Mobile, TFB = Timeline Follow-Back method (amount of alcohol in grams over the past 7 days)

Table 3a: Alcohol consumption trials

Reference	Intervention group	Participant characteristics	Intervention description
Dulin, 2022 (14, 40-42)	Step Away Chatbot	Number allocated: Not stated Number of withdrawals (%): Not stated Proportion female: 56% Mean age in years: 40.82 (SD: 12.54) Mean drinks per day: 2.64 (SD: 1.26) Mean percent days abstinent: 22% (SD: 22%) Mean heavy drinking days: 7.49 (SD: 7.98) Mean US-AUDIT score: 16.28 (SD: 3.49)	Intervention description: A chatbot that incorporates all the content of the <i>Step Away</i> app (see <i>Step Away</i> app). AI details: The study stated the chatbot was "Artificially intelligent" in the protocol, no further information. Intervention length: 12 weeks
	Step Away App	Number allocated: Not stated Number of withdrawals (%): Not stated Proportion female: 54% Mean age in years: 42.58 (SD: 13.49) Mean drinks per day: 2.69 (SD: 1.72) Mean percent days abstinent: 24% (SD: 28%) Mean heavy drinking days: 7.69 (SD: 8.33) Mean US-AUDIT score: 15.25 (SD: 4.35)	Intervention description: An alcohol assessment and intervention app, including motivational enhancement, relapse prevention, and community reinforcement. AI details: No AI Intervention length: 12 weeks
	Assessment only	Number allocated: Not stated Number of withdrawals (%): Not stated Proportion female: 64% Mean age in years: 41.51 (SD: 13.07) Mean drinks per day: 2.50 (SD: 1.14) Mean percent days abstinent: 21% (SD: 24%) Mean heavy drinking days: 6.30 (SD: 5.65) Mean US-AUDIT score: 15.60 (SD: 4.42)	Intervention description: Assessment only AI details: No AI Intervention length: 12 weeks
Gurtler, 2025 (17, 43-47)	Ready4life app	Number allocated: 1,266 Number of withdrawals (%): 948 (74.9%) Proportion female: 45.3% Mean age in years: 19.51 (SD: 3.56) Alcohol use in last month: 70.9% Median number of alcoholic standard drinks per day: 0.23 (IQR: 1.00)	Intervention description: An app for addiction prevention, which provided modules with individually tailored coaching from a rules-based chatbot. Users selected 2 of 6 program modules: cannabis, social media and gaming, alcohol, tobacco, stress management, or social competence. Users received 8 weeks of tailored coaching from the chatbot for each selected module, including weekly dialogues (around 5 minutes each) and other conversations as needed, incorporating motivation, feedback, tailored information, and media (videos, images, links). Users could also chat with addiction prevention experts as needed. AI details: Rules-based chatbot Intervention length: 16 weeks, with 12 months follow-up

Reference	Intervention group	Participant characteristics	Intervention description
	Control	Number allocated: 1,279 Number of withdrawals (%): 846 (66.1%) Proportion female: 45.9% Mean age in years: 19.85 (SD: 3.73) Alcohol use in last month: 67.7% Median number of alcoholic standard drinks per day: 0.20 (IQR: 0.90)	Intervention description: Access to the app for screening and individualized feedback on participants' risk, with a link to information on how to improve health behaviours (no further access to app, including the modules and chatbot). AI details: None Intervention length: 12 months follow-up
Haug, 2022 (18, 48)	<i>Ready4life</i> app	Number allocated: 688 Number of withdrawals (%): 248 (36.0%) Proportion female: 41.7% Mean age in years: 17.3 (SD: 2.7) At risk drinking in past 30 days: 31.0% Mean number of alcoholic drinks consumed in past 30 days: 14.8 (SD: 34.5)	Intervention description: An app for addiction prevention, which provided modules with individually tailored coaching from a chatbot (likely rules-based, as in Guertler, 2025). Users selected 2 of 6 program modules: stress, social skills, internet use, tobacco/e-cigarettes, cannabis, or alcohol. Users received 8 weeks of tailored coaching from the chatbot for each selected module, including weekly dialogues and other conversations as needed, incorporating motivation, feedback, and tailored information. Users could also chat with addiction prevention experts as needed. AI details: Chatbot (likely rules-based) Intervention length: 16 weeks, with 4 months follow-up
	Delayed access	Number allocated: 663 Number of withdrawals (%): 154 (23.2%) Proportion female: 45.2% Mean age in years: 17.4 (SD: 3.2) At risk drinking in past 30 days: 35.1% Mean number of alcoholic drinks consumed in past 30 days: 15.1 (SD: 33.0)	Intervention description: Delayed access to the <i>ready4life</i> app. AI details: None Intervention length: 4 months follow-up
Zill, 2019 (49-52)	<i>Vorvida</i>	Number allocated: 306 Number of withdrawals (%): 114 (37%) Proportion female: 56% Mean age in years: 40.4 (SD: 11.2) Mean QFI: 63.69 (SD: 61.84) Mean TFB: 52.91 (SD: 56.68) Mean number of days of binge drinking within the past 30 days: 16.79 (SD: 11.45) Mean number of days of drunkenness within the past 30 days: 4.42 (SD: 5.15)	Intervention description: Internet-based intervention based on principles in cognitive behavioural therapy, comprising 4 modules that were tailored by a rules-based AI. Recommended to be used for 2 hours a week. AI details: None: the study just stated a rules-based "Artificial intelligence" custom-tailored the information in the webpage for each person. Intervention length: 180 days
	Usual care	Number allocated: 302 Number of withdrawals (%): 69 (23%) Proportion female: 49 Mean age in years: 40.7 (SD:12.1) Mean QFI: 61.64 (SD: 58.84) Mean TFB: 46.82 (SD: 41.18) Mean number of days of binge drinking within the past 30 days: 15.27 (SD: 11.72) Mean number of days of drunkenness within the past 30 days: 4.09 (SD: 4.67)	Intervention description: Usual care (no further information) AI details: No AI Intervention length: 180 days

Table 3b: Smoking trials

Reference	Intervention group	Participant characteristics	Intervention description
Chatbots			
Bricker, 2024 (15, 53)	QuitBot	Number allocated: 200 Number of withdrawals (%): Not stated Proportion female: 70.5% Mean age in years: 35.9 (SD: 9.9) Smokes more than one pack per day: 16% Smoked for at least 10 years: 80.5%	Intervention description: "Digital coach" chatbot called "Ellen" on Facebook Messenger, daily 2-to-3-minute conversations about the importance of quitting smoking, setting a quit date, preparing to quit, quitting, and maintaining abstinence, as well as messages check in about quit status. Keywords can be sent to receive help at any time. AI details: Chatbot built using the Microsoft Bot Framework and the Microsoft Language Understanding (LUIS) platform for natural language processing. Intervention length: 42 days
	SmokefreeTXT	Number allocated: 149 Number of withdrawals (%): Not stated Proportion female: 69.1% Mean age in years: 36.2 (SD: 11.2) Smokes more than one pack per day: 13.4% Smoked for at least 10 years: 75.2%	Daily text messages about the importance of quitting smoking, setting a quit date, preparing to quit, quitting, and maintaining abstinence, as well as messages check in about quit status. Keywords can be sent to receive help at any time. AI details: no AI Intervention length: 42 days
	Delayed access	Number allocated: 55 Number of withdrawals (%): Not stated Proportion female: 70.9% Mean age in years: 35.6 (SD: 9.6) Smokes more than one pack per day: 25.5% Smoked for at least 10 years: 80%	Intervention description: No intervention for 3 months, then QuitBot. AI details: no AI Intervention length: 42 days
Guertler, 2025 (17, 43-47)	Ready4life app	Number allocated: 1,266 Number of withdrawals (%): 948 (74.9%) Proportion female: 45.3% Mean age in years: 19.51 (SD: 3.56) Cigarette smoking in last month: 32.8% Median number of cigarettes per day: 0 (IQR: 1.13)	Intervention description: An app for addiction prevention, which provided modules with individually tailored coaching from a rules-based chatbot. Users selected 2 of 6 program modules: cannabis, social media and gaming, alcohol, tobacco, stress management, or social competence. Users received 8 weeks of tailored coaching from the chatbot for each selected module, including weekly dialogues (around 5 minutes each) and other conversations as needed, incorporating motivation, feedback, tailored information, and media (videos, images, links). Users could also chat with addiction prevention experts as needed. AI details: Rules-based chatbot Intervention length: 16 weeks, with 12 months follow-up
	Control	Number allocated: 1,279 Number of withdrawals (%): 846 (66.1%) Proportion female: 45.9% Mean age in years: 19.85 (SD: 3.73) Cigarette smoking in last month: 30.6% Median number of cigarettes per day: 0 (IQR: 0.53)	Intervention description: Access to the app for screening and individualized feedback on participants' risk, with a link to information on how to improve health behaviours (no further access to app, including the modules and chatbot). AI details: None Intervention length: 12 months follow-up

Reference	Intervention group	Participant characteristics	Intervention description
Guo, 2023 (16)	Chatbot	<p>Number allocated: 332 Number of withdrawals (%): 243 (26.8%) Proportion female: 25.0% Age: 18 to 29 years: 30.3%; 30 to 39 years: 31.8%; 40 to 49 years: 23.9%; 50 to 59 years: 10.7%; 60 or more years: 3.4%</p> <p>1 to 10 daily cigarettes consumed: 69.9% 11 to 20 daily cigarettes consumed: 27.4% At least 21 daily cigarettes consumed: 2.7%</p> <p>More than 60 minutes to first cigarette: 29.3% 31 to 60 minutes to first cigarette: 17.2% 6 to 30 minutes to first cigarette: 26.9% No more than 5 minutes to first cigarette: 26.6%</p> <p>Low cigarette dependence (heaviness of smoking index 0 to 2): 64.2% Moderate cigarette dependence (heaviness of smoking index 3 to 4): 34.0% High cigarette dependence (heaviness of smoking index 5 to 6): 1.8%</p> <p>Previous quit attempt: 38.6%</p>	<p>Intervention description: Instant messaging chatbot (<i>Quit-Buddy</i>), along with brief advice, nicotine replacement therapy, and weekly personalised behavioural support 12 weeks delivered by smoking cessation advisors via instant messaging.</p> <p>AI details: The <i>Quit-Buddy</i> chatbot was rules-based with 5 layers of pre-programmed options and text.</p> <p>Intervention length: 12 weeks</p>
	Control	<p>Number allocated: 332 Number of withdrawals (%): 243 (26.8%) Proportion female: 26.2% Age: 18 to 29 years: 31.9%; 30 to 39 years: 33.8%; 40 to 49 years: 21.4%; 50 to 59 years: 9.6%; 60 or more years: 3.4%</p> <p>1 to 10 daily cigarettes consumed: 71.1% 11 to 20 daily cigarettes consumed: 27.7% At least 21 daily cigarettes consumed: 1.2%</p> <p>More than 60 minutes to first cigarette: 31.3% 31 to 60 minutes to first cigarette: 12.1% 6 to 30 minutes to first cigarette: 26.2% No more than 5 minutes to first cigarette: 30.4%</p> <p>Low cigarette dependence (heaviness of smoking index 0 to 2): 60.5% Moderate cigarette dependence (heaviness of smoking index 3 to 4): 38.3% High cigarette dependence (heaviness of smoking index 5 to 6): 1.2%</p> <p>Previous quit attempt: 42.2%</p>	<p>Intervention description: Brief advice, regular SMS messages on healthy lifestyles.</p> <p>AI details: None</p> <p>Intervention length: 12 months</p>

Reference	Intervention group	Participant characteristics	Intervention description
Haug, 2022 (18, 48)	<i>Ready4life</i> app	Number allocated: 688 Number of withdrawals (%): 248 (36.0%) Proportion female: 41.7% Mean age in years: 17.3 (SD: 2.7) Tobacco or e-cigarette smoking in past 30 days: 36.6% Mean number of cigarettes smoked in past 30 days: 89.9 (SD: 199.9)	Intervention description: An app for addiction prevention, which provided modules with individually tailored coaching from a chatbot (likely rules-based, as in Guertler, 2025). Users selected 2 of 6 program modules: stress, social skills, internet use, tobacco/e-cigarettes, cannabis, or alcohol. Users received 8 weeks of tailored coaching from the chatbot for each selected module, including weekly dialogues and other conversations as needed, incorporating motivation, feedback, and tailored information. Users could also chat with addiction prevention experts as needed. AI details: Chatbot (likely rules-based) Intervention length: 16 weeks, with 4 months follow-up
	Delayed access	Number allocated: 663 Number of withdrawals (%): 154 (23.2%) Proportion female: 45.2% Mean age in years: 17.4 (SD: 3.2) Tobacco or e-cigarette smoking in past 30 days: 37.1% Mean number of cigarettes smoked in past 30 days: 78.0 (SD: 176.0)	Intervention description: Delayed access to the <i>ready4life</i> app. AI details: None Intervention length: 4 months follow-up
Jackson, 2024 (60-63)	<i>Smoke Free</i> app	Number allocated: 1,564 Number of withdrawals (%): 1,036 (66.2%) Proportion female: 74.0% Mean age in years: 49.2 (SD: 11.6) Mean cigarettes per day: 18.0 (SD: 8.7) 5 or fewer minutes to first cigarette: 44.6% 6 to 30 minutes to first cigarette: 39.1% 31 to 60 minutes to first cigarette: 9.3% More than 60 minutes to first cigarette: 7.0% Never had a serious quit attempt: 6.9% Had a serious quit attempt not in the past year: 58.3% Had a serious quit attempt in the last year: 34.9%	Intervention description: Offered the <i>Smoke Free</i> app, which includes 10 components to help with quitting smoking, including a chatbot: (1) A calculator which tracks the total amount of money not spent on buying cigarettes and the number of cigarettes not smoked (2) A calendar which tracks the amount of time elapsed since cessation (3) A scoreboard which awards virtual ‘badges’ to users for not smoking (4) Progress indicators which inform users of the health improvements made since the start of their quit attempt (e.g. pulse rate, oxygen levels, carbon monoxide levels) (5) A diary which tracks the frequency, strength, location and triggers of cravings to smoke (6) A graph which displays the frequency, location, strength and triggers of cravings to smoke (7) Daily missions which are assigned from the start of a user’s quit date for one calendar month (8) Constant access to National Centre for Smoking Cessation and Training trained advisors (9) Advisor-led stop smoking clinics held in-app four times a day (10) A chatbot AI details: The chatbot delivered evidence-based guidance about quitting smoking via a conversational interface which resembled text messaging (no further information). Intervention length: 6 months

Reference	Intervention group	Participant characteristics	Intervention description
	Assessment-only	<p>Number allocated: 1,579 Number of withdrawals (%): 1,004 (63.6%) Proportion female: 75.5% Mean age in years: 48.9 (SD: 11.4)</p> <p>Mean cigarettes per day: 18.2 (SD: 10.0)</p> <p>5 or fewer minutes to first cigarette: 46.0% 6 to 30 minutes to first cigarette: 40.2% 31 to 60 minutes to first cigarette: 7.8% More than 60 minutes to first cigarette: 6.0%</p> <p>Never had a serious quit attempt: 7.3% Had a serious quit attempt not in the past year: 59.6% Had a serious quit attempt in the last year: 33.1%</p>	<p>Intervention description: Assessment only</p> <p>AI details: None</p> <p>Intervention length: 6 months</p>
Masaki, 2020 (64, 65)	CASC app	<p>Number allocated: 285 Number of withdrawals (%): 40 (14.0%) Proportion female: 24.2% Mean age in years: 47 (SD: 11)</p> <p>Median years of smoking: 25 (IQR: 19 to 32) Median cigarettes per day: 20 (IQR: 15 to 20) Median pack-years: 21 (IQR: 14 to 30)</p>	<p>Intervention description: Phone app with 4 components: (1) keeping a smoking cessation digital diary with daily entries; (2) viewing animated videos and educational tutorials designed to help users learn how to quit smoking; (3) participating in interactive counseling with a personalized chatbot (an automated guidance system for communication with users several times a day), described as an "AI nurse"; and (4) measuring and recording exhaled CO concentrations at home once a day using a mobile CO checker. A web-based version of CASC enabled physicians to review participants' progress at the clinic, and also provided tips to assist the physicians in counseling participants, following the national clinical guidelines. Additionally, 12-week standard smoking cessation treatment, including counseling and access to varenicline and nicotine patches.</p> <p>AI details: The AI nurse assembled tailor-made smoking cessation programs suitable to each participant based on their personal information (no further information).</p> <p>Intervention length: 6 months</p>
	Control app	<p>Number allocated: 287 Number of withdrawals (%): 42 (14.6%) Proportion female: 26.8% Mean age in years: 45 (SD: 12)</p> <p>Median years of smoking: 24 (IQR: 17 to 33) Median cigarettes per day: 20 (IQR: 15 to 20) Median pack-years: 20 (IQR: 13 to 31)</p>	<p>Intervention description: Phone app with 6 components: (1) showing the user guide; (2) entering participants' profiles and setting a target quit date; (3) displaying the schedule of five visits during the 12-week treatment with a summary of objectives of each visit; (4) showing the date of the next appointment; (5) getting the contact form for technical support; and (6) displaying an app version, privacy policy, and administrative information. Additionally, 12-week standard smoking cessation treatment, including counseling and access to varenicline and nicotine patches.</p> <p>AI details: no AI</p> <p>Intervention length: 6 months</p>

Reference	Intervention group	Participant characteristics	Intervention description
Olano-Espinosa, 2022 (66-69)	<i>Dejal@bot</i>	Number allocated: 242 Number of withdrawals (%): 138 (57.1%) Proportion female: 60.3% Mean age in years: 49.01 (SD: 11.22) Mean number of daily cigarettes: 16.70 (SD: 7.43) Mean number of previous tobacco withdrawal attempts: 2.60 (SD: 3.00) Mean heavy smoking index: 2.71 (SD: 1.59)	Intervention description: Chatbot with similar behavioural treatment content as usual clinical practice, delivered through Telegram. No face-to-face meetings with health care professionals. AI details: Expert system with natural language processing, using a probabilistic interpretation of participant messages (Bayes' theorem), which either delivers a specific script (if the system tags the participant as requiring special attention), or a script in a pre-designated order set by the expert system. Intervention length: 6 months
	Usual clinical practice	Number allocated: 271 Number of withdrawals (%): 143 (52.8%) Proportion female: 58.3% Mean age in years: 50.66 (SD: 10.42) Mean number of daily cigarettes: 16.32 (SD: 8.04) Mean number of previous tobacco withdrawal attempts: 2.37 (SD: 2.83) Mean heavy smoking index: 2.65 (SD: 1.68)	Intervention description: Behavioural and pharmacological treatments, face-to-face meetings with health care professionals, as per usual clinical practice. AI details: no AI Intervention length: 6 months
Perski, 2019 (70)	Pro app with AI chatbot	Number allocated: 5,339 Number of withdrawals (%): 4,278 (80.1%) Proportion female: Not stated Mean age in years: Not stated Less than 5 minutes to first cigarette: 17.2% 5 to 30 minutes to first cigarette: 18.9% 31 to 60 minutes to first cigarette: 37.0% more than 60 minutes to first cigarette: 26.5% Mean number of cigarettes per day: 16.0 (SD: 11.4)	Intervention description: The pro version of the Smoke Free app (see "Pro app" intervention description), with the addition of an AI chatbot. AI details: The chatbot guided users through the UK Stop Smoking Services' standard smoking cessation programme in a friendly, knowledgeable tone of voice (no further information). Intervention length: 1 month
	Pro app	Number allocated: 51,875 Number of withdrawals (%): 46,825 (90.3%) Proportion female: Not stated Mean age in years: Not stated Less than 5 minutes to first cigarette: 19.3% 5 to 30 minutes to first cigarette: 19.0% 31 to 60 minutes to first cigarette: 37.8% more than 60 minutes to first cigarette: 23.6% Mean number of cigarettes per day: 14.7 (SD: 8.9)	Intervention description: The pro version of the Smoke Free app included: (1) a calculator which tracks the total amount of money not spent on buying cigarettes and the number of cigarettes not smoked; (2) a calendar which tracks the amount of time elapsed since cessation; (3) a scoreboard which awards virtual 'badges' to users for not smoking; (4) progress indicators which inform users of the health improvements made since the start of their quit attempt (for example, pulse rate, oxygen levels, carbon monoxide levels); (5) a diary which tracks the frequency, strength and location of cravings to smoke; (6) a graph which displays the frequency, strength and location of cravings to smoke; and (7) daily missions which are assigned from the start of a user's quit date for one calendar month. AI details: no AI Intervention length: 1 month
Recommender systems			

Reference	Intervention group	Participant characteristics	Intervention description
Carrasco-Hernandez, 2020 (19)	So-Lo-Mo	Number allocated: 120 Number of withdrawals (%): 69 (57.5%) Proportion female: 54.2% Mean age in years: 48.38 (9.49) Mean daily cigarettes: 21.45 (SD: 8.97) Mean smoking cessation attempts (mean, SD): 0.88 (SD: 1.08) Mean Maximum abstinence time (mean, SD): 10.45 (SD: 25.49)	<p>Intervention description: App plus usual therapy (bupropion or varenicline plus behavioral therapy). The app used a recommender system to select and send short pre-designed messages (less than 100 words) in simple Spanish, and a close and friendly tone. The app also had a user profile linked to physical activity, four smoking cessation benefit indicators (savings, smoke-free days, regained life hours by not smoking, and number of non-smoked cigarettes since quitting), text-based information about smoking cessation, and a section containing relaxing and distracting elements (breathing exercises and minigames). Behavioural therapy included various psychological techniques, including motivational interviews and cognitive-behavioural therapy.</p> <p>AI details: The AI system was designed to learn from patient interests through their interactions with the app to dynamically: (1) determine, personalize, and send motivational messages; (2) schedule the message delivery frequency; and (3) calculate the most convenient time to send a motivational message</p> <p>Intervention length: 12 months</p>
	Usual therapy	Number allocated: 120 Number of withdrawals (%): 75 (62.5%) Proportion female: 43.3% Mean age in years: 50.93 (10.85) Mean daily cigarettes: 20.75 (SD: 9.39) Mean smoking cessation attempts: 1.14 (SD: 1.07) Mean maximum abstinence time: 13.68 (SD: 25.08)	<p>Intervention description: Bupropion or varenicline plus behavioral therapy</p> <p>AI details: no AI</p> <p>Intervention length: 12 months</p>
Faro, 2023 (20, 54-57)	CTHC System	Number allocated: 741 Number of withdrawals (%): 329 (44.4%) Proportion female: 72.9% Age: 19 to 34 years: 27.9% 35 to 54 years: 35.2% 55 years and over: 36.8% Thinking of quitting, or have set a quit date: 82.1% 0 to 5 cigarettes smoked per day: 12.4% 6 to 20 cigarettes smoked per day: 67.6% At least 21 cigarettes smoked per day: 20.0%	<p>Intervention description: Emails sent containing messages to help people stop smoking, with messages chosen by a recommender system. Also randomized to access to viral peer-recruitment tool kit, allowing and encouraging participants to recruit friends and family, and giving access to online training videos and a recruitment tracker</p> <p>AI details: Machine learning recommender system, trained on participant feedback from prior data collection (no further information).</p> <p>Intervention length: 6 months</p>
	Standard messaging	Number allocated: 746 Number of withdrawals (%): 357 (48.2%) Proportion female: 75.2% Age: 19 to 34 years: 31.8% 35 to 54 years: 33.1% 55 years and over: 35.1% Thinking of quitting, or have set a quit date: 78.1% 0 to 5 cigarettes smoked per day: 13.8% 6 to 20 cigarettes smoked per day: 64.9% At least 21 cigarettes smoked per day: 21.2%	<p>Intervention description: Emails sent containing messages to help people stop smoking, with messages chosen based on baseline readiness to quit. Also randomized to access to viral peer-recruitment tool kit, allowing and encouraging participants to recruit friends and family, and giving access to online training videos and a recruitment tracker</p> <p>AI details: no AI</p> <p>Intervention length: 6 months</p>

Reference	Intervention group	Participant characteristics	Intervention description
Hors-Fraile, 2022 (58, 59)	Hybrid Algorithm	Number allocated: 120 Number of withdrawals (%): 75 (62.5%) Proportion female: 43.3% Mean age in years: 50.93 (10.85) Mean nicotine dependence score: 5.17 (SD: 2.50) Mean motivation to quit score: 7.55 (SD: 1.80)	Intervention description: App that sent tailored motivational messages to participants, selected using a two-step algorithm: (1) the knowledge-based algorithm (below); (2) selection of a motivational message, prioritizing those found relevant by similar participants. Five messages sent on quit day, 1 per day for a week, then 3 messages per week. AI details: Motivation messages limited by the knowledge-based algorithm, which limited the pool of possible messages to those matching the characteristics of the participant (age, gender, quitting date, number of smoked cigarettes, weekly tobacco expenditure, time of day), then prioritised based on those found relevant by similar participants (Pearson nearest neighbour). Intervention length: 6 months
	Knowledge-based algorithm	Number allocated: 181 Number of withdrawals (%): Not stated Proportion female: 23.2% Mean age in years: 37.71 (SD: 10.78) Mean nicotine dependence score: 5.08 (SD: 2.69) Mean motivation to quit score: 7.54 (SD: 2.03)	Intervention description: App that sent tailored motivational messages to participants, selected using a knowledge-based algorithm, which limited the pool of possible messages to those matching the characteristics of the participant (age, gender, quitting date, number of smoked cigarettes, weekly tobacco expenditure, time of day). Five messages sent on quit day, 1 per day for a week, then 3 messages per week. AI details: Motivation messages limited by the knowledge-based algorithm, which limited the pool of possible messages to those matching the characteristics of the participant (age, gender, quitting date, number of smoked cigarettes, weekly tobacco expenditure, time of day), then selected randomly. Intervention length: 6 months
Sadasivam, 2016 (71)	<i>PERSPeCT</i> system	Number allocated: 74 Number of withdrawals (%): 16 (21.6%) Proportion female: 0.62 Age: 19 to 34 years: 34% 35 to 44 years: 28% 45 years and over: 38% Wants to stop smoking cigarettes: 80% Stopped smoking for one day or longer to try to quit smoking: 42%	Intervention description: Daily emails sent using a hybrid recommender system, using the following data sources: (1) metadata description of the messages, (2) implicit, and (3) explicit user feedback data. AI details: The system used Bayesian probabilistic matrix factorization to select messages. Intervention length: 1 month
	CTHC system	Number allocated: 46 Number of withdrawals (%): 9 (19.6%) Proportion female: 0.67 Age: 19 to 34 years: 24% 35 to 44 years: 37% 45 years and over: 39% Wants to stop smoking cigarettes: 80% Stopped smoking for one day or longer to try to quit smoking: 46%	Intervention description: Daily emails sent using a rules-based system that tailored which messages were sent to participants based on their readiness to quit. AI details: no AI Intervention length: 1 month

Table 4: Trial results

Acronyms: CASC = CureApp Smoking Cessation, CI = confidence interval, CTHC = computer-tailored health communication, d = Cohen's d, IRR = incidence rate ratio, NA = not applicable, OR = odds ratio, PERSPeCT = Patient Experience Recommender System for Persuasive Communication Tailoring, QFI = Quantity-Frequency-Index (amount of alcohol in grams over the past 30 days), So-Lo-Mo = Social-Local-Mobile, TFB = Timeline Follow-Back method (amount of alcohol in grams over the past 7 days), η^2 = partial eta-squared

Where multiple results were presented at the same timepoint, the most adjusted result from intention-to-treat analyses (over per protocol) with multiple imputation (followed by missing assumed to be smoking, then complete case) was presented. Full results are available in **Supplement B**.

Table 4a: Alcohol consumption trials

Reference	Timepoint	Outcome	Intervention group	N	Mean (SE)	Result
Dulin, 2022 (14, 40-42)	12 weeks	Change in drinks per day	Step Away chatbot	39	-0.89	$\eta^2=0.03$, $p=0.18$
			Step Away app	42	-1.18	
			Assessment only	33	-0.62	
		Change in percent days abstinent	Step Away chatbot	39	14	Not reported
			Step Away app	42	20	
			Assessment only	33	18	
		Change in heavy drinking days	Step Away chatbot	39	-3.95	$\eta^2=0.04$, $p=0.11$
			Step Away app	42	-4.4	
			Assessment only	33	-1.36	
Gurtler, 2025 (17, 43-47)	6 months	Alcohol consumption (number of alcoholic drinks in past 30 days)	ready4life app	1,266	3.05 (0.20)	Not reported
	Control		1,279	3.20 (0.20)		
	12 months		ready4life app	1,266	2.35 (0.21)	Time x group effect = -0.011 (-0.025 to 0.004), $p=0.15$
			Control	1,279	2.63 (0.21)	
Haug, 2022 (18, 48)	6 months	Change in at-risk drinking in past 30 days	ready4life app	Not reported	-10.9	OR = 0.68 (0.52 to 0.89), $p<0.01$
			Control		-7.6	
		Change in mean quantity of alcohol used in past 30 days	ready4life app		-8	-5.6 (d=0.07), $p<0.01$
			Control		-5.6	
		Age x group interaction (all outcomes)	NA		Not reported	No statistically significant moderators identified
		Sex x group interaction (all outcomes)				
Zill, 2019 (49-52)	3 months	QFI	Vorvida	306	40.8 (3.3)	d = 0.278, $p=0.001$
			Usual care	302	56.8 (3.3)	
		TFB	Vorvida	306	34.3 (1.3)	d = 0.419, $p<0.001$
			Usual care	302	43.7 (1.3)	
		Days of binge drinking (past 30 days)	Vorvida	306	8.1 (0.4)	d = 0.873, $p<0.001$
			Usual care	302	14.6 (0.4)	
		Days of drunkenness (past 30 days)	Vorvida	306	2.9 (0.2)	d = 0.392, $p<0.001$
			Usual care	302	4.6 (0.2)	
	6 months	QFI	Vorvida	306	32.3 (2.1)	d = 0.327, $p<0.001$
			Usual care	302	44.1 (2.1)	
		TFB	Vorvida	306	25.7 (1.5)	d = 0.540, $p<0.001$
			Usual care	302	38.6 (1.4)	
		Days of binge drinking (past 30 days)	Vorvida	306	4.6 (0.4)	d = 1.400, $p<0.001$
			Usual care	302	14.5 (0.4)	
		Days of drunkenness (past 30 days)	Vorvida	306	1.5 (0.2)	d = 0.742, $p<0.001$
			Usual care	302	4.4 (0.2)	

Table 4b: Smoking trials

Reference	Timepoint	Outcome	Intervention group	n/N (%)	Result
Chatbots					
Bricker, 2024 (15, 53)	3 months	30-day cigarette abstinence	QuitBot	59/200 (31%)	OR for QuitBot vs SFT = 0.81 (95% CI: 0.50 to 1.29), p=0.36 OR for QuitBot vs delayed = 5.97 (95% CI: 2.04 to 17.45), p=0.002
			SmokefreeTXT	50/149 (35%)	
			Delayed access	4/55 (7%)	
		7-day cigarette abstinence	QuitBot	91/200 (48%)	OR for QuitBot vs SFT = 0.79 (95% CI: 0.51 to 1.22), p=0.28 OR for QuitBot vs delayed = 10.08 (95% CI: 3.79 to 26.80), p<0.001
			SmokefreeTXT	76/149 (53%)	
			Delayed access	5/55 (9%)	
Guertler, 2025 (17, 43-47)	6 months	Cigarettes per day	ready4life app	1,266	Mean = 0.08 (SE: 0.013) (no time x group effect or p value for comparison)
	12 months		Control	1,279	Mean = 0.08 (SE: 0.015)
			ready4life app	1,266	Time x group effect = -0.031 (95% CI: -0.053 to -0.009), p=0.007
			Control	1,279	
Guo, 2023 (16)	6 months	7-day cigarette abstinence (validated)	Chatbot	Not reported	OR = 1.22 (95% CI: 0.53 to 2.82), p=0.64
			Control		
		24-week cigarette abstinence (self-report)	Chatbot		OR = 0.91 (95% CI: 0.48 to 1.72), p=0.78
			Control		
	12 months	7-day cigarette abstinence (validated)	Chatbot		OR = 1.14 (95% CI: 0.56 to 2.33), p=0.72
			Control		
		24-week cigarette abstinence (self-report)	Chatbot		OR = 0.88 (95% CI: 0.49 to 1.59), p=0.67
			Control		
	6 months	Gender x group interaction (7-day cigarette abstinence [validated])	NA		p=0.13
	12 months	cigarette abstinence [validated])	NA		p=0.09
	6 months	Age x group interaction (7-day cigarette abstinence [validated])	NA		p=0.46
	12 months	cigarette abstinence [validated])	NA		p=0.17
	6 months	Education x group interaction (7-day cigarette abstinence [validated])	NA		p=0.46
	12 months	cigarette abstinence [validated])	NA		p=0.49
Haug, 2022 (18, 48)	6 months	Change in tobacco or e-cigarette use in past 30 days	ready4life app	Not reported	OR = 0.74 (95% CI: 0.55 to 1.01), p=0.06
			Delayed access		
		Change in mean number of cigarettes smoked in past 30 days	ready4life app		-6.0 (d=0.07), p=0.40
			Delayed access		
		Age x group interaction (all outcomes) Sex x group interaction (all outcomes)	NA		No statistically significant moderators identified
Jackson, 2024 (60-63)	4 months	3-month cigarette abstinence	Smoke Free app	299/1,564 (19.1%)	RR = 1.12 (95% CI: 0.91 to 1.39), p=0.29
		Assessment-only	269/1,579 (17.0%)		
	7 months	6-month cigarette abstinence	Smoke Free app	350/1,564 (22.4%)	RR = 1.12 (95% CI: 0.94 to 1.33), p=0.21
		Assessment-only	316/1,579 (20.0%)		
	4 months	Gender x group interaction (3-month cigarette abstinence)	NA	Not reported	RR = 1.03 (95% CI: 0.57 to 1.86), p=0.91
		Age x group interaction (3-month cigarette abstinence)			RR = 1.21 (95% CI: 0.59 to 2.49), p=0.60
		Education x group interaction (3-month cigarette abstinence)			RR = 0.47 (95% CI: 0.18 to 1.16), p=0.11
		Financial situation x group interaction (3-month cigarette abstinence)			RR = 1.02 (95% CI: 0.75 to 1.40), p=0.89
	7 months	Gender x group interaction (6-month cigarette abstinence)			RR = 1.18 (95% CI: 0.52 to 2.70), p=0.69

Reference	Timepoint	Outcome	Intervention group	n/N (%)	Result
		Age x group interaction (6-month cigarette abstinence)			RR = 0.81 (95% CI: 0.31 to 2.13), p=0.67
		Education x group interaction (6-month cigarette abstinence)			RR = 0.80 (95% CI: 0.14 to 4.43), p=0.79
		Financial situation x group interaction (6-month cigarette abstinence)			RR = 0.97 (95% CI: 0.59 to 1.58), p=0.89
Masaki, 2020 (64, 65)	4 weeks	7-day cigarette abstinence	CASC app	Not reported	OR = 1.67 (95% CI: 1.17 to 2.38), p=0.004
			Control app		
	8 weeks		CASC app	Not reported	OR = 1.63 (95% CI: 1.11 to 2.39), p=0.012
			Control app		
	12 weeks		CASC app	Not reported	OR = 1.56 (95% CI: 1.06 to 2.30), p=0.024
			Control app		
		3-week smoking abstinence	CASC app	215/285 (75.4%)	OR = 1.57 (95% CI: 1.09 to 2.27), p=0.016
			Control app	190/287 (66.2%)	
	24 weeks	7-day cigarette abstinence	CASC app	Not reported	OR = 1.88 (95% CI: 1.33 to 2.68), p<0.001
		Control app			
		15-week smoking abstinence	CASC app	182/285 (63.9%)	OR = 1.73 (95% CI: 1.24 to 2.42), p=0.001
			Control app	145/287 (50.5%)	
	52 weeks	7-day cigarette abstinence	CASC app	Not reported	OR = 1.80 (95% CI: 1.29 to 2.52), p<0.001
		Control app			
		43-week smoking abstinence	CASC app	149/285 (52.3%)	OR = 1.55 (95% CI: 1.11 to 2.16), p=0.01
			Control app	119/287 (41.5%)	
Olano-Espinosa, 2022 (66-69)	6 months	6-month cigarette abstinence	Dejal@bot	63/242 (26%)	OR = 1.52 (95% CI: 0.99 to 2.33), p=0.053
			Usual clinical practice	51/271 (18.8%)	
Perski, 2019 (70)	1 month	1-month cigarette abstinence	Pro app with AI chatbot	Not reported	OR = 2.38 (95% CI: 2.19 to 2.58), p<0.001
			Pro app		
Recommender systems					
Carrasco-Hernandez, 2020 (19)	12 months	1-year smoking abstinence	So-Lo-Mo	27.5%	OR = 3.13 (95% CI: 1.53 to 6.71), p=0.002
			Usual therapy	15%	
Faro, 2023 (20, 54-57)	6 months	7-day cigarette abstinence	CTHC System	Not reported	OR = 0.86 (95% CI: 0.63 to 1.18), p=0.35
		Change in cigarettes smoked per day	Standard messaging		Mean = -8.9 (SD: 10.5), p value for difference = 0.2
			CTHC System		Mean = -9.9 (SD: 10.8)
			Standard messaging		
Hors-Fraile, 2022 (58, 59)	6 months	7-day cigarette abstinence	Hybrid Algorithm	3.3%	OR = 0.957 (95% CI: 0.610 to 1.501), p=0.847
			Knowledge-based algorithm	3.4%	
Sadasivam, 2016 (71)	1 month	Stopped smoking for at least 1 day	PERSPeCT system	20/55 (36%)	p value for difference = 0.7
			CTHC system	11/34 (32%)	
		Quit smoking during intervention	PERSPeCT system	15	No p value reported
			CTHC system	11	

Table 5: RoB2 Assessments

Risk of bias assessments for the primary outcome in each trial using the Cochrane RoB2 tool (34). Full assessments, including the rationale for indicator question decisions, are available in **Supplement B**.

Table 5a: Alcohol consumption trials

Reference	1. Randomization	2. Deviations from intended interventions	3. Missing outcome data	4. Outcome measurement	5. Selection of reported result	Overall risk of bias judgement
Dulin, 2022 (14, 40-42)	Some concerns	Low risk	High risk	High risk	Some concerns	High risk
Gurtler, 2025 (17, 43-47)	Low risk	Low risk	High risk	High risk	Low risk	High risk
Haug, 2022 (18, 48)	Low risk	Low risk	High risk	High risk	Low risk	High risk
Zill, 2019 (49-52)	Low risk	Low risk	High risk	High risk	Low risk	High risk

Table 5b: Smoking trials

Reference	1. Randomization	2. Deviations from intended interventions	3. Missing outcome data	4. Outcome measurement	5. Selection of reported result	Overall risk of bias judgement
Chatbots						
Bricker, 2024 (15, 53)	Some concerns	Low risk	Low risk	Low risk	Low risk	Some concerns
Guertler, 2025 (17, 43-47)	Low risk	Low risk	High risk	High risk	Low risk	High risk
Guo, 2023 (16)	Low risk	Low risk	High risk	Low risk	Low risk	High risk
Haug, 2022 (18, 48)	Low risk	Low risk	High risk	High risk	Low risk	High risk
Jackson, 2024 (60-63)	Low risk	Low risk	High risk	High risk	Low risk	High risk
Masaki, 2020 (64, 65)	Some concerns	Low risk	Low risk	Low risk	Low risk	Some concerns
Olano-Espinosa, 2022 (66-69)	Low risk	Low risk	High risk	Low risk	Low risk	High risk
Perski, 2019 (70)	High risk	Low risk	High risk	High risk	Low risk	High risk
Recommender systems						
Carrasco-Hernandez, 2020 (19)	High risk	Low risk	High risk	Low risk	Some concerns	High risk
Faro, 2023 (20, 54-57)	Low risk	Low risk	Low risk	High risk	Low risk	High risk
Hors-Fraile, 2022 (58, 59)	Some concerns	High risk	High risk	Low risk	High risk	High risk
Sadasivam, 2016 (71)	Some concerns	Low risk	Low risk	High risk	Some concerns	High risk

Discussion

This review summarised evidence showing the effectiveness of AI-assistance for public health interventions of alcohol consumption and smoking. Overall, there was little consistent evidence that AI-assistance was beneficial for either alcohol consumption or smoking. While some trials suggested the interventions were effective, this must be balanced against other trials showing no effect, comparisons of multi-component interventions that included AI-assistance with usual practice, as well as the high risks of bias across almost all trials.

The evidence we found was also limited. We did not conduct meta-analyses due to the heterogeneity of interventions, comparators, outcomes, and timepoints. While this means we presented a narrative rather than quantitative synthesis, the heterogeneity and high risks of bias across trials means a quantitative synthesis would likely have been misleading. Aside from expert systems, which we excluded to focus on more modern AI technologies, we only found evidence for AI-assisted interventions that used rules-based chatbots, recommender systems, and AI-tailoring. We found no interventions that used LLMs or other more modern AIs, despite the recent widespread uptake of LLMs across fields. As rules-based chatbots have only shown limited and variable evidence of effectiveness, there is little current evidence to suggest future interventions using LLMs would necessarily be effective.

Stakeholder Consultations

Stakeholders recognised the potential of AI-assistance in delivering behaviour change interventions but highlighted a number of key knowledge gaps that need to be attended to moving forward. First, stakeholders noted limited reporting of the extent to which interventions were co-produced with the target audience, which raises important considerations of how co-production methods can be optimally used in AI-based research. Second, stakeholders discussed the need for participants to have readiness and motivation to engage with AI, and if skill development may be required. Third, stakeholders queried the strength of implementation science in this area. For example,

they considered if apps would be hosted by developers or Local Authorities, and what resources and capabilities would local public health teams require to support AI-assisted approaches. Fourth, stakeholders commented on the methodological limitations of evaluation, and whether new appraisal tools would need to be developed to account for the specific challenges and limitations associated with AI. Specifically, there was discussion of whether AI approaches have the potential to exacerbate health inequities and causes unintended harms, which have not yet been fully theorised or translated into appraisal criteria.

Limitations

Despite the comprehensive search strategies, it is possible that relevant trials may have been missed. One reason for this is that searching for AI-assisted interventions was complex, particularly as article abstracts often only noted the intervention name and not that the intervention included AI. Notably, some trials were only found by citation searching as both the direct searches for trials and searching previous reviews failed to find them. Additionally, we excluded non-English language articles, potentially missing otherwise eligible interventions reported in other languages.

Implications for research and practice

There was limited evidence of effectiveness of AI-assistance in public health interventions for reducing alcohol consumption or smoking in high-income countries. Due to the relatively small number of heterogeneous trials, this does not necessarily mean AI-assistance is not effective for reducing alcohol consumption or smoking, but it should not be assumed that AI-assistance is beneficial or free from risks. Indeed, our review of the potential roles and risks of AI in public health identified many risks of AI use, some of which were substantial enough to potentially pose a threat to trust in public health itself (23). The potential for AI-assisted interventions to maintain or exacerbate existing health inequalities was also raised (23); while some included trials in this review conducted equity-relevant analyses, future research should embed equity considerations into their design and analysis to ensure already disadvantaged

groups are not harmed further by the adoption of AI-assisted interventions in public health.

Given the difficulty of searching for AI-assisted interventions, future research should also better describe public health interventions that use AI. Although focussed on more clinical settings, AI-specific reporting guidelines, such as SPIRIT-AI (73), CONSORT-AI (74) and DECIDE-AI (75), may be useful in prompting more informative and standardised descriptions of AI-assisted interventions in public health.

Conclusion

There is no strong evidence of a beneficial effect of AI-assistance in public health interventions for reducing alcohol consumption or smoking in high-income countries. We found no evidence for more recent interventions using LLMs or other more advanced AIs.

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