Smoking Detection and Cessation: An Updated Scoping Review of Digital and Mobile Health Technologies

Mirko Casu, Francesco Guarnera, Giusy Rita Maria La Rosa, Sebastiano Battiato, *Senior Member, IEEE*, Pasquale Caponnetto, Riccardo Polosa, and Rosalia Emma

***Abstract*—Digital and mobile health technologies offer promising solutions for smoking detection and cessation. This scoping review examines the current state of research and development in this field, encompassing smartphone applications, wearable devices, and sensor-based systems. We analyzed 49 studies published between 2019 and 2023 from PubMed and ACM Digital Library, focusing on technology features, outcomes, and evaluation methods. Wearable sensors and smartphone apps show potential in combating smoking addiction and improving quit rates. Motion sensors for hand-to-mouth gesture detection achieve high accuracy in controlled settings but face challenges in real-world applications. Machine learning models and wireless signal detection techniques yield encouraging results but require further refinement. Smartphone apps provide personalized plans and progress tracking, though most rely on manual logging and lack rigorous scientific evaluation. Our findings suggest that digital health technologies could significantly enhance smoking cessation efforts. However, more robust evaluation methods and integration of sensor data with machine learning are needed to improve usability and effectiveness. Continued research and innovation in this field are crucial for developing reliable, practical solutions and integrating these technologies into clinical programs.**

***Index Terms*—Smoking detection, health technologies, smoking cessation, medical mobile apps, technology review, wearable devices.**

Received 17 September 2024; revised 23 December 2024 and 27 January 2025; accepted 3 March 2025. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The work of Riccardo Polosa (as task leader), Mirko Casu, Sebastiano Battiato and Rosalia Emma has been supported by Ministry of University and Research (MUR) in the framework of the National Recovery and Resilience Plan (PNRR)E63C22000900006, SPOKE 1, Work Page Health under project SAMOTHRACE (Sicilian Micro and Nano Technology Research and Innovation Center). The work of Francesco Guarnera has been supported by MUR in the framework of PNRR PE0000013, under project "Future Artificial Intelligence Research – FAIR". *(Corresponding author: Mirko Casu.)*

Mirko Casu is with the Department of Mathematics and Computer Science, University of Catania, 95123 Catania, Italy, and also with the Department of Educational Sciences, Section of Psychology, University of Catania, 95123 Catania, Italy (e-mail: mirko.casu@phd.unict.it).

Francesco Guarnera is with the Department of Mathematics and Computer Science, University of Catania, 95123 Catania, Italy (e-mail: francesco.guarnera@unict.it).

Giusy Rita Maria La Rosa is with the Department of Clinical & Experimental Medicine, University of Catania, 95123 Catania, Italy (e-mail: giusy.larosa@unict.it).

Sebastiano Battiato is with the Department of Mathematics and Computer Science, University of Catania, 95123 Catania, Italy, and also with the Center of Excellence for the Acceleration of Harm Reduction, University of Catania, 95123 Catania, Italy (e-mail: battiato@dmi.unict.it).

Pasquale Caponnetto is with the Department of Educational Sciences, Section of Psychology, University of Catania, 95123 Catania, Italy, and also with the Center of Excellence for the Acceleration of Harm Reduction, University of Catania, 95123 Catania, Italy (e-mail: p.caponnetto@unict.it).

Riccardo Polosa and Rosalia Emma are with the Department of Clinical & Experimental Medicine, University of Catania, 95123 Catania, Italy, and also with the Center of Excellence for the Acceleration of Harm Reduction, University of Catania, 95123 Catania, Italy (e-mail: polosa@unict.it; rosalia.emma@unict.it).

Digital Object Identifier 10.1109/JBHI.2025.3549255

I. Introduction

TOBACCO smoking remains a leading cause of preventable illness and premature death worldwide, despite declining prevalence rates [1], [2]. In the U.K., smoking-related deaths accounted for 16% of all deaths in 2016 [1]. The economic impact of smoking is substantial, with global annual costs exceeding US$500 billion [3]. Smoking behavior is maintained by nicotine's reinforcing properties and the distant nature of health consequences [2]. Effective interventions to reduce smoking prevalence include tax increases, social marketing, and brief advice from health professionals [2]. Workplace smoking cessation programs have shown cost-effectiveness, with benefit-cost ratios up to 8.75 and significant employer cost savings [3]. While various cessation measures have proven effective and cost-effective, challenges remain in addressing persistent inequalities in smoking rates among certain groups, such as manual workers and individuals with serious mental illness [1].

Over the past decade, we have witnessed a rapid proliferation of portable devices that have become central to our daily lives [4], [5]. Notably, smartphone technology, coupled with ever-expanding bandwidth connectivity and the growth of social networks, has fundamentally transformed the way we conduct nearly all our daily activities, ushering in an era of pervasive digital technology [4], [6], [7], [8]. In addition to smartphones, there has been a significant uptick in the adoption of various wearable devices and home/office installations [9], [10], [11], [12], all interconnected and controllable through simple smartphone applications. This interconnected device ecosystem is geared towards enhancing the intelligence of our devices and environments, leading to the emergence of concepts like smart homes and smart offices [13], [14], [15], [16]. Crucially, these wearable and remote devices are equipped with specific sensors that can capture data related to individuals or their surroundings, which can then be shared and processed collaboratively among different devices [17], [18], [19]. The goal is to derive insights and create added value for the user experience, offering opportunities for both data capture and user support. A novel and innovative application of smart device technology lies in its potential to assist with smoking cessation treatments [20], [21], [22]. In the realm of smoking detection and cessation technologies, there is a recognized issue that these technologies are not fully optimized for real-life scenarios. While existing technologies have demonstrated potential, their performance in real-life scenarios continues to pose a challenge. The present work is a scoping review updating a previously published work [17] with the aim of conducting a comparative examination of various smartphone applications (apps), wearable technologies designed for automatic smoking detection, and other instances where technology can play a role in supporting smoking cessation interventions.

In this paper, we aim to provide an overview and analysis of the current state-of-the-art technology focusing on automated smoking detection and smoking cessation technologies. An automatic smoking detection technology is a solution designed to ascertain the number of cigarettes smoked by an individual within a specified observation period [16], [23]. This encompasses approaches that necessitate minimal user intervention (i.e., automatic), encompassing all stages involved in detecting smoking events, from collecting sensory data to making the final inference, as opposed to solutions reliant on self-reporting by participants (e.g., diary apps). In the following sections, the most relevant apps and technologies designed to help people stop smoking are shown and compared. A summary of the revised solutions to help users quit smoking is presented in the Discussion.

II. Methods

A. Research Question

This scoping review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Extension for Scoping Reviews (Suppl. Mater.1) [24]. The aim was to synthesize and explore the current applications of digital devices for automatically detecting the use of cigarettes. Additionally, this review will also report on the use of smoking cessation smartphone applications, which represent a significant stride in leveraging technology to aid in smoking cessation. Our study, structured following the PICO format [25], focused on **individuals who smoke (P)**, examining the application of digital health technologies, such as smartphone apps, wearable devices, sensors, and machine learning techniques, **to detect smoking events and support smoking cessation (I)**. These innovative approaches were compared to **traditional methods**, including manual self-monitoring, standard behavioral therapies, or the absence of intervention **(C)**. The outcomes of interest included **improvements in the automatic detection of smoking events**, such as recall rates and accuracy, increased smoking cessation rates, usability and acceptance of these technologies, and their successful integration into clinical practice **(O)**.

B. Systematic Search of Patents

A systematic search was conducted on Google Patents to identify patents related to smoking cessation systems and technologies. Google Patents was chosen as the search engine due to its comprehensive coverage of patent databases from multiple jurisdictions, including the United States Patent and Trademark Office (USPTO), European Patent Office (EPO), and World Intellectual Property Organization (WIPO). The search strategy was designed to be broad to capture as many relevant patents as possible. The search terms used were combinations of the following keywords: (“smoking cessation system” OR “automated smoking detection”) AND (“patent” OR “application” OR “method”). The search, unrestricted by date or jurisdiction, screened all results for relevance based on title and abstract. Patents detailing smoking cessation systems or technologies were further analyzed. Additional relevant patents were identified through screening the reference lists of these patents. Data extracted from each patent, including title, number, filing and publication dates, inventors, assignees, abstract, and claims, provided an overview of the latest technology in automated smoking detection and cessation systems. The systematic search results were incorporated into the PRISMA flow diagram (Fig. 1), visually representing the search and selection process for transparency and reproducibility of the study.

C. Literature Search

An updated search for smoking detection technologies and smoking cessation applications was conducted in December 2023 using PubMed and ACM Digital Library databases. The following search strategy was used: (“smoking” AND “detection system”) OR (“smoking” AND “sensor”) OR ((“smoking” AND “detection system”) OR (“smoking” AND “sensor”)) OR ((“smoking cessation”) AND (“application” OR “app” OR “smartphone app”)). The full search strategy is provided in Suppl. Mater. 2. All the studies published since 2019, year of publication of the previous review, were included. There were no limitations based on language. The reference lists of the included studies underwent additional scrutiny to identify additional potential studies. We manually searched key peer-reviewed scientific journals in the field of tobacco research (specifically, Nicotine & Tobacco Research, Tobacco Control, Carcinogenesis, Health Education Research, and Contributions to Tobacco and Nicotine Research). Two authors of the review independently examined and chose studies from the conducted searches. Any disagreements were resolved through discussion or, if necessary, with the involvement of a third reviewer.

1) Web-Based Search for Smoking Cessation Applications: For smoking cessation applications, an additional web-based search was carried out. The selection process was conducted as follows: we performed multiple searches using Bing, Google,

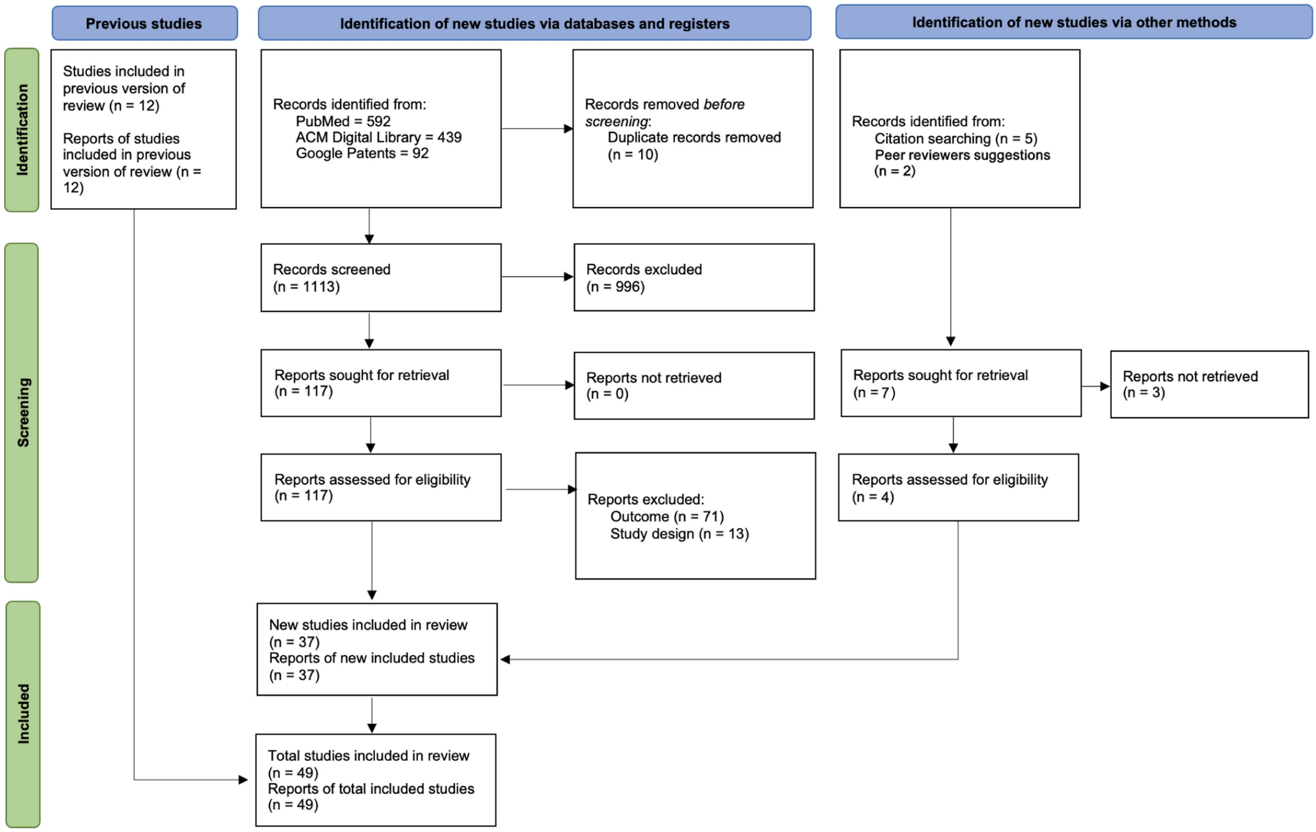

Fig. 1. PRISMA-ScR (Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews) flow diagram representing the article selection process in accordance with the guidelines for updates of systematic reviews [24].

and DuckDuckGo search engines using the query "quit smoking apps." From the initial search results, we excluded entries related to sponsored links promoting specific apps. Instead, we focused on links associated with blogs dedicated to health topics (e.g., healthline.com). From this resulting list of apps, we chose those with high average user ratings in the Android and iOS app stores (i.e., ratings of 4/5 or higher). Then, a further literature search was conducted on Google Scholar combining the names of app identified via web as follows: ("name of the application" AND "application"). This additional step, which was performed for each application, enabled verification of which apps were clinically assessed.

D. Eligibility Criteria

The eligibility criteria for the inclusion of studies in this scoping review were as follows:

- Studies that reported on development, evaluation, or application of a digital or mobile health technology for smoking detection or cessation.
- Technology that involved smartphone, smartwatch, wearable device, or other sensor-based system.
- Studies in the form of original research articles (including randomized controlled trials), cross-sectional, cohorts, brief reports, case reports, case series communications, methodologies, and methods.
- Studies published in peer-reviewed journals or conference proceedings.
- Studies published between 2019 and 2023.

E. Exclusion Criteria

The exclusion criteria were the following:

- Studies that did not focus on smoking detection or cessation as a primary or secondary outcome.
- Technology that did not involve sensor or motion data collection or analysis.
- Studies not written in English.
- Apps that were not available in English.
- Studies in the forms of abstract, preprint, editorial, commentary, letter, or review.
- Studies published before 2019 (except those included in the previous version of this review).

F. Data Extraction

Two reviewers independently performed data extraction. Any inconsistencies were resolved through discussion or with the assistance of a third reviewer. In our analysis, we categorized the reviewed technologies into two main groups: smoking detection technologies and smoking cessation applications.

1) Smoking Detection Technologies: For each study, the following elements were systematically extracted and compiled in study tables: product, technology, operating system (OS), goal, participants, hours, recall, F-score and Area Under Curve (AUC).

2) Smoking Cessation Applications: For each study, the following items were extracted and adapted into appropriate tables: product, technology, mobile operating systems, scientific evaluation (Sc. Eval.), public availability, and list price. Within each category, we also highlighted whether smoking cessation applications have been supported by scientific articles and whether these have undergone assessment, for example, on a clinical level. Smartphone applications were divided into two subsections based on whether they have been subjected to clinical assessment or not, and therefore at least one phase of testing on real samples.

III. Results

A. Study Characteristics

The search yielded a total of 37 distinct documents, to be added to 12 studies retrieved from the previous version of the review (6 related to smoking detection technologies, and 6 related to smoking cessation applications). Given that the utilization of wearable devices for smoking detection is relatively recent, most of the located works pertain to products currently undergoing evaluation or still in the experimental prototype phase. The article selection process is reported in the PRISMA-ScR, compiled in accordance with the guidelines for updates of systematic reviews (Fig. 1). The full list of included studies is reported in Table I. A total of 26 studies were identified for smoke detection technologies and 20 for smoking cessation applications, 2 of which were subsequently added to suggestions obtained through the review process. Furthermore, 3 studies related to generic smoking detection were included. The main characteristics of the included studies are explained below. The remaining 60 references cited throughout this paper provide contextual background, theoretical framing, or supplementary discussion but were excluded from formal analysis to maintain focus on the core research questions. This approach aligns with scoping review methodologies, which prioritize depth on key themes while acknowledging broader scholarly discourse.

B. Technologies for Smoking Events Detection

The technologies discussed in this paragraph aim to detect smoking events in real-time, eliminating manual tracking. Some are market-ready, others are under evaluation. They typically use a wearable device and smartphone app to identify smoking-related movements like hand-to-mouth actions.

The development of smoking detection systems has undergone significant advancements, particularly in leveraging wearable technologies and machine learning. Lopez-Meyer et al. [26], [27] laid early foundations using respiratory inductive plethysmography (RIP) sensors and wrist-worn devices to detect smoking gestures (see Fig. 2). Their approach utilized Support Vector Machines (SVM) and threshold-based algorithms, achieving recall rates of 80–90%. However, their system was limited to controlled settings, requiring offline processing

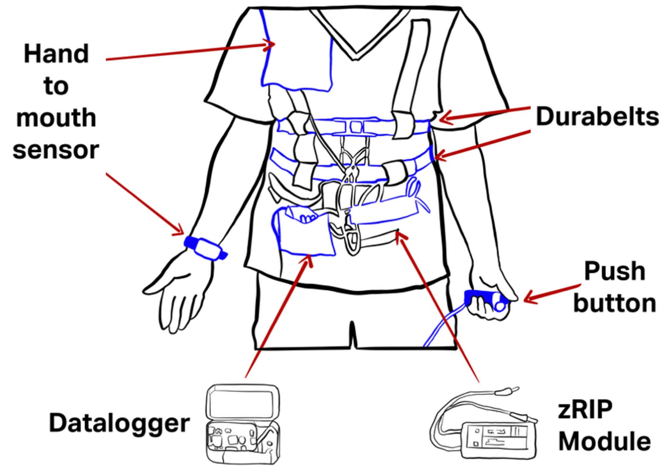

Fig. 2. Sensors of the system depicted in Lopez-Meyer et al.'s work [26].

and providing minimal adaptability to free-living environments. Moving forward, systems like SmokeBeat [28] enhanced detection by incorporating accelerometers and gyroscopes into commercial smartwatches. SmokeBeat combined probabilistic models with gesture segmentation, yielding precision and recall rates exceeding 85%. Similarly, RisQ [29] leveraged Conditional Random Fields to sequence smoking gestures in free-living conditions, while StopWatch [30] adopted Random Forest classifiers to distinguish smoking from other activities. These systems demonstrated the potential for low-cost, user-friendly platforms, achieving operational accuracies between 70–90%.

Post-2020 studies demonstrated remarkable advances in smoking behavior detection through increasingly sophisticated methodological approaches. Senyurek and colleagues [31] developed a wearable system integrating respiratory inductive plethysmography (RIP) and inertial measurement unit (IMU) sensors, employing a hybrid deep learning framework combining convolutional neural networks (CNN) and long short-term memory (LSTM) networks. Their research utilized a comprehensive dataset evaluated through leave-one-subject-out cross-validation, achieving an F1-score of 78%. Similarly, Kirmizis et al. [32] employed an artificial neural network with convolutional and recurrent layers, utilizing the Smoking Event Detection (SED) and Smoking Event Detection Free-Living (SED-FL) datasets. Their two-step methodology leveraged smartwatch data to detect individual puffs and localize smoking sessions, achieving impressive weighted accuracies of 0.968 and F1-scores of 0.878. Agac et al. [33] advanced sensor fusion methodologies, utilizing accelerometers and gyroscopes from smartwatches (LG Watch R, LG Watch Urbane or Sony Watch 3) and smartphones (Samsung Galaxy S2 or S3). Their framework incorporated user-specific features, such as body dimensions, into a Random Forest classifier to achieve 83% recall in distinguishing smoking gestures from other hand-to-mouth activities. They validated the model using a comprehensive dataset collected under free-living conditions, demonstrating the importance of personalization in wearable systems. More recent advancements, such as Hnoohom et al.'s [34], advanced

TABLE I
SUMMARY OF THE STUDIES INCLUDED IN THIS SCOPING REVIEW, LISTED IN THE ORDER THEY APPEAR IN THE TEXT, REFLECTING THEIR RELEVANCE TO DIFFERENT TOPICS AND SECTIONS OF THE ARTICLE

Author(s)	**Year**	**Study Design**	**Outcome**
Lopez-Meyer et al.	2012	Observational Study	Smoking Detection
Lopez-Meyer et al.	2013	Observational Study	Smoking Detection
Reuven Dar	2018	Pilot Randomized Controlled Trial	Smoking Detection
Skinner et al.	2019	Observational Study	Smoking Detection
Parate et al.	2014	Experimental Study	Smoking Detection
Agac et al.	2020	Supervised Learning	Smoking Detection
Kirmizis et al.	2021	Experimental Study	Smoking Detection
Hnoohom et al.	2022	Experimental Study	Smoking Detection
Thakur et al.	2022	Experimental Study	Smoking Detection
Maguire et al.	2022	Experimental Study	Smoking Detection
Sharma et al.	2023	Observational Study	Smoking Detection
Mukhopadhyay et al.	2023	Experimental Study	Smoking Detection
Alharbi et al.	2023	Observational Study	Smoking Detection
Chen et al.	2018	Experimental Study	Sm. Cessation App
Marler et al.	2021	Cohort Study	Sm. Cessation App
Marler et al.	2022	Pilot Randomized Controlled Trial	Sm. Cessation App
Marler et al.	2019	Cohort Study	Sm. Cessation App
Patrick et al.	2018	Cohort Study	Sm. Cessation App
Garrison et al.	2020	Randomized Controlled Trial	Sm. Cessation App
Iacoviello et al.	2017	Retrospective Cohort Study	Sm. Cessation App
Bricker et al.	2017	Single-arm Clinical Trial	Sm. Cessation App
Caponnetto et al.	2023	Uncontrolled pre-test post-test Open Study	Sm. Cessation App
Gowarty et al.	2021	Mixed Methods Study	Sm. Cessation App
O'Connor et al.	2020	Randomized Controlled Trial	Sm. Cessation App
Bricker et al.	2020	Randomized Controlled Trial	Sm. Cessation App
Rajani et al.	2021	Observational Study	Sm. Cessation App
Lin et al.	2018	Observational Study	Sm. Cessation App
Tudor-Sfetea et al.	2018	Qualitative Short-term Longitudinal Study	Sm. Cessation App
Webb et al.	2020	Randomized Controlled Trial	Sm. Cessation App
Rajani et al.	2021	Observational Study	Sm. Cessation App
Rajani et al.	2023	Observational Study	Sm. Cessation App
Bustamante & Romo	2022	Observational Study	Sm. Cessation App
Sanchez et al.	2022	Systematic Search	Sm. Cessation App
Macalisang et al.	2020	Observational Study	Smoking Detection
Wei et al.	2021	Experimental Study	Smoking Detection
Zhang et al.	2021	Experimental Study	Smoking Detection
Jiang Chong	2023	Experimental Study	Smoking Detection
Gaur et al.	2020	Literature Review	Smoking Detection
Saponara et al.	2021	Observational Study	Smoking Detection
Gu et al.	2020	Experimental Study	Smoking Detection
Jeong & Ha	2023	Experimental Study	Smoking Detection
Lai et al.	2021	Observational Study	Smoking Detection
Song et al.	2021	Experimental Study	Human Motion Detection
Battalio et al.	2021	Micro-Randomized Trial	Smoking Detection
Hernandez et al.	2021	Micro-Randomized Trial	Smoking Detection
Horvath et al.	2021	Feasibility Trial Protocol	Smoking Detection
Hnoohom et al.	2021	Observational Study	Smoking Detection
Agac et al.	2021	Observational Study	Smoking Detection
Patel et al.	2020	Observational Study	Smoking Detection

smoking gesture detection through a sophisticated ResNetSE framework, integrating deep residual networks with attention mechanisms. By analyzing the UT-Smoke dataset collected from 11 volunteers over three months, the researchers compared their approach against five baseline models (CNN, LSTM, BiLSTM, GRU, and BiGRU; see Fig. 3). The ResNetSE model demonstrated exceptional performance, consistently achieving top accuracy and F1-scores of 98.65%, 98.39%, and 98.63% across multiple scenarios, highlighting its superior capabilities in real-time gesture recognition.

Thakur and colleagues [35] developed a robust activity recognition framework using a 6-axis inertial measurement unit (IMU) sensor, exploring multi-class classification models including Logistic Regression, k-Nearest Neighbor, Adaptive Boosting, Random Forest, Support Vector Machine, and Decision Tree. Maguire et al. [21] introduced a particularly innovative multimodal system combining a smartwatch (with accelerometers and gyroscopes) and a wearable finger sensor, and an Android app (Fig. 4), using a TensorFlow Lite model for activity classification. Their smartwatch-only system achieved accuracy improvements from 75.8% to 85.5% by integrating the finger sensor. Furthermore, Sharma et al. [22] advanced the field with a microcontroller-based system employing a convolution-based network and Neural Architecture Search (NAS) to develop custom Deep Neural Network (DNN) models. Mukhopadhyay's research [36] utilized reinforcement learning to optimize CNN

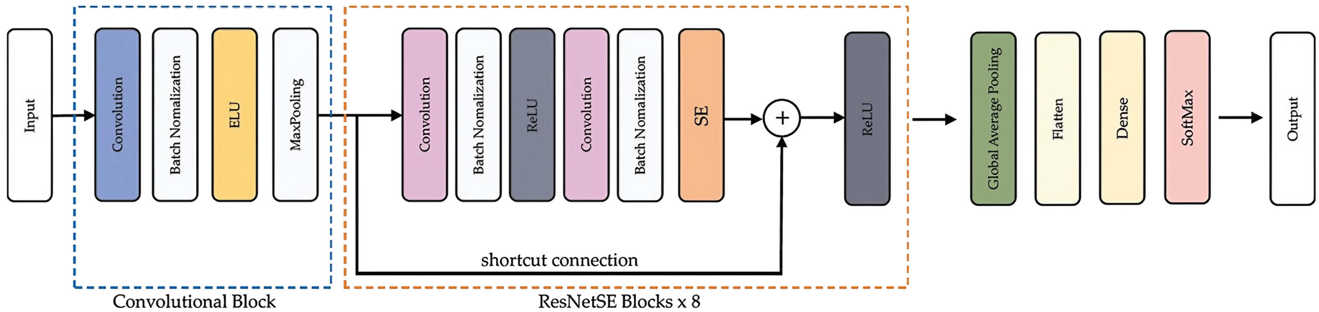

Fig. 3. ResNetSE model included in Hnoohom and colleagues' work [34].

TABLE II
SUMMARY OF THE SMOKING DETECTION TECHNOLOGIES DESCRIBED IN THIS ARTICLE

Product	Technology	OS	Goal	Participants	Hours	Recall	F-Score	AUC
Lopez-Meyer et al. [26]	Hand-to-mouth and chest sensors		SD	20	About 20 hours	81%	81%	N/A
Lopez-Meyer et al. [27]	Hand-to-mouth sensor		SD	20	About 20 hours	90%	N/A	N/A
SmokeBeat [28]	App + Smartwatch	Android/iOS	SD	40	About 20 hours	80%	N/A	N/A
StopWatch [30]	Smartwatch	Android	SD	13	N/A	92%	N/A	N/A
RisQ [29]	App + wrist sensors	Android	SD	15	About 32 hours	81%	N/A	N/A
Agac et al. [33]	Smartwatch	Android	SD	11	45	N/A	98%	N/A
Senyurek et al. [31]	RIP + IMU sensors		SD	24	About 120 hours	N/A	78%	N/A
Kirmizis et al. [32]	App + Smartwatch	Android	SD	11	45	N/A	86%	N/A
Hnoohom et al. [34]	Smartwatch	Android	CHA	11	N/A	N/A	98%	N/A
Thakur et al. [35]	Prototypal wristband		SD	13	About 5 hours	N/A	N/A	99
Maguire et al. [21]	Smartwatch + finger sensor	Android	SD	5	N/A	88%	86%	N/A
Sharma et al. [22]	Prototypal wrist		SD	39	42.5	N/A	81%	N/A
TinyPuff [36]	Unspecified body worn device		SD	7	78.3	N/A	81%	N/A
SmokeMon [37]	Chest-worn system		SD	19	110	95%	90%	N/A

F-Score, AUC, and Hours are the newly added columns. The values of Recall and F-Score are related to the results reported in the respective documents. However, since each document applies its own evaluation protocol, and each study assesses the method on a different dataset, Recall values are not directly comparable. The term 'OS' stands for operating system, 'SD' stands for smoke detection, and 'CHA' stands for complex human activity.

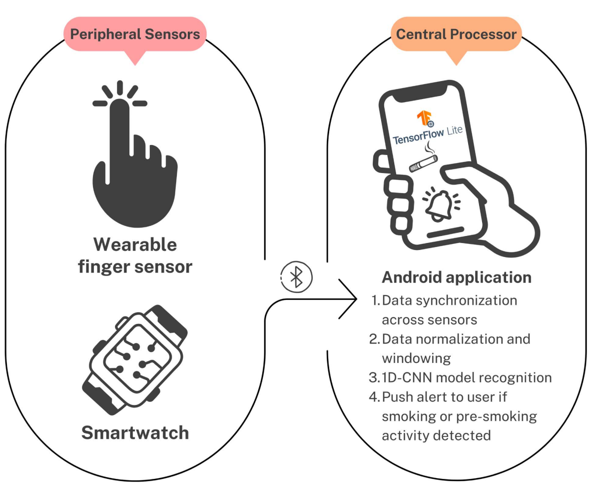

Fig. 4. Diagram of smoking cessation technology described by Maguire and colleagues [21].

architectures, achieving a puff detection F1-score of 0.81, while Alharbi et al. [37] introduced SmokeMon, a chest-worn thermal-sensing system that demonstrated high-precision smoking event detection across laboratory and real-world environments.

A summary of these studies and their recall rates can be seen in Table II, while a summary of the smartwatches employed in them can be found in Table III.

TABLE III
SUMMARY OF THE COMMERCIALLY AVAILABLE-TO-PUBLIC SMARTWATCH EMPLOYED IN THE STUDIES INCLUDED IN THIS SCOPING REVIEW

Manufacturer	Model	Year of Release	Reason(s) to Use
LG Electronics	LG Watch-R	2014	Equipped with the necessary sensors, such as an accelerometer, gyroscope, and linear acceleration [33].
LG Electronics	LG Watch Urbane	2015	Equipped with the necessary sensors, such as an accelerometer, gyroscope, and linear acceleration [33].
LG	LG G-	2014	Balance of usability, data collection capabilities, and cost-effectiveness [30].
Sony	Sony Watch 3	2015	Used in conjunction with smartphones to recognize smoking activities through motion sensor data [33].
Mobvoi	TicWatch E	2018	Ability to provide the necessary 3D acceleration and orientation velocity measurements required by the study's algorithm to detect smoking gestures and sessions [32].

C. Smoking Cessation Applications

The applications delineated in this section are founded upon the annotation of smoking behaviors, accomplishments, and instances of craving. These applications have attained exceedingly elevated mean feedback ratings from users and have experienced substantial rates of downloads within the application markets.

1) Clinically Assessed Applications: Smoking cessation applications highlights a robust and innovative landscape of digital interventions, each employing unique strategies to support users in their quitting journeys. Through scientific third-party evaluation or endorsement, these applications demonstrate a commitment to integrating evidence-based methodologies, personalized features, and advanced technologies to enhance user engagement and efficacy.

Chen et al. [38] showcased an Android-based system combining wearable sensors and tailored quitting plans, emphasizing personalization through demographic and behavioral data. This approach aligns closely with mindfulness-based strategies, such as the RAIN method [39], to aid in managing cravings, while integrating supportive messaging for both users and their social networks. Pivot, a widely evaluated program, stands out for its incorporation of an FDA-cleared breath sensor that offers real-time physiological feedback, alongside a comprehensive app providing customized lessons, progress tracking, and coaching. Its compatibility with iOS and Android platforms, coupled with multiple clinical validations [40], [41], [42], [43], underscores its scalability and effectiveness. Similarly, CureApp Smoking Cessation (CASC) integrates behavioral and pharmacological therapies with a mobile exhaled CO checker, demonstrating significant improvements in abstinence rates and reductions in nicotine dependence compared to control groups [44]. This app exemplifies the potential of hybrid digital and pharmacological approaches.

Apps like SmartStop and Craving To Quit! focus on combining technology with behavioral science. SmartStop leverages a programmable nicotine patch synchronized with a smartphone app to address peak craving periods, while Craving To Quit! integrates cognitive behavioral therapy (CBT) and mindfulness practices to disrupt smoking patterns [45], [46]. These interventions highlight the interconnected physiological and psychological dimensions of smoking cessation. By examining how stress compromises prefrontal cortex function and increases smoking vulnerability, researchers illuminate the neurological underpinnings of addiction [47]. Mindfulness therapy offers a promising approach to modulating desire and cigarette use, revealing the complex mechanisms that sustain tobacco dependency [48].

Apps employing gamification and interactive features, such as Clickotine, Smoke Free, Kwit, and Quit Genius, have demonstrated effectiveness in enhancing self-efficacy and motivation through rewards systems, progress tracking, and engaging challenges [49], [50], [51], [52], [53], [54], [55], [56]. In this regard, QuitSTART exemplifies another facet of smoking cessation support, combining progress tracking with strategies to manage cravings and negative moods. The app employs user data to offer personalized challenges, advice, and motivation, ensuring an interactive and engaging cessation journey [57]. Gamified elements appear particularly influential in fostering user engagement and addressing cognitive factors critical to quitting.

Notably, Acceptance and Commitment Therapy (ACT) has emerged as a recurrent theme, underpinning the design of 2MorrowQuit, SmartQuit, and iCanQuit [12], [58], [59]. These apps leverage ACT principles [60] to build psychological flexibility, mitigate cravings, and promote mindfulness, with promising outcomes in abstinence rates and behavior modification. Finally, Quit Genius and other CBT-based apps demonstrate a holistic approach, addressing not only smoking cessation but also broader addiction challenges. Their integration of personalized plans, extensive CBT exercises, and supportive communities reflects a comprehensive strategy aimed at sustaining long-term change [61], [62].

2) Applications Not Yet Clinically Assessed: Several publicly available apps aid in smoking cessation and do not, yet, provide clinical assessment. The LIVESTRONG MyQuit Coach and Quit Smoking: Cessation Nation offer goal-setting and community support. Quit Now! provides motivational messages and supports multiple languages. The Quit Smoking with Andrew Johnson app uses self-hypnosis, while Butt Out provides insights for a smoke-free lifestyle. Get Rich or Die Smoking motivates through monetary incentives, and SmokeFree—Quit Smoking Slowly offers options to quit abruptly or gradually. The Quit Smoking NOW—Max Kirsten app uses hypnosis and NLP techniques, and the Quit Tracker: Stop Smoking app displays financial savings and health benefits. Quit It Lite helps users set personalized goals, and Quit Smoking Hypnosis offers daily hypnosis sessions. Quitter's Circle supports smoking cessation with resources and a quit fund tool. EasyQuit provides a personalized quit plan and a distraction game. Flamy offers personalized plans and rewards, and Smoking Log helps reduce cigarette consumption. All these apps are available on iOS and Android, with some offering premium features. This subsection provided a brief summary of some smartphone apps designed for smoking cessation that lack published peer-review. A more complete list can be found in Table IV.

3) Smartphone Apps Limitations: Engagement with smartphone apps, particularly those designed for smoking cessation, faces several limitations. One key issue is the lack of personalization and adaptability to the user's changing needs and contexts, which can lead to decreased engagement over time [63], [64]. Moreover, many apps do not adequately assess the user's readiness to quit smoking or arrange follow-up, which are crucial for maintaining engagement [65]. Improving engagement could involve incorporating more user-centered design principles, such as real-time messaging with support networks and reducing barriers to access [63]. Furthermore, the use of assessment tools like the Mobile Application Rating Scale (MARS) can provide valuable insights into app quality, including engagement, functionality, aesthetics, and information quality [66], [67], [68]. However, it's important to note that commercialization of apps does not necessarily imply widespread availability to the general public. For instance, the Pivot App operates on a B2B model [69], [70], [71], which may limit its accessibility to only certain organizations or groups. Therefore, while commercial apps may be widely marketed, their actual accessibility may be more limited [72], [73].

4) Apps Usability: The usability and convenience of the described applications play a crucial role. While a generic application may achieve high performance in terms of smoking detection, it could prove inconvenient to use. A fundamental distinction exists between apps that provide information in a standalone manner, without the need for additional devices, and those that operate with multimodal information from multiple sources. Table IV illustrates that most of the described applications do not require additional devices, making them user-friendly tools. However, it is evident that applications utilizing supplementary information, such as SmartStop, Pivot, and CureApp Smoking

TABLE IV
SUMMARY OF THE QUIT SMOKING APPLICATIONS DESCRIBED IN THIS STUDY, INCLUDING THOSE WITH "FREEMIUM" MODELS, WHERE THE APP IS FREE TO DOWNLOAD AND USE, BUT OFFERS ADDITIONAL PAID FEATURES OR CONTENT

Product	Technology	iOS	Android	Sc. Eval.	Availability	Price
LIVESTRONG MyQuit Coach	App	✓	✓		✓	Free
Quit Smoking: Cessation Nation	App		✓			Free
SmartStop	App + Smart Patch			✓		Product under development
Pivot	App + Property Breath Sensor	✓	✓	✓	✓	Under request
CureApp Smoking Cessation	App + Mobile Exhaled CO checker			✓		Private
Craving to Quit!	App	✓	✓	✓	✓	Free (3 days)
QuitNow!	App	✓	✓		✓	Free
Quit Smoking with A. Johnson	App	✓	✓		✓	$2.99
Smoke Free	App	✓	✓	✓	✓	Freemium
Kwit	App	✓	✓	✓	✓	Freemium
Butt Out	App	✓	✓		✓	$6.99 iOS; $2.99 Android
Get Rich or Die Smoking	App		✓		✓	Free
Smoke Free Quit Smoking Slowly	App		✓		✓	Free
Quit Smoking NOW M. Kirsten	App	✓	✓		✓	$4.99
Quit Tracker: Stop Smoking	App	✓	✓		✓	Free
Quit It Lite	App	✓	✓		✓	Free
Quit Smoking Hypnosis	App	✓	✓		✓	Free
quitSTART	App	✓	✓	✓	✓	Free
Quitter's Circle	App	✓	✓		✓	Free
Clickotine	App	✓	✓	✓	✓	Free
2MorrowQuit	App	✓	✓	✓	✓	Free
EasyQuit	App	✓	✓		✓	Freemium
Quit Genius	App	✓	✓	✓	✓	Freemium
Flamy	App		✓		✓	Freemium
Smoking Log	App		✓		✓	Freemium

Cessation, achieve higher performance, following the principle that more data equates to greater knowledge and, consequently, better performance. On the other hand, however, the use of additional devices is in some cases an unfeasible and in others an inconvenience that discourages their long-term use. Therefore, although it will always be easier to use a stand-alone application and simpler to use a multimodal system, the correct trade-off depends on the scenarios where it is to be used.

D. Nicotine Detection in Smoke Detection Systems

Tai et al. [74] introduced the "s-band," a wearable nicotine sensor employing a gold nanodendrite-modified working electrode and a self-assembled monolayer, enabling high sensitivity and stability in detecting nicotine from human sweat. Validated in both buffer solutions and real-world samples from smokers, the sensor reliably identified nicotine levels consistent with cigarette nicotine content, highlighting its potential for public health and personalized medicine applications. Rani et al. [75] advanced the field with a metal-organic nanotube (MONT) sensor capable of selectively detecting nicotine in cigarette smoke at concentrations below 23.3 μ M. The MONT's porous structure, combined with rapid response times (20 seconds) and sunlight stability at room temperature, allows for efficient nicotine detection through visible light-driven binding to metal ions. Its reusability after heating at 110°C under vacuum enhances cost-effectiveness and practicality across gaseous and solution-phase applications. Meanwhile, Rahman et al. [76] developed a wireless, battery-free, skin-mounted nicotine sensor using vanadium dioxide (VO2) technology to detect nicotine vapor from e-cigarettes. By leveraging electron transfer between nicotine molecules and the VO2 surface, this sensor achieves precise vaporized nicotine detection, supported by density functional theory (DFT) calculations and compositional analysis. Its lightweight design facilitates continuous monitoring for both personal and environmental use.

E. Non-Wearable Smoking Detection: Deep Learning, Wireless Signals, Trials, Dataset, and Gesture Detection

1) Smoking Detection Through Vision: Recent advancements in non-wearable smoking detection have made significant strides, leveraging deep learning techniques and novel system designs to enhance accuracy and efficiency. Macalisang et al. [77] developed a smoking detection system using a dataset of 300 images and the YOLOv3 model, achieving high training and validation accuracies of 98.10% and 98.22%, though challenges with detection angles and video quality remained, with accuracies varying from 63% to 98% in real-world testing. Wei et al. [78] expanded this work by building a larger dataset of 9,424 smoking images and employing data augmentation techniques such as Mosaic enhancement, which improved generalization. Their model, optimized with the DIoU_Loss function and adjusted learning rates, showed enhanced performance, particularly in Average Precision (AP) and Intersection over Union (IoU), underscoring the model's robustness. Zhang et al. [79] introduced CBAM-Tiny, a lightweight attention mechanism designed to improve small target detection by refining spatial features with global pooling and utilizing a custom DenseBlock module for better gradient flow. Their model achieved an mAP of 86.32% and a frame rate of 55 frames per second, demonstrating both precision and speed, which is crucial for real-time applications. Finally, Chong [80] developed a real-time system utilizing the Real-Time Streaming Protocol (RTSP) to capture video frames and process them through a custom model trained on the Tsinghua-Tencent 100 K dataset. This system employed

Non-Maximum Suppression (NMS) and a context information correlation algorithm to improve detection accuracy and processing speed, outperforming models like YOLOv3, SSD, and RetinaNet.

2) Detection of Non-Cigarette Smoke: Gaur et al.'s review [81] explores smoking detection, discussing challenges with smoke obscuring data and the features used in algorithms. They highlight the need for dataset testing and advanced methods like quaternionic wavelet features, Kalman filtering, and transmission-based detection. Xu and Xu [82] combined static and dynamic features for AI-based detection. Saponara et al. [83] used deep learning for real-time fire and smoking detection, leveraging the NVIDIA Jetson Nano's CPU (Central Processing Unit) and GPU to parallelize neural networks. They focused on the YOLOv2 detector, achieving a detection rate of 21 FPS. Gu et al.'s study [84] evaluates a Deep Dual-Channel Convolutional Neural Network (DCNN) for smoking detection, which outperforms other models in terms of stability and efficiency. The DCNN surpasses processing times of other models and excels at extracting detailed and basic features. These studies collectively usher in a new era in algorithm-driven fire and smoking detection.

3) Smoking Detection Using Deep Learning: Jeong and Ha [85] explored a deep learning-based system for smoking detection using CCTV footage, integrating OpenPose-based skeleton analysis with specialized hardware for enhanced recognition. Their system preprocesses image data to recognize smoking behavior, coupling it with sensor-equipped devices to detect smoke components, triggering warnings for non-smoking areas. A neural network built with TensorFlow and Keras, optimized with MobileNetV2, achieves 75% accuracy for smoking images and 70% for non-smoking images, offering a promising real-time smoking detection framework. On a different front, Lai et al. [86] focused on smoking cessation by leveraging data from a program in northern Taiwan spanning from 2010 to 2018. Using machine learning models like artificial neural networks (ANN), support vector machines (SVM), random forests (RF), and others, they aimed to predict smoking cessation probabilities based on factors such as patient characteristics, smoking habits, and nicotine dependence scores. The ANN model outperformed others with an accuracy of 0.640 and an ROC value of 0.660, offering a valuable predictive tool for smoking cessation programs. Both studies contribute to the understanding of smoking behavior and cessation, with Jeong and Ha's work enhancing real-time detection through image processing and hardware integration, while Lai et al.'s research provides insights into machine learning's potential in predicting successful smoking cessation.

4) Human Behavior Detection With Wireless Signals: Song et al. [10] developed a contactless AI technology using Channel State Information (CSI) from wireless signals to detect human motion, focusing on distinguishing between sitting and standing. They used USRP devices to collect CSI data from volunteers and analyzed it using MATLAB and scikit-learn. Machine learning models were built and tested, with Random Forest (RF) performing well and K-Nearest Neighbors (KNN) being less effective. An ensemble classifier improved performance, and the CSI dataset outperformed a benchmark dataset. The model was effective in practical applications, with local tests providing GUI predictions and real-time tests offering CSI amplitude graphs and web interface predictions.

5) Smoking Detection Trials: The smoking detection trials conducted across various studies demonstrate the potential for integrating real-time, personalized interventions in smoking cessation. Battalio et al. [87] utilized a Just-in-Time Adaptive Intervention (JITAI) model to help smokers manage stress, a key trigger for relapse. The study incorporated multiple sensors, including chestbands and wristbands, to gather physiological and behavioral data for real-time analysis. By using stress-detection algorithms, the system provided individualized treatment options, such as stress management prompts, to prevent smoking episodes during high-stress moments. In a similar vein, Hernandez et al. [88] focused on the feasibility and effectiveness of mindfulness-based interventions delivered via wearable sensors that tracked physiological indicators associated with negative affect, self-regulation, and smoking behaviors. Using deep learning techniques, the study personalized interventions based on real-time data, offering a more dynamic and tailored approach to smoking cessation. Horvath et al. [89] explored the effectiveness of a smartband-based system that provided automatic smoking detection and mindfulness interventions, including the RAIN technique, which was tailored to help participants recognize and manage cravings. In this trial, data collected from the wearable devices were used to assess treatment fidelity, adherence, and user satisfaction, with smoking behavior and abstinence rates also being tracked.

6) Gesture Detection: Gesture detection has evolved through various approaches, each contributing to the accuracy and efficiency of activity recognition systems. Hnoohom et al. [90] developed an innovative Human Activity Recognition (HAR) workflow incorporating data collection from wearables, pre-processing, model training, and assessment. They introduced the Att-BiLSTM model, which integrated a BiLSTM layer, an attention layer, and a fully connected layer, demonstrating superior performance on the WISDM-HARB Dataset. This model achieved higher accuracy and F1-scores when combining wrist-worn accelerometer and gyroscope data with a 20-second window size, evaluated using metrics such as F-Score, Recall, Precision, and confusion matrices. In contrast, Agac et al. [91] focused on a dynamically adaptable parameter selection method with the Conawact algorithm for activity recognition, which tailored sensor parameters based on activity complexity. This dynamic approach significantly improved the F1-score by 7% for complex activities and by 6% overall, while also reducing energy consumption by 38%, maintaining memory size, and lowering CPU usage by 15%. Their method proved to be particularly effective for activities like "smoking in a group" and "drinking while sitting down," showing improvements of over 20%. Meanwhile, Patel et al. [92] explored 3D gesture recognition through wearables, emphasizing the integration of sensor data from smartwatches and armbands with image/video data. Their work aimed at improving human-machine collaboration, with a focus on gesture and pattern recognition to enhance interaction accuracy and privacy. Although they addressed the complexity of both hardware and software, their study provided a comprehensive gesture-based system designed to streamline interaction, reduce system complexity, and enhance efficiency. Together, these studies highlight significant advancements in gesture detection, with improvements in both accuracy and computational efficiency, contributing to more intuitive and effective human-machine interactions.

IV. Discussion

A. Final Remarks

In this paper, we outlined key strategies for smoking cessation and explored the associated technological advancements. These solutions primarily harness smartphone technology, supported by recent scientific studies like those by Whittaker et al. [93] and Haskins et al. [94]. Imtiaz et al. [95] also conducted a review on wearable technology monitoring of cigarette smoking, providing an organized classification of methods based on technology exploitation, such as inertial sensors, breathing sensors, acoustic sensors, and cameras. Our study delves deeper into smoking detection technologies, focusing on detailed explanations of employed algorithms and corresponding experimental outcomes. Additionally, we examined various smartphone applications designed to aid smoking cessation, emphasizing apps supported by rigorous scientific evaluation and approval.

Many cyberpsychological interventions focus on altering user behavior. These behavioral interventions are classified using the Behavior Change Technique Taxonomy v1 (BCTTv1) [96]. Without this classification, researchers cannot specify the precise behavioral techniques applied in technology designed to promote health empowerment. For instance, multiple researchers or technology developers might claim to use "motivational strategies" to encourage people to quit smoking. However, each of them might employ different behavioral techniques while using the same label. While some recent scientific studies demonstrate promising results, they also present challenges when it comes to real-life applications. For example, the research by Chen et al. cited in Reference [38] exhibits impressive outcomes. Nevertheless, its evaluation protocol only considers six movements performed by right-handed smokers in highly controlled conditions, rendering it incomparable to the variability of real-life scenarios where users engage in diverse daily activities in unique ways. Additionally, the system relies on two armbands, making it suitable only for experimental settings and challenging to translate into a practical product.

B. Comparison With Previous Review

Smoking detection technologies have evolved significantly, driven by advancements in hardware and software. Modern approaches outperform earlier methods [17], leveraging sophisticated sensors, network architectures, and autonomous systems with minimal reliance on external devices. Recent studies [33], [34] report high performance, with F1-scores exceeding 95%, underscoring the potential of these innovations. Our research builds on these developments, proposing an integrated framework that combines wearable sensors, machine learning, and mobile applications to enable real-time, adaptive interventions. This comprehensive approach addresses limitations in traditional methods by offering continuous monitoring, personalized feedback, and discreet digital health solutions.

Despite these advancements, significant challenges persist, including limited standardization, scalability issues, and insufficient clinical validation. Prior reviews [64], [97], [98] primarily focus on application quality, often neglecting the role of emerging technologies like machine learning-enhanced interventions. While studies such as Zhou's [99] explored SMS-based strategies, the efficacy of app-based solutions remains inconsistent. Our review emphasizes the need for adaptive, evidence-based tools that integrate behavioral science with advanced analytics, bridging the gap between experimental findings and practical usability. By addressing these gaps, the proposed framework represents a pivotal step toward scalable, user-centered solutions that transform digital smoking cessation interventions.

C. Limitations

One notable limitation of this scoping review is that it was not preregistered, which may affect the transparency and reproducibility of the review process. Preregistration would help ensure clarity in the review's methodology and reduce the potential for bias. Also, while this review highlights promising advancements, it notes a lack of standardization in evaluation methods across studies, making direct comparisons difficult. Future research should focus on developing robust, real-world testing frameworks and fostering cross-disciplinary collaborations to ensure these technologies can transition effectively from experimental to clinical and public health settings. Furthermore, the evaluation protocols used in the aforementioned scientific papers have limitations, such as a small number of participants/sample data, limited diversity in data collection (e.g., right/left-handed, male/female, etc.), and lack of comparison with other state-of-the-art methods using the same dataset and evaluation protocol. Most of the described research works face these challenges. Our goal is to develop a comprehensive system that incorporates the most promising solutions and rigorously assesses their suitability for clinical programs. While many apps depend on participant self-report (e.g., diary apps), solutions like SmokeBeat, which utilize wearable sensors (e.g., armbands/smartwatches), have the potential to enhance existing approaches by offering automatic feedback and objective confirmation of smoking status. We advocate for increased investment from both the research community and the industry in this direction.

D. Beyond Technical Limitations

Smoking detection technologies, particularly those using wearable devices and AI, show promise in identifying smoking events [35], [100]. However, real-life applications face several challenges, such as the dynamic nature of environments, varying conditions, and obstacles that affect smoking detection algorithms [100]. Moreover, systems that perform well in controlled settings often struggle in real-life scenarios due to variability in gestures and environmental factors [17]. The constant monitoring required by these technologies may also impact personal autonomy [101], potentially leading to resistance and reduced effectiveness. Social norms around smoking can further influence the acceptability of these technologies [102], [103].

The development of effective smoking cessation technologies is hindered by limitations in hardware, sensors, and software. Current wearable devices rely on indirect indicators like heart rate, which are influenced by factors beyond smoking, making the development of accurate sensors (e.g., for carbon monoxide or nicotine detection) essential. Moreover, sensor reliability is compromised by placement, movement, and environmental conditions. Software also faces challenges with user engagement, dropout rates, and motivation, which can be improved through personalization, gamification, and cognitive-behavioral therapy. Machine learning algorithms, while helpful, may struggle with data quality and bias, requiring advancements for better feedback and outcomes. Overcoming these obstacles, along with integrating technologies into healthcare systems and addressing health disparities, will be crucial for improving long-term cessation success. These technologies can be particularly useful in healthcare settings for real-time feedback and monitoring, supporting users in understanding their habits and empowering informed decisions on quitting [104].

E. Implications and Future Perspectives

The findings of this scoping review highlight the substantial potential of digital and mobile health technologies in smoking detection and cessation. Wearable sensors, machine learning models, and smartphone applications have demonstrated high accuracy and engagement in controlled settings [33], [34], [45], offering real-time feedback and personalized support. These tools could significantly enhance clinical smoking cessation programs, increasing quit rates and improving user adherence [40], [44]. However, their real-world application faces challenges, including variability in user behaviors, environmental contexts, and device usability [34], [38], [100]. Many solutions lack rigorous scientific validation and standardized evaluations, limiting their generalizability and adoption [40], [45]. Overcoming these barriers requires a focus on inclusivity, ensuring tools address diverse populations, and investment in developing technologies that balance efficiency, usability, and effectiveness [34], [48].

Looking ahead, integrating smoking cessation tools into broader health ecosystems could revolutionize efforts to combat tobacco addiction. Drawing parallels with advances in physiological monitoring, such as Trenta's work on non-invasive heart rate variability tracking for driver safety, future smoking cessation technologies could leverage similar contactless measurement approaches to assess stress levels and craving states [45], [97], [105]. Just as wearable devices and machine learning can be used to track visitors' behavior in cultural heritage sites, similar methodologies could be applied to monitor smokers' behaviors in real-time. The use of egocentric video and sensor-based technologies to assess visitors' interactions with cultural environments can inspire innovations for smoking cessation, where data from wearables or environmental sensors can be analyzed to identify patterns of craving, stress, and relapse, enabling more personalized interventions [106], [107]. Future research should focus on real-world testing frameworks and leveraging advanced technologies like AI for dynamic and adaptive interventions.

V. Conclusion

While some solutions are promising and supported by experimental data, many commercially available products lack the reliability needed for clinical integration. Wearable systems, for instance, can be affected by individual factors such as posture or dominant hand, leading to performance variations. Cole et al. [108] addressed these issues by standardizing accelerometer data from various smartwatch positions, which improved the accuracy of pre-trained predictors like Artificial Neural Networks. Everyday use also varies widely; for example, some users smoke while driving or working. Additionally, battery-powered devices face challenges with limited battery life. Real-time signal processing algorithms must be optimized for these constraints, as exemplified by the energy-efficient Bluetooth Low Energy (BLE) protocol [109]. To overcome these challenges, increased investment in the study, development, and scientific evaluation of smoking cessation technology is essential to ensure reliable and high-performance systems in real-life scenarios.

References

[1] R. O'Connor, "Health matters: Stopping smoking–what works?" 2018. (Accessed: Nov. 22, 2024) [Online]. Available: https://api.semanticscholar.org/CorpusID81102058

[2] R. West, "Tobacco smoking: Health impact, prevalence, correlates and interventions," *Psychol. Health*, vol. 32, no. 8, pp. 1018–1036, Aug. 2017.

[3] V. U. Ekpu and A. K. Brown, "The economic impact of smoking and of reducing smoking prevalence: Review of evidence," *Tobacco Use Insights*, vol. 8, Jan. 2015, Art. no. TUI.S15628.

[4] L. Silver and C. Huang, "In emerging economies, smartphone and social media users have broader social networks," 2019. (Accessed: Nov. 22, 2024). [Online]. Available: https://www.tinyurl.com/2ywqambu/

[5] E. S. Gritti, R. F. Bornstein, and B. Barbot, "The smartphone as a "significant other": Interpersonal dependency and attachment in maladaptive smartphone and social networks use," *BMC Psychol.*, vol. 11, no. 1, Sep. 2023, Art. no. 296.

[6] MIT Technol. Rev., "Smartphone innovation in the third decade of the 21st century," 2020. (Accessed: Nov. 22, 2024). [Online]. Available: https://www.technologyreview.com/2020/03/05/905500/smartphone-innovation-in-the-third-decade-of-the-21st-century/

[7] R. Wike et al., "Internet, smartphone and social media use in advanced economies," 2022. (Accessed: Nov. 22, 2024). [Online]. Available: https://www.tinyurl.com/29kxkr59/

[8] G. Harari, "Phones are making people more, not less, social, researcher says," *Phys.org*, 2020. (Accessed: Nov. 22, 2024). [Online]. Available: https://phys.org/news/2020-01-people-social.html

[9] J. B. Sanger, L. Sitanayah, and V. D. Kumenap, "Detection system for cigarette smoke," in *Proc. 4th Int. Conf. Inf. Technol. Inf. Syst. Elec. Eng.*, Nov. 2019, pp. 145–149.

[10] Y. Song, W. Taylor, Y. Ge, K. Dashtipour, M. A. Imran, and Q. H. Abbasi, "Design and implementation of a contactless ai-enabled human motion detection system for next-generation healthcare," in *Proc. IEEE Int. Conf. Smart Internet Things (SmartIoT)*, Aug. 2021, pp. 112–119.

[11] Y. Valikhujaev, A. Abdusalomov, and Y. I. Cho, "Automatic fire and smoke detection method for surveillance systems based on dilated CNNs," *Atmosphere*, vol. 11, no. 11, Nov. 2020, Art. no. 1241.

[12] J. B. Bricker, N. L. Watson, K. E. Mull, B. M. Sullivan, and J. L. Heffner, "Efficacy of smartphone applications for smoking cessation," *JAMA Intern. Med.*, vol. 180, no. 11, pp. 1–9, Sep. 2020.

[13] International Electrotechnical Commission (IEC), "New standards for wearable technologies," 2021. (Accessed: Nov. 22, 2024 [Online]. Available: https://etech.iec.ch/issue/2021-04/new-standards-for-wearable-technologies

[14] Built In, "What is wearable technology? examples of wearables," 2024. (Accessed: Nov. 22, 2024). [Online]. Available: https://builtin.com/wearables

[15] M. PC, "Must-have devices for your home office," 2024. (Accessed: Nov. 22, 2024). [Online]. Available: https://www.pcmag.com/picks/must-have-devices-for-your-home-office

[16] Smart Offices and Smart Homes, "Smart offices and smart homes," (Accessed: Nov. 22, 2024). [Online]. Available: https://smartofficesandsmarthomes.com

[17] A. Ortis, P. Caponnetto, R. Polosa, S. Urso, and S. Battiato, "A report on smoking detection and quitting technologies," *Int. J. Environ. Res. Public Health*, vol. 17, no. 77, Jan. 2020, Art. no. 2614.

[18] Web MD, "'smart' jewelry could be the future of quitting cigarettes," 2023. (Accessed: Nov. 22, 2024). [Online]. Available: https://www.webmd.com/smoking-cessation/news/20230330/smart-jewelry-could-be-future-quitting-cigarettes

[19] N. Atlas, "Wearable electronic device could help smokers kick the habit," 2014. (Accessed: Nov. 22, 2024). [Online]. Available: https://newatlas.com/smartstop-quit-smoking-wearable/32537

[20] J. I. Vidrine et al., "Comparison of an automated smartphone-based smoking cessation intervention versus standard quitline-delivered treatment among underserved smokers: Protocol for a randomized controlled trial," *BMC Public Health*, vol. 22, no. 1, Mar. 2022, Art. no. 563.

[21] G. Maguire, H. Chen, R. Schnall, W. Xu, and M.-C. Huang, "Smoking cessation system for preemptive smoking detection," *IEEE Internet Things J.*, vol. 9, no. 5, pp. 3204–3214, Mar. 2022.

[22] V. Sharma, S. Mukhopadhyay, S. Bhattacharya, S. Dey, and A. Ghose, "Puffconv: A system for online and on-device puff detection for smoking cessation," in *Proc. IEEE Int. Conf. Pervasive Comput. Commun. Workshops other Affiliated Events (PerCom Workshops)*, Mar. 2023, pp. 595–600.

[23] Expansive, "What is a smart office?," 2021. Accessed: Nov. 22, 2024. [Online]. Available: https://expansive.com/what-is-a-smart-office

[24] M. J. Page et al., "The prisma 2020 statement: An updated guideline for reporting systematic reviews," *BMJ*, vol. 372, no. 71, Mar. 2021.

[25] M. B. Eriksen and T. F. Frandsen, "The impact of patient, intervention, comparison, outcome (PICO) as a search strategy tool on literature search quality: A systematic review," *J. Med. Library Assoc.*, vol. 106, no. 4, Oct. 2018.

[26] P. Lopez-Meyer, S. Tiffany, and E. Sazonov, "Identification of cigarette smoke inhalations from wearable sensor data using a support vector machine classifier," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*. IEEE, 2012, pp. 4050–4053.

[27] P. Lopez-Meyer, Y. Patil, T. Tiffany, and E. Sazonov, "Detection of hand-to-mouth gestures using a rf operated proximity sensor for monitoring cigarette smoking," *Open Biomed. Eng. J.*, vol. 7, pp. 41–49, Apr. 2013.

[28] R. Dar, "Effect of real-time monitoring and notification of smoking episodes on smoking reduction: A pilot study of a novel smoking cessation app," *Nicotine Tobacco Res.*, vol. 20, no. 12, pp. 1515–1518, 2018.

[29] A. Parate et al., "RisQ: Recognizing smoking gestures with inertial sensors on a wristband," in *Proc. 12th Annu. Int. Conf. Mobile Syst. Appl. Serv.* MobiSys '14. New York, NY, USA: Association for Computing Machinery, Jun. 2014, pp. 149–161.

[30] A. L. Skinner, C. J. Stone, H. Doughty, and M. R. Munafó, "Stopwatch: The preliminary evaluation of a smartwatch-based system for passive detection of cigarette smoking," *Nicotine & Tobacco Research: Official J. Soc. Res. Nicotine Tobacco*, vol. 21, pp. 257–261, Jan. 2019.

[31] V. Y. Senyurek, M. H. Imtiaz, P. Belsare, S. Tiffany, and E. Sazonov, "A CNN-LSTM neural network for recognition of puffing in smoking episodes using wearable sensors," *Biomed. Eng. Lett.*, vol. 10, no. 2, pp. 195–203, Jan., 2020.

[32] A. Kirmizis, K. Kyritsis, and A. Delopoulos, "A bottom-up method towards the automatic and objective monitoring of smoking behavior in-the-wild using wrist-mounted inertial sensors," in *Proc. 43rd Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*. IEEE, 2021, pp. 6867–6870.

[33] S. Agac, M. Shoaib, and O. Durmaz Incel, "Smoking recognition with smartwatch sensors in different postures and impact of user's height," *J. Ambient Intell. Smart Environments*, vol. 12, no. 3, pp. 239–261, Apr. 2020.

[34] N. Hnoohom, S. Mekruksavanich, and A. Jitpattanakul, "An efficient ResNetSE architecture for smoking activity recognition from smartwatch," *Intell. Automat. Soft Comput.*, vol. 35, no. 1, pp. 1245–1259, 2022.

[35] S. S. Thakur, P. Poddar, and R. B. Roy, "Real-time prediction of smoking activity using machine learning based multi-class classification model," *Multimedia Tools Appl.*, vol. 81, pp. 14529–14551, Feb. 2022.

[36] S. Mukhopadhyay, S. Dey, and A. Ghose, "Tinypuff: Automated design of tiny smoking puff classifiers for body worn devices," in *Proc. 8th Workshop Body-Centric Comput. Syst.*, New York, NY, USA: Association for Computing Machinery, Jun. 2023, pp. 7–12.

[37] R. Alharbi et al., "Smokemon: Unobtrusive extraction of smoking topography using wearable energy-efficient thermal," *Proc. ACM Interactive Mobile Wearable Ubiquitous Technol.*, vol. 6, no. 4, pp. 1–25, Jan. 2023.

[38] T. Chen et al., "Are you smoking? automatic alert system helping people keep away from cigarettes," *Smart Health*, vol. 9, no. 10, pp. 158–169, 2018.

[39] M. Lewis-Duarte, "RAIN: A mindful framework for addressing anxious thoughts," 2021. (Accessed: Sep. 12, 2024). [Online]. Available: https://adaa.org/living-with-anxiety/personal-stories/rain-mindful-framework-addressing-anxious-thoughts

[40] J. D. Marler, C. A. Fujii, J. A. Galanko, D. J. Balbierz, and D. S. Utley, "Durability of abstinence after completing a comprehensive digital smoking cessation program incorporating a mobile app, breath sensor, and coaching: Cohort study," *J. Med. Internet Res.*, vol. 23, no. 2, Feb. 2021, Art. no. e25578.

[41] J. D. Marler, C. A. Fujii, M. T. Utley, D. J. Balbierz, J. A. Galanko, and D. S. Utley, "Outcomes of a comprehensive mobile smoking cessation program with nicotine replacement therapy in adult smokers: Pilot randomized controlled trial," *JMIR mHealth uHealth*, vol. 10, no. 11, Nov. 2022, Art. no. e41658.

[42] J. D. Marler, C. A. Fujii, D. S. Utley, L. J. Tesfamariam, J. A. Galanko, and H. Patrick, "Initial assessment of a comprehensive digital smoking cessation program that incorporates a mobile app, breath sensor, and coaching: Cohort study," *JMIR mHealth uHealth*, vol. 7, no. 2, Feb. 2019, Art. no. e12609.

[43] H. Patrick, C. A. Fujii, D. B. Glaser, D. S. Utley, and J. D. Marler, "A comprehensive digital program for smoking cessation: Assessing feasibility in a single-group cohort study," *JMIR mHealth uHealth*, vol. 6, no. 12, Dec. 2018, Art. no. e11708.

[44] K. Masaki et al., "A randomized controlled trial of a smoking cessation smartphone application with a carbon monoxide checker," *npj Digit. Med.*, vol. 3, no. 1, Mar. 2020, Art. no. 35.

[45] K. A. Garrison et al., "Craving to quit: A randomized controlled trial of smartphone app–based mindfulness training for smoking cessation," *Nicotine Tobacco Res.*, vol. 22, no. 3, pp. 324–331, 2020.

[46] J. A. Brewer et al., "Mindfulness training for smoking cessation: Results from a randomized controlled trial," *Drug Alcohol Dependence*, vol. 119, no. 3, pp. 72–80, 2011.

[47] A. F. T. Arnsten, "Stress signalling pathways that impair prefrontal cortex structure and function," *Nature Reviews. Neurosci.*, vol. 10, no. 6, pp. 410–422, Jun. 2009.

[48] H. M. Elwafi, K. Witkiewitz, S. Mallik, T. A. Thornhill, and J. A. Brewer, "Mindfulness training for smoking cessation: Moderation of the relationship between craving and cigarette use," *Drug Alcohol Dependence*, vol. 130, no. 1–3, pp. 222–229, 2013.

[49] J. Webb et al., "Preliminary outcomes of a digital therapeutic intervention for smoking cessation in adult smokers: Randomized controlled trial," *JMIR Ment. Health*, vol. 7, no. 10, Oct. 2020, Art. no. e22833.

[50] N. B. Rajani, N. Mastellos, and F. T. Filippidis, "Impact of gamification on the self-efficacy and motivation to quit of smokers: Observational study of two gamified smoking cessation mobile apps," *JMIR Serious Games*, vol. 9, Apr. 2021, Art. no. e27290.

[51] B. M. Iacoviello et al., "Clickotine, a personalized smartphone app for smoking cessation: Initial evaluation," *JMIR mHealth uHealth*, vol. 5, no. 4, p. e56, 2017.

[52] C. Tudor-Sfetea et al., "Evaluation of two mobile health apps in the context of smoking cessation: Qualitative study of cognitive behavioral therapy (CBT) versus non-CBT-based digital solutions," *JMIR mHealth uHealth*, vol. 6, Apr. 2018, Art. no. e9405.

[53] N. B. Rajani, L. Bustamante, D. Weth, L. Romo, N. Mastellos, and F. T. Filippidis, "Engagement with gamification elements in a smoking cessation app and short-term smoking abstinence: Quantitative assessment," *JMIR Serious Games*, vol. 11, Feb. 2023, Art. no. e39975.

[54] S. Sanchez, A. Kundu, E. Limanto, P. Selby, N. B. Baskerville, and M. Chaiton, "Smartphone apps for vaping cessation: Quality assessment and content analysis," *JMIR mHealth uHealth*, vol. 10, Mar. 2022, Art. no. e31309.

[55] L. A. Bustamante and L. Romo, "Validation of the french smoking cessation motivation scale with french smokers using a mobile app for smoking cessation," *Eur. J. Investigation Health, Psychol. Educ.*, vol. 12, no. 88, pp. 1179–1190, 2022.

[56] P. Caponnetto, M. Casu, D. Crane, L. Ross, M. C. Quattropani, and R. Polosa, "User evaluation and feasibility test of an app designed for smoking cessation in italian people who smoke: Preliminary findings from an uncontrolled pre-test post-test open study," *BMC Psychol.*, vol. 11, no. 1, 2023, Art. no. 387.

[57] M. A. Gowarty, M. R. Longacre, R. Vilardaga, N. J. Kung, A. E. Gaughan-Maher, and M. F. Brunette, "Usability and acceptability of two smartphone apps for smoking cessation among young adults with serious mental illness: Mixed methods study," *JMIR Ment. Health*, vol. 8, no. 7, 2021, Art. no. e26873.

[58] J. B. Bricker et al., "Single-arm trial of the second version of an acceptance & commitment therapy smartphone application for smoking cessation," *Drug Alcohol Dependence*, vol. 170, pp. 37–42, 2017.

[59] M. O'Connor, R. Whelan, J. Bricker, and L. McHugh, "Randomized controlled trial of a smartphone application as an adjunct to acceptance and commitment therapy for smoking cessation," *Behav. Ther.*, vol. 51, no. 1, pp. 162–177, Jan. 2020.

[60] M. P. Twohig, "Acceptance and commitment therapy: Introduction," *Cogn. Behav. Pract.*, vol. 19, no. 4, pp. 499–507, Nov. 2012.

[61] N. B. Rajani, N. Mastellos, and F. T. Filippidis, "Self-efficacy and motivation to quit of smokers seeking to quit: Quantitative assessment of smoking cessation mobile apps," *JMIR mHealth uHealth*, vol. 9, Apr. 2021, Art. no. e25030.

[62] Y. Lin, C. Tudor-Sfetea, S. Siddiqui, Y. Sherwani, M. Ahmed, and A. B. Eisingerich, "Effective behavioral changes through a digital mhealth app: Exploring the impact of hedonic well-being, psychological empowerment and inspiration," *JMIR mHealth uHealth*, vol. 6, no. 6, 2018, Art. no. e10024.

[63] J. Chen, J. Chu, S. Marsh, T. Shi, and C. Bullen, "Smartphone app-based interventions to support smoking cessation in smokers with mental health conditions: A systematic review," *Psych*, vol. 5, no. 44, pp. 1077–1100, 2023.

[64] K. W. Bold et al., "Smartphone apps for smoking cessation: Systematic framework for app review and analysis," *J. Med. Internet Res.*, vol. 25, no. 1, Oct. 2023, Art. no. e45183.

[65] B. B. Hoeppner et al., "How smart are smartphone apps for smoking cessation? a content analysis," *Nicotine Tobacco Res.*, vol. 18, no. 5, pp. 1025–1031, May 2016.

[66] L. Hides, D. Kavanagh, S. Stoyanov, O. Zelenko, D. Tjondronegoro, and M. Mani, "The mobile application rating scale (MARS): A new tool for assessing the quality of health apps," in Young and *Proc. Well Cooperative Res. Centre (CRC) Connect Nat. Conf.*, 2014, pp. 3–4.

[67] S. R. Stoyanov, L. Hides, D. J. Kavanagh, O. Zelenko, D. Tjondronegoro, and M. Mani, "Mobile app rating scale: A new tool for assessing the quality of health mobile apps," *JMIR mHealth uHealth*, vol. 3, Mar. 2015, Art. no. e3422.

[68] Y. Terhorst et al., "Validation the mobile application rating scale (MARS)," *PLoS One*, vol. 15, Nov. 2020.

[69] É. G. Caya, "How to pivot startups in b2b - the complete guide," 2015. (Accessed: Nov. 22, 2024). [Online]. Available: https://leanb2bbook.com/blog/how-to-pivot-a-b2b-startup

[70] F. Moretti, "Startup pivot, ovvero l'arte di cambiare il modello di business (in corsa)," 2017. (Accessed: Nov. 22, 2024). [Online]. Available: http://res-group.eu/articoli/startup-pivot-ovvero-come-cambiare-il-modello-di-business

[71] E. Abirascid, "Startup pivot, circleme diventa anche B2B," 2017. (Accessed: Nov. 22, 2024). [Online]. Available: https://www.startupbusiness.it/startup-pivot-circleme-diventa-anche-business-to-business/91570/

[72] Z. Huang and M. Benyoucef, "A systematic literature review of mobile application usability: Addressing the design perspective," *Universal Access Inf. Soc.*, vol. 22, no. 3, pp. 715–735, Aug. 2022.

[73] A. S. Alrumayh, S. M. Lehman, and C. C. Tan, "Emerging mobile apps: Challenges and open problems," *CCF Trans. Pervasive Comput. Interaction*, vol. 3, no. 1, pp. 57–75, Feb. 2021.

[74] L.-C. Tai et al., "Nicotine monitoring with a wearable sweat band," *ACS Sensors*, vol. 5, no. 6, pp. 1831–1837, May 2020.

[75] D. Rani, K. K. Bhasin, and M. Singh, "Visible-light-assisted gasochromic sensing of nicotine from cigarette smoke by metal-organic nanotube," *ACS Mater. Lett.*, vol. 2, no. 1, pp. 9–14, Nov. 2019.

[76] M. A. Rahman et al., "Nicotine sensors for wearable battery-free monitoring of vaping," *ACS Sensors*, vol. 7, no. 1, pp. 82–88, Dec. 2021, pMID: 34877860.

[77] J. R. Macalisang, N. E. Merencilla, M. A. D. Ligayo, M. P. Melegrito, and R. R. Tejada, "Eye-smoker: A machine vision-based nose inference system of cigarette smoking detection using convolutional neural network," in *Proc. IEEE 7th Int. Conf. Eng. Technol. Appl. Sci.*. IEEE, 2020, pp. 1–5.

[78] Z. Wei, Y. X. Zhu, Q. X. Li, and C. Wang, "Improved smoking target detection algorithm based on yolov3," *Proc. J. Physics: Conf. Ser.*, vol. 1883, no. 1, Apr. 2021, Art. no. 012052.

[79] Z. Zhang, H. Chen, R. Xiao, and Q. Li, "Research on smoking detection based on deep learning," *Proc. J. Phys.: Conf. Ser.*, vol. 2024, no. 1, Sep. 2021, Art. no. 012042.

[80] J. Chong, "An intelligent detection approach for smoking behavior," *Int. J. Cogn. Inform. Natural Intell.*, vol. 17, no. 1, pp. 1–18, 2023.

[81] A. Gaur, A. Singh, A. Kumar, A. Kumar, and K. Kapoor, "Video flame and smoke based fire detection algorithms: A literature review," *Fire Technol.*, vol. 56, no. 5, pp. 1943–1980, Apr. 2020.

[82] Z. Xu and J. Xu, "Automatic fire smoke detection based on image visual features," in *Proc. Int. Conf. Comput. Intell. Secur. Workshops (CISW 2007)*, Dec. 2007, pp. 316–319.

[83] S. Saponara, A. Elhanashi, and A. Gagliardi, "Real-time video fire/smoke detection based on CNN in antifire surveillance systems," *J. Real-Time Image Process.*, vol. 18, pp. 889–900, Nov. 202o.

[84] K. Gu, Z. Xia, J. Qiao, and W. Lin, "Deep dual-channel neural network for image-based smoke detection," *IEEE Trans. Multimedia*, vol. 22, no. 2, pp. 311–323, Feb. 2020.

[85] T.-Y. Jeong and I.-K. Ha, "Openpose based smoking gesture recognition system using artificial neural network," *Tehnički Glasnik*, vol. 17, no. 2, pp. 251–259, 2023.

[86] C.-C. Lai, W.-H. Huang, B. C.-C. Chang, and L.-C. Hwang, "Development of machine learning models for prediction of smoking cessation outcome," *Int. J. Environ. Res. Public Health*, vol. 18, no. 5,2021, Art. no. 2584.

[87] S. L. Battalio et al., "Sense2stop: A micro-randomized trial using wearable sensors to optimize a just-in-time-adaptive stress management intervention for smoking relapse prevention," *Contemporary Clin. Trials*, vol. 109, 2021, Art. no. 106534.

[88] L. M. Hernandez, D. W. Wetter, S. Kumar, S. K. Sutton, and C. Vinci, "Smoking cessation using wearable sensors: Protocol for a microrandomized trial," *JMIR Res. Protoc.*, vol. 10, no. 2, 2021, Art. no. e22877.

[89] M. Horvath et al., "Smartband-based automatic smoking detection and real-time mindfulness intervention: Protocol for a feasibility trial," *JMIR Res. Protoc.*, vol. 10, no. 11, 2021, Art. no. e32521.

[90] N. Hnoohom, A. Jitpattanakul, I. You, and S. Mekruksavanich, "Deep learning approach for complex activity recognition using heterogeneous sensors from wearable device," in *Proc. Res. Invention Innov. Congr. Innov. Electricals Electron.*, 2021, pp. 60–65.

[91] S. Agac, M. Shoaib, and O. D. Incel, "Context-aware and dynamically adaptable activity recognition with smart watches: A case study on smoking," *Comput. Elect. Eng.*, vol. 90, 2021, Art. no. 106949.

[92] H. I. Patel, S. A. Senanayake, and J. Triloka, "Human-system interaction interface utilizing 3 D gesture recognition techniques based on wearable technology," in *Proc. 5th Int. Conf. Innov. Technol. Intell. Syst. Ind. Appl.*, Nov. 2020, pp. 1–9.

[93] R. Whittaker, H. McRobbie, C. Bullen, A. Rodgers, Y. Gu, and R. Dobson, "Mobile phone text messaging and app-based interventions for smoking cessation," *Cochrane Database Systematic Rev.*, vol. 10, no. 1, Oct. 2019, Art. no. CD006611.

[94] B. L. Haskins, D. Lesperance, P. Gibbons, and E. D. Boudreaux, "A systematic review of smartphone applications for smoking cessation," *Transl. Behav. Med.*, vol. 7, no. 2, pp. 292–299, 2017.

[95] M. H. Imtiaz, R. I. Ramos-Garcia, S. Wattal, S. Tiffany, and E. Sazonov, "Wearable sensors for monitoring of cigarette smoking in free-living: A systematic review," *Sensors*, vol. 19, no. 21, 2019, Art. no. 4678.

[96] S. Michie et al., "The behavior change technique taxonomy (V1) of 93 hierarchically clustered techniques: Building an international consensus for the reporting of behavior change interventions," *Ann. Behav. Med.*, vol. 46, no. 1, pp. 81–95, Aug. 2013.

[97] Y. E. Fang et al., “Effectiveness of ehealth smoking cessation interventions: Systematic review and meta-analysis,” *J Med Internet Res*, vol. 25, Jul. 2023, Art. no. e45111.

[98] S. Li, Z. Qu, Y. Li, and X. Ma, “Efficacy of E-Health Interventions for Smoking Cessation Management in Smokers: A Systematic Review and Meta-Analysis,” *eClinicalMedicine*, vol. 68, 2024, Art. no. 102412.

[99] X. Zhou et al., “Mobile phone–based interventions for smoking cessation among young people: Systematic review and meta-analysis,” *JMIR Mhealth Uhealth*, vol. 11, Sep. 2023, Art. no. e48253.

[100] A. Khan, S. Khan, B. Hassan, and Z. Zheng, “CNN-based smoker classification and detection in smart city application,” *Sensors*, vol. 22, no. 3, 2022, Art. no. 892.

[101] D. Halliday, “Tobacco bans and smokers’ autonomy,” *J. Med. Ethics*, vol. 42, no. 5, pp. 303–304, 2016.

[102] C. Tate et al., “Socio-environmental and psychosocial predictors of smoking susceptibility among adolescents with contrasting socio-cultural characteristics: A comparative analysis,” *BMC Public Health*, vol. 21, Dec. 2021, Art. no. 2240.

[103] J. Badham, H. McAneney, L. Dunne, F. Kee, A. Thurston, and R. F. Hunter, “The importance of social environment in preventing smoking: An analysis of the dead cool intervention,” *BMC Public Health*, vol. 19, no. 1, 2019, Art. no. 1182.

[104] C. Morriscey, A. Shephard, A. v. Houdt, D. Kerr, and S. P. Barrett, “Using ’smart’ technology to aid in cigarette smoking cessation: Examining an innovative way to monitor and improve quit attempt outcomes,” *J. Smoking Cessation*, vol. 14, no. 3, pp. 149–154, Sep. 2019.

[105] F. Trenta, S. Conoci, F. Rundo, and S. Battiato, “Advanced motion-tracking system with multi-layers deep learning framework for innovative car-driver drowsiness monitoring,” in *Proc. 14th IEEE Int. Conf. Autom. Face & Gesture Recognit.*, 2019, pp. 1–5.

[106] F. Ragusa, A. Furnari, S. Battiato, G. Signorello, and G. M. Farinella, “EGO-CH: Dataset and fundamental tasks for visitors behavioral understanding using egocentric vision,” *Pattern Recognit. Lett.*, vol. 131, pp. 150–157, 2020.

[107] A. Ortis, G. M. Farinella, V. D’Amico, L. Addesso, G. Torrisi, and S. Battiato, “Organizing egocentric videos of daily living activities,” *Pattern Recognit.*, vol. 72, pp. 207–218, 2017.

[108] C. A. Cole, J. F. Thrasher, S. M. Strayer, and H. Valafar, “Resolving ambiguities in accelerometer data due to location of sensor on wrist in application to detection of smoking gesture,” in *Proc. IEEE EMBS Int. Conf. Biomed. Health Informat.*, 2017, pp. 489–492.

[109] M. Honkanen, A. Lappetelainen, and K. Kivekas, “Low end extension for bluetooth,” in *Proc. IEEE Radio Wireless Conf.*. IEEE, 2004, pp. 199–202.