Addressing Psychosocial and Lifestyle Risk Factors to Promote Primary Cancer Prevention: an integrated platform to promote behavioural change (IBeCHANGE)

Project Number: 101136840

D2.1 - Mapping of Behavioural and Psychosocial Protective and Risk Factors

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List of Abbreviations

ABR	Area-based Residential
ACE	Adverse Childhood Experience
AN	Anorexia Nervosa
BMI	Body Mass Index
BR	Breast cancer
CC	Colorectal cancer
CCA	Cholangiocarcinoma
CI	Confidence Interval
CG	Cancer in general
CNS	Central Nervous System
CRC	Colorectal Cancer
EA	Educational Attainment
EC	Esophageal Cancer
ES	Effect-size
GL	Grey Literature
HG	Health in general
HR	Hazard Ratio
LC	Lung cancer
MA	Meta-analysis
MR	Mendelian Randomization
MVPA	Moderate-to-vigorous physical activity
N/A	Not Applicable
OC	Oral Cancer
OCC	Oral Cavity Cancer
OCPC	Oral and Oropharyngeal Cancer
OR	Odds Ratio
OSC	Occupational Social Class
PTSD	Post-traumatic Stress Disorder
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RL	Reference List
SEP	Socio-economic Position
SES	Socio-economic Status
SIA	Small Intestine Adenocarcinoma
SIR	Standardized Incidence Ratio
SR	Systematic Review
SRMA	Systematic Review and Meta-analysis
TPA	Total physical activity
RR	Relative Risk
WD	Wearable Device

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Executive Summary

The current deliverable (**D2.1**) reflects the work carried out under Work Package 2 (WP2) of the iBeChange project. Specifically, the reported results relate to **Task 2.1 -** "Psychological and ontological mapping of lifestyle risk and protective factors" and **Task 2.2 -** "Psychological and ontological mapping of psychosocial risk and protective factors". The results obtained in D.2.1 will inform the complex and dynamic interaction between psychosocial and behavioural variables and their impact on cancer diagnosis, thus defining the theoretical and methodological basis for the development of the iBeChange platform. Consistently, the main objective of this **D2.1** is to illustrate the procedure and methodology used to define psychological, social and behavioural factors contributing to cancer diagnosis for effective monitoring of psychosocial and behavioural risk factors in people enrolled in screening programs for breast, colorectal and lung cancer. Results retrieved in this **D2.1** will inform the identification of the PROM/self-reported measures of psychosocial and lifestyle risk factors in **Task 2.5**. To achieve this goal, a qualitative approach based on literature reviews was adopted. Consistently, the following topics will be discussed in detail in the current document: i) methodology and study design of the studies; ii) preliminary results; and iii) implications for the development of the iBeChange platform.

1. Introduction

This deliverable presents the findings from the literature reviews conducted within Tasks 2.1 and 2.2 of Work Package 2 (WP2) of our project. The primary objectives of WP2 include identifying **effective measures of behavioural, physiological, and psychological factors**, determining the most effective Behavioural Change Techniques (BCTs), and identifying the best digital interventions to provide psychological support to end-users. The activities carried out within WP2 will provide crucial information for the development of the iBeChange platform.

Task 2.1 focuses on identifying lifestyle and behavioural factors related to cancer onset and evaluating digital devices and wearables that can passively monitor these factors through systematic literature and umbrella reviews. Promoting sustainable behavioural changes is crucial for the primary prevention of breast, lung, and colorectal cancers, as long-term adoption of healthy behaviours reduces cancer risk and improves overall health. A **systematic review** was conducted to analyze lifestyle risk factors and provide evidence-based recommendations for effective behavioural changes. Additionally, an **umbrella review** was performed to synthesize the latest evidence on digital solutions and wearable technologies for unobtrusively monitoring these key risk factors. The insights gained will guide the development of effective lifestyle monitoring solutions through the iBeChange platform, offering continuous and objective data that complement self-report measures. **Task 2.2** aims to identify individual factors associated with risky behaviours and their relationship with disease onset. There is evidence suggesting that psychosocial factors – which encompass a broad spectrum of emotional, psychological, and social aspects – can affect an individual's susceptibility to cancer by influencing health behaviours and biological processes (Cohen, 2004; Mössinger & Kostev, 2023; Reiche et al., 2004). However, the literature lacks comprehensive evidence from multiple existing reviews that identify the psychosocial areas most involved in cancer onset, and that have to be considered to improve **cancer management** in the general healthy population. Therefore, we conducted an **umbrella review** aiming to provide a comprehensive overview of psychosocial areas involved in cancer onset by synthesizing existing evidence. Insights from this umbrella review will not only enhance our understanding of these relationships, but will also allow us to identify the key areas we should assess by PROMs/self-reported measures (**Task 2.5**) and collect within the iBeChange platform. The results from this task will also help in the identification of digital devices and wearables that can monitor psychosocial factors passively and non-intrusively.

Together, the findings from **Tasks 2.1** and **2.2** will provide a comprehensive understanding of the behavioural and psychosocial factors related to cancer onset and will highlight which wearable devices allow to passively and non-intrusively monitor them.

2. Systematic review of recommendations and clinical guidelines regarding healthy lifestyles and behavioural change for breast, colorectal and lung cancer primary prevention

Identifying and understanding lifestyle risk factors is crucial for the primary prevention of breast, lung, and colorectal cancers. These cancers are significantly influenced by lifestyle choices, such as maintaining a healthy weight, regular physical activity, a balanced diet, moderating alcohol intake, and avoiding smoking. Evidence-based recommendations help develop strategies to detect unhealthy behaviours, build risk stratification models, and deliver personalized interventions. For example, smoking cessation reduces lung cancer risk (Godtfredsen et al., 2005), while a healthy diet and regular exercise are vital for preventing colorectal and breast cancers (Rock et al., 2020).

Promoting healthy habits and sustainable behavioural change is essential for reducing cancer risk and improving overall health. Long-term adoption of healthy behaviours requires continuous commitment to lifestyle practices. Thus, it is crucial to collect a comprehensive overview of lifestyle risk factors and identify evidence-based recommendations for healthy habits and behavioural changes to prevent breast, colorectal, and lung cancers.

2.1. Aim

In summary, this subtask within the iBeChange project aimed to identify lifestyle risk factors and clinical guidelines for the primary prevention of breast, colorectal, and lung cancers. We focused on gathering recommendations, guidelines, consensus statements, and summary reports for the general population, including individuals at any risk level, to highlight lifestyle risk factors and suggested healthy habits. The goal is to analyze existing recommendations related to physical activity, diet, alcohol consumption, smoking, weight management, and other lifestyle modifications. This task will identify key lifestyles and behavioural changes to promote in the iBeChange project. Moreover, the results of this activity will contribute to the iBeChange project by providing updated scientific evidence that can inform:

- The identification of individuals at risk based on their habits.
- The selection of the most effective self-report measures for assessing adherence to lifestyle recommendations.
- The monitoring of adherence to behavioural change recommendations.

2.2. Methods

We employed a comprehensive methodology to identify relevant documents providing information about lifestyle risk factors and healthy lifestyle recommendations for the primary prevention of breast, colorectal, and lung cancers. This approach combined systematic reviews with grey literature and reference list searches to ensure thorough identification of relevant documents.

The review adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2020). The systematic review involved searching four main databases: PubMed, Scopus, EMBASE, and EBSCOHost, with the search conducted in late May 2024. The search strategy, developed in PubMed, was adapted for other databases using terms aligned with the PICOS criteria: (1) lifestyle recommendations (e.g., guideline, recommendation, consensus, expert opinion), (2) cancer prevention (e.g., cancer, oncology, tumor), (3) prevention and risk reduction (e.g., prevention, risk, determinant), (4) lifestyle factors (e.g., physical activity, diet, alcohol, smoking, weight management), and (5) specific cancer types (e.g., breast, colorectal, lung). Additional searches included grey literature searches for guidelines and reports from governmental and health organizations. Inclusion criteria focused on documents addressing the general population or individuals at risk with recommendations for preventing breast, colorectal, and lung cancers, discussing lifestyle factors like physical activity, diet, alcohol consumption, smoking cessation, and weight management. Only documents published in English within the last 10 years were considered.

Initial search results were screened for relevance based on titles and abstracts. Items were managed using Rayyan software (Ouzzani et al., 2016), with duplicates identified and verified manually. Documents were screened by two reviewers from UNIPA. Eligibility was assessed based on title and abstract, with decisions reported in Rayyan to ensure unbiased evaluation. Conflicts were resolved through discussion. Full-text screening followed, with conflicts resolved similarly. Data extraction was conducted by one author and validated by another UNIPA reviewer for accuracy and completeness. The data extraction phase focused on key elements such as author(s), year, title, document type, institution/organization, target country, reported lifestyle risk factors, and related recommendations.

2.3. Results

Our search and screening process identified 16 guidelines, recommendations, summary reports, or consensus statements. These were complemented with 22 items coming from the grey literature search and 5 from reviewing the reference lists of identified items. Thus, a total of 43 documents were considered. Figure 1 reports a detailed log of the screening procedure.

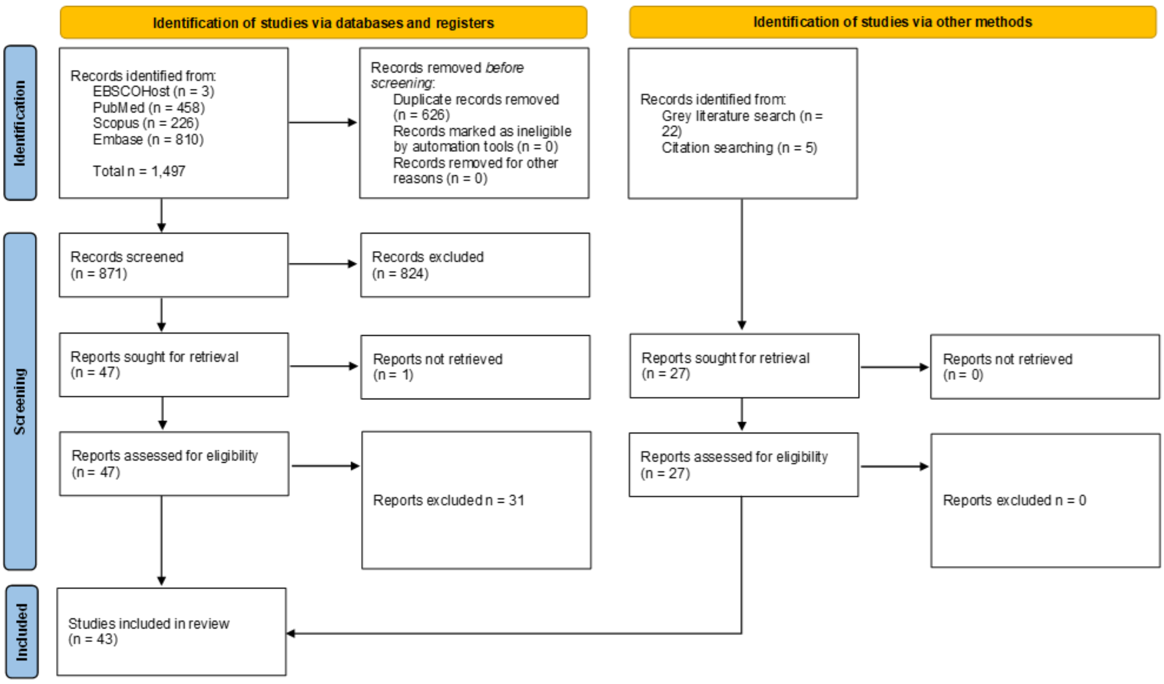

Figure 1. PRISMA 2020 flow diagram for this systematic review

The characteristics and main information of the documents are summarized in Table 1 and Table 2. The review includes items published between 2014 and 2024. The majority of the documents are general medical information for the public (37.2%), followed by recommendations (16.3%), consensus recommendations (14.0%), expert consensus reports (9.3%), guidelines (7.0%), summary reports (7.0%), clinical guidelines (4.7%), white papers (2.3%), and position statements (2.3%). The focus of the documents is predominantly on lung cancer (39.5%), followed by colorectal cancer (25.9%) and breast cancer (20.9%). Additionally, 11.6% of the items promote healthy habits for the general population by addressing lifestyle risk factors and providing guidelines for preventing breast, colorectal, and lung cancers.

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Table 1. Main results of the systematic review (ID, source, author, year, title, publication type, institution)

ID	Source	Author	Year	Title	Publication Type	Institution
1	SR	Allehebi et al.	2024	Recommended approaches for screening and early detection of lung cancer in the Middle East and Africa (MEA) region: a consensus statement.	Consensus recommendations	None
2	SR	Boyeras et al.	2023	Argentine consensus recommendations for lung cancer screening programmes: A RAND/UCLA-modified Delphi study	Consensus recommendations	None
3	GL	Digestive Cancers Europe	2024	Colorectal Cancer (Bowel Cancer) Risk Factors and Prevention	Medical information	Digestive Cancers Europe
4	GL	Europa Donna - European Breast Cancer Coalition	2024	Primary Prevention and Breast Health	Medical information	Europa Donna - European Breast Cancer Coalition
5	GL	European Society for Medical Oncology	2018	Colorectal Cancer: An ESMO Guide For Patients	Medical information	European Society for Medical Oncology
6	GL	European Society for Medical Oncology	2019	Non-small-cell lung cancer (NSCLC): An ESMO guide for patients	Medical information	European Society for Medical Oncology
7	GL	European Society for Medical Oncology; Anticancer Fund	2016	Colorectal Cancer: A Guide For Patients	Medical information	European Society for Medical Oncology
8	SR	Fang et al.	2014	Consensus on the Prevention, Screening, Early Diagnosis and Treatment of Colorectal Tumors in China: Chinese Society of Gastroenterology, October 14–15, 2011, Shanghai, China	Consensus recommendations	Chinese Society of Gastroenterology
9	SR	Fucito et al.	2016	Pairing smoking-cessation services with lung cancer screening: a clinical guideline from the Association for the Treatment of Tobacco Use and Dependence and the Society for Research on Nicotine and Tobacco	Clinical guideline	the Association for the Treatment of Tobacco Use and Dependence; the Society for Research on Nicotine and Tobacco
10	GL	Glynne-Jones et al.	2017	Rectal cancer: ESMO Clinical Practice Guidelines for diagnosis, treatment and follow-up	Clinical guideline	European Society for Medical Oncology
11	SR	Goday et al.	2015	Obesity as a risk factor in cancer: A national consensus of the Spanish Society for the Study of Obesity and the Spanish Society of Medical Oncology	Consensus recommendations	Spanish Society for the Study of Obesity; the Spanish Society of Medical Oncology
12	SR	Golubnitschaja et al.	2016	Breast cancer epidemic in the early twenty-first century: evaluation of risk factors, cumulative questionnaires and recommendations for preventive measures	Recommendations	None
13	SR	Kauczor et al.	2015	ESR/ERS white paper on lung cancer screening	White paper	European Society of Radiology (ESR); the European Respiratory Society (ERS)
14	SR	Koegelenberg et al.	2019	Recommendations for lung cancer screening in Southern Africa	Reccomendations	South African Thoracic Society
15	SR	Koh et al.	2016	Asian consensus on the relationship between obesity and gastrointestinal and liver diseases	Consensus recommendations	The Gut and Obesity in Asia Workgroup
16	SR	Krist et al.	2021	Screening for Lung Cancer US Preventive Services Task Force Recommendation Statement	Reccomendations	US Preventive Services Task Force
17	SR	Kromhout ET AL.	2016	The 2015 Dutch food-based dietary guidelines.	Guideline	Committee Dutch Dietary Guidelines
18	SR	Lam et al.	2023	Lung Cancer Screening in Asia: An Expert Consensus Report	Expert consensus report	None
19	GL	Lung Cancer Europe	2024	Lung Cancer: Risk factors and causes	Medical information	Lung Cancer Europe
20	GL	Mayo Clinic	2024a	Breast Cancer	Medical information	Mayo Clinic
21	GL	Mayo Clinic	2024b	Lung Cancer	Medical information	Mayo Clinic
22	GL	Mayo Clinic	2024c	Colorectal Cancer	Medical information	Mayo Clinic
23	SR	Oudkerk et al.	2017	European position statement on lung cancer screening	Position statement	European Union (EU)
24	GL	National Cancer Institute	2024a	Colorectal Cancer Prevention (PDQ®)–Patient Version	Summary	National Cancer Institute
25	GL	National Cancer Institute	2024b	Breast Cancer Prevention (PDQ®)–Patient Version	Summary	National Cancer Institute
26	GL	National Cancer Institute	2024c	Lung Cancer Prevention (PDQ®)–Patient Version	Summary	National Cancer Institute
27	RL	Piercy et al.	2020	The Physical Activity Guidelines for Americans	Guideline	US Department of Health and Human Services
28	SR	Sung et al.	2014	An updated Asia Pacific Consensus Recommendations on colorectal cancer screening	Consensus recommendations	The Asia Pacific Colorectal Cancer Working Group
29	GL	American Cancer Society	2024a	Can Colorectal Cancer Be Prevented?	Medical information	American Cancer Society
30	GL	American Cancer Society	2024b	Lung Cancer Risk Factors	Medical information	American Cancer Society
31	GL	American Cancer Society	2024c	Can Lung Cancer Be Prevented?	Medical information	American Cancer Society
32	GL	American Cancer Society	2024d	Lifestyle-related Breast Cancer Risk Factors	Medical information	American Cancer Society
33	SR	Tsang et al.	2022	Update on the recommendations on breast cancer screening by the cancer expert working group on cancer prevention and screening	Reccomendations	Cancer Expert Working Group on Cancer Prevention and Screening
34	SR	Wolf et al.	2023	Screening for lung cancer: 2023 guideline update from the American Cancer Society	Guideline	American Cancer Society
35	RL	World Cancer Research Fund, American Institute for Cancer Research	2018a	Diet, nutrition, physical activity and lung cancer	Expert consensus report	World Cancer Research Fund, American Institute for Cancer Research
36	RL	World Cancer Research Fund, American Institute for Cancer Research	2018b	Diet, nutrition, physical activity and breast cancer	Expert consensus report	World Cancer Research Fund, American Institute for Cancer Research
37	RL	World Cancer Research Fund, American Institute for Cancer Research	2018c	Diet, nutrition, physical activity and colorectal cancer	Expert consensus report	World Cancer Research Fund, American Institute for Cancer Research

ID	Source	Author	Year	Title	Publication Type	Institution
38	RL	World Cancer Research Fund, American Institute for Cancer Research	2018d	Recommendations and public health and policy implications	Recommendations	World Cancer Research Fund, American Institute for Cancer Research
39	GL	World Health Organization	2023a	Colorectal Cancer	Medical information	World Health Organization
40	GL	World Health Organization	2023b	Lung Cancer	Medical information	World Health Organization
41	GL	World Health Organization	2024c	Preventing cancer	Reccomendations	WHO Global Action Plan for the Prevention and Control of NCDs 2013–2020
42	GL	World Health Organization	2024d	Cancer, Prevention	Recommendations	World Health Organization
43	GL	World Health Organization	2024e	Breast Cancer	Medical information	World Health Organization

Note: SR= from systematic review; GL= from grey literature; RL= from reference list

The following sections present results related to lifestyle risk factors, healthy habits, and behavioural change recommendations for breast, colorectal, and lung cancers (see Table 2). The analysis highlights the level of consensus among the identified documents regarding each risk factor (i.e., physical activity, diet, smoking, alcohol consumption, and weight) for each type of cancer. Consensus levels are categorized as follows: "strong consensus" (≥75% agreement), "weak consensus" (50%–74% agreement), and "no consensus" (<50% agreement). The next three sections will summarize results related to the three cancer types targeted by the iBeChange project, while other two sections will summarize results from documents offering general recommendations for cancer prevention and health promotion through physical activity.

2.3.1. Documents targeting breast cancer

There is strong consensus among the documents that alcohol consumption and excessive weight are key risk factors for breast cancer, with 100% (i.e. 9 in 9) of the identified sources highlighting these factors. However, specifics on the thresholds for excessive weight and alcohol consumption are often lacking.
Alcohol consumption: the American Cancer Society notes that the risk of breast cancer increases with alcohol consumption, with a 7-10% higher risk for one drink per day and a 20% higher risk for two to three drinks per day (American Cancer Society, 2024d).
Overweight: the report also emphasizes that being overweight or obese post-menopause increases breast cancer risk. Similarly, Europa Donna - European Breast Cancer Coalition (2024) links obesity (Body Mass Index [BMI] ≥30) and weight gain in adulthood, along with alcohol consumption, to a higher risk of breast cancer.
Regarding recommendations, four documents emphasize maintaining an optimal weight and avoiding obesity through balanced diet and physical activity (e.g., Europa Donna - European Breast Cancer Coalition, 2024; Golubnitschaja et al., 2016). For alcohol intake, it is advised to avoid alcohol altogether for cancer prevention, but if consumed, moderation is recommended—no more than one unit (10 ml or 8 g of pure alcohol) per day or one drink per day (Golubnitschaja et al., 2016; American Cancer Society, 2024d).
Physical activity: a weak consensus exists on the role of physical inactivity in breast cancer risk, with 66.6% (i.e., 6 in 9) of documents identifying this association. Some reports highlight that a sedentary lifestyle increases risk (e.g., Europa Donna - European Breast Cancer Coalition, 2024; Golubnitschaja et al., 2016; Tsang et al., 2022), while others stress that regular physical activity offers protection (e.g., American Cancer Society, 2024d; National Cancer Institute, 2024b; World Cancer Research Fund & American Institute for Cancer Research, 2018b). Recommendations generally advise engaging in moderate exercise for at least 30-60 minutes daily, including activities like walking, gardening, and dancing. The American Cancer Society (2024d) recommends 150 to 300 minutes of moderate-intensity or 75 to 150 minutes of vigorous-intensity exercise per week.
No consensus was found regarding smoking (22.2%) and diet (11.1%) as risk factors for breast cancer.

2.3.2. Documents targeting colorectal cancer

Overweight: there is strong consensus among documents identifying overweight and obesity as critical risk factors for colorectal cancer, with 81.8% (i.e., 9 in 11) of reports highlighting these issues. Specifically, overweight, obesity, and body fatness are consistently recognized as risk factors. Recommendations emphasize maintaining a healthy weight through a balanced diet and regular physical activity. Individuals who are already at a healthy weight are advised to sustain it through these practices, while those seeking to lose weight should consult healthcare providers for safe and effective methods (e.g., Digestive Cancers Europe, 2024; Mayo Clinic, 2024c).
A weak consensus is evident regarding the impact of physical activity, diet, smoking, and alcohol consumption on colorectal cancer risk, with 63.6% (i.e., 7 in 11) of documents addressing each factor.

Physical Activity: The literature presents conflicting perspectives on physical activity. Some documents suggest that a sedentary lifestyle, independent of weight, can increase colorectal cancer risk (e.g., European Society for Medical Oncology & Anticancer Fund, 2016; Mayo Clinic, 2024c). Conversely, other sources highlight the protective benefits of regular exercise in reducing this risk (e.g., Mayo Clinic, 2024c; National Cancer Institute, 2024a). Recommendations generally advise incorporating physical activity into daily routines to mitigate cancer risk. Engaging in regular exercise, ideally at least 30 minutes most days of the week, is emphasized. For those new to exercise, a gradual increase in duration and intensity is recommended until reaching the daily goal (e.g., Digestive Cancer Europe, 2024; European Society for Medical Oncology & Anticancer Fund, 2016).

Diet: Dietary factors are also viewed variably. Diets high in red and processed meats, fat, refined grains (e.g., white rice, white flour), and low in fiber and non-starchy vegetables are associated with an increased risk of colorectal cancer (e.g., Digestive Cancer Europe, 2024; European Society for Medical Oncology & Anticancer Fund, 2016; Mayo Clinic, 2024c; World Cancer Research Fund & American Institute for Cancer Research, 2018c). Conversely, a diet rich in garlic, milk, calcium, fish, high dietary fiber, vegetables, fruits, and whole grains is considered protective (e.g., American Cancer Society, 2024a; Glynne-Jones et al., 2017; World Cancer Research Fund & American Institute for Cancer Research, 2018c). Recommendations focus on consuming a variety of fruits, vegetables, and whole grains while limiting red and processed meats. While specific portion sizes are not detailed, the emphasis is on the types of foods to prioritize and limit (e.g., American Cancer Society, 2024a; Mayo Clinic, 2024c).

Smoking: About 63.6% of documents report that smoking increases colorectal cancer risk. For instance, Digestive Cancers Europe (2024) notes that smokers are approximately 18% more likely to develop colorectal cancer than non-smokers. Recommendations stress that quitting smoking is crucial for reducing cancer risk and improving overall health. Seeking support from healthcare professionals is encouraged to effectively quit smoking and enhance healthier outcomes (e.g., Digestive Cancer Europe, 2024; Fang et al., 2014; National Cancer Institute, 2024a).

Alcohol Consumption: The literature indicates that increased alcohol consumption is linked to a higher risk of colorectal cancer (e.g., American Cancer Society, 2024a). Some reports specify that moderate to heavy alcohol consumption is associated with a 1.2 to 1.5 times increased risk of colorectal cancer (Digestive Cancer Europe, 2024) or that drinking three or more alcoholic beverages per day raises the risk (National Cancer Institute, 2024a). Recommendations suggest either avoiding alcohol or limiting intake to no more than one drink per day for women and two drinks per day for men to reduce colorectal cancer risk (e.g., American Cancer Society, 2024a; Mayo Clinic, 2024c). Overall, guidance favors minimizing alcohol consumption or abstaining as part of a comprehensive approach to reducing cancer risk.

2.3.3. Documents targeting lung cancer

Smoking: There is unanimous consensus among documents identifying cigarette smoking as the primary risk factor for lung cancer. All identified sources (i.e., 16 in 16) agree on this modifiable risk factor. According to the ESMO guide for patients, the duration of smoking is considered more significant than the number of cigarettes smoked per day (European Society for Medical Oncology, 2019). Additionally, documents consistently support the use of pack-year history as a key criterion for identifying individuals at higher risk who should be included in systematic screening programs.

The National Cancer Institute defines a pack-year as “a measure of the amount a person has smoked over a long period. It is calculated by multiplying the number of packs of cigarettes smoked per day by the number of years the person has smoked. For example, 1 pack-year is equal to smoking 1 pack per day for 1 year, or 2 packs per day for half a year, and so on” (National Cancer Institute, 2024d). The majority of documents suggest that individuals with a smoking history of at least 30 pack-years are considered at higher risk (e.g., Boyeras et al., 2023; Kauczor et al., 2015; Koegelenberg et al., 2019).

However, recent guidelines indicate that those with a 20 pack-year history also qualify as higher risk (Allehebi et al., 2024; Krist et al., 2021; Lam et al., 2023; Wolf et al., 2023).
Among the reviewed documents, 64.7% provide recommendations on healthy habits and behavioural changes related to cigarette smoking. The consensus is clear that non-smokers should avoid starting smoking, and current smokers should aim to quit smoking completely rather than merely reducing their cigarette intake (e.g., American Cancer Society, 2024b; Mayo Clinic, 2024b). The benefits of quitting smoking are emphasized over merely cutting down, with the ESMO guide highlighting that quitting entirely is more advantageous than reducing cigarette consumption (European Society for Medical Oncology, 2019). However, since the risk of lung cancer increases with the number of cigarettes a person smokes each day (Mayo Clinic, 2024b), it is important to note that even reducing the number of cigarettes smoked might be beneficial and reduce the overall health risks compared to maintaining the same level of consumption.
Several strategies are suggested to support smoking cessation, including the use of nicotine replacement therapies, medications, and participation in support groups. Additionally, avoiding exposure to secondhand smoke is crucial for protecting health. Recommendations stress the importance of integrating smoking cessation programs within lung cancer screening initiatives for those who smoke (Boyeras et al., 2023; Krist et al., 2021; Lam et al., 2023). Smokers should be informed about the risks of continued smoking and provided with comprehensive support, including evidence-based behavioural and pharmacological treatments, to facilitate quitting.
No consensus was found regarding the role of physical activity (5.9%), diet (5.9%), alcohol (5.9%), and weight (0.0%) as risk factors for lung cancer.

2.3.4. Documents targeting overall cancer prevention

Five documents offer general information about lifestyle risk factors, healthy habits, and behavioural change recommendations for the primary prevention of cancer, covering multiple cancer types, including breast, colorectal, and lung cancer. These documents were included because they provide relevant insights that complement cancer-specific recommendations.
Overweight: the documents emphasize that obesity and overweight are significant risk factors for several cancers, including breast, colorectal, and lung cancer (Godaly et al., 2015; World Health Organization, 2024c). They report a strong epidemiological link between obesity and breast cancer, particularly in post-menopausal women, with a hazard ratio (HR) greater than 1.5, indicating a substantial increase in risk (Goday et al., 2015). The association between obesity and colorectal cancer is also noted, though the risk is somewhat lower, with an HR ranging from 1 to 1.5.
Recommendations focus on preventing obesity and managing weight effectively. It is advised to avoid weight gain and aim for gradual weight loss for those who are overweight. Maintaining a Body Mass Index (BMI) within the healthy range of 18.5 to 24.9 kg/m² is emphasized as a key strategy to reduce cancer risk (Kromhout et al., 2016).
Dietare highlighted as crucial in modulating cancer risk. For colorectal cancer, consuming vegetables and fruits is associated with a lower risk. High intake of dietary and cereal fiber, along with whole-grain products, is also linked to reduced risk. Conversely, high consumption of red and processed meats is associated with increased risk. Dairy products and calcium intake are noted for their protective effects against colorectal cancer (Kromhout et al., 2016). For lung cancer, fruit consumption is associated with a lower risk, while red and processed meats may increase the risk. However, the documents do not provide specific dietary patterns or food items related to breast cancer risk, limiting a comprehensive discussion on dietary influences for this cancer type.
The general dietary recommendations include a diet rich in fruits and vegetables, with a daily intake of at least 200 grams each of vegetables and fruits. Incorporating whole grains is advised, with a minimum of 90 grams per day of whole-grain products like brown bread or wholemeal bread. Dairy products,

including milk and yogurt, should be consumed in moderate amounts daily, as they provide calcium and vitamin D beneficial for overall health. The documents recommend prioritizing plant-based foods over animal-based ones, limiting red meat to about three portions per week (350 to 500 grams or 12 to 18 ounces) and avoiding processed meats (Kromhout et al., 2016; World Health Organization, 2024b). Alcohol consumption is stressed as a significant risk factor for several cancers (Godaly et al., 2015; World Health Organization, 2024a). The documents report that high alcohol intake is associated with an elevated risk of breast cancer. Similarly, colorectal cancer risk is reported to increase with high alcohol consumption. In the context of lung cancer, the documents highlight that high consumption of beer and spirits is linked to an increased risk, while low levels of beer and wine consumption are associated with a lower risk. The considered documents provide clear recommendations regarding alcohol consumption in relation to cancer prevention. They advocate moderation or abstinence from alcohol, highlighting its significant role as a risk factor for various cancers (Kromhout et al., 2016; World Cancer Research Fund & American Institute for Cancer Research, 2018d). Specifically, one document suggests limiting alcohol intake to no more than one glass per day (Kromhout et al., 2016).
The documents do not provide specific details about the impact of physical activity on the risks of breast, colorectal, or lung cancer.

2.3.5. Documents targeting health promotion

One document focuses on the promotion of health and primary cancer prevention through physical activity (Piercy et al., 2020). It stresses that regular physical activity can lower the risk for several types of cancer, including also breast, colorectal and lung cancer. The document provides recommendations about health physical activity guidelines for Americans, emphasizing their role in health promotion in general, not only in the primary prevention of cancer. For adults, the guidelines suggest moving more and sitting less throughout the day, with any amount of moderate-to-vigorous physical activity providing health benefits. For substantial benefits, adults should engage in 150-300 minutes of moderate-intensity, or 75-150 minutes of vigorous-intensity aerobic activity weekly, ideally spread throughout the week, along with muscle-strengthening activities on 2 or more days per week. For older adults, in addition to the general adult guidelines, it is recommended to include multicomponent physical activity that involves balance training, aerobic, and muscle-strengthening activities. They should adjust their activity level based on their fitness and chronic conditions, and remain as active as their abilities allow if unable to meet the 150-minute guideline. For adults with chronic health conditions or disabilities, similar guidelines apply, recommending 150-300 minutes of moderate-intensity, or 75-150 minutes of vigorous-intensity aerobic activity weekly, along with muscle-strengthening activities on 2 or more days per week, adjusted according to their abilities. Those unable to meet these guidelines should stay as active as possible and consult healthcare professionals about suitable activities.

Table 2. Main results of the systematic review (type of cancer, risk factors, and related recommendations)

ID	Year	Type of cancer	Risk factors	Recommendations
1	2024	LC	"However, in the majority of countries within the region, the criteria for identifying high-risk populations who are eligible for screening should meet the following: […] Individuals who smoked or had at least a 20-pack-year history of smoking"; Quality of evidence: NA; Classification of recommendation: NA (p. 2147)	None
2	2023	LC	"High-risk was defined as follows: persons who were between 55 and 74 years old, of any sex, with a smoking history of ≥30 pack-years, current smokers or former smokers who had quit smoking within 15 years, and without comorbid conditions, implying a risk of death greater than the risk of death from LC"; Quality of evidence: NA; Classification of recommendation: NA (pp. 4-5) "A smoking of ≥30 packs-year is considered high-risk"; Quality of evidence: NA; Classification of recommendation: Strongly recommended (p. 6) "Likewise, former smokers with more than 30 packs-year who quit smoking within 15 years are also considered high-risk"; Quality of evidence: NA; Classification of recommendation: Strongly recommended (p. 6)	"Participants agreed […] that every lung cancer screening programme should […] offer a smoking cessation programme for current smokers. Quality of evidence: NA; Classification of recommendation: NA (p. 5) "Every smoker enrolled in the screening programme should be offered a smoking cessation programme, integrated with the screening programme, to reduce the long-term burden of this disease"; Quality of evidence: NA; Classification of recommendation: Strongly recommended (p. 6)
3	2024	CC	"Risk factors for colorectal cancer that can be controlled include: Being overweight/obese: People who are obese are about 30% more likely to develop colorectal cancer than normal-weight people. A person with a body mass index (BMI) of 30 or more is generally considered obese. A person with a BMI equal to or more than 25 is considered overweight. There are many BMI calculators available online to help you calculate your BMI. Please note that BMI is not a perfect measurement, and other factors (such as waist size) should also be taken into consideration. Certain types of diet: Diets high in red and processed meats, fat, refined grains (e.g. white rice, white flour) and high-calorie beverages are associated with a higher risk for developing colorectal cancer. Smoking: Smoking is a risk factor for all cancers and many other serious diseases. Smokers are around 18% more likely to develop colorectal cancer than non-smokers. Drinking alcohol: Moderate to heavy alcohol consumption is associated with 1.2- to 1.5-fold increased risk of cancers of the colon and rectum compared with no alcohol consumption"; Quality of evidence: NA; Classification of recommendation: NA (p. NA)	"Primary prevention practices include the following: Maintain a healthy weight. Avoiding obesity can reduce the risk of colorectal cancer. If you are overweight, a good starting point can be to try to stop gaining weight, which has health benefits by itself. Then, for a bigger health boost, slowly work to lose some weight over time. Also try to be physically active several times a week. Limit alcohol and tobacco use. Smoking and drinking are major risk factors for most types of cancer, including colorectal cancer. Eat a healthy diet and limit red and processed meats. Try to limit intake of red meat, which includes steaks, burgers and pork, and processed meats such as bacon, sausages and processed sandwich meat. Eating healthy and unprocessed or limited processed foods, including plenty of fruits, vegetables, and whole grains, limiting red and processed meats and sugary drinks, lowers the overall risk of colorectal cancer. Quality of evidence: NA; Classification of recommendation: NA (p. NA)
4	2024	BC	"Not being active enough may increase the risk of breast cancer. Prolonged sedentary behaviour is associated with an increased risk of breast cancer, according to meta-analyses. The risk increases slightly with increased sedentary time, particularly with watching television. Being sedentary at work is linked to a more than 15% increase in the risk of breast cancer"; Quality of evidence: NA; Classification of recommendation: NA (p. NA) "Weight and risk of breast cancer differ by menopausal status. Women who are lean before menopause have an increased risk of breast cancer, whereas obesity in menopause (body mass index [BMI] of 30 or higher) and gaining weight in adulthood are associated with an increased risk. "; Quality of evidence: NA; Classification of recommendation: NA (p. NA) "There is a link between alcohol consumption and risk of breast cancer. This risk increases with increasing alcohol intake, although any amount of alcohol has an associated risk. This is true for all types of alcoholic beverages, including beer, wine and spirits. In the WHO European region in 2018, 25% of new cases of breast cancer were attributed to drinking a maximum of 2 drinks (20 g pure alcohol) per day, and 46% were attributed to 3 to 6 drinks (60 g pure alcohol) per day"; Quality of evidence: NA; Classification of recommendation: NA (p. NA)	"To reduce their risk of breast cancer women should: Stay healthy and active; Engage in moderate exercise for at least 30-60 minutes every day; Keep in mind that physical activity is not only sport, but also walking, gardening, occupational, housework, dancing, etc"; Quality of evidence: NA; Classification of recommendation: NA (p. NA) "Women should pursue a healthy lifestyle that will reduce the known breast cancer risk factors as much as possible, including avoiding obesity and being overweight, increasing physical activity and adopting healthy habits. "; Quality of evidence: NA; Classification of recommendation: NA (p. NA)
5	2018	BC	"Most important risk factors: […] Obesity; […] Alcohol"; Quality of evidence: NA; Classification of recommendation: NA (p. 12)	None
6	2019	LC	"Tobacco smoking is the leading cause of lung cancer. In Europe, it is responsible for 90% of cases in men and 80% of cases in women. The number of years that a person has been a smoker is more important than the number of cigarettes smoked per day; therefore, giving up smoking at any age can reduce the risk of developing lung cancer more than cutting down on the number of cigarettes smoked per day. Passive smoking, also referred to as 'second-hand smoke' or 'environmental tobacco smoke', increases the risk of developing NSCLC, but to a lesser extent than if you are a smoker"; Quality of evidence: NA; Classification of recommendation: NA (p. 12)	None
7	2016	CC	"The main risk factors of colorectal cancer are: […] Diet: diet is the most important environmental risk factor for colorectal cancer. A diet that is high in red meat (beef, lamb, or pork) and processed meat (hot dogs and some luncheon meats), high in fat and/or low in fiber can increase the risk of developing colorectal cancer. High consumption of alcohol is also a risk factor for colorectal cancer. Obesity: overweight increases the risk of developing colorectal cancer. Sedentary lifestyle: individuals who are	"Some factors may have a protective effect against the development of colorectal cancer: A diet high in vegetables, fruit, and whole grains decrease the risk of colorectal cancer. An increase in physical activity may help to reduce this risk of colorectal cancer"; Quality of evidence: NA; Classification of recommendation: NA (p. 7)

ID	Year	Type of cancer	Risk factors	Recommendations
			not very physically active are at a higher risk of developing colorectal cancer. This is independent of the person's weight[…] Smoking: smoking increases the risk of developing large colorectal polyps, which are well-known precancerous lesions"; Quality of evidence: NA; Classification of recommendation: NA (p. 6)	
8	2014	CC	None	"Primary prevention of adenomas includes (i) improved diet with more fiber, (ii) supplements containing calcium and vitamin D, (iii) supplements containing folic acid for those with lower plasma folate concentrations, and (iv) cessation of tobacco smoking"; Quality of evidence: NA; Classification of recommendation: NA (p. 67)
9	2016	LC	"Current smokers as well as former smokers who quit within the past 15 years (ie, the patients eligible for lung cancer screening) remain at heightened risk for lung cancer"; Quality of evidence: NA; Classification of recommendation: NA (p. 1151) "With respect to lung cancer specifically, it is well documented that smoking is the primary causal factor".; Quality of evidence: NA; Classification of recommendation: NA (p. 1152)	"Smoking cessation, however, clearly and unequivocally reduces risk of lung cancer.10,25 Data from case-control studies demonstrate that former smokers have a 20% to 90% reduction in lung cancer risk compared with current smokers. The reduction in risk is evident within 5 years of smoking cessation and increases with longer smoking abstinence"; Quality of evidence: NA; Classification of recommendation: NA (p. 1152) "For smokers who present for lung cancer screening, it is recommended that they be encouraged to quit smoking at each visit regardless of lung cancer screening results"; Quality of evidence: NA; Classification of recommendation: NA (p. 1157) "For smokers who present for lung cancer screening, it is recommended that they be assisted with access to evidence-based, comprehensive behavioural and pharmacologic treatments as outlined in the PHS Tobacco Clinical Practice Guidelines to facilitate quitting or smoking reduction, which may lead to eventual cessation. Assistance"; Quality of evidence: NA; Classification of recommendation: NA (p. 1157)
10	2017	CC	"A healthy lifestyle and exercise can reduce the risk of developing rectal cancer. Consumption of garlic, milk, calcium and high dietary fibre are regarded as protective"; Quality of evidence: NA; Classification of recommendation: NA (p. iv22)	None
11	2015	CG	"An epidemiological association has been found between obesity and cancer, with a HR > 1.5 for breast cancer in post-menopausal women, endometrial cancer and renal carcinoma"; Quality of evidence: NA; Classification of recommendation: NA (p. 765) "A weaker positive association has also been found, with a HR of 1–1.5, for colorectal cancer"; Quality of evidence: NA; Classification of recommendation: NA (p. 765) "Various studies have examined the relationship between BMI and the risk of lung cancer, and one or two of them have suggested that patients with higher BMI have a lower incidence of lung cancer"; Quality of evidence: NA; Classification of recommendation: NA (p. 769)	None
12	2016	BC	"Nowadays, sedentary lifestyle is getting more and more ubiquitous that has adverse health effects in general and specifically increases breast cancer risk"; Quality of evidence: NA; Classification of recommendation: NA (p. 12943) "Breast cancer risk is increased the most (25%) in women who started smoking younger than 18 years old, smoked longer than 35 years and, in average, smoked more than 25 cigarettes per day"; Quality of evidence: NA; Classification of recommendation: NA (p. 12949) "Low BMI is a risk factor for breast cancer later in life. Adulthood: the most optimal BMI ranges from 20 to 25"; Quality of evidence: NA; Classification of recommendation: NA (p. 12949) "Increased alcohol intake is a risk factor for BC, particularly sensitive is the period between the first menstrual period and first full-term pregnancy"; Quality of evidence: NA; Classification of recommendation: NA (p. 12949)	"Regular body activity is beneficial for BC prevention and better outcomes in breast cancer management. About 3–4-h walking per week may reduce breast cancer incidence […]; 30-60 min of moderate to vigorous activity daily is recommended; in physically active subjects, the risk reduction is about 25–30%"; Quality of evidence: NA; Classification of recommendation: NA (p. 12948) "The general recommendation is to keep a control over individually optimised weight; dietary habits and physical activity play a key role"; Quality of evidence: NA; Classification of recommendation: NA (p. 12949) "Alcohol intake should be avoided in early adulthood; later in life, it should not be more than 1 unit of alcohol (1 unit = half a pint of 4 % strength beer or cider or 25 ml of 40 % strength spirits; a small 125-ml glass of 12 % strength wine as 1.5 units) daily"; Quality of evidence: NA; Classification of recommendation: NA (p. 12949)
13	2015	LC	"We suggest the following minimum requirements for the implementation of lung cancer screening: […] Inclusion criteria: age between 55 and 80 years, tobacco smoking history of at least 30 pack-years, and current smoker or ex-smoker who has quit smoking within the last 15 years"; Quality of evidence: NA; Classification of recommendation: NA (p. 2528)	"Strong smoking cessation programme and experienced staff providing effective cessation and long-term abstinence advice"; Quality of evidence: NA; Classification of recommendation: NA (p. 2528)
14	2019	LC	"Current or former smokers (having quit within the preceding 15 years) with at least a 30 pack year history"; Quality of evidence: NA; Classification of recommendation: NA (p. 3699)	None
15	2016	CC	"Obesity increases the risk of colorectal neoplasia in Asians. Quality of evidence: 68.8% high; 18.8% moderate; 12.5% low; and 0% very low.; Classification of recommendation: 75.0% accept completely; 12.5% accept with minor reservations; 12.5% accept with major reservations; 0% reject with reservation; and 0% reject completely (p. 1409)	

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16	2021	LC	“The most important risk factor for lung cancer is smoking. Smoking is estimated to account for about 90% of all lung cancer cases, with a relative risk of lung cancer approximately 20-fold higher in smokers than in non smokers”; Quality of evidence: NA; Classification of recommendation: NA (p. 962) “Adults aged 50 to 80 years who have a 20 pack-year smoking history and currently smoke or have quit within the past 15 years”; Quality of evidence: NA; Classification of recommendation: NA (p. 963) “The USPSTF considers adults aged 50 to 80 years who have a 20 pack-year smoking history and currently smoke or have quit within the past 15 years to be at high risk and recommends screening for lung cancer with annual LDCT in this population”; Quality of evidence: NA; Classification of recommendation: NA (p. 964)”	“If the person currently smokes, they should receive smoking cessation interventions”; Quality of evidence: NA; Classification of recommendation: NA (p. 962) “All persons enrolled in a screening program who are current smokers should receive smoking cessation interventions. To be consistent with the USPSTF recommendation on counseling and interventions to prevent tobacco use and tobacco-caused disease, persons referred for lung cancer screening through primary care should receive these interventions concurrent with referral. Because many persons may enter screening through pathways besides referral from primary care, the USPSTF encourages incorporating such interventions into all screening programs”; Quality of evidence: NA; Classification of recommendation: NA (p. 964)”
17	2016	CG	“Vegetables and fruits [are associated] with lower colorectal cancer risk”; Quality of evidence: NA; Classification of recommendation: NA (p. 870)” “Fruit consumption was associated with a lower risk of lung cancer”; Quality of evidence: NA; Classification of recommendation: NA (p. 870)” “The committee concludes that it is plausible that the consumption of red meat and processed meat is associated with a higher risk of stroke, diabetes, colorectal and lung cancer”; Quality of evidence: NA; Classification of recommendation: NA (p. 870) “The committee concludes that it is plausible that the consumption of dairy and milk is associated with a lower risk of colorectal cancer [..]. The conclusion about colorectal cancer is supported by the finding that the intake of calcium from supplements was associated with a lower risk of this disease. The calcium intake from supplements was approximately about half the amount from dairy”; Quality of evidence: NA; Classification of recommendation: NA (p. 870) “In addition, a high intake of alcohol was associated with a higher risk of breast cancer and colorectal cancer, and a high consumption of beer and spirits was associated with a higher risk of lung cancer. Low levels of alcohol intake (<15 g per day) were associated with a lower risk of […] breast cancer as compared with (almost) no alcohol intake. […] A low level of beer and wine was associated with a lower risk of lung cancer”; Quality of evidence: NA; Classification of recommendation: NA (p. 872) “The different recommended dietary patterns were also associated with a lower risk […] colorectal cancer”; Quality of evidence: NA; Classification of recommendation: NA (p. 873) “A high intake of dietary and cereal fibre and whole-grain products was also related to a lower risk of [...] colorectal cancer.; Quality of evidence: NA; Classification of recommendation: NA (p. 871)	“Eat at least 200 g of vegetables and at least 200 g of fruit daily”; Quality of evidence: NA; Classification of recommendation: NA (p. 870)” “Limit the consumption of red meat, particularly processed meat”; Quality of evidence: NA; Classification of recommendation: NA (p. 870)” “Take a few portions of dairy produce daily, including milk or yogurt”; Quality of evidence: NA; Classification of recommendation: NA (p. 870)” “Eat at least 90 g of brown bread, wholemeal bread or other whole-grain products.; Quality of evidence: NA; Classification of recommendation: NA (p. 871) “Do not drink alcohol or do not drink more than one glass daily.; Quality of evidence: NA; Classification of recommendation: NA (p. 872) “Follow a dietary pattern that involves eating more plant-based and less animal-based food, as recommended in the guidelines”; Quality of evidence: NA; Classification of recommendation: NA (p. 873)
18	2023	LC	“Smoking history quantified in pack-years, is the most prominent risk factor for lung cancer among smokers”; Quality of evidence: NA; Classification of recommendation: NA (p. 1309) “While selecting high-risk patients for LDCT screening, smoking history and age must be taken into consideration. […] Smoking history of more than or equal to 20 packyears. Years after quitting smoking: individuals who quit smoking less than or equal to 15 years are still at a risk”; Quality of evidence: NA; Classification of recommendation: NA (p. 1310)	“Incorporation of smoking cessation programs along with the lung cancer screening program is necessary”; Quality of evidence: NA; Classification of recommendation: NA (p. 1314)
19	2024	LC	“Smoking tobacco is the biggest risk factor for lung cancer. The more a person smokes, the greater the risk of suffering from lung cancer. If a person stops smoking, the risk decreases. But the risk is higher in those who have been smokers than in those who have never smoked. And the risk of lung cancer is greater among people exposed to second-hand smoke than in people without any exposure to smoke”; Quality of evidence: NA; Classification of recommendation: NA (p. NA)	None
20	2024a	BC	“Factors that may increase the risk of breast cancer include: […] Drinking alcohol. Drinking alcohol increases the risk of breast cancer; Obesity. People with obesity have an increased risk of breast cancer”; Quality of evidence: NA; Classification of recommendation: NA (p. NA)	“Making changes in your daily life may help lower your risk of breast cancer. Try to: […] Drink alcohol in moderation, if at all. Limit the amount of alcohol you drink to no more than one drink a day, if you choose to drink. For breast cancer prevention, there is no safe amount of alcohol. So if you’re very concerned about your breast cancer risk, you may choose to not drink alcohol; Exercise most days of the week. Aim for at least 30 minutes of exercise on most days of the week. If you haven’t been active lately, ask a healthcare professional whether it’s OK and start slowly.; Maintain a healthy weight. If your weight is healthy, work to maintain that weight. If you need to lose weight, ask a healthcare professional about healthy ways to lower your weight. Eat fewer calories and slowly increase the amount of exercise”; Quality of evidence: NA; Classification of recommendation: NA (p. NA)
21	2024b	LC	“Risk factors for lung cancer include: Smoking. Your risk of lung cancer increases with the number of cigarettes you smoke each day. Your risk also increases with the number of years you have smoked. Quitting at any age can significantly lower your risk of developing lung cancer. Exposure to secondhand smoke. Even if you don’t smoke, your risk of lung cancer increases if you’re around people who are smoking. Breathing the smoke in the air from other people who are smoking is called secondhand smoke”; Quality of evidence: NA; Classification of recommendation: NA (p. NA)	“There’s no sure way to prevent lung cancer, but you can reduce your risk if you: Don’t smoke. If you’ve never smoked, don’t start. Talk to your children about not smoking so that they can understand how to avoid this major risk factor for lung cancer. Begin conversations about the dangers of smoking with your children early so that they know how to react to peer pressure; Stop smoking. Stop smoking now. Quitting reduces your risk of lung cancer, even if you’ve smoked for years. Talk to your healthcare team about strategies and aids that can help you quit. Options include nicotine replacement products, medicines and support groups; Avoid secondhand smoke. If you live or work with a person who smokes, urge them to quit. At the very least, ask them to smoke outside. Avoid areas where people smoke, such as bars. Seek out smoke-free options”; Quality of evidence: NA; Classification of recommendation: NA (p. NA)

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22	2024c	CC	"Factors that may increase the risk of colon cancer include: […] Low-fiber, high-fat diet. Colon cancer and rectal cancer might be linked with a typical Western diet. This type of diet tends to be low in fiber and high in fat and calories. Research in this area has had mixed results. Some studies have found an increased risk of colon cancer in people who eat a lot of red meat and processed meat; Not exercising regularly. People who are not active are more likely to develop colon cancer. Getting regular physical activity might help lower the risk; […] Obesity. People who are obese have an increased risk of colon cancer. Obesity also increases the risk of dying of colon cancer; Smoking. People who smoke can have an increased risk of colon cancer; Drinking alcohol. Drinking too much alcohol can increase the risk of colon cancer"; Quality of evidence: NA; Classification of recommendation: NA (p. NA)	"Making changes in everyday life can reduce the risk of colon cancer. To lower the risk of colon cancer: Eat a variety of fruits, vegetables and whole grains. Fruits, vegetables and whole grains have vitamins, minerals, fiber and antioxidants, which may help prevent cancer. Choose a variety of fruits and vegetables so that you get a range of vitamins and nutrients; Drink alcohol in moderation, if at all. If you choose to drink alcohol, limit the amount you drink to no more than one drink a day for women and two for men; Stop smoking. Talk to your health care team about ways to quit; Exercise most days of the week. Try to get at least 30 minutes of exercise on most days. If you've been inactive, start slowly and build up gradually to 30 minutes. Also, talk with a health care professional before starting an exercise program; Maintain a healthy weight. If you are at a healthy weight, work to maintain your weight by combining a healthy diet with daily exercise. If you need to lose weight, ask your health care team about healthy ways to achieve your goal. Aim to lose weight slowly by eating fewer calories and moving more"; Quality of evidence: NA; Classification of recommendation: NA (p. NA)
23	2017	LC	"The concept of clearly defining a target population for lung cancer screening is gaining importance.19,27 Selection on the basis of age alone, as in most other cancer screening disease settings (eg, breast and colon), is insufficient in lung cancer because of other powerful risk factors, the most important of which is exposure to tobacco smoke."; Quality of evidence: NA; Classification of recommendation: NA (p. e756)	"Effective implementation of lung cancer screening programmes also includes recognition of the benefits of maximising smoking cessation within CT screening programmes. Smokers should be informed of the dangers of continuing to smoke for their own general health and should be offered suitable support to help quit.48–50 CT methodologies for early lung cancer"; Quality of evidence: NA; Classification of recommendation: NA (p. e758) "Smoking cessation advice should be offered to all active smokers"; Quality of evidence: NA; Classification of recommendation: NA (p. e763)
24	2024a	CC	"The following risk factors increase the risk of colorectal cancer: […] Alcohol; Cigarette smoking; […] Obesity"; Quality of evidence: NA; Classification of recommendation: NA (p. NA) "The following protective factors decrease the risk of colorectal cancer: Physical activity"; Quality of evidence: NA; Classification of recommendation: NA (p. NA) "Drinking 3 or more alcoholic beverages per day increases the risk of colorectal cancer. Drinking alcohol is also linked to the risk of forming large colorectal adenomas (benign tumors)"; Quality of evidence: NA; Classification of recommendation: NA (p. NA) "Cigarette smoking is linked to an increased risk of colorectal cancer and death from colorectal cancer. Smoking cigarettes is also linked to an increased risk of forming colorectal adenomas. Cigarette smokers who have had surgery to remove colorectal adenomas are at an increased risk for the adenomas to recur (come back)"; Quality of evidence: NA; Classification of recommendation: NA (p. NA) "Obesity is linked to an increased risk of colorectal cancer and death from colorectal cancer"; Quality of evidence: NA; Classification of recommendation: NA (p. NA) "A lifestyle that includes regular physical activity is linked to a decreased risk of colorectal cancer"; Quality of evidence: NA; Classification of recommendation: NA (p. NA)	"Avoiding cancer risk factors may help prevent certain cancers. Risk factors include smoking, having overweight, and not getting enough exercise. Increasing protective factors such as quitting smoking and exercising may also help prevent some cancers. Talk to your doctor or other health care professional about how you might lower your risk of cancer"; Quality of evidence: NA; Classification of recommendation: NA (p. NA)
25	2024b	BC	"The following are risk factors for breast cancer: […] Obesity; Drinking alcohol"; Quality of evidence: NA; Classification of recommendation: NA (p. NA) "The following are protective factors for breast cancer: […] Getting enough exercise"; Quality of evidence: NA; Classification of recommendation: NA (p. NA) "Obesity increases the risk of breast cancer, especially in postmenopausal women who have not used hormone replacement therapy. Drinking alcohol increases the risk of breast cancer. The level of risk rises as the amount of alcohol consumed rises"; Quality of evidence: NA; Classification of recommendation: NA (p. NA)	None
26	2024c	LC	"The following are risk factors for lung cancer: Cigarette, cigar, and pipe smoking; Secondhand smoke"; Quality of evidence: NA; Classification of recommendation: NA (p. NA) "Tobacco smoking is the most important risk factor for lung cancer. Cigarette, cigar, and pipe smoking all increase the risk of lung cancer. Tobacco smoking causes about 9 out of 10 cases of lung cancer in men and about 8 out of 10 cases of lung cancer in women. Studies have shown that smoking low tar or low nicotine cigarettes does not lower the risk of lung cancer. Studies also show that the risk of lung cancer from smoking cigarettes increases with the number of cigarettes smoked per day and the number of years smoked. People who smoke have about 20 times the risk of lung cancer compared to those who do not smoke. Being exposed to secondhand tobacco smoke is also a risk factor for lung cancer. Secondhand smoke is the smoke that comes from a burning cigarette or other tobacco product, or that is exhaled by smokers. People who inhale secondhand smoke are exposed to the same cancer-causing agents as smokers, although in smaller amounts. Inhaling secondhand smoke is called involuntary or passive smoking"; Quality of evidence: NA; Classification of recommendation: NA (p. NA)	"Smokers can decrease their risk of lung cancer by quitting. In smokers who have been treated for lung cancer, quitting smoking lowers the risk of new lung cancers. Counseling, the use of nicotine replacement products, and antidepressant therapy have helped smokers quit for good"; Quality of evidence: NA; Classification of recommendation: NA (p. NA)

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27	2020	HG	“Health Benefits Associated With Regular Physical Activity: Lower risk of cancers of the bladder, breast, colon, endometrium, esophagus, kidney, lung, and stomach”; Quality of evidence: NA; Classification of recommendation: NA (p. 15)	“Key Guidelines for Adults: Adults should move more and sit less throughout the day. Some physical activity is better than none. Adults who sit less and do any amount of moderate-to-vigorous physical activity gain some health benefits. For substantial health benefits, adults should do at least 150 minutes (2 hours and 30 minutes) to 300 minutes (5 hours) a week of moderate-intensity, or 75 minutes (1 hour and 15 minutes) to 150 minutes (2 hours and 30 minutes) a week of vigorous-intensity aerobic physical activity, or an equivalent combination of moderate- and vigorous-intensity aerobic activity. Preferably, aerobic activity should be spread throughout the week. Additional health benefits are gained by doing physical activity beyond the equivalent of 300 minutes (5 hours) of moderate-intensity physical activity a week. Adults should also do muscle-strengthening activities of moderate or greater intensity that involve all major muscle groups on 2 or more days a week, as these activities provide additional health benefits”; Quality of evidence: Na; Classification of recommendation: NA (p. 18) “Key Guidelines for Older Adults: The key guidelines for adults also apply to older adults. In addition, the following key guidelines are just for older adults: As part of their weekly physical activity, older adults should do multicomponent physical activity that includes balance training as well as aerobic and muscle-strengthening activities. Older adults should determine their level of effort for physical activity relative to their level of fitness. Older adults with chronic conditions should understand whether and how their conditions affect their ability to do regular physical activity safely. When older adults cannot do 150 minutes of moderate-intensity aerobic activity a week because of chronic conditions, they should be as physically active as their abilities and conditions allow”; Quality of evidence: Na; Classification of recommendation: NA (p. 19) “Key Guidelines for Adults With Chronic Health Conditions and Adults With Disabilities: Adults with chronic conditions or disabilities, who are able, should do at least 150 minutes (2 hours and 30 minutes) to 300 minutes (5 hours) a week of moderate-intensity, or 75 minutes (1 hour and 15 minutes) to 150 minutes (2 hours and 30 minutes) a week of vigorous-intensity aerobic physical activity, or an equivalent combination of moderate- and vigorous-intensity aerobic activity. Preferably, aerobic activity should be spread throughout the week. Adults with chronic conditions or disabilities, who are able, should also do muscle-strengthening activities of moderate or greater intensity that involve all major muscle groups on 2 or more days a week, as these activities provide additional health benefits. When adults with chronic conditions or disabilities are not able to meet the above key guidelines, they should engage in regular physical activity according to their abilities and should avoid inactivity. Adults with chronic conditions or symptoms should be under the care of a health care practitioner. People with chronic conditions can consult a health care professional or physical activity specialist about the types and amounts of activity appropriate for their abilities and chronic conditions”; Quality of evidence: Na; Classification of recommendation: NA (p. 21)
28	2014	CC	“In the Asia Pacific region, age, male gender, family history, smoking and obesity are risk factors for CRC and advanced neoplasia. Quality of evidence: II-2 (Evidence obtained from well-designed control trials without randomisation); Classification of recommendation: A (Accept completely) (p. 3)	None
29	2024a	CC	“Being overweight or obese increases the risk of colorectal cancer in both men and women, but the link seems to be stronger in men”; Quality of evidence: NA; Classification of recommendation: NA (p. NA) “Being more active lowers your risk of colorectal cancer and polyps. Regular moderate to vigorous activity can lower the risk” ; Quality of evidence: NA; Classification of recommendation: NA (p. NA) “Overall, diets that are high in vegetables, fruits, and whole grains, and low in red and processed meats, probably lower colorectal cancer risk, although it’s not exactly clear which factors are important. Many studies have found a link between red meats (beef, pork, and lamb) or processed meats (such as hot dogs, sausage, and lunch meats) and increased colorectal cancer risk. In recent years, some large studies have shown conflicting evidence that fiber in the diet lowers colorectal cancer risk. Research in this area is still under way”; Quality of evidence: NA; Classification of recommendation: NA (p. NA) “Several studies have found a higher risk of colorectal cancer with increased alcohol intake, especially among men.”; Quality of evidence: NA; Classification of recommendation: NA (p. NA) “Long-term smoking is linked to an increased risk of colorectal cancer, as well as many other cancers and health problems”; Quality of evidence: NA; Classification of recommendation: NA (p. NA)	“Staying at a healthy weight may help lower your risk”; Quality of evidence: NA; Classification of recommendation: NA (p. NA)Increasing the amount and intensity of your physical activity may help reduce your risk”; Quality of evidence: NA; Classification of recommendation: NA (p. NA) “Limiting red and processed meats and eating more vegetables, fruits, and whole grains may help lower your risk”; Quality of evidence: NA; Classification of recommendation: NA (p. NA) “Not drinking alcohol may help reduce your risk”; Quality of evidence: NA; Classification of recommendation: NA (p. NA) “Several studies have found a higher risk of colorectal cancer with increased alcohol intake, especially among men. It is best not to drink alcohol. For people who do drink, they should have no more than 1 drink per day for women or two drinks per day for men”; Quality of evidence: NA; Classification of recommendation: NA (p. NA) “Quitting smoking may help lower you risk of colorectal cancer and many other types of cancer, too”; Quality of evidence: NA; Classification of recommendation: NA (p. NA)
30	2024b	LC	“Smoking is by far the leading risk factor for lung cancer. About 80% of lung cancer deaths are thought to result from smoking, and this number is probably even higher for small cell lung cancer (SCLC) It’s rare for someone who has never smoked to have SCLC. The risk of lung cancer for people who smoke is many times higher than for people who don’t smoke. The longer you smoke and the more packs a day you smoke, the greater your risk. Cigar smoking, pipe smoking, and menthol cigarette smoking are almost as likely to cause lung cancer as cigarette smoking. Smoking low-tar or “light” cigarettes increases lung cancer risk as much as regular cigarettes”; Quality of evidence: NA; Classification of recommendation: NA (p. NA) “If you don’t smoke, breathing in the smoke of others (called secondhand smoke or environmental tobacco smoke) can increase your risk of developing lung cancer. Secondhand smoke is the third most common cause of lung cancer in the United States”; Quality of evidence: NA; Classification of recommendation: NA (p. NA)	None
31	2024c	LC	“The best way to reduce your risk of lung cancer is not to smoke and to avoid breathing in other people’s smoke.”; Quality of evidence: NA; Classification of recommendation: NA (p. NA)	“The best way to reduce your risk of lung cancer is not to smoke and to avoid breathing in other people’s smoke. “If you stop smoking before a cancer develops, your damaged lung tissue gradually starts to repair itself. No matter what your age or how long

ID	Year	Type of cancer	Risk factors	Recommendations
				you've smoked, quitting will lower your risk of lung cancer and help you live longer"; Quality of evidence: NA; Classification of recommendation: NA (p. NA) "A healthy diet with lots of fruits and vegetables may also help reduce your risk of lung cancer. Some evidence suggests that a diet high in fruits and vegetables may help protect people who smoke and those who don't against lung cancer. But any positive effect of fruits and vegetables on lung cancer risk would be much less than the increased risk from smoking"; Quality of evidence: NA; Classification of recommendation: NA (p. NA)
32	2024d	BC	"Drinking alcohol is clearly linked to an increased risk of breast cancer. The risk increases with the amount of alcohol consumed. Women who have 1 alcoholic drink a day have a small (about 7% to 10%) increase in risk compared with those who don't drink, while women who have 2 to 3 drinks a day have about a 20% higher risk. Alcohol is linked to an increased risk of other types of cancer, too"; Quality of evidence: NA; Classification of recommendation: NA (p. NA) "Being overweight or obese after menopause increases breast cancer risk"; Quality of evidence: NA; Classification of recommendation: NA (p. NA) "Evidence is growing that regular physical activity reduces breast cancer risk, especially in women past menopause. The main question is how much activity is needed. Some studies have found that even as little as a couple of hours a week might be helpful, although more seems to be better"; Quality of evidence: NA; Classification of recommendation: NA (p. NA)	"It is best not to drink alcohol. Women who do drink should have no more than 1 a day. A drink is 12 ounces of beer, 5 ounces of wine, or 1.5 ounces of 80-proof distilled spirits (hard liquor)"; Quality of evidence: NA; Classification of recommendation: NA (p. NA) "The American Cancer Society recommends you stay at a healthy weight throughout your life and avoid excess weight gain by balancing your food and drink intake with physical activity"; Quality of evidence: NA; Classification of recommendation: NA (p. NA) "The American Cancer Society recommends that adults get 150 to 300 minutes of moderate intensity or 75 to 150 minutes of vigorous intensity activity each week (or a combination of these) Getting to or going over the upper limit of 300 minutes is ideal"; Quality of evidence: NA; Classification of recommendation: NA (p. NA)
33	2022	BC	"Established risk factors for breast cancer include […] alcohol consumption, obesity after menopause, and physical inactivity"; Quality of evidence: NA; Classification of recommendation: NA (p. 162)	None
34	2023	LC	"The American Cancer Society recommends annual screening for lung cancer with low-dose computed tomography in asymptomatic individuals aged 50 to 80 years who currently smoke or formerly smoked and have a ≥20 pack-year smoking history"; Quality of evidence: Moderate; Classification of recommendation: Strong (p. 52) "The ACS recommends that individuals aged 50–80 years who currently smoke, or formerly smoked, and are at high risk for lung cancer because of a ≥20 pack-year history of cigarette smoking undergo annual LCS with LDCT"; Quality of evidence: NA; Classification of recommendation: NA (p. 56)	"Before undergoing lung cancer screening, individuals should receive evidence-based smoking-cessation counseling and offered interventions if they currently smoke;"; Quality of evidence: NA; Classification of recommendation: NA (p. 52) "Individuals who smoke should be advised to quit and offered evidence-based smoking-cessation counseling and pharmocotherapy to assist in quitting. Eligible individuals should undergo SDM with a qualified health professional"; Quality of evidence: NA; Classification of recommendation: NA (p. 56) "This guideline emphasizes smoking-cessation counseling and offering interventions to quit for persons who currently smoke as part of the discussion about LCS. Among persons who currently smoke, it should be emphasized that quitting smoking is the most effective way to lower their risk of developing lung cancer and that combining smoking cessation with LCS is the optimal strategy to reduce their risk of dying from lung cancer"; Quality of evidence: NA; Classification of recommendation: NA (p. 72)
35	2018a	LC	"Smoking is the main cause of lung cancer. It is estimated that over 90 percent of cases among men and over 80 percent among women worldwide are attributable to tobacco use. Passive smoking is also a cause of lung cancer"; Quality of evidence: NA; Classification of recommendation: NA (p. 6) "There is some evidence that suggests consuming red meat, processed meat and alcoholic drinks increases the risk of lung cancer"; Quality of evidence: Limited evidence; Classification of recommendation: NA (p. 7) "In current smokers and former smokers there is some evidence that suggests consuming vegetables and fruit decreases the risk of lung cancer"; Quality of evidence: Limited evidence; Classification of recommendation: NA (p. 7) "There is some evidence that suggests consuming foods containing retinol, beta-carotene or carotenoids decreases the risk of lung cancer"; Quality of evidence: Limited evidence; Classification of recommendation: NA (p. 7) "In current smokers there is some evidence that suggests consuming foods containing vitamin C decreases the risk of lung cancer"; Quality of evidence: Limited evidence; Classification of recommendation: NA (p. 7) "; In people who have never smoked there is some evidence suggesting that consuming foods containing isoflavones (constituent of plants with oestrogen-like properties) decreases the risk of lung cancer"; Quality of evidence: Limited evidence; Classification of recommendation: NA (p. 7) "There is some evidence that suggests being physically active decreases the risk of lung cancer"; Quality of evidence: Limited evidence; Classification of recommendation: NA (p. 7) "The evidence suggesting that consumption of alcoholic drinks increases the risk of lung cancer is limited"; Quality of evidence: Limited evidence; Classification of recommendation: NA (p. 45)	None
36	2018b	BC	"Vigorous physical activity: Vigorous physical activity probably protects against premenopausal breast cancer"; Quality of evidence: Probable evidence; Classification of recommendation: NA (p. 96) "Body fatness: Greater body fatness in women before the menopause (marked by BMI, waist circumference and waist–hip ratio) probably protects against premenopausal breast cancer"; Quality of evidence: Probable evidence; Classification of recommendation: NA (p. 96) "Body fatness in young adulthood: Greater body fatness in young women (aged about 18 to 30 years) (marked by BMI) probably protects against premenopausal breast cancer"; Quality of evidence: Probable evidence; Classification of recommendation: NA (p. 96)	None

ID	Year	Type of cancer	Risk factors	Recommendations
			"Alcoholic drinks: Consumption of alcoholic drinks is probably a cause of premenopausal breast cancer"; Quality of evidence: Probable evidence; Classification of recommendation: NA (p. 96) "Non-starchy vegetables: The evidence suggesting that consumption of non-starchy vegetables decreases the risk of oestrogen-receptor-negative (ER–) breast cancer (unspecified) is limited"; Quality of evidence: Limited evidence; Classification of recommendation: NA (p. 96) "Dairy products: The evidence suggesting that consumption of dairy products decreases the risk of premenopausal breast cancer is limited"; Quality of evidence: Limited evidence; Classification of recommendation: NA (p. 96) "Foods containing carotenoids: The evidence suggesting that consumption of foods containing carotenoids decreases the risk of breast cancer (unspecified) is limited"; Quality of evidence: Limited evidence; Classification of recommendation: NA (p. 96) "Diets high in calcium: The evidence suggesting that diets high in calcium decrease the risk of premenopausal breast cancer is limited"; Quality of evidence: Limited evidence; Classification of recommendation: NA (p. 96) "Total physical activity: The evidence suggesting that being physically active decreases the risk of premenopausal breast cancer is limited"; Quality of evidence: Limited evidence; Classification of recommendation: NA (p. 97) "Alcoholic drinks: Consumption of alcoholic drinks is a convincing cause of postmenopausal breast cancer"; Quality of evidence: Convincing evidence; Classification of recommendation: NA (p. 97) "Body fatness: Greater body fatness throughout adulthood (marked by BMI, waist circumference and waist–hip ratio) is a convincing cause of postmenopausal breast cancer"; Quality of evidence: Convincing evidence; Classification of recommendation: NA (p. 97) "Adult weight gain: Greater weight gain in adulthood is a convincing cause of postmenopausal breast cancer"; Quality of evidence: Convincing evidence; Classification of recommendation: NA (p. 97) "Total (including vigorous) physical activity: Being physically active (including vigorous physical activity) probably protects against postmenopausal breast cancer"; Quality of evidence: Probable evidence; Classification of recommendation: NA (p. 97) "Body fatness in young adulthood: Greater body fatness in young women (aged about 18 to 30 years) (marked by BMI) probably protects against postmenopausal breast cancer"; Quality of evidence: Probable evidence; Classification of recommendation: NA (p. 97) "Non-starchy vegetables: The evidence suggesting that consumption of non-starchy vegetables decreases the risk of oestrogen-receptor-negative (ER–) breast cancer (unspecified) is limited"; Quality of evidence: Limited evidence; Classification of recommendation: NA (p. 97) "Foods containing carotenoids: The evidence suggesting that consumption of foods containing carotenoids decreases the risk of breast cancer (unspecified) is limited"; Quality of evidence: Limited evidence; Classification of recommendation: NA (p. 97) "Diets high in calcium: The evidence suggesting that diets high in calcium decrease the risk of postmenopausal breast cancer is limited"; Quality of evidence: Limited evidence; Classification of recommendation: NA (p. 97)	
37	2018c	CC	"Physical activity: Physical activity convincingly protects against colon cancer"; Quality of evidence: Convincing evidence; Classification of recommendation: NA (p. 85) "Processed meat: Consumption of processed meat is a convincing cause of colorectal cancer"; Quality of evidence: Convincing evidence; Classification of recommendation: NA (p. 85) "Alcoholic drinks: Consumption of alcoholic drinks is a convincing cause of colorectal cancer. This is based on evidence for intakes above 30 grams per day (about two drinks a day)"; Quality of evidence: Convincing evidence; Classification of recommendation: NA (p. 85) "Body fatness: Greater body fatness is a convincing cause of colorectal cancer"; Quality of evidence: Convincing evidence; Classification of recommendation: NA (p. 85) "Wholegrains: Consumption of wholegrains probably protects against colorectal cancer"; Quality of evidence: Probable evidence; Classification of recommendation: NA (p. 85) "Dietary fibre: Consumption of foods containing dietary fibre probably protects against colorectal cancer"; Quality of evidence: Probable evidence; Classification of recommendation: NA (p. 85) "Dairy products: Consumption of dairy products probably protects against colorectal cancer"; Quality of evidence: Probable evidence; Classification of recommendation: NA (p. 85) "Calcium supplements: Taking calcium supplements probably protects against colorectal cancer"; Quality of evidence: Probable evidence; Classification of recommendation: NA (p. 85) "Red meat: Consumption of red meat is probably a cause of colorectal cancer"; Quality of evidence: Probable evidence; Classification of recommendation: NA (p. 85) "Foods containing vitamin C: The evidence suggesting that foods containing vitamin C decreases the risk of colon cancer is limited"; Quality of evidence: Limited evidence; Classification of recommendation: NA (p. 86) "Fish: The evidence suggesting that consumption of fish decreases the risk of colorectal cancer is limited"; Quality of evidence: Limited evidence; Classification of recommendation: NA (p. 86) "Vitamin D: The evidence suggesting that vitamin D decreases the risk of colorectal cancer is limited"; Quality of evidence: Limited evidence; Classification of recommendation: NA (p. 86) "Multivitamin supplements: The evidence suggesting that taking multivitamin supplements decreases the risk of colorectal cancer is limited"; Quality of evidence: Limited evidence; Classification of recommendation: NA (p. 86)	None

ID	Year	Type of cancer	Risk factors	Recommendations
			"Non-starchy vegetables: The evidence suggesting that low consumption of nonstarchy vegetables increases the risk of colorectal cancer is limited"; Quality of evidence: Limited evidence; Classification of recommendation: NA (p. 86) "Fruits: The evidence suggesting that low consumption of fruit increases the risk of colorectal cancer is limited"; Quality of evidence: Limited evidence; Classification of recommendation: NA (p. 86) "Foods containing haem iron: The evidence suggesting that consumption of foods containing haem iron increases the risk of colorectal cancer is limited"; Quality of evidence: Limited evidence; Classification of recommendation: NA (p. 86)	
38	2018d	CG	None	"Be a healthy weight: Keep your weight within the healthy range and avoid weight gain in adult life. (The healthy (or, as defined by WHO, 'normal') range of BMI for adults is 18.5–24.9 kg/m2. Different reference ranges have been proposed for Asian populations. Where these ranges differ from the WHO definition, they are to be used as the guide. Further research is required to establish appropriate thresholds in other ethnic groups. The healthy range for BMI during childhood varies with age.)"; Quality of evidence: Na; Classification of recommendation: NA (p. 15) "Be physically active: Be physically active as part of everyday life – walk more and sit less. Be at least moderately physically active, and follow or exceed national guidelines. Limit sedentary habits. (Moderate physical activity increases heart rate to about 60 to 75 per cent of its maximum)"; Quality of evidence: Na; Classification of recommendation: NA (p. 19) "Eat a diet rich in wholegrains, vegetables, fruit and beans: Make wholegrains, vegetables, fruit, and pulses (legumes) such as beans and lentils a major part of your usual daily diet. Consume a diet that provides at least 30 grams per day of fibre from food sources. Include in most meals foods containing wholegrains, non-starchy vegetables, fruit and pulses (legumes) such as beans and lentils. Eat a diet high in all types of plant foods including at least five portions or servings (at least 400 grams or 15 ounces in total) of a variety of non-starchy vegetables and fruit every day. If you eat starchy roots and tubers as staple foods, eat non-starchy vegetables, fruit and pulses (legumes) regularly too if possible"; Quality of evidence: Na; Classification of recommendation: NA (p. 22) "Limit consumption of 'fast foods' and other processed foods high in fat, starches or sugars: Limiting these foods helps control calorie intake and maintain a healthy weight"; Quality of evidence: Na; Classification of recommendation: NA (p. 26) "Limit consumption of red and processed meat: Eat no more than moderate amounts of red meat, such as beef, pork and lamb. Eat little, if any, processed meat. If you eat red meat, limit consumption to no more than about three portions per week. Three portions is equivalent to about 350 to 500 grams (about 12 to 18 ounces) cooked weight of red meat. Consume very little, if any, processed meat. (The term 'red meat' refers to all types of mammalian muscle meat, such as beef, veal, pork, lamb, mutton, horse and goat. The term 'processed meat' refers to meat that has been transformed through salting, curing, fermentation, smoking or other processes to enhance flavour or improve preservation. 500 grams of cooked red meat is roughly equivalent to 700–750 grams of raw meat, but the exact conversion depends on the cut of meat, the proportions of lean meat and fat, and the method and degree of cooking.)"; Quality of evidence: Na; Classification of recommendation: NA (p. 29) "Limit consumption of sugar sweetened drinks: Drink mostly water and unsweetened drinks. Do not consume sugar sweetened drinks (Sugar sweetened drinks are defined here as liquids that are sweetened by adding free sugars, such as sucrose, high fructose corn syrup and sugars naturally present in honey, syrups, fruit juices and fruit juice concentrate. This includes, among others, sodas, sports drinks, energy drinks, sweetened waters, cordials, barley water, and coffee- and tea-based beverages with sugars or syrups added. This does not include versions of these drinks which are 'sugar-free' or sweetened only with artificial sweeteners.)"; Quality of evidence: Na; Classification of recommendation: NA (p. 32) "Limit alcohol consumption: For cancer prevention, it's best not to drink alcohol"; Quality of evidence: Na; Classification of recommendation: NA (p. 34)
39	2023a	CC	"Several lifestyle factors contribute to the development of colorectal cancer such as a high intake of processed meats and low intake of fruits and vegetables, sedentary lifestyle, obesity, smoking, and excessive alcohol consumption"; Quality of evidence: NA; Classification of recommendation: NA (p. NA) "Factors that may increase the risk of developing colorectal cancer include: […] lifestyle factors: unhealthy lifestyle choices, such as a diet high in processed meats and low in fruits and vegetables, sedentary behaviour, obesity, smoking and excessive alcohol consumption, can increase the risk"; Quality of evidence: NA; Classification of recommendation: NA (p. NA)	"Lifestyle changes to help prevent colorectal cancer include: eating a healthy diet rich in fruits and vegetables not smoking tobacco keeping an active lifestyle limiting alcohol consumption avoiding exposure to environmental risk factors"; Quality of evidence: NA; Classification of recommendation: NA (p. NA)
40	2023b	LC	"Smoking is the leading cause of lung cancer, responsible for approximately 85% of all cases"; Quality of evidence: NA; Classification of recommendation: NA (p. NA)	"In public health, these [primary] preventive measures include smoking cessation, promoting smoke-free environments, implementing tobacco control policies"; Quality of evidence: NA; Classification of recommendation: NA (p. NA)
41	2024c	CG	"Alcohol, as classified by the International Agency for Research on Cancer, is a toxic, psychoactive, and dependence-producing substance and a Group 1 carcinogen that is causally linked to 7 types of cancer, including [...] colorectal, and breast cancers"; Quality of evidence: NA; Classification of recommendation: NA (p. NA) "Overweight and obesity are linked to many types of cancer such as [...] colorectal, [and] breast, endometrial and kidney. [...] Excess body mass was responsible for 3.4% of cancers in 2012, including 110 000 cases of breast cancer per year. Alcohol use is a risk factor for many cancer types including cancer of [...] colorectal and breast. Risk of cancer increases with the amount of alcohol consumed"; Quality of evidence: NA; Classification of recommendation: NA (p. NA)	None

ID	Year	Type of cancer	Risk factors	Recommendations
42	2024d	CG	None	“avoid tobacco use, including cigarettes and smokeless tobacco; maintain a healthy weight; eat a healthy diet with plenty of fruit and vegetables; exercise regularly”; Quality of evidence: NA; Classification of recommendation: NA (p. NA)
43	2024e	BC	“Certain factors increase the risk of breast cancer including increasing age, obesity, harmful use of alcohol, […] tobacco use”; Quality of evidence: NA; Classification of recommendation: NA (p. NA)	None

Note: BR= Breast cancer; CC= Colorectal cancer; LC= Lung cancer; CG= Cancer in general; HG= Health in general

2.4. Summary

The documents targeting breast, colorectal, and lung cancer focus predominantly on identifying risk factors rather than providing detailed recommendations to mitigate cancer risk. The consensus is strongest for alcohol consumption and excessive weight as key risk factors for breast and colorectal cancer, and smoking for lung cancer. Physical inactivity is also noted as a significant risk factor, though there is less agreement on its impact compared to other factors.

For breast cancer, all documents agree that alcohol consumption and excessive weight are major risk factors. Recommendations include avoiding alcohol and maintaining an optimal weight. Specific thresholds for alcohol intake and weight are mentioned but vary across documents. Physical inactivity is also identified as a risk factor, with suggestions to engage in regular physical activity.

Colorectal cancer documents highlight overweight and obesity as primary risk factors, with recommendations to maintain a healthy weight through diet and exercise. Physical inactivity, unhealthy diet, smoking, and alcohol are also noted as risk factors, with general advice to incorporate physical activity and a healthy diet, avoid smoking, and limit alcohol intake.

Lung cancer documents unanimously point to smoking as the primary risk factor, emphasizing the importance of quitting smoking and avoiding secondhand smoke. Recommendations are less detailed for physical activity, diet, alcohol, and weight.

General cancer prevention documents stress obesity, diet, and alcohol consumption as significant risk factors across multiple cancer types, including breast, colorectal, and lung cancer. Recommendations focus on maintaining a healthy BMI, consuming a balanced diet rich in fruits, vegetables, and whole grains, and limiting alcohol intake.

The majority of the documents provide vague recommendations without specifying thresholds or detailed guidelines for mitigating cancer risk. Only a few studies offer practical and specific advice on lifestyle modifications. Table 3 is a summary table of the detailed and practical recommendations for each lifestyle factor across different cancer types.

Table 3. Summary table of detailed and practical recommendations

Cancer type	Lifestyle factor	Detailed practical recommendations
Breast Cancer	Alcohol	It's better to avoid alcohol, but if you do, limit to one drink per day.
	Weight	Maintain optimal weight, avoid obesity, balance food and drink intake with physical activity.
	Physical Activity	Engage in at least 30-60 minutes of moderate exercise daily.
	Smoking	N/A
	Diet	N/A
Colorectal Cancer	Alcohol	It's better not to drink alcohol at all, but if you do, limit alcohol to no more than one drink per day for women and two drinks per day for men.
	Weight	Maintain a healthy weight through balanced diet and regular physical activity.
	Physical Activity	Engage in at least 30 minutes of exercise on most days.
	Smoking	Quit smoking and avoid secondhand smoke.
	Diet	Consume a variety of fruits, vegetables, and whole grains; limit red and processed meats.

Lung Cancer	Smoking	Quit smoking entirely, avoid exposure to secondhand smoke, use cessation support programs.
	Weight	N/A
	Physical Activity	N/A
	Diet	N/A
	Alcohol	N/A
General Prevention	Alcohol	Limit alcohol intake, avoid high consumption of beer and spirits.
	Weight	Maintain a BMI of 18.5 to 24.9 kg/m², avoid obesity, gradual weight loss if overweight.
	Physical Activity	Move more, sit less, aim for 150-300 minutes of moderate-intensity or 75-150 minutes of vigorous-intensity aerobic activity weekly.
	Diet	Eat at least 200 grams each of vegetables and fruits daily, include whole grains, limit red and processed meats, prioritize plant-based foods.

3. Umbrella review to identify solutions and methodologies for passive monitoring of lifestyles

As highlighted previously, the results from the earlier subtask emphasize the significant role of obesity, physical inactivity, unhealthy diet, alcohol consumption, and smoking as modifiable risk factors for breast, colorectal, and lung cancers. In line with the goals of Europe's Beating Cancer Plan, the iBeChange project aims at addressing these behavioural risk factors using also innovative digital solutions. In **Task 2.1**, we also conducted an umbrella review to synthesize evidence on digital solutions, wearable devices, and methodologies to monitor these risk factors passively and unobtrusively.

3.1. Aims

In summary, this subtask within the iBeChange project aimed to systematically synthesize the latest evidence on digital solutions, wearable technologies, and methodologies that passively and unobtrusively monitor key behavioural risk factors for breast, colorectal, and lung cancers. The results of this umbrella review will inform the development of the iBeChange platform's monitoring solutions. These methodologies offer advantages over self-report measures by providing more accurate, continuous, and objective data without relying on user recall. By synthesizing the latest evidence, we aim to enhance our ability to detect and address unhealthy behaviours, informing and improving primary prevention strategies for breast, colorectal, and lung cancers.

3.2. Methods

This umbrella review screened systematic reviews, narrative reviews, and meta-analyses from the last 10 years, focusing on technological solutions for passive lifestyle monitoring. Passive monitoring of Psychological risk factors is targeted in Task2.2. We included studies targeting various populations, regardless of health status, and examined interventions such as digital phenotyping, digital biomarkers, digital footprints, passive sensing, mobile sensing, and related tools. The primary outcome was the identification and assessment of these technologies for monitoring behaviours like physical activity, diet, alcohol consumption, smoking, weight loss, and obesity.

We conducted the review using four main databases: PubMed, Scopus, EMBASE, and EBSCOHost, with searches performed in late June 2024. The search strategy was first developed in PubMed and then adapted for the other databases, using a combination of terms related to lifestyle behaviours and digital solutions.

Inclusion criteria:

- Systematic reviews, narrative reviews, and meta-analyses discussing technological solutions for passive monitoring of lifestyle behaviours.
- Studies involving the general population or specific groups, without health status restrictions.
- Interventions encompassing digital phenotyping, digital biomarkers, passive sensing, mobile sensing, wearable devices, mobile apps, and related tools.
- Documents published in English within the last 10 years.

Titles and abstracts were screened for relevance, and all items were uploaded into Rayyan software (Ouzzani et al., 2016) to facilitate the process. Initial duplicates were identified using Rayyan and manually verified. Documents were then independently screened by two reviewers from UNIPA based on titles and abstracts. Eligibility assessments were blinded to ensure unbiased evaluation, with conflicts resolved through discussion. Identified documents underwent full-text screening by the same reviewers. Data extraction was performed by one author and validated by another reviewer from UNIPA. Key elements extracted included author(s), publication year, title, aims, included databases, number of studies, type of review, number of participants and their age, targeted population, monitored lifestyle factor, monitoring methodology, and findings related to the efficacy, validity, reliability, acceptance, acceptability, and usability of the technology/methodology.

3.3. Results

Our search and screening process identified 69 literature reviews. Figure 2 reports a detailed log of the screening procedure.

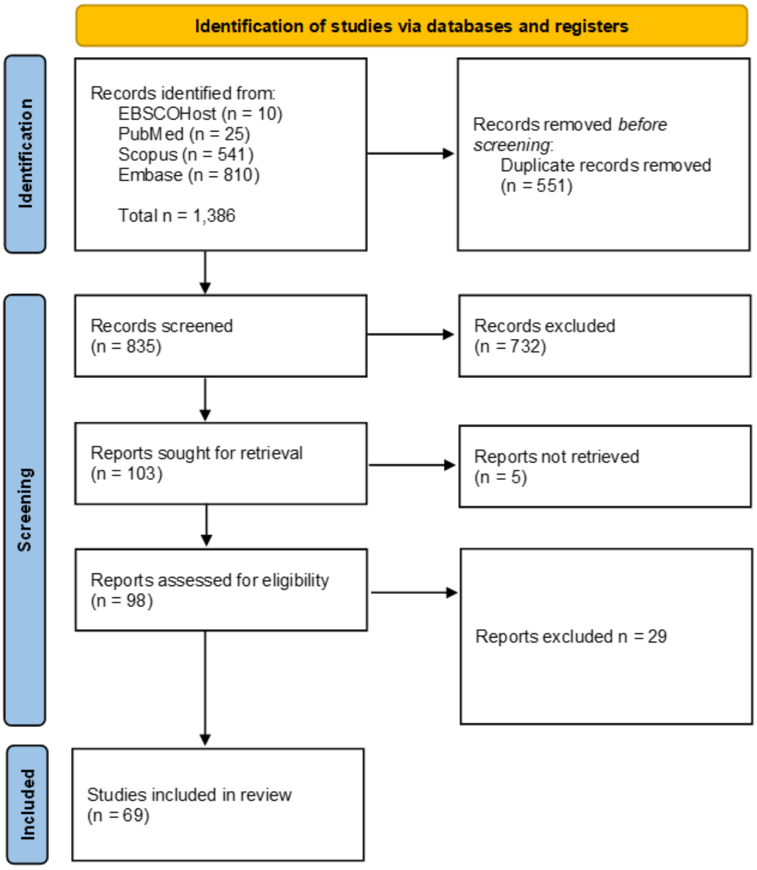

Figure 2. PRISMA 2020 flow diagram for this umbrella review to identify solutions and methodologies for passive monitoring of lifestyles

The characteristics and main information of the documents are summarized in Table 4 and Table 5. The reviewed items span from 2014 to 2024, with the majority being systematic reviews or meta-analyses (44.7%). The focus areas are physical activity (68.1%), diet (18.8%), alcohol consumption (7.2%), and cigarette smoking (1.1%). There were no studies targeting weight management and obesity, and only one study targeted multiple lifestyles (i.e., diet, alcohol, and smoking). The populations studied range from healthy individuals (5.8%) to those with specific diseases or conditions, such as neurodegenerative disorders, heart failure, stroke, and HIV infection. Over 1,754,533 individuals are included, with ages ranging from 4 to 86 years. The databases used were PubMed (59.4%), Scopus (34.7%), Embase (31.9%), Medline (29.0%), Web of Science (24.6%), CINAHL (21.7%), SportDiscus (17.4%), IEEEXplore (17.4%), Cochrane (10.1%), PsycINFO (9.6%), Google Scholar (8.7%), Ovid (5.8%), and EBSCO (2.9%).

Table 4. Main results of the umbrella review (ID, author(s), year, title, review aims, included databases, number of included studies, if systematic review or meta-analysis, number of participants, age description, if healthy population)

ID	Authors	Year	Title	Review aim	Included databases	Number of included studies	Systematic review/meta-analysis?	Number of participants
1	Allahbakhshi et al.	2019	The Key Factors in Physical Activity Type Detection Using Real-Life Data: A Systematic Review.	To systematically review the existing methodologies that meet the three main criteria: (1) they detect PA types; (2) the PA data collection is performed in real-life settings; and (3) portable devices used include accelerometer sensors (and possibly additional sensors).	Web of Science, Scopus, PsycINFO, and PubMed	21	Yes	Not reported
2	Banerjee et al.	2022	Food Detection and Recognition Using Deep Learning - A Review	To investigate a number of vision-based techniques for detecting food images	Not reported	Not reported	No	Not reported
3	Barton et al.	2017	A review of physical activity monitoring and activity trackers for older adults	To review the methods of measuring physical activity, adoption of wearable devices in older adults	Not reported	Not reported	No	Not reported
4	Bate et al.	2023	The Role of Wearable Sensors to Monitor Physical Activity and Sleep Patterns in Older Adult Inpatients: A Structured Review	This review aimed to provide an overview of the use of wearable sensors in older adult inpatient populations, including models used, body placement and outcome measures.	PubMed, Ovid Embase, Scopus, Web of Science and Cochrane	89	No	Not reported
5	Benson et al.	2018	The use of wearable devices for walking and running gait analysis outside of the lab: A systematic review	The purpose of this systematic review was to identify how wearable devices are being used for gait analysis in out-of-lab settings.	PubMed, Medline, CINAHL, Embase, and SportDiscus	61	Yes	Not reported
6	Block et al.	2016	Remote Physical Activity Monitoring in Neurological Disease: A Systematic Review	To perform a systematic review of studies using remote physical activity monitoring in neurological diseases, highlighting advances and determining gaps.	PubMed/MEDLINE, CINAHL and SCOPUS	137	Yes	Not reported
7	Bort-Roig et al.	2014	Measuring and influencing physical activity with smartphone technology: a systematic review.	To systematically review evidence on smartphones and their viability for measuring and influencing physical activity.	Web of Knowledge, PubMed, PsycINFO, EBSCO, ScienceDirect.	26	Yes	Not reported
8	Breasail et al.	2021	Wearable GPS and Accelerometer Technologies for Monitoring Mobility and Physical Activity in Neurodegenerative Disorders: A Systematic Review.	To summarize the literature targeting the use of wearable GPS or accelerometers to monitor physical activity or mobility in patients with common neurodegenerative disorders	MEDLINE, Embase, AMED (Allied and Complementary Medicine), APA PsycINFO	28	Yes	Not reported
9	Brobbin et al.	2022	Acceptability and Feasibility of Wearable Transdermal Alcohol Sensors: Systematic Review	To evaluate the acceptability and feasibility of the currently available transdermal alcohol sensor devices.	CINAHL, Embase, Google Scholar, MEDLINE, PsycINFO, PubMed, Scopus	22	Yes	821
10	Brobbin et al.	2022	Accuracy of Wearable Transdermal Alcohol Sensors: Systematic Review.	To assess wearable transdermal alcohol sensor accuracy.	INAHL, Embase, Google Scholar, MEDLINE, PsycINFO, PubMed, Scopus	32	Yes	1,128
11	Buendia et al.	2024	Wearable Sensors to Monitor Physical Activity in Heart Failure Clinical Trials: State-of-the-Art Review.	To provide recommendations to include actigraphy to measure physical activity in heart failure clinical trial	Not reported	Not reported	No	Not reported
12	Cabot et al.	2022	First Systematic Review and Meta-analysis of the Validity and Test-Retest Reliability of Physical Activity Monitors for Estimating Energy Expenditure During Walking in Individuals With Stroke.	To evaluate the validity and test-retest reliability of physical activity trackers, including accelerometer, multi-sensor, smartphone, and pedometer, for the estimation of energy expenditure during walking in individuals with stroke	Webline, Medline, Scopus, ScienceDirect, Bielefeld Academic Search Engine and Wiley Online Library	8	Yes	184
13	Chan et al.	2022	Reporting adherence, validity and physical activity measures of wearable activity trackers in medical research: A systematic review	to identify the activity tracker-derived measures and evaluate the relations of reported adherence, validity, and physical activity types across currently available literature.	PubMed and Embase	27	Yes	1,700,948
14	Chen et al.	2023	Vision-Based Methods for Food and Fluid Intake Monitoring: A Literature Review.	To review the existing literature on vision-based intake monitoring methods for food and fluid and identify the current challenges and research gaps	PubMed, SCOPUS, IEEE Xplore, ACM Digital Library, Web of Science, Google Scholar	253	Yes	Not reported
15	Chevance et al.	2022	Accuracy and Precision of Energy Expenditure, Heart Rate, and Steps Measured by Combined-Sensing Fitbits Against Reference Measures: Systematic Review and Meta-analysis	To examine, quantify, and report the current state of evidence for the validity of energy expenditure, heart rate, and steps measured by recent combined-sensing Fitbits.	PubMed, Embase	52	Yes	1,628
16	Dagenais et al.	2019	Wireless Physical Activity Monitor Use among Adults Living with HIV: A Scoping Review	To examine wireless physical activity monitor use in people living with HIV	MEDLINE, Embase, CINAHL, PubMed, Cochrane, PyscINFO	25	No	1,421
17	Davis-Martin et al.	2022	Alcohol Use Disorder in the Age of Technology: A Review of Wearable Biosensors in Alcohol Use Disorder Treatment	This review examines the state of research in the area of treatment of alcohol use disorders, to examine how researchers are utilizing existing wearable technologies in treatments for AUD.	Not reported	Not reported	No	Not reported
18	Egmond et al.	2020	Wearable Transdermal Alcohol Monitors: A Systematic Review of Detection Validity, and Relationship Between Transdermal and Breath Alcohol Concentration and Influencing Factors.	To provide an overview of transdermal alcohol concentration monitors' reliability in detecting alcohol consumption and methods to estimate breath alcohol concentration and number of standard drinks consumed in a given time frame.	MEDLINE, PsycINFO, SCOPUS, Engineering Village, and CINAHL	13	Yes	Not reported

ID	Authors	Year	Title	Review aim	Included databases	Number of included studies	Systematic review/meta-analysis?	Number of participants
19	Fuller et al.	2020	Reliability and Validity of Commercially Available Wearable Devices for Measuring Steps, Energy Expenditure, and Heart Rate: Systematic Review	To examine the validity and reliability of commercial wearables in measuring step count, heart rate, and energy expenditure.	PubMed, Embase, SPORTDiscus	158	Yes	5,934
20	Giggins et al	2017	Physical Activity Monitoring in Patients with Neurological Disorders: A Review of Novel Body-Worn Devices	to examine the literature reporting the validity and reliability of wearable physical activity monitoring in individuals with neurological disorders	PubMed and CINAHL	23	Yes	Not reported
21	Gorzelitz et al.	2020	Accuracy of Wearable Trackers for Measuring Moderate-to Vigorous-Intensity Physical Activity: A Systematic Review and Meta-Analysis	To review validation studies published since 2012 using consumer-based wearable activity trackers to measure moderate- to vigourous-intensity physical activity.	PubMed, Scopus, SPORTDiscus, Cochrane Library	22	Yes	876
22	Hammond-Haley et al.	2021	Utility of wearable physical activity monitors in cardiovascular disease: a systematic review of 11464 patients and recommendations for optimal use.	To systematically review the existing literature on the use of wearable activity monitors in patients with cardiovascular diseases. This included examining how these devices have been utilized to measure physical activity in this patient population	PubMed, Embase	108	Yes	11,464
23	Hassannejad et al.	2017	Automatic diet monitoring: a review of computer vision and wearable sensor-based methods	This article reviews the most relevant and recent research on automatic diet monitoring.	IEEEXplore, Google Scholar and Scopus	Not reported	No	Not reported
24	He et al.	2020	A comprehensive review of the use of sensors for food intake detection	The paper reports some of the essential works done on the utilization of sensors for the detection of food intake.	Not reported	Not reported	No	Not reported
25	Imtiaz et al.	2019	Wearable Sensors for Monitoring of Cigarette Smoking in Free-Living: A Systematic Review.	To review the literature on current and forthcoming wearable technologies to monitor cigarette smoking, with a focus on sensing elements, body placement, detection accuracy, underlying algorithms and applications.	PubMed, Google Scholar, Science Direct,Wiley Online Library, ACM Digital library, MDPI, IEEE Explore	86	Yes	Not reported
26	Keikha et al.	2022	Telerehabilitation and Monitoring Physical Activity in Patient with Breast Cancer: Systematic Review	to review the different technology-assisted interventions for improving physical activity in breast cancer patients	PubMed, Scopus, Google Scholar, and Web of Science	45	Yes	Not reported
27	Keogh et al.	2021	Assessing the usability of wearable devices to measure gait and physical activity in chronic conditions: a systematic review.	Tis systematic reviewed aimed to explore the usability of wearable devices to measure gait and physical activity in a range of cohorts with chronic health conditions.	PubMed, Embase, Medline and Cinhal Plus	37	Yes	Not reported
28	Khanal et al.	2022	A Review on Computer Vision Technology for Physical Exercise Monitoring	To review physical exercise monitoring using non-contact techniques	IEEE Xplore, ScienceDirect, Web of Science, Spring link, PubMed, Psych info, ACM digital library, and Human and kinetics journals	86	Yes	Not reported
29	Krishna et al.	2022	A Review on Sensors based Quantifying Device to Oversee the Mealtime Dietary Intake	To discuss various food weight detection systems	Not reported	Not reported	No	Not reported
30	Kristoffersson & Lindén	2022	A Systematic Review of Wearable Sensors for Monitoring Physical Activity	To reviews the use of wearable sensors for the monitoring of physical activity (PA)	Web of Science Core Collection, MEDLINE, Scopus, ScienceDirect, Academic Search Elite, ACM Digital Library and IEEE Xplore	54	Yes	Not reported
31	Larsen et al.	2022	Effectiveness of physical activity monitors in adults: systematic review and meta-analysis	To estimate the effectiveness of physical activity monitor (PAM) based interventions among adults and explore reasons for the heterogeneity	MEDLINE, Embase, SPORTDiscus, CINAHL, Cochrane Central Register of Controlled Trials (CENTRAL)	121	Yes	16,743
32	Leung et al.	2021	Factors associated with validity of consumer-oriented wearable physical activity trackers: a meta-analysis.	To examine the strength of criterion validity evidence of various consumer-oriented wearable physical activity trackers, the influence of different brands on this validity, and the factors contributing to differences in the strength of this evidence.	MEDLINE, SPORTDiscus, Web of Science, and Academic Search Premier	29	Yes	891
33	Mansouri et al.	2023	Deep Learning for Food Image Recognition and Nutrition Analysis Towards Chronic Diseases Monitoring: A Systematic Review	A systematic review is presented for the application of deep learning in food image recognition and nutrition analysis.	Not reported	57	Yes	Not reported
34	Martinko et al.	2020	Accuracy and Precision of Consumer-Grade Wearable Activity Monitors for Assessing Time Spent in Sedentary Behavior in Children and Adolescents: Systematic Review	To investigate and communicate findings on the accuracy and precision of consumer-grade physical activity monitors in assessing the time spent in sedentary behaviour in children and adolescents.	PubMed, Scopus, SPORTDiscus, ProQuest, Open Access Theses and Dissertations, DART Europe E-theses Portal, Networked Digital Library of Theses and Dissertations	8	Yes	392
35	McCullagh et al.	2016	A Review of the Accuracy and Utility of Motion Sensors to Measure Physical Activity of Frail, Older Hospitalized Patients	The purpose of this review was to examine the utility and accuracy of commercially available motion sensors to measure step-count and time-spent-upright in frail older hospitalised patients	PubMed, Cumulative Index to Nursing and Allied Health Literature (CINAHL)	24	Yes	Not reported
36	Moguel et al.	2019	Systematic Literature Review of Food-Intake Monitoring in an Aging Population	To evaluate existing technological proposals for food-intake monitoring	Scopus	29	Yes	Not reported

ID	Authors	Year	Title	Review aim	Included databases	Number of included studies	Systematic review/meta-analysis?	Number of participants
37	Molina-Garcia et al.	2022	Validity of Estimating the Maximal Oxygen Consumption by Consumer Wearables: A Systematic Review with Meta-analysis and Expert Statement of the INTERLIVE Network.	To quantitatively summarize studies investigating the validity of the VO2max estimated by consumer wearables and provide best-practice recommendations	PubMed, Web of Sciences, Scopus	14	Yes	403
38	Mortazavi & Gutierrez-Osuna	2023	A Review of Digital Innovations for Diet Monitoring and Precision Nutrition	To provide an overview of current technology for Diet Monitoring and Precision Nutrition	Not reported	Not reported	No	Not reported
39	Nasruddin et al.	2023	Physical Activity Surveillance in Children and Adolescents Using Smartphone Technology: Systematic Review	to explore the use of smartphone technology for PA surveillance in children and adolescents, specifically focusing on the use of smartphone apps	PubMed, Scopus, CINAHL, MEDLINE, and Web of Science	8	Yes	881
40	Negrini et al.	2021	Reliability of activity monitors for physical activity assessment in patients with musculoskeletal disorders: A systematic review	describing the assessment of physical activity by commercially available portable activity monitors in patients with musculoskeletal disorders	PubMed, Embase, PEDro, Web of Science, Scopus and CENTRAL	10	Yes	Not reported
41	Neves et al.	2022	Thought on Food: A Systematic Review of Current Approaches and Challenges for Food Intake Detection	This paper presents a systematic review of the use of technology for food intake detection, focusing on the different sensors and methodologies used.	PubMed, Springer, ACM, IEEE Xplore, MDPI, and Elsevier.	30	Yes	Not reported
42	O'Driscoll et al.	2020	How well do activity monitors estimate energy expenditure? A systematic review and meta-analysis of the validity of current technologies.	To determine the accuracy of wrist and arm-worn activity monitors' estimates of energy expenditure.	SportDISCUS, PubMed, MEDLINE, PsycINFO, Embase, CINAHL.	60	Yes	1,946
43	Ocagli et al.	2023	Physical activity assessment with wearable devices in rheumatic diseases: a systematic review and meta-analysis	To evaluate how the use of wearable devices (WDs) impacts physical activity in patients with noninflammatory and inflammatory rheumatic diseases.	PubMed, Embase, CINAHL and Scopus	51	Yes	7,488
44	Panicker & Chandrasekaran	2022	"Wearables on vogue": a scoping review on wearables on physical activity and sedentary behavior during COVID-19 pandemic	To provide the readers with a broader knowledge of the impact of wearables on physical health during the pandemic.	Web of Science, Scopus, Ovid Medline, Cumulative Index to Nursing and Allied Health Literature and Embase	17	No	Not reported
45	Pericleous & van Staa	2019	The use of wearable technology to monitor physical activity in patients with COPD: a literature review	To assess the performance of wearable technology in monitoring and improving physical activity in COPD patients from published studies.	Medline, Cochrane, Dare, Embase and PubMed	13	No	Not reported
46	Qi et al.	2018	Examining sensor-based physical activity recognition and monitoring for healthcare using Internet of Things: A systematic review	To provide a systematic review of current research of Physical Activity Recognition and Monitorin from an IoT layer-based perspective.	IEEE Xplore, ACM, Springer digital library and Science-Direct	17	Yes	Not reported
47	Raju et al.	2021	A Systematic Review of Sensor-Based Methodologies for Food Portion Size Estimation	Presents a comprehensive review of the use of sensor methodologies for portion size estimation.	PubMed, Science Direct, SCOPUS, ACM Digital library, and IEEE Explore	67	No	Not reported
48	Sardinha & Júdice	2017	Usefulness of motion sensors to estimate energy expenditure in children and adults: a narrative review of studies using DLW.	To assess the usefulness and validity of motion sensors, particularly accelerometers, in estimating physical activity energy expenditure (PAEE) and total energy expenditure (TEE) in children and adults compared to the gold standard doubly labeled water (DLW) method.	Not reported	Not reported	No	Not reported
49	Silva et al.	2020	Mobile Apps to Quantify Aspects of Physical Activity: a Systematic Review on its Reliability and Validity.	To systematically review and evaluate the evidence on the accuracy and consistency of mobile apps to quantify physical activity.	PubMed, Science Direct,Web of Science, Physiotherapy Evidence Database (PEDro), Academic Search Complete, IEEE Xplore	25	Yes	Not reported
50	Sousa et al.	2023	The Use of Wearable Technologies in the Assessment of Physical Activity in Preschool- and School-Age Youth: Systematic Review	This present systematic review aimed to examine the current research about the utilization of wearable technology in the evaluation in physical activities of preschool- and school-age children.	Web of Science, PubMed and Scopus	21	Yes	Not reported
51	Stålesen et al.	2020	A Mapping Review of Physical Activity Recordings Derived From Smartphone Accelerometers	To map and report studies that have validated the PA measurement properties of smartphone accelerometer recordings across the intensity spectrum of body movement against research-grade PA monitors containing accelerometers or other objective methods measuring PA continuously, and to report the effects of different smartphone placements on the accuracy of PA measurement.	PubMed, Embase, SPORTDiscus, and Scopus	9		Not reported
52	Suau et al.	2024	Current Knowledge about ActiGraph GT9X Link Activity Monitor Accuracy and Validity in Measuring Steps and Energy Expenditure: A Systematic Review	To synthesize the current evidence for the criterion validity of the ActiGraph GT9X in measuring steps and energy expenditure	PubMed, Web of Science, SPORTDiscus	8	Yes	558
53	Teixera et al.	2021	Wearable Devices for Physical Activity and Healthcare Monitoring in Elderly People: A Critical Review.	To summarize the state-of-the-art scientific evidence about the usefulness of wearable devices to monitor physical activity and health-related outcomes in older people	Not reported	Not reported	No	Not reported
54	Thilarajah et al.	2016	Wearable sensors and Mobile Health (mHealth) technologies to assess and promote physical activity in stroke: A narrative review	To review the devices available for assessment of physical activity in stroke and discuss potential technologies to promote physical activity in this population	Not reported	Not reported	No	Not reported

ID	Authors	Year	Title	Review aim	Included databases	Number of included studies	Systematic review/meta-analysis?	Number of participants
55	Thornton et al.	2022	Measurement Properties of Smartphone Approaches to Assess Diet, Alcohol Use, and Tobacco Use: Systematic Review.	To identify existing smartphone-based approaches to measure diet, physical activity, and alcohol consumption and evaluate the quality of their measurement properties.	Ovid MEDLINE, Embase, Cochrane Library, PsycINFO, CINAHL, Web of Science, SPORTDiscus, IEEE Xplore Digital Library	72	Yes	Not reported
56	Torriani-Pasin et al.	2021	mHealth technologies used to capture walking and arm use behavior in adult stroke survivors: a scoping review beyond measurement properties.	To provide a review of measurement properties of mHealth technologies to measure the amount and intensity of functional skills in stroke survivors, and to identify facilitators and barriers toward adoption in research and clinical practice.	MEDLINE, PubMed, CINAHL, Scopus, Embase	64	No	Not reported
57	Trumpf et al.	2023	Physical activity monitoring-base interventions in geriatric patients: a scoping review on intervention components and clinical applicability	To identify and analyze the components applied in interventions using physical activity (PA) monitoring in geriatric patients and determine their feasibility and applicability.	PubMed, Embase, SPORTDiscus, CINAHL, Web of Science, and GeroLit	17	No	827
58	Veerubhotla et al.	2022	Wearable devices for tracking physical activity in the community after an acquired brain injury: A systematic review.	To provide insights on the application and metrics of wearable devices for physical activity monitoring of people with acquired brain injuries	PubMed, Google Scholar	20	Yes	Not reported
59	Veiga et al.	2022	A systematic review on smartphone uses for activity monitoring during exercise therapy in intermittent claudication	This review aims to assess current use of smartphone technology (ie, mobile apps) for monitoring or tracking patients' activity in exercise therapy for peripheral arterial disease (PAD).	PubMed	7	Yes	Not reported
60	Verceles & Hager	2015	Use of Accelerometry to Monitor Physical Activity in Critically Ill Subjects: A Systematic Review.	To assess the use of accelerometry to measure physical activity in critically ill, mechanically ventilated adult Intensive Care Unit patients	PubMed	104	Yes	Not reported
61	Wan et al.	2020	Literature review of the application of wearable device GT3X in monitoring physical activity	To systematically explain the basic principles of GT3X and the research status of GT3X in monitoring daily physical activities	Not reported	Not reported	No	Not reported
62	Wang et al.	2017	A Review of Wearable Technologies for Elderly Care that Can Accurately Track Indoor Position, Recognize Physical Activities and Monitor Vital Signs in Real Time.	To review state-of-the-art wearable technologies that can be used for elderly care.	Not reported	Not reported	No	Not reported
63	Wang et al.	2022	Enhancing Nutrition Care Through Real-Time, Sensor-Based Capture of Eating Occasions A Scoping Review	To identify and collate sensor-based technologies that are feasible for dietitians to use to assist with performing dietary assessments in real-world practice settings	ACM digital library, CINAHL (EBSCO), Embase (Ovid) (Embase, RRID:SCR_001650), IEEE Xplore (IEEE), PubMed, Scopus (Elsevier), and Web of Science (Clarivate Analytics)	54	No	Not reported
64	Weakley et al.	2021	The Validity and Reliability of Commercially Available Resistance Training Monitoring Devices: A Systematic Review	A systematic review of studies that investigate the validity and/or reliability of commercially available devices that quantify kinetic and kinematic outputs during resistance training.	SPORTDiscus, Web of Science, and Medline.	44	Yes	Not reported
65	Wei et al.	2022	A review of chewing detection for automated dietary monitoring	To investigate various chewing signal detection approaches and their sensing tools. The scope of the review included chewing activity detection methods and chewing signal processing strategies as a part of automatic dietary monitoring.	Google scholar	Not reported	No	Not reported
66	Weizman et al.	2023	The Use of Wearable Devices to Measure Sedentary Behavior during COVID-19: Systematic Review and Future Recommendations	This comprehensive review aims to establish a framework encompassing recent studies concerning wearable sensor applications to measure sedentary behaviour parameters during the COVID-19 pandemic, spanning December 2019 to December 2022.	Cochrane Library, IEEE Xplore, PubMed and MEDLINE	7	Yes	Not reported
67	Wu et al.	2017	Wearable food intake monitoring technologies: A comprehensive review	To review the latest literature on sensing platforms and data analytic approaches for food-intake monitoring that can identify food types and caloric content through image processing techniques.	Not reported	Not reported	No	Not reported
68	Yu et al.	2022	Validating transdermal alcohol biosensors: a meta-analysis of associations between blood/breath-based measures and transdermal alcohol sensor output.	To synthesize the results from studies that examined the associations between transdermal alcohol sensor output and blood and breath-based alcohol measures, to characterize the validity of transdermal sensors for assessing alcohol consumption.	PubMed, PsycINFO	21	Yes	Not reported

The following sections report the results related to digital solutions, wearables, and methodologies to passively and unobtrusively monitor the targeted behavioural risk factors, namely physical activity, diet, smoking, and alcohol consumption (see Table 5).

3.3.1. Documents targeting physical activity

The review highlighted a diverse array of physical activity metrics and outcomes, underscoring the comprehensive nature of research in this field. The primary focus was on detecting different types of physical activity, such as posture (e.g., sitting, standing) and motion activities (e.g., walking, running), rather than solely measuring overall physical activity intensity. This approach allows for a more nuanced understanding of physical behaviour patterns and their potential impacts on health.

Key physical activity metrics considered in the identified reviews included step count, activity count and bouts, active minutes, energy expenditure, physical activity levels, intensity gradient, and walking patterns. Various methods and technologies were used to monitor physical activity, prominently featuring wearable devices due to their ability to provide continuous and objective monitoring.

The most commonly adopted methods and technologies were:

- Accelerometers: Devices like ActiGraph, ActivPAL, and Fitbit provided detailed movement patterns, typically placed on the waist or hip (e.g., Allahbakhshi et al., 2019; Dagenais et al., 2019).
- Pedometers: Devices like the Yamax Digiwalker and OMRON pocket pedometer, primarily used for step counting (Bort-Roig et al., 2014; Hammond-Haley et al., 2021)
- Multi-sensor devices: Combining accelerometers with sensors like heart rate monitors (e.g., Fitbit Charge HR, Garmin Vivoactive) for comprehensive physical activity and energy expenditure assessments (e.g., Khanal et al., 2022; Fuller et al., 2020)
- Smartphones: Leveraging in-built accelerometers and gyroscopes, despite challenges like shorter battery life and uneven sampling rates (e.g., Bort-Roig et al., 2014)
- GPS devices: Tracking physical activity by monitoring outdoor positioning, movement patterns, and distances traveled (e.g., Negrini et al., 2021).

Several commercial and research-grade devices were used, including ActiGraph, Fitbit (various models like Charge HR, Blaze, and Versa), Garmin (Vivosmart and Vivoactive), Samsung Gear (Fit 2 and Fit 2 Pro), Axivity AX3, GENEActiv, and SenseWear armband. Sensor placement was crucial for accurate data capture, with common placements being the waist or hip, wrist, ankle, and upper arm.

Outcomes of these studies varied, reflecting the different ways physical activity can impact health. Key outcomes measured included non-sedentary time, walking speed and distance, intensity of activity, energy expenditure, heart rate, and variability. Studies consistently reported high classification accuracies for detecting various physical activities using real-life data, with technologies like wearable motion detectors performing robustly. However, findings often relied on small samples performing standardized activity trials, potentially limiting generalizability (Bort-Roig et al., 2014; Leung et al., 2021). Device-specific assessments revealed variability across different brands and models (Fuller et al., 2020). Omron devices generally showed higher validity compared to Fitbit and Garmin, influenced by device placement and population characteristics (Leung et al., 2021). This underscores the need for standardized protocols to ensure consistent results across studies.

In terms of reliability, a minimal sensor configuration of two 3D accelerometers sampling at 20 Hz was recommended (Allahbakhshi et al., 2019). Despite advances, challenges persist due to the lack of standardized data collection frameworks and openly available reference datasets, limiting transparent comparisons and the reliability of remote physical activity monitoring.

Advancements in wireless sensing technologies, multi-sensor integration, and deep learning algorithms hold promise for improving exercise monitoring accuracy. However, current methodologies often focus on single-sensor approaches, highlighting the potential benefits of adopting comprehensive, multi-sensor solutions for enhanced measurement accuracy across diverse populations and activity contexts.

3.3.2. Documents targeting diet

This umbrella review highlights significant advancements in food item detection using image recognition and classification technologies. Various methods have been explored, including Support Vector Machines (SVM; e.g., Banerjee et al., 2022), Convolutional Neural Networks (CNN; e.g. Mansouri et al., 2023), and Vision Transformer models (e.g., Banerjee et al., 2022). These approaches are crucial for automating the identification and categorization of food items based on visual data, thus enhancing the accuracy and efficiency of dietary monitoring systems.

Vision-based methods are pivotal for monitoring food and fluid intake, employing both first-person and third-person perspectives (Chen et al., 2023). First-person methods use RGB cameras embedded in wearable devices like smartwatches or smart glasses, often combined with non-vision sensors such as accelerometers and gyroscopes for gesture recognition during eating activities. In contrast, third-person methods involve external cameras or sensors like Microsoft Kinect, positioned overhead to provide a comprehensive top-down view of dining activities.

The technologies employed for food intake monitoring include a variety of devices:

- Image analysis: Techniques such as food segmentation, recognition, and portion size estimation using camera-based systems (e.g., Hassannejad et al., 2017).
- Wearable sensors: Devices that monitor chewing (e.g., acoustic sensors, piezoelectric films), swallowing (e.g., EMG sensors, pressure sensors), and eating behaviours (e.g., accelerometers, gyroscopes) (e.g., Hassannejad et al., 2017).
- Audio-based sensors: Microphone-based systems for detecting eating events based on sound cues (He et al., 2020).
- Other sensing systems: Piezoelectric-based, radio frequency-based, and body-attached wearable sensors for comprehensive monitoring (He et al., 2020).

The review emphasizes several diet-related outcomes and metrics crucial for understanding nutritional patterns and dietary habits, including nutritional patterns, dietary habits, and food intake patterns.

Studies on the accuracy, validity, and reliability of digital solutions for dietary assessment revealed that image-based methods perform well in controlled environments with regulated lighting and food presentation. However, their effectiveness decreases in real-world scenarios with variable food types and environmental conditions, posing challenges for consistent food intake detection (Hassannejad et al., 2017; Hassannejad et al., 2017; Krishna et al., 2022).

The literature shows variability in sensor-based dietary assessment approaches, with preferences for load cells over force sensors due to cost-effectiveness and precision. Devices like the "Bite Counter" utilize gyroscopic tracking to enhance measurement reliability (Krishna et al., 2022).

Despite advancements, challenges remain in the adoption of passive monitoring technologies for dietary assessment.

Usability, acceptability, and user experience vary across different approaches. Image-based methods are relatively user-friendly but require manual input for estimating portion sizes (Hassannejad et al., 2017). Wearable sensors, while more automated, can be burdensome due to the need to wear multiple devices (Hassannejad et al., 2017; Krishna et al., 2022). Mobile applications and integrated wearable sensor systems have been well-received for their convenience but face issues with manual data input and regular updates (Krishna et al., 2022).

3.3.3. Documents targeting smoking

This section synthesizes findings from a comprehensive review of studies on metrics and outcomes related to smoking, highlighting the use of innovative methods and devices. It is important to note that the insights presented are primarily derived from a single review (Imtiaz et al., 2019), indicating a need for further research and validation in diverse contexts.

The review identified various wearable sensors designed to capture both behavioural and physiological aspects, including respiration patterns, of smoking. Key metrics and technologies include:

- Lighting Events: Sensors integrated into commercially available cigarette lighters detect when a cigarette is lit, providing a direct measure of smoking initiation.
- Hand-to-Mouth Proximity: Radio frequency proximity sensors attached to the chest and wrist monitor hand-to-mouth gestures, a critical behavioural indicator of smoking.
- Smoking Hand Gestures: Inertial measurement units (IMUs) track the inclination and movement of the smoking hand, enhancing the characterization of smoking gestures.
- Smoking-Specific Respiration Patterns: Respiratory inductance plethysmography detects distinctive respiration patterns associated with smoking, offering insights into physiological responses.
- Breathing Sound: Non-invasive acoustic sensors placed on the throat identify unique breathing sounds linked to smoking, providing detailed respiratory behaviour data.
- Egocentric Vision: Wearable cameras capture smoking events from the user's perspective, including environmental context, body posture, and concurrent activities.

The review underscores the integration of cutting-edge technologies to monitor smoking behaviour, including IMUs, respiratory devices, acoustic sensors, and egocentric cameras. Each technology offers distinct advantages in analyzing smoking-related behaviours, reflecting a multidisciplinary approach in digital phenotyping research. However, no single sensor system has achieved comprehensive and accurate detection of smoking or assessment of smoking-related behaviours. Wearable sensors like wristbands and smartwatches show promise in detecting hand-to-mouth gestures and physiological changes but are limited by issues with false positives and negatives due to variability in human movements and device placement. Environmental sensors measure air quality and tobacco smoke but cannot provide individual-level data and are affected by other pollutants. Intraoral sensors, which detect smoke-related chemicals in saliva or breath, offer direct measurements of smoke exposure but face challenges related to user comfort and development.

A multimodal approach combining wearable, environmental, and intraoral sensors may improve accuracy and reliability in smoking detection. Future research should focus on developing sophisticated algorithms to handle sensor data variability and enhance robustness across different settings and populations. Additionally, integrating body-worn chemical sensors could complement motion and environmental data for a more comprehensive assessment of smoke exposure.

Usability, acceptability, and user acceptance of these technological solutions were not addressed in the review.

3.3.4. Documents targeting alcohol consumption

The advent of transdermal alcohol sensor devices represents a significant advancement in the continuous, real-time monitoring of alcohol consumption. These devices measure alcohol vapors emitted through the skin via sweat, offering valuable insights into drinking behaviours. Several notable devices have been developed to monitor alcohol consumption through the skin:

- SCRAM (Secure Continuous Remote Alcohol Monitoring): Measures transdermal alcohol concentration (TAC) continuously, commonly used in legal and clinical settings (e.g., Brobbin et al., 2022; Brobbin et al., 2022; Davis-Martin et al., 2022; Egmond et al., 2020).
- WrisTAS: A wrist-worn sensor that tracks alcohol vapors emitted through the skin (e.g., Brobbin et al., 2022; Brobbin et al., 2022; Davis-Martin et al., 2022; Egmond et al., 2020).
- BACtrack Skyn: Another wrist-worn device known for its accuracy in measuring TAC and providing insights into alcohol consumption patterns (e.g., Brobbin et al., 2022; Brobbin et al., 2022; Davis-Martin et al., 2022).
- Quantac Tally: Monitors alcohol levels through skin contact (e.g., Brobbin et al., 2022; Brobbin et al., 2022; Davis-Martin et al., 2022).
- ION Milo Sensor: Measures alcohol concentration via transdermal detection (Brobbin et al., 2022).
- MOX Sensor: Designed for unobtrusive alcohol monitoring through sweat analysis (Brobbin et al., 2022).
- Proton-Exchange Membrane (PEM) Fuel Cell Sensor: Utilized in some transdermal alcohol sensors for accurate measurement of alcohol concentration (Brobbin et al., 2022).

In addition to monitoring alcohol consumption, as reported by Davis-Martin and colleagues, (2022), several devices are specifically designed to assess alcohol intoxication levels, providing critical data on the immediate impacts of alcohol use:

- Giner WrisTAS: Similar to WrisTAS, used for precise intoxication monitoring.
- Proof: A wearable device providing real-time alcohol intoxication levels.
- Iontophoretic-Biosensing System: Combines iontophoresis and biosensing for accurate alcohol detection.
- AlcoWear: A wearable sensor detecting alcohol levels in the body.
- Sensor-Equipped Smart Shoes: Incorporate sensors to monitor alcohol intoxication through sweat analysis.
- AlcoGait: Tracks gait changes related to alcohol consumption.
- DrinkTRAC: An advanced system for monitoring alcohol intoxication.

It's noteworthy that monitoring alcohol intoxication is beyond the aims of iBeChange; however, we considered these approaches worth mentioning. Regarding accuracy, validity, and reliability, wearable transdermal alcohol devices such as SCRAM, WrisTAS, and BACtrack Skyn have demonstrated moderate to strong accuracy in detecting alcohol consumption across various settings (Brobbin et al., 2022; Egmond et al., 2020; Yu et al., 2022). The accuracy of these devices can be influenced by several factors, including the amount of alcohol consumed, environmental conditions (laboratory vs. real-world settings), user age, and the device's placement on the body (Brobbin et al., 2022).
A meta-analysis by Yu and colleagues (2022) reported a high correlation between transdermal alcohol concentration (TAC) and blood alcohol concentration (BAC), with a correlation coefficient of 0.87 (95% CI = 0.80, 0.93) in primarily laboratory settings. This high correlation indicates that, under controlled conditions, transdermal alcohol sensors are effective in assessing BAC. However, the analysis also highlighted a significant lag time, with TAC lagging behind BAC by an average of 95.90 minutes (95% CI = 55.50, 136.29). The lag time varies by sensor placement; for example, devices worn on the ankle exhibit approximately double the lag time compared to those worn on the arm, hand, or wrist.
The review notes variability in the validity and reliability of different brands and models. SCRAM, WrisTAS, and BACtrack Skyn generally show strong correlation with breath alcohol concentration and self-reported alcohol intake. However, SCRAM's conservative detection thresholds limit its ability to detect lower-to-moderate drinking levels. In contrast, WrisTAS and BACtrack Skyn, while capable of

detecting a broader range of consumption levels, have higher failure rates, raising concerns about their reliability. The context of use significantly impacts device performance. Devices tend to perform more reliably in laboratory settings compared to real-world environments, where uncontrolled variables can affect accuracy. Environmental factors and user behaviours in real-world settings introduce inconsistencies that are less prevalent in controlled settings. Despite these challenges, transdermal alcohol sensor devices are considered acceptable and feasible for objective alcohol consumption monitoring (Brobbin et al., 2022; Davis-Martin et al., 2022). Users find these sensors practical and easy to integrate into their daily routines. In treatment settings, participants generally report high levels of feasibility and acceptability, viewing these devices as valuable tools that complement traditional treatment methods and enhance the overall treatment experience.

Table 5. Main results of the umbrella review (targeted lifestyle, information about passive monitoring approaches, validity, reliability, usability and acceptance)

ID	Lifestyle	How each lifestyle has been measured	Main results about validity and reliability	Main results about acceptability/acceptance/use
1	Physical activity	The review focused on detecting different types of physical activity, such as posture (e.g. sitting, standing) and motion activities (e.g. walking, running), rather than just measuring overall physical activity intensity. The most commonly used commercial device was Actigraph, which supports continuous tracking over several days. Smartphones were also considered due to their ubiquity and multiple sensors, though they have shorter battery life and uneven sampling rates compared to dedicated devices. 3D accelerometers were the most common sensor type, typically sampling at over 20 Hz in real-life settings. The most common sensor placements were on the waist or hip, close to the central part of the body. Devices include: - ActiGraph - Tracmor - IDEE -BENECA - IPAS - TS - mHealth App - UWALK	Results found that existing studies generally reported high to near-perfect classification accuracies for detecting physical activity types using real-life data, though data collection protocols and performance reporting varied significantly. In terms of reliability, the review recommends using a minimal sensor configuration of two 3D accelerometers sampling at 20 Hz, and notes that decision trees are the most common reliable classifier used in practical applications with real-life data. However, the review also underscores the need for standardized data collection and evaluation frameworks, as the lack of labeled, fully documented, and openly available reference datasets hinders transparent comparison of methods across studies.	NA
2	Diet	Food item detection through image recognition and classification with different methods, including: - SVM - CNN - Vision Transformer	Convolutional neural networks (CNNs) are extensively used and provide superior results in food detection compared to other models, Vision Transformers perform better with large datasets, and a hybrid model could enhance accuracy; Vision Transformers, when pre-trained on large data and applied to smaller benchmarks, yield excellent results with significantly lower CPU resource requirements during training.	NA
3	Physical activity	Physical activity: - Self-report - Vdeo-recording - Smart Home and Ambient Assisted Living (SHAAL) - Doubly Labeled Water (DLW), Indirect Calorimetry, and Heart-Rate Recording - Wearable Motion Detector	Among the several devices considered for this purpose, it has been reported that wearable motion detectors are the most promising technology enabling an automatic, continuous and long-term assessment of subjects in free-living environments.	NA
4	Physical activity	Physical activity was measured by wearable sensors, including: ActivPAL, Actigraph and Fitbit.	NA	Limited information was reported regarding the acceptance and compliance of wearing the sensors. Direct participant feedback was reported in only three studies. This feedback suggests that wearables were well tolerated in older inpatients.
5	Physical activity	All walking and running studies used some type of accelerometer (wearable device). Only a study used a footswitch. The purpose of the walking studies was to quantify walking patterns among a specified group and/or to compare the walking patterns of that group to a set of control participants. The running studies either determined injury status, examined runners of different experience levels, captured the effect of fatigue, or detected run characteristics such as heel-strike and toe-off events, stride time, or foot strike pattern.	NA	The usability of common wearable devices for gait analysis appears reasonable, but accurate reporting of study dropout rates, missing data, and participant feedback is lacking.
6	Physical activity	The review found that studies measured a variety of physical activity metrics, including step count, activity count, activity bouts, active minutes, and energy expenditure. The review indicates that the studies utilized accelerometers, pedometers, and gyroscopes to remotely monitor physical activity, including these devices: - ActiGraph 7164 - OMRON pocket pedometer - TriTrac RT3 - Step Watch - Yamax SW 200 - Intelligent Device for Energy Expenditure	The review indicates that existing studies generally reported high to near-perfect classification accuracies for detecting physical activity types using real-life data, though data collection protocols and performance reporting varied significantly. It highlights the importance of real-life study designs and standardized data collection protocols to ensure the reliability and validity of remote physical activity monitoring in neurological diseases.	NA
7	Physical activity	Regarding objective measurement of physical activity, studies used either external devices or smartphone features, including: - pedometers - accelerometer-based motion sensors -multi-sensor devices with accelerometers and heart rate sensors - digital watch controls for estimating energy expenditure - phone signal strength fluctuation monitoring - kinematic sensors (accelerometer, gyroscope, magnetic sensor)	Results showed that mobile phone placement in the waist-to-hip area yielded average-to-excellent measurement accuracy. Activities such as sitting, standing, walking, and jogging were recognized with high accuracy using in-built tri-axial accelerometers, gyroscopes, and magnetic sensors. However, accuracy was mainly assessed with small samples performing standardized activity trials	NA

8	Physical activity	Physical activity was measured by considering trip frequency, time spent outside, time spent in sedentary and active episodes, step count, moderate-to-vigorous activity, energy expenditure, metabolic equivalent of task, activity type, and activity intensity. Several wearable devices were used, including: - WIMU-GPS, DynaPort Minimod, Fitbit Charge HR, ACtigraph GT3X+, SenseWear activity-armband, ActivPAL3, ActiGraph GT9X Link, StepWatch 3 Step Activity Monitorm Dynaport Hybrid, ActiGraph GT1M, Axivity AX3, ACtiwatch AW-4, SenseWear Professional 8 armband, SenseWear Armband, ActiGraph GT3x, Actiwatch, Phillips Acti-watch 2, uSense sensor device, Actisplee+, BioStampRC, Actiwatch Spectrum Plus	Results indicate that wearable GPS and accelerometer technologies show promise as objective biomarkers for monitoring mobility and physical activity changes in neurodegenerative diseases, though more research is still needed to fully establish their clinical utility	Results indicate that the acceptability of GPS watches for patients with dementia and their caregivers ranged from fair to good. However, product satisfaction significantly decreased at home.
9	Alcohol	Through transdermal alcohol sensor device able to measure alcohol consumption from vapors off the skin via sweat: - SCRAM - WrisTAS - BACtrack Skyn - Quantac Tally - BACtrack Skyn	NA	The available data suggest that transdermal alcohol sensors devices are acceptable, feasible, and have the potential to monitor objective alcohol consumption data
10	Alcohol	Through transdermal alcohol sensor device able to measure alcohol consumption from vapors off the skin via sweat: - SCRAM - WrisTAS - BACtrack Skyn - ION Milo sensor - Quantac Tally - MOX sensor - proton-exchnage membrane (PEM) fule cell sensor	Wearable transdermal alcohol devices could detect alcohol consumption with moderate to strong accuracy over various periods. However, factors such as the amount of alcohol consumed, the environment (laboratory and self-dose real-world setting), age, and where the device is worn must be considered. The findings differed across transdermal alcohol sensor brands included, and studies on each brand reported different limitations.	NA
11	Physical activity	Different outcomes of physical activity were measured, including step count, non-sedentary time, average acceleration, walking speed, intensity gradient, moderate to vigorous physical activity, and energy expenditure. Several wearables were considered, including: - Samsung Gear 2 Smartwatch - MoveMonitor - Fitbit (Charge HR, Ionic) - Garmin (Vivosmart, Vivofit 2, Vivofit 3, Vivoactiv HR, Vivoactiv 3) - Apple Watch (Sport, Series 1) - Samsung Gear (Fit 2, Fit 2 Pro) - Axivity AX3 - GENEActiv Original - ActiGraph GT9X	Results indicate varying levels of accuracy, validity, and reliability for different actigraphy measures in clinical trials. Step count is recognized as meaningful and easy to communicate, but its accuracy needs further research, especially for heart failure (HF) patients, making it the most suitable measure despite potential algorithm limitations. Nonsedentary time is also meaningful and familiar, with good potential accuracy, though heart failure-specific thresholds were derived from a small sample. Average acceleration shows low estimation error and is close to raw data, but its clinical interpretability is limited, making it potentially good. Walking speed and intensity gradient, while meaningful, currently suffer from inaccuracies and limited clinical interpretability, respectively, and could be considered but with caution. Moderate to vigorous physical activity and energy expenditure, despite being recognized as meaningful, are currently estimated inaccurately, making them unlikely to be suitable for reliable use in clinical trials.	NA
12	Physical activity	Energy expenditure measured through: - Uniaxial accelerometer - Triaxial accelerometers - Pedometers - Multi-sensors - Smartphone application	The meta-analysis revealed low to very low correlations between physical activity monitors and reference methods, high test-retest reliability, no significant effect of device placement or sensor type on correlation levels, and the best correlation from a pedometer (r=0.66) with a mean bias of -0.23 kcal/min.	NA
13	Physical activity	The review found that studies measured a variety of physical activity metrics using wearable activity trackers, including step count, activity count, activity bouts, active minutes, and energy expenditure. These metrics were used to assess patterns of physical activity and correlate them with various health outcomes. The studies utilized a range of wearable activity trackers, with the most commonly used being ActiGraph (41%), Fitbit (15%), and Axivity (11%).	The raw data collected are interpreted using proprietary algorithms to provide metrics like step count, energy expenditure, and activity intensity. However, the accuracy and reliability of these algorithms vary, leading to differences in the validity and inter-device reliability of activity trackers. Therefore, the selection of suitable activity trackers should be based on the specific physical activity measures being assessed. Collaboration between companies and standardization of algorithms are crucial to address these discrepancies.	NA
14	Diet	In the literature review on vision-based methods for food and fluid intake monitoring, both first-person and third-person approaches have been explored. First-person methods primarily use RGB cameras (for food recording) with additional non-vision sensors like accelerometers and gyroscopes (for gesture recognition to identify the eating activity). Examples include smartwatches with built-in cameras or smart glasses. Third-person approaches involve external single or multiple cameras (generally placed on the ceiling for a top-down view) or sensors such as Microsoft Kinect. Adopted devices include: - Smartwatches with built-in cameras - wearable RGB cameras - smart glasses - external cameras - accelerometers - gyroscopes - flex sensors - proximity sensors	Vision-based methods for food and fluid intake monitoring show promise in tasks like recognition and estimation. However, challenges like occlusion and privacy issues affect their reliability. Validity concerns include incomplete food observation and wear-time issues. Further research is needed to enhance accuracy and address limitations for practical implementation.	NA

15	Physical activity	Energy expenditure: - Fitbit Charge HR - Fitbit Charge 2 - Fitbit Blaze - Fitbit Versa - Fitbit Surge Heart rate: - Fitbit Charge HR - Fitbit Charge 2 - Fitbit Blaze - Fitbit Surge - Fitbit Versa - Fitbit Charge 3 - Fitbit Ionic Steps: - Fitbit Surge - Fitbit Charge HR - Fitbit Charge 2	The results of this systematic review and meta-analysis showed that Fitbit devices are likely to underestimate heart rate, energy expenditure, and steps.	NA
16	Physical activity	Different physical activity outcomes, including time spent in moderate or vigorous physical activity, heart rate, energy expenditure, sedentary time, steps taken, and distance walked, measured with diiferent devices, including: - Accelerometer-based activity trackers such as Fitbit, Actigraph, and ActivPAL - Pedometers that tracked step count	Results indicate that slower gait speeds can lead to inaccurate measurements of physical activity by wireless devices, particularly in step counts, active minutes, and distance walked. Passive monitoring of physical activity has been shown to be less accurate at slower walking speeds, especially in individuals who have sustained a stroke. Consequently, passive monitoring may not provide accurate and reliable measurements of physical activity for adults living with HIV who have gait impairments. Older adults with HIV, who are more likely to have concurrent health conditions like peripheral neuropathy and diabetes, may experience gait impairments that further affect accuracy. Therefore, the properties of WPAMs need careful consideration in the context of HIV infection.	NA
17	Alcohol	Alcohol intoxication: -SCRAM -Giner WrisTAS -BACtrack Skyn -Proof -Quantac Tally -Iontophoretic-biosensing system -AlcoWear -Sensor-equipped smart shoes -AlcoGait -DrinkTRAC	wearable biosensors have demonstrated their utility in improving delivery of cost-effective, evidence-based treatments for AUD and are currently being explored in novel ways to further improve AUD treatment options and access.	In treatment studies utilizing wearable biosensors, participants generally report good feasibility and acceptability of the devices, suggesting that integration into treatment may be acceptable among patients
18	Alcohol	Alcohol concentration was measured through different devices, including SCRAM, SCRAM II, SCRAMx, WrisTAS, and Skyn TAC.	The review highlighted that TAC data from SCRAM, WrisTAS, and Skyn strongly correlate with breath alcohol concentration and self-reported drinks. However, SCRAM's conservative thresholds limit detection of lower-to-moderate drinking levels, unlike WrisTAS and Skyn, which face higher failure rates, questioning their reliability. The findings suggest ongoing development and validation are crucial before exclusively relying on TAC monitors in research and clinical settings.	NA
19	Physical activity	Heart rate, energy expenditure, and steps were measured through consumer-grade devices, including: - Apple Watch, Watche Series 2 - Fitbit Alta, Blaze, Charge, Charge 2, Charge HR, Classic, Flex, Flex 2, Force, One, Surge, Ultra, Zip - Garmin Fenix3 HR, Forerunner 222, Forerunner 235, Forerunner 405CX, Forerunner735XT, Forerunner 920XT, Vivoactive, Vivofit, Vivofit 2, Vivofit 3, Vivosmart, Vivosmart HR - Mio Alpha, Fuse - Misfit Flash, Shine - Polar A300, A360, Active, Loop, M600, V800 - Samsung Gear 2, Gear S, Gear S2, Gear S3 - Withings Pulse, Pulse O2, Pulse Ox - Xiaomi Mi Band, Mi BAnd 2	The systematic review demonstrated that validity was generally better in controlled settings compared to free-living conditions, with heart rate measurements being the most accurate, followed by step count, and energy expenditure showing the most variability. For step count, Apple Watch and Garmin had the highest validity, while Fitbit, Samsung, and Withings devices had a mean percentage error within ±3%. Fitbit Classic tended to overestimate steps, whereas Fitbit Charge underestimated them. For heart rate, Apple, Fitbit, and Garmin devices measured heart rate accurately within ±3% error in controlled settings, though Fitbit might underestimate heart rate in free-living conditions depending on activity intensity. Energy expenditure estimates varied widely, with Fitbit providing the closest estimates to acceptable limits, though still variable; Fitbit Classic significantly underestimated, while Fitbit Charge HR overestimated energy expenditure.	NA
20	Physical activity	Daily steps: - StepWatch - ActiGraph GT3X - SWA - Digi-Walker pedometer	There is conflicting evidence regarding the validity and reliability of wearable activity monitors in measuring activity counts, while accelerometer-type devices appear to be more appropriate in estimating energy expenditure than multisensor devices	NA
21	Physical activity	Consumer-grade wearable activity trackers to collect minutes of moderate- to vigorous-intensity physical activity: - Fitbit Flex - Fitbit Charge HR - Fitbit Charge 2		Across different populations using different wearable devices, moderate to high correlations were found between moderate- to vigorous-intensity phsycal activity on the wearable and the criterion assessment.

		- Fitbit One - Fitbit Zip - Garmin vivosmartHR+		
22	Physical activity	The paper summarizes the use of wearable physical activity monitors in patients with cardiovascular disease by focusing on the following physical activity metrics: - Steps per day - Time spent in moderate-to-vigorous physical activity (MVPA) - Total daily energy expenditure The devices used in the reviewed studies include: - Pedometers: Yamax Digiwalker SW-200, Omron HJ-720ITC - Accelerometers: ActiGraph GT3X+, ActivPAL3, SenseWear Armband, Actiwatch 2, GENEActiv, Actical, Actiheart, Dynaport MoveMonitor, Sensewear Mini Armband, Sensewear Pro 3 Armband, Actigraph GT1M, Actigraph 7164, Actigraph 7164 accelerometer, Actigraph GT3X, Actigraph GT1M accelerometer, ActivPAL, SenseWear Pro Armband, SenseWear Mini Armband, Actiwatch 2 accelerometer, GENEActiv accelerometer, Actical accelerometer, Actiheart accelerometer, Dynaport MoveMonitor accelerometer	The paper notes that while wearable activity monitors are promising tools to measure real-world physical activity, there are challenges facing their use in elderly, multimorbid cardiology patients. The authors state that "most validation studies are limited to healthy young adults, while the paucity of methodological information disclosed renders interpretation of results and cross-study comparison challenging." The paper does not provide a detailed summary of the accuracy, validity, or reliability of the passive monitoring methods across the studies reviewed	NA
23	Diet	Food intake: Image analysis (food segmentation, recognition, and portion size estimation) Wearable sensors able to: -Chewing (Acoustic sensors, piezoelectric films, in-ear microphones) -Swallowing (EMG sensors, electroglottographs, pressure sensors in clothing) -Eating behaviours (accelerometers, gyroscopes on wrist/upper arm to detect eating-related hand movements)	The review suggests that while image-based methods can achieve high accuracy in controlled settings, they face challenges in real-world applications due to variability in food presentation and lighting conditions	Image-based methods are generally more user-friendly but still require user input for portion size estimation. Wearable sensors, while potentially more automated, often impose a burden on users due to the necessity of wearing multiple devices.
24	Diet	Food intake: - Microphone-based sensors - Camera-based sensing systems - Piezoelectric-based sensing systems - Radio Frequency-based sensing systems - Body-attached wearable sensing systems - Multiple sensors-based sensing systems	It is seen that although these sensors have operated with different sensing prototypes in terms of structure, working principle and communication protocol, they have been successful in detecting the episodes related to food intake. The differences in each of those sensors lie in the material used to develop them, the cost of fabrication, their sensing approach, applications, challenges, locations of attachment to the body, and communication protocol.	NA
25	Smoking	Studies employed different wearable sensors to address behavioural and physiological manifestations associated with smoking, including lighting events (e.g., embedding sensors in commercially available cigarette lighters), hand-to-mouth proximity (e.g., by using radio frequency proximity sensors attached to the chest and the wrist), smoking hand gestures (e.g., through inertial measurement units measuring the inclination of the smoking hand), smoking-specific respiration pattern (e.g., through respiratory inductance plethysmography technology), breathing sound (e.g., through non-invasive acoustic sensors applied to the throat), and egocentric vision (e.g., with wearable egocentric camera capturing scenes contain details of the smoking event, smoking environment, body posture and activities during smoking).	Results indicate that no single sensor system offers a complete and accurate solution for detecting smoking, characterizing smoke exposure, or other smoking-related behaviours. While wearable sensors have revealed interesting smoking-related phenomena, they face various challenges. No wearable sensor has achieved 100% accuracy in detecting smoking-related features, even in controlled settings. Current research targets major behavioural and physiological aspects of smoking, but body-worn or intraoral chemical sensors could be further explored for detecting smoking and measuring smoke exposure.	NA
26	Physical activity	Physical activity was measured by considering different outcomes and metrics, including physical activity levels, fitness, muscle strength, cardio-respiratory capacity, arm and shoulder exercises. This was done by adopting different methods and devices, including: - ActiGraph - Booklet - MapMyFitness - BENECA - IPAS - TS - mHealth App - UWALK	NA	The review notes that while the majority of participants were satisfied with the technology-assisted interventions, some patients were unsatisfied due to the complexity of the technology
27	Physical activity	Gait & Physical Activity: Measured with different methods, including: - Mc10 Biostamp - Axivity - Fitbit - Fitbit Zip - Omron HJ – 720ITC - Tractivity - MOX5 - EXLs3 - ESUMS Wearable Device - iPhone 6Se and apple Watch 1st gen	NA	Usability of wearable devices is a poorly measured and reported variable in chronic health conditions. Although the heterogeneity in how these devices are implemented implies acceptance, the patient voice should not be assumed
28	Physical activity	Heart rate: - Doppler-baesd system	Most of the research studies presented in the review focused only on one type of sensor to extract the physiological parameters. The accuracy of the physiological parameters'	NA

		- Near-infrared spectroscopy (NIR) - Photoplethysmography (PPG) - Video-based image processing - Facial ecpression Heart rate variability: - Pupil Size Variability (PSV) Blood pressure: - Photoplethysmography (PAT) - Pulse transmit time (PPT) Energy expenditure: - Thermal imaging - RGB-Depth - Near-infrared spectroscopy Respiratory rate: - Near-infrared spectroscopy - Video-based - Doppler-based system - Infrared Camera - RGB-Depth Muscle fatigue: - Video-based (RGB) - Infrared camera - Thermal camera Oxygen uptake (VO2): - Doppler-based system Muscle Oxygenation: - Near-infrared spectroscopy Kee Load Estimation: - Camera based Delayed Onset Muscle soreness (DOMS): - Infrared technology Exercise intensity analysis (Facial expression): - Camera based	measurement could be improved by considering multi-sensor technology. With an improvement in wireless sensing technology, exercise monitoring using physiological parameters can be improved and expanded to multiple parameters using the same modalities. Recent computer vision technology is leading with deep learning, which can also help to upgrade exercise monitoring technology.	
29	Diet	Food intake - Load cells - Manual food waste methods - Wearable sensors (such as Bite Counter device) - Mobile applications and smartphone-based systems - Visual Estimation Methods	The review highlights the reliability of load cells over force sensors due to their cost-effectiveness and precision. The “Bite Counter” device was noted for its ability to reduce biases and provide consistent measurements through gyroscope-based tracking. Visual estimation methods were compared to direct weighing methods, demonstrating reasonable accuracy for quantifying dietary intake in children.	The use of automated systems, such as mobile applications and wearable sensors, was generally favored for their ease of use and minimal need for manual input. The review discussed the development of smartphone applications that provide dietary suggestions and track food intake, indicating positive acceptance among users for their convenience and practicality. Specific challenges, such as the need for continuous updates and potential inaccuracies in manually logged data, were identified as areas for improvement to enhance user acceptance and system usability.
30	Physical activity	The review summarizes the use of wearable sensors for monitoring various physical activity outcomes, including: - Gait and balance assessment: inertial measurement units (IMUs) like accelerometers and gyroscopes are commonly used to assess gait parameters and detect falls; pressure sensors in insoles can also measure plantar pressure distribution during walking. - Fall prevention and detection: Wearable sensors like IMUs, ECG, PPG, and EMG are used to detect falls and monitor fall risk factors like gait abnormalities and postural instability; combining data from multiple sensors like accelerometers and heart rate monitors can improve fall detection accuracy.	The article highlights flaws in how studies based on previously collected datasets report on study samples and the data collected, which makes the validity and generalizability of those studies low. Exceptions exist, such as the promising recently reported open dataset FallAllD, wherein a longitudinal study with older adults is ongoing.	none of the studies were conducted in real-life conditions. Hence, there is still important work to be done in order to increase the usefulness of wearable sensors in these areas.

		- Physical activity recognition: MUs, especially when placed at multiple body locations, can recognize various physical activities like walking, running, sitting, standing, etc. Machine learning models are commonly used to classify activities from sensor data		
31	Physical activity	Physical Activity: -Daily step counts -Daily meters walked -Energy expenditure Moderate to Vigorous Physical Activity (MVPA): -Accelerometers -Heart Rate Monitors Sedentary Time -Accelerometer -Inclinometers	The consistency of measurements (reliability) is good, meaning that these devices produce stable and repeatable data under similar conditions. However, the reliability can be influenced by participant characteristics like age and activity level	Physical activity monitor (PAM) interventions were found to be effective in increasing physical activity and MVPA among healthy and patient populations. The overall evidence was low to moderate, suggesting that PAMs are generally well-accepted and useful for promoting physical activity.
32	Physical activity	Through consumer-grade wearable activity trackers from different brands - including: - Omron - Tanita - Misfit - Epson - Apple - Jawbone - Fitbit - Samsung - Nike - Basis - Withings - Garmin - Personal Activity Monitor - Microsoft - Sqord - Technogym - DHS Group - Hope Lab - Adidas - Mio - TomTom - Polar	The results reveal significant variability in validity evidence among consumer-oriented wearable physical activity trackers, with Omron devices showing the highest validity and Garmin the lowest, influenced by device placement and population factors, highlighting the need for improved accuracy to ensure credibility and consumer trust. Validity coefficients ranged from excellent to inadequate levels, with 4 out of 12 brands demonstrating validity coefficients below r = .70, indicating that a significant portion of these devices may not provide reliable measurements.	NA
33	Diet	Food intake: - Food image classification (included RCNN, inception-v3, inception-v4, Xception, inceptionRestNetV2, Quantized deep residual convolutional neural networks (DRNN)) - Food image segmentation (included GoFood, Mask RCNN, VGG image annotator (VIA)) - Food volume estimation (included 3D model, MobileNet model, Generative Adversarial Networks (GAN))	Deep learning approaches are the most commonly utilized method in these studies, indicating impressive results and outperforming conventional machine learning methods	NA
34	Physical activity	Consumer-grade wearable activity trackers: - Fitbit - Polar active watch - Movband - Sqord - Zamzee	It seems that consumer-grade physical activity monitors did not generate equivalent estimates of sedentary behaviour compared with research-grade monitors, with a tendency toward overestimation for these devices.	NA
35	Physical activity	Pedometer: - Omron HJ113-E - Omron HJ-720ITC - Yamax DW-200 19 - Yamax SW-200 - Yamax PW610 - Kenz Lifecorder - Digiwalker SW701 - SC Step MX Accelerometers to detect accurate posture and position changes: - AugmenTec - DynaPort	Postures and postural 21 changes can be measured accurately for older adults in all settings. Accuracy of motion sensors deteriorates when walking speeds reduce to approximately 1.0 to 0.8 m/sec 1 which is considerably faster than the typical speed of 3 hospitalised, frail older adults (0.5m/sec). This suggests that many motion sensors are invalid for step-count measurement in frail hospitalised patients. Thirdly, the SAM appears to be the only motion sensor that accurately measures step-count for slow walkers. Postures and postural changes can be accurately measured in frail older medical patients by the AugmenTec and the ActivPAL. The results from the DynaPort MoveMonitor are inconclusive. Its detection of sitting and standing appears poor, especially in the older-old. The SmartShoe shows excellent accuracy in a small community-based study, but its feasibility for hospital use is limited. Most accelerometers tested for older adults accurately detected steps ibut this accuracy deteriorated when walking was slower than 19 0.5m/sec. The only step-count 20 accuracy study using frail older hospitalised patients found that the ActivPal did not measure step-count accurately. Although the	NA

		- DynaPort Minimod - DynaPort MoveMonitor - SmartShoe - Activity Monitor (VitaPort 3) - ActivPAL Step-count: - Actigraph GT3X+ - ActiHealth - Dynaport Minimod and Dynaport Micromod - ActivPAL - SenseWear Armband - Stepwatch Activity Monitor	SWA has been found accurate in measuring energy expenditure, it did not measure step-count accurately at any walking speed. Alternatively, there is strong evidence that the SAM appears the most sensitive for slower walkers and for cane-users. One reason for the considerable difference might be related to their position on the body. While the SWA is worn on the arm, the Stepwatch Activity Monitor is attached to the ankle. This may affect their sensitivity to the trajectories of the foot while stepping. It may also explain its loss of accuracy when 5 cane-mounted or when worn on the paretic limb. Another reason may be that the SAM must be calibrated specifically to each participant.	
36	Diet	Diet outcomes and metrics considered: - Nutritional patterns: These include the number of vitamins, minerals, and other substances ingested by individuals. Nutritional patterns are a valid parameter for predicting the quality of life in elderly populations. - Dietary habits: The study focuses on the impact of dietary habits on health conditions, particularly in elderly populations. Nutrient losses due to poor dietary habits can significantly affect cognitive and functional states. - Food intake patterns: The review includes the monitoring of food intake patterns, which are essential for identifying nutritional problems and their relationships with diseases such as obesity, Alzheimer's disease, depression, and metabolic syndrome Both manual recording and technological solutions were considered. Regarding technological solutions, different devices and technologies have been proposed to automate food intake monitoring. These include: - Smartphones and apps: Applications like FoodScan, which scan grocery receipts to manage food intake, are designed for elderly people with limited technical knowledge. - Sensors and IoT devices: These devices can detect and monitor different aspects of the food intake process, such as the type of food and the amount of ingested calories. - Tablets and Computers: The emphasis is on tablet computers and broadband internet access for nutrition care, as these devices are more accessible and user-friendly for older adults.	There is a clear interest for food control of the elderly, but it is still in an initial state and needs more efforts from all involved actors.	NA
37	Physical activity	Physical activity was measured by considering maximal oxygen consumption (VO2max), the most accepted measure of cardiorespiratory fitness. Specifically, VO2max was collected through consumer-grade wearables, including: - Garmin Fenix 5X, Fenix 3, Forerunner 920XT, Forerunner 230, GF5 - Polar A300, S410, F11, FT40, RS300X, F6, V800 - Fitbit Charge 2 Heart rate was collected through chest HR strap or wrist-measured (i.e., photoplethysmography) HR Two main methodologies to measure VO2mx were identified: - the resting conditions that evaluate users lying in a supine position and/or standing still - the exercise-based methodologies that evaluate users while performing physical activity.	Results indicate that consumer wearables using exercise tests provide more accurate VO2max estimates compared to resting tests, with exercise tests showing nearly zero systematic error. However, both methods exhibit large random errors, though exercise-based estimations are somewhat smaller yet still significant for individual measurements. Thus, exercise-based estimationcan be used for application at the population level, yet the estimation error at the individual level and, therefore, use for sport/clinical purposes still needs further improvement.	NA
38	Diet	Food intake: - Mobile apps (MyFitness Pal, Lose It!,CalorieMama,Snaq, Undermyfork) - Physical sensors (electromyography, piezoelectric, and acoustic sensors - Chemical sensors (Continuous Glucose Monitoring - CGM, continuous ketone monitors - CKMs, respiratory exchange ratio - RER)	The authors found a low degree of concordance between the meal rankings obtained from the 2 CGM devices. While some of these discrepancies could be explained by the fact that the 2 CGMs were placed at different anatomical locations (upper arm for Abbott, lower abdomen for Dexcom), this result raises important questions about the effectiveness of personalized dietary recommendations based on CGM measurements that are imprecise.	With diet monitoring tools, the hope is that reducing burden will result in increased adherence and eventually better clinical outcomes (eg, weight loss, glucose control). However, there is a well-established "law of attrition"51 in eHealth trials, which tend to experience significantly higher dropout rates than drug trials. Thus, it seems likely that adherence to dietary monitoring tools will decrease with time, no matter how low burden the tool is. A further issue is whether full automation of diet monitoring (ie, no burden) is desirable, as it may prevent users from developing the in-the-moment awareness that comes with food logging. Thus, there appears to be a tradeoff between developing tools that reduce user burden and allowing the users to form the critical habit of monitoring their diet.
39	Physical activity	The physical actvity outcomes/metrics considered in these studies included: - Energy expenditure - Step count - Physical activity levels (e.g. moderate-to-vigorous PA)	The review found that the evidence on the validity and reliability of using smartphone apps for PA surveillance in children and adolescents was insufficient. The authors concluded that more research is needed, especially in low- and middle-income countries, to further assess the feasibility and validity of using smartphone technology for PA surveillance in this population. The main limitations were	NA

		The methods used to measure these outcomes included: - Smartphone apps specifically developed for the studies -Commercially available smartphone apps downloaded from app stores Devices/apps include: - MoSeBo - DiaTrace - SCRIIN activity tracker - Pedometer - Pacer Step Counter - Google Fit - Apple Health - MapMyFitness - Samsung Health - Pacer Step Counter - Pedometer - Weight Loss Coach (for step count)	that the studies were all conducted in high-income settings, the number of studies was small, and smartphone apps are continuously evolving so the findings may not apply to the latest apps.	
40	Physical activity	Physical activity was measured by considering the following outcomes and metrics: - physical activity levels (PALs): Measured to assess overall physical activity. - step counts: Quantified to evaluate daily movement. - energy expenditure (EE): Assessed to determine the amount of energy consumed during physical activity. - intensity of physical activity: Measured to distinguish between light, moderate, and vigorous physical activity. They were measured through accelerometers, pedometers, heart rate monitors, global positioning system (GPS) devices. Adopted devices include: - ActiGraph - ActivPAL - Step-N-tune - Activ4Life - Intelligent Device for Energy Expenditure - Activity monitors - Tri-axial accelerometer - Actical accelerometer - Fitbit-Zip accelerometer	NA	NA
41	Diet	The paper reviews various approaches and sensors used for detecting and monitoring food intake, with a focus on the following diet-related outcomes and metrics: - food intake episodes: the primary focus is on accurately detecting and monitoring food intake episodes, i.e. when a person is consuming food. - nutritional habits and patterns: the paper discusses how accurate food intake detection can provide insights into a person's overall nutritional habits and patterns over time. The paper reviews a variety of sensor-based methods and devices used for passive monitoring of food intake, including: - cameras: visual recognition of eating gestures and food consumption using wearable or ambient cameras. - inertial sensors: detecting eating motions and gestures using wearable accelerometers, gyroscopes, etc. - acoustic sensors: monitoring chewing, swallowing and other audio cues related to eating using microphones. - electrogastrography: measuring gastric electrical activity to infer food intake.	The reviewed studies demonstrate the potential of using sensors to accurately detect food intake episodes, with high precision and recall rates reported. However, challenges remain in achieving robust and reliable food intake detection across diverse real-world settings and populations. More research is needed to further improve the validity and reliability of these passive monitoring approaches, especially for long-term continuous assessment of dietary intake.	NA
42	Physical activity	The studies included in the meta-analysis used activity monitors, both wrist-worn and arm-worn devices, including both research-grade and commercial consumer devices. Specific device brands/models were not consistently reported. Key technologies used in the devices: Accelerometry, heart rate sensing, heat sensing	The review concludes that estimates of energy expenditure from wrist and arm-worn activity monitors vary in accuracy depending on the type of activity being performed. Adding physiological sensors like heart rate to accelerometry can improve the accuracy of EE estimates. Research-grade devices tend to be more accurate for total EE compared to commercial devices, but commercial devices may be more accurate for specific activity types like ambulation and sedentary behaviour. The findings highlight the need to continue improving the accuracy of energy expenditure estimates from wearable activity monitors, particularly by incorporating heart rate data along with accelerometry.	NA
43	Physical activity	The two main physical activity outcomes measured were number of daily steps and moderate-to-vigorous physical activity (MVPA). Adopted devices include ActiGraph, Fitbit and Omron	The main results related to the accuracy, validity, and reliability of wearable devices in assessing physical activity indicate significant variability in the measurement of daily steps and moderate-to-vigorous physical activity across different studies. This variability stems from the inconsistent metabolic equivalent (MET) scales and accelerometric criteria used. The type of wearable device is also important, as each brand and model has unique sensitivity and calibration. Omron devices tend to provide more consistent results compared to Fitbit and other brands, likely because Omron offers	NA

			fewer and more standardized models. Additionally, there is complexity in translating three-dimensional movements into meaningful data and in measuring oxygen consumption, which is a critical variable for evaluating physical activity intensity that wearable devices cannot directly provide.	
44	Physical activity	Physical activity: - Smartphone-based physical activity measurement through inbuilt accelerometers - Wrist bands and wristwatches of multiple technology firms and wearable research-based accelerometers	NA	It was found a significant increase in the use of wearables to improve physical activity during the confinement or lockdown periods. Most of the studies observed the increased use of wearables in healthy adults followed by elderly, children and pregnant women. Furthermore, wearables embedded with behaviour change techniques such as goal setting, information/counseling, prompts, motivation and social support make wearables a potential choice for increased compliance to behaviour interventions and long-term behaviour change.
45	Physical activity	A pedometer or an accelerator. The primary outcomes that were evaluated in this review included step and activity counts or walk distance in miles as estimated by the monitor and the time spent in exercise.	The review has identified that physical activity monitors will need to become more accurate (insensitive to low walking speeds, altering readings when shaken, memory storage problems, high signal-to-noise ratio).	Our review has identified that physical activity monitors' placement will need to make more comfortable for the COPD users.
46	Physical activity	Dynamic activity, motion and static postures: - inertial sensors, such as gyroscopes, accelerometers, pressure senosors, magnetic filed sensors - location sensors, like GPS Physiological data: - physiological sensors, such as blood pressure cuffs, electrocardiograms, spirometers, electrooculography, skin temperature sensors Activity recognition through: - environment sensors, such as thermometer, hygrometer, energy sensors - binary sensors, such as window contact, door contact, remote control switch - location detectors, such as infra-red and active RFID - tags, such as RFID tags and NFC tags	Using multiple sensors can achieve high accuracy in physical activity recognition, but these setups tend to be obtrusive, uncomfortable, impractical, and expensive. Consequently, many studies opt for a single wearable sensor placed on specific body parts like the hip, back, wrist, chest, waist, or thigh. Wearable and mobile devices are popular for their portability and low cost. However, personal physical activity data from these devices exhibit significant variability due to environmental factors and positioning, which impacts the reliability of the data. Low-cost, easy-to-install on-object sensors like environmental sensors, binary sensors, or RFID can provide this data unobtrusively and privately. Indoor localization sensors, including Bluetooth and RFID, and outdoor localization such as GPS, are effective for complex activity recognition without needing many on-object sensors.	NA
47	Diet	Food portion Size Estimation: Traditional FPSE (House Measures; Visual Approximation) Sensor-Based FPSE - Strain Sensors (Piezoelectic Sensor) - Acoustic Sensors (Microphone) - Motion Sensors (Accelerometer, Gyroscope, Magnetometer) - Imaging Sensors (Mobile phones, Digital Cameras, Depth Sensors, Customized Cameras) - Weighing Sensors (Weigh-scales, Smart plate, Mandometer)	The review found that the present-day research is now focusing on improving accuracy, testing outside of restricted laboratory conditions, including mixed meals with more challenging models such as irregular shaped food and non-rigid food items. If these existing challenges can be addressed, SB-FPSE can be exploited to be used in free-living with minimal human intervention in the estimation process. Indirect methods using wearable technologies can be robust to food shape and size since they are derived from the physiological indicators such as chewing, swallowing, hand gestures, or head movements. The accuracy of FPSE in these methods is lower than with the direct methods. If indirect methods are more extensively explored and the accuracy is improved, they can well be the future of SB-FPSE.	The most significant open problem is in the applicability of any given sensor-based solution to everyday use Weighing and imaging sensors require a significant user burden and may lead to underreporting of the intake. Wearable sensors may require fewer user actions, just cooperation with the wear regiment, but these sensors need to address the issues of accuracy, social acceptance, and data privacy before being widely adopte
48	Physical activity	The paper focused on two key metrics related to physical activity and energy expenditure: physical activity energy expenditure (PAEE) and total energy expenditure (TEE). The paper reviewed studies that used accelerometers, either alone or in combination with other indicators, to estimate PAEE and TEE and compared the results to double labeled water measurements (DLW).	The paper discusses the validity of motion sensors in estimating energy expenditure and physical activity energy expenditure compared to the gold standard methods such as doubly labeled water and calorimetry. The key findings were that accelerometers alone explained 13% of the variance in DLW-measured PAEE and 31% of the variance in DLW-measured TEE in children, while in adults, accelerometers explained 29% of the variance in DLW-measured PAEE and 44% of the variance in DLW-measured TEE. Adding heart rate to accelerometer data improved the estimation of PAEE in both children and adults, as heart rate provides an additional physiological indicator of energy expenditure. Identifying postures (e.g. sitting, standing, walking) also seems relevant for improving PAEE estimates in both children and adults, as different activities have different energy costs. It highlights that motion sensors have been validated against these reference methods and can provide accurate estimates at the group level, but individual bias is high even when combining biometric or physiological indicators.	NA
49	Physical activity	Physical activity was measured by considering: - number of steps, assessed with Pedometer FREE GPS app, Argus Motion, Fitness Tracker, Runtastic Pedometer Step Counter, Noom Walk, iPedometer, Walk@Work-Application, STARFISH, Moves, StepUp, Pedometer Pacer Works, Pedometer Tayutau, Accupedo, Google Fit, Dongdong, Ledongli - distance, assessed with Runkeeper app, MotionX GPS, Runtastic, Nike+ Running, Endomondo,	There is conflicting evidence on the reliability of step-counting apps, and insufficient evidence for measuring distance and energy expenditure. App accuracy is affected by velocity and smartphone placement, being less accurate at lower speeds and when carried at hip level. Studies indicate that many apps are not valid for counting steps in daily activities. Errors may be acceptable for promoting physical activity but can mislead individuals about their activity levels and pose risks for those with specific health conditions. Therefore, apps should be rigorously tested for reliability and validity before widespread use.	NA

		Sports Tracker, Strava, Dongdong; Ledongli - energy expenditure, assessed with Runkeeper app, Movn, Dongdong, Ledongli		
50	Physical activity	Accelerometers (ActiTrainerTM, SenseWear Armband, Actigraph GT3X+, Actigraph GT3X, Fitbit Zip, Fitbit flex, RT3@ triaxial, Actigraph GT1M, Caltrac one-axial, Actical Mini-Mitter, CSA 7164) and pedometers (Yamax Digiwalker SW-700/701, Yamax Digiwalker SW-200).	Pedometers are usually simple and inexpensive devices, giving real-time feedback in terms of measuring the number of steps taken on a daily basis. The pedometers revealed low accuracy at slower speeds, particularly the ones that used a spring-suspended horizontal lever arm mechanism. In addition, pedometers may have low accuracy when they are attached to other parts of the body or when they are attached to certain clothing items (e.g., when wearing a dress). Compared to pedometers, accelerometers are the devices that are most often used by researchers and in clinical settings because they have more variables that can be analyzed. For example, while pedometers only assess the distance covered by the number of steps, accelerometers allow us to assess the frequency, duration and intensity of PA. Both of the devices showed good validity in terms of activity count (number of steps) and energy expenditure in different populations (healthy and chronically ill populations). the ActiGraph accelerometers (in particular, the GT3X versions), Actical and ActiTrainer, have the best measurement properties to assess common movement-related outcomes (e.g., example, MVPA and TPA) for school-based activities for preschool- and school-aged children, and they should be the tools of choice where resources permit it is and where it is logistically possible. On the other hand, Fitbit Zip and Fitbit Flex also showed very promising results; however, these were based on a very limited sample of studies. On the other hand, we found that the Yamax Digi-Walker (SW-200) and Yamax DigiWalker (SW-700 and 701) pedometers have the best measurement characteristics related to movement (e.g., example, MVPA and VPA).	NA
51	Physical activity	Physical activity derived from smartphone accelerometers: - Samsung Galaxy SII / Android / 3-axis - Samsung Galaxy xCover, LG Nexus4 / Android / 3-axis - Samsung Galaxy Trend PLUS / Android / 3-axis - Samsung Galaxy Nexus / Android / 3-axis - Samsung Galaxy SII / Android / 3-axis - Motorola Cliq, HTC MyTouch, Google/HTC Nexus One / Android - Google G1 / Android / 3-axis - iPhone 3G / iOS / 3-axis - Motorola Mobility LLC / Android / Not Reported	Results showed moderate-to-good agreement with the validation device in a controlled setting, and 4 similarly in a free-living setting. Overall, these studies collectively suggest that smartphone accelerometers can be valid tools for measuring physical activity, particularly in controlled settings. However, accuracy can vary significantly based on factors like the specific smartphone model, application used, placement of the device, and the nature of the activities being monitored.	NA
52	Physical activity	Step Count: ActiGraph GT9X (hip, wrist, Ankle) Energy Expenditure: ActiGraph GT9X (hip, wrist)	The validity and accuracy of the device in measuring steps seem to be influenced by gait speed, device placement, filtering process, and monitoring conditions; and there is a lack of evidence regarding the accuracy of step counting in free-living conditions and regarding energy expenditure estimation.	NA
53	Physical activity	Physical activity metrics, including steps count, time spent in different activities with varying intensity, sedentary behaviour, and daily energy expenditure, were mainly measured through accelerometers. Research-grade accelerometers Heart rate was measured through wrist-worn wearable devices using photoplethysmography.	Results indicate concerns about accelerometer validity for populations other than healthy adults, particularly the elderly, as wearables show low accuracy at slow walking speeds (<2 km/h). Validation studies for elderly populations often use inappropriate reference criteria based on metrics for adults, leading to misleading conclusions. Studies comparing wearable devices for heart rate monitoring reveal varying accuracy across different brands and exercise intensities, though wrist-worn devices generally provide accurate measurements compared to clinical-grade ECG and chest-strap monitors. Standardized protocols and measures are needed for more accurate evaluations	NA
54	Physical activity	Physical activity was measured mainly through accelerometers (wore on wrist, arm, hip, or ankle), portable global positioning systems, pedometers, smartwatches, mobile sensors or mobile apps.	Results indicate that pedometers can shows only modest validity for stroke patients, particularly at slower walking speeds and with asymmetrical gait patterns. This inaccuracy may stem from the pedometer's mechanism or algorithms not detecting smaller hip displacements. Ankle-worn pedometers are more accurate at slow speeds but still undercount steps compared to accelerometers. The validity of wrist-worn activity trackers for stroke patients is uncertain, with potential limitations due to algorithms designed for healthy adults. Additionally, hip-mounted accelerometers, like pedometers, may not accurately account for gait asymmetries.	Results reveal that patients encountered usability barriers with a health app, including the need for assistance with downloading and setup, resetting the app, carrying the phone, and increased battery consumption. However, positive aspects such as automatic background operation, a large simple display, and a home screen icon enhanced usability. Recommendations for wearable devices for older adults (also applicable to stroke patients) include a focus on aesthetics, being lightweight, comfortable, waterproof, easy to operate, inexpensive, with long battery life, accurate activity assessment, immediate feedback, and easy data transmission.
55	Diet, alcohol, smoking	The review identified both self-report and objective measures of the three targeted lifestyles. Regarding objective measures only, diet was measured through: - manually analyzed food photography methods (i.e., participants took photos of their food, which were then sent to researchers for analysis) - automatically analyzed food photography methods (i.e., images of food were captured by participants using specialized apps, which then analyzed images and calculated the energy and nutrient content of foods pictured automatically) Alcohol consumption was measured through:	Regarding diet, the literature suggests that manually analyzed food photography may be valid and reliable in a general adult population. However, because of the need for highly trained individuals to analyze every captured image, this approach is unlikely to be scalable or sustainable outside of a research context. Novel approaches of using smartphones to capture images and voice, extract food intake information from these data, and access external databases to retrieve nutrient information report encouraging results, but most of these studies confined their investigations to a small number of food items.	NA

		- a mobile-based test of psychomotor performance to measure alcohol-induced impairment - an optical attachment for smartphones to identify the results of saliva alcohol concentration test strips - multiple smartphone sensors and machine learning to recognize drinking behaviour by considering location (GPS or Wi-Fi), movement (accelerometer), social context (density of nearby Bluetooth devices), and phone use (battery, screen, and app use) on weekend nights Smoking was assessed through: - the measurement of expired CO using a smartphone app - heart rate measured by a smartphone - accelerometer and gyroscope data collected from smartwatches and smartphones to test a 2-layer hierarchical smoking detection algorithm - data collected from the GPS, Wi-Fi, and accelerometer within the smartphones of participants classify smoking and nonsmoking periods	Regarding alcohol, the literature suggests that smartphone-based measures of psychomotor performance may be able to validate alcohol-induced impairment. Finally, using in-built phone sensors to infer and even predict alcohol use may be a promising assessment method. Regarding smoking, studies support the methodological soundness of measuring expired CO using smartphones (and expired CO monitors). Moreover, using apps that measure users' heart rate was also found to be a promising way to quickly and easily verify smoking abstinence. Passive measurement approaches using wrist-worn and in-phone sensors also show promise.	
56	Physical activity	Locomotion, the amount of upper limb movements, and phsyical activity intensity were measured through: - movement intensity using metrics of energy expenditure, levels of physical activity, and/or time in body position - the amount of upper limb use (activity counts) - locomotor behaviour quantified by step count, spatial-temporal parameters, speed, or walking distance. Upper limb activities were measured through both commercial (i.e., Actical, Crossbow iMote2, Actigraph, Actiwatch AW7, and Micro-mini motion logger) and non-commercial wearable sensors. Locomotion was assessed through smartphone applications (i.e., Google Fit, Health, STEPZ, PACER, X sensor Pro), commercial wearable sensors measuring mainly step counts and gait kinematic parameters (e.g., Actigraph GT3X, FITBit One, Garmin VivoFit, and OMRON pedometer, or non-commercial devices. Physical activity intensity was measured through applications (i.e., GoogleFit) or commercial devices.	Results showed that the validity of upper limb commercial wearable sensors was moderate to good. Compared to a criterion-standard measure, validity of applications measuring locomotion ranged from poor to good and depended on smartphone operating system (e.g., the validity of the PACER application was high for iOS and moderate for Android). Test–retest reliability ranged between poor and good for Google Fit, Health, STEPZ, and PACER, with lower reliability reported for the Android operating system. Validity of commercial devices measuring locomotion ranged from poor to good, depending on sensor position and walking speed. For example, Actigraph GT3X had poor accuracy when positioned at the hip or paretic ankle but had good accuracy when positioned on the non-paretic ankle. Similarly, the FITBit One had better accuracy when placed on the non-paretic ankle compared to the hip and the Garmin VivoFit had poor accuracy when positioned on the non-paretic side.	NA
57	Physical activity	Pedometer (limited to the assessment of steps during walking) PA monitor (enable to assess other activities) Consumer grade device Research grade device	the PA monitors were most frequently combined with structured behavioural health interventions, an indication-specific intervention or usual carethe traditional devices often do not enable automatic data transmission, requiring users to manually transcribe data to activity logs which limits their applicability for long-term PA monitoring. Furthermore, the lacking accuracy of simple pedometers in the assessment of steps often lead to overestimations in step counts, which might induce higher effect sizes when compared to accelerometer- based PA monitors	NA
58	Physical activity	Different metrics of physical activity were considered, including step count, MET equivalent, walking ability, activity intensity, and time spent sitting/standing/walking. They were measured through accelerometer-based wearable devices (i.e, Step Watch, ActivPAL3, ActiGraph GT3X+, Sensewear, Samsung Galaxy S4, Step Activity Monitors, Fitbit One, SyepWatch 3 Activity Monitor, Axivity AX3), pedometers (i.e., UW-100, UW-101 A&D) or inertial measurement unit sensors (i.e., Shimmer 3). Wear-loaction includes waist, wrists, upper arms, thighs, trunk, ankles, lower back, and hips	Results show no consensus on the best wear location for wearables in stroke patients, with studies using varied locations and none reporting participants' perspectives. Walking was the most common activity measured, with metrics including step count, activity volume, frequency, and time. Only a few studies aimed to validate these metrics for stroke patients in the community. Validity and accuracy of complex accelerometer data metrics need robust validation under community conditions over time, as most validations were brief or conducted on healthy individuals, not adequately reflecting long-term accuracy for stroke patients.	NA
59	Physical activity	Physical Activity: WAMs were used: - FitBit Charge - FitBit Flex - Nikeþ - FuelBand - GPS-enabled sport watch - Garm Forerunner 21019 Mobile apps: Use of commercially available fitness apps that synchronized with corresponding WAMs	The incorporation of monitoring and feedback into HBET programs using smart WAM devices that communicate with smartphone apps or PAD-specific apps can potentially improve the effectiveness of these programs.	PAD-specific apps are presently scarce. There is, however, increasing interest in this type of technology, with newer apps incorporating PAD-oriented elements that intend to motivate, educate, and engage patients in their own treatment plan. A high level of acceptance and satisfaction was reported for PAD-specific TrackPAD app users.
60	Physical activity	The review focused on studies using accelerometry (e.g., through accelerometer or actigraph) to measure physical activity in critically ill, mechanically ventilated adult ICU patients. The specific devices used were not listed, only that accelerometry is a technique used to measure physical activity that has been validated in several ambulatory populations	Results found that accelerometry correlates well with direct observation in reporting frequency and duration of various types of physical activity (rolling, sitting up, transferring, walking), but cannot differentiate various intensities of activity or whether movements are voluntary or involuntary concerning effort. Thus, accelerometry may serve as a useful adjunct in reporting the temporality of physical activity in critically ill patients, but other objective information may be needed to accurately record the frequency, duration, and intensity of activity in this population	NA
61	Physical activity	Daily physical activity, intensity, and activity patterns and energy expenditure monitored with GT3X sensor devices	The monitoring of daily physical activity of GT3X is very accurate, and the reliability and validity of the prediction of body strength and energy consumption are very high.	NA
62	Physical activity	These technologies are categorized into three types: Positiong: - outdoor and indoor positioning	The indoor location schemes using geomagnetism or motion sensors (an integration of a three-axis gyroscope, three-axis magnetometer, and three-axis accelerometer) seem to be suitable for the elderly care scenarios because of low-cost, no extra devices, and can serve to position at unpredicted areas. But, the accuracies of geomagnetic IPS or PDR systems (which range from 0.1 m to 2 m and from 1 m to 5 m, respectively) are not precise enough to meet the demands of AAL in elderly care scenarios.	NA

		Physical Activity: - activity recognition (Vision-based recognition, Radio-based recognition, Sensor-based recognition) Vital sign: - real time vital sign monitoring (body temperature, heart rate, respiration rate, blood pressure, pulse oxygenation, blood glucose)	Therefore, a supplementary approach must be adopted to achieve a robust and precise indoor positioning and tracking system. HAR systems that rely solely on accelerometers do not perform well in some complex activity recognition scenarios because an accelerometer provides only acceleration information. Consequently, sensors such as gyroscopes, magnetometers, and barometric pressure sensors have been combined with accelerometers to improve the performance of complex activity recognition.	
63	Diet	Food intake: -Wrist-Worn Devices (measure hand-to-mouth (HTM)) -Neck-Worn Devices (microphones, piezoelectric sensors) -Ear-Worn Devices -Glasses-Like Devices -Other Devices	The accuracy of these devices varies, with many achieving an F1-score or accuracy of ≥80% in detecting eating behaviours. However, none of the devices fully met all feasibility criteria,	Social acceptability and comfort were major concerns for neck-worn devices and those with continuous camera capture, which raised privacy issues. Battery life was often insufficient for continuous day-long monitoring, a critical requirement for practical use in real-world settings.
64	Physical activity	Seven accelerometers (Push Band, Push Band 2.0, Beast Sensor, Bar Sensei, MyoTest, Wimu System and RehaGait), 10 linear transducers [GymAware, SmartCoach, 1080Q, T-Force, Chronojump, Tendo, Speed4Lift, FitroDyne (Fitronic), Open Barbell System, and Musclelab (Ergotest)], three mobile applications (PowerLift/MyLift, iLoad, and Kinovea), and two optic devices (Velowin and Flex). The most common exercises assessed were the squat and bench press, either within the Smith machine or with freeweights, while velocity outputs were the most commonly assessed kinetic or kinematic variable.	Linear transducers have shown the greatest accuracy with mean concentric velocity. When these devices have been compared during free-weight exercises, it appears that the GymAware provides the greatest accuracy. Accelerometer devices have shown promise, but their accuracy is still questionable. Of these devices, the Push 2.0 may have the greatest accuracy during free-weight exercises. Finally, it appears that smart phone and tablet apps may be an alternative for a quick 'snap-shot' of training intensity, but substantial inter-device error may exist. Therefore, unless monitoring is done by a single individual with the same device, accurate tracking of performance may be limited. Nevertheless, the use of optic laser devices is a promising alternative that can provide accurate, real-time feedback. While further research is still warranted on additional variables (e.g., peak velocity), this provides an additional cost-effective method for monitoring resistance training.	NA
65	Diet	Chewing activity: - Contact sensors (Electrode, BioRadio, BIOPAC) - Contactless sensors (Inductive, Capacitive, Photoelectric, Ultrasonic, Piezoelectric, IR-Photodetector, ToF, VCSEL, Organic Crystal)	Chewing detection based on contactless sensors in various applications showed potential for application in comfortable wearable sensors and high classification accuracy.	NA
66	Physical activity	The Fitbit wristband (Fitbit, Inc., San Francisco, CA, USA), the ActiGraph (ActiGraph, Pensacola, FL, USA), the Shimmer tracker (Shimmer, Dublin, Ireland), and the WHOOP strap (WHOOP, Inc., Boston, MA, USA). All studies focused on investigating the total number of steps taken per minute, per day, throughout the entire duration of the study and walking poses. Additionally, some studies collected heart rate data and sleep-related parameters such as bed and lying time.	Some studies used consumer-grade wearables to measure physical activity and sleep. While these devices are convenient and widely used, they may be less valid than research-grade devices for assessing activity intensity and sleep quality.	On the other hand, these devices present a multitude of advantages for health research. They are not only more cost-effective than premium research devices, but also boast comfort in wear, making them easily accessible to consumers at an affordable price.
67	Diet	Different food intake monitoring approaches were detected, including methods targeting: - caloric intake by using a wearable ear pad sensor system for food classification complemented with acoustic sensors to detect chewing sounds - eating behaviour by adopting an acoustic approach that targets the sounds produced from chewing and swallowing events for food intake detection. This approach can also be complemented with a visual approach (wearable camera) to detect chewing sounds and food portions by time during the eating process through image processing of snapshots of the meal over time - motion of the eating process, especially wrist motion, by using gyroscopes and accelerometers.	Results indicate varying levels of accuracy and suitability among different modalities for detecting food intake and related activities. The acoustic approach demonstrates an accuracy of 85% for swallowing and chewing event detection and 98.5% for food state classification. The visual approach shows high accuracy, with 90.6% for food type classification and 94.3% for volume estimation from large image datasets. This method offers the highest accuracy for food type classification and is highly suitable for real-life scenarios due to its unobtrusiveness. The inertial approach has an accuracy of 89.5% for eating detection and 94% for eating gesture detection. It is suitable for integration into wearable items and is unobtrusive.	NA
68	Alcohol	The meta-analysis focused on the correlation between transdermal alcohol concentration (TAC) and blood alcohol concentration (BAC) or breath alcohol concentration (BrAC) as the key alcohol consumption metrics. It did not provide specific details on the commercial names or models of the transdermal alcohol sensors included in the analysis	The meta-analysis found that, in the primarily laboratory-derived sample of studies, the average correlation between transdermal alcohol concentration (TAC) and blood alcohol concentration (BAC) was large in magnitude ($r = 0.87$, 95% CI = 0.80, 0.93). This indicates that transdermal alcohol sensors perform strongly in assessing blood/breath alcohol concentration under controlled conditions. The meta-analysis also found that TAC lagged behind BAC by an average of 95.90 minutes (95% CI = 55.50, 136.29). The body position of the transdermal sensor significantly moderated both the TAC-BAC correlation and the lag time. Specifically, lag times for ankle-worn devices were approximately double those for arm/hand/wrist-worn devices, and TAC-BAC correlations also tended to be stronger for arm/hand/wrist-worn sensors	NA

3.4. Summary

This umbrella review explores the advancements in passive monitoring technologies used to track four key lifestyle factors: physical activity, diet, alcohol consumption, and smoking. Each lifestyle factor is monitored using various metrics and methods, supported by different devices and technologies. The detailed summaries of monitoring methods and technologies for each lifestyle factor are provided below (see Table 6).

Table 6. Summary of passive monitoring approaches for physical activity, diet, smoking, and alcohol consumption

Lifestyle factor	Targeted metrics	Devices	Details
Physical Activity	Step count	Accelerometers (e.g., ActiGraph, ActivPAL, Fitbit)	Wearable devices capture detailed movement patterns, commonly placed on the waist or hip for accuracy.
		Pedometers (e.g., Yamax Digiwalker, OMRON)	Primarily used for step counting, placed on the hip or waist.
	Active minutes	Multi-sensor devices (e.g., Fitbit Charge HR, Garmin Vivoactive)	Combine accelerometers with heart rate monitors for comprehensive activity assessment.
	Energy expenditure	Smartphones	Use in-built accelerometers and gyroscopes
	Physical activity levels	GPS devices	Track outdoor positioning and movement patterns for detailed spatial activity insights.
	Intensity gradient	Commercial and research-grade devices (e.g., ActiGraph, Fitbit, Garmin)	Various models are used to monitor steps, heart rate, and energy expenditure.
	Walking patterns	Video recordings	Used for specific gait and running studies, focusing on metrics like stride time and foot strike patterns.
Diet	Nutritional patterns	Image analysis (e.g., food segmentation, recognition)	Utilizes camera-based systems for food item detection and portion size estimation.
	Dietary habits	Wearable sensors (e.g., acoustic sensors, EMG sensors)	Monitor chewing, swallowing, and eating behaviours using various sensors.
	Food intake patterns	Audio-based sensors (e.g., microphone-based systems)	Detect eating events based on sound cues.
		Non-vision sensors (e.g., accelerometers, gyroscopes)	Assist in gesture recognition for eating activities.
Smoking	Lighting events and hand-to-mouth proximity	Wearable sensors (e.g., proximity sensors, IMUs)	Detect instances of cigarette lighting and hand-to-mouth gestures.
	Inhalation	Respiratory inductance plethysmography	Monitor smoking-specific respiration patterns.
		Acoustic sensors	Detect unique breathing sounds associated with smoking.
	Smoking-specific patterns	Egocentric cameras	Capture detailed scenes of smoking events.
Alcohol Consumption	Alcohol concentration	Transdermal alcohol sensors (e.g., SCRAM, WrisTAS, BACtrack Skyn)	Measure transdermal alcohol concentration (TAC) for continuous monitoring.
		Proton-Exchange Membrane (PEM) fuel cell sensors	Used in transdermal sensors for accurate alcohol concentration measurement.
	Alcohol intoxication levels	Devices like Proof, AlcoWear, Sensor-Equipped smart shoes	Monitor real-time alcohol intoxication levels through various sensors.

4. Mapping Psychosocial Determinants for Cancer Onset: An Umbrella Review

4.1. Primary endpoint

This umbrella review aims to provide a comprehensive overview of the psychosocial factors associated with cancer onset by synthesising existing evidence and will help us identify the psychosocial areas to consider for the development of the iBeChange platform.

4.2. Methods

4.2.1. Study design

This umbrella review was conducted following the guidelines provided by the **Joanna Briggs Institute** (Page et al., 2020) to address the research question: "What are the psychosocial factors related to cancer onset?". The results are presented in accordance with the PRISMA. A narrative synthesis was performed to report the findings.

4.2.2. Data sources and search strategy

PubMed, Embase, and Scopus were the databases used to identify systematic reviews and meta-analyses assessing the psychosocial factors associated with cancer onset. The search strategy was optimized with the assistance of a research librarian, and the final search string consisted of the combination of the following terms: psycho-social, risk factors, cancer, onset, health behaviours. The search string syntax was first developed for PubMed and Embase, then modified accordingly for Scopus. The final database search was conducted in March 2024.

4.2.3. Eligibility criteria

The **inclusion criteria** for this umbrella review were as follows: (1) systematic reviews and/or meta-analyses, (2) examining at least one psychosocial factor in relation to cancer onset/incidence/risk, (3) written in English, and (4) published after the year 2000, (5) in academic journals, (6) including at least two studies focusing on psychosocial variables. Studies presenting the following criteria were **excluded**: (1) non-systematic reviews, (2) meta-analyses not providing information on the study identification and selection process, (3) published before 2000, (4) written in languages other than English, (5) studies focusing solely on non-psychosocial factors (e.g., only behavioural, or medical/biological factors) in relation to cancer onset, (6) including only one study focusing on psychosocial variables, (7) focusing only on children/adolescents, (8) focusing only on cancer outcomes (e.g., mortality, survival). No restriction on geographical location was applied.

4.2.4. Study selection

The abstract screening was organised in the online software Rayyan (Ouzzani et al., 2016). Search results were imported into Rayyan, and duplicates were identified and removed. The preliminary screening based on titles, abstracts, and keywords was conducted independently by two researchers (E.T. and P.D.) that were blinded to each other's decisions. All the potentially relevant articles retrieved for full-text screening were selected according to the inclusion and exclusion criteria. Any disagreements concerning the eligibility of studies were resolved through discussion and consensus.

4.2.5. Data extraction

The following data were extracted from the retrieved articles: publication data (i.e., name of the first author, year of publication, study origin, study design), the aim of the research, characteristics of the included studies (i.e., number and type of studies included in the review, date range, and country of origin of the included studies), participants' characteristics (i.e., sample size, socio-demographic characteristics), cancer type, investigated factors (psychological factors, social factors, other behavioural factors), results (i.e., relation to cancer onset).

It is to note that in studies with multiple aims/endpoints and/or evaluating also the relationship between other factors (e.g., behavioural, biological/medical factors) and other outcomes (e.g., mortality, survival, etc.), only the information related to our research question has been extracted. Behavioural factors were considered only if evaluated as covariates, mediators, or confounders to provide a more comprehensive understanding of the interplay between psychosocial factors and cancer onset.

Regarding the results, a narrative synthesis of the results was performed for systematic reviews, whereas estimates of associations were reported for meta-analysis when they were present and statistically significant (p<0.05). When multiple estimates were reported, the range of these estimates was provided without including the confidence intervals. Regarding heterogeneity between studies, we reported I^2 statistics when available, but only if it exceeded the 50% cut-off indicating significant heterogeneity, as appropriate (Deeks, Higgins & Altman, 2020). When I^2 was not provided, other metrics were reported, but only if the corresponding p-value was <0.05. In Table 7, the characteristics and results of the studies are detailed, while the following paragraphs summarize the particularly relevant findings with respect to the objective of **Task 2.2** of the iBeChange project.

4.3. Results

4.3.1. Results of the selection process

The search in 3 electronic databases (PubMed, Embase, and Scopus) identified 3,536 references, and 39 papers have been included in the present umbrella review. All the details regarding the selection process are shown in the PRISMA 2020 flow diagram (Figure 3).

4.3.2 Characteristics of the included studies

The summary of the study characteristics is represented in Table 7.

Figure 3. PRISMA 2020 flow diagram: summary of study selection through the application of the eligibility criteria via databases and registers.

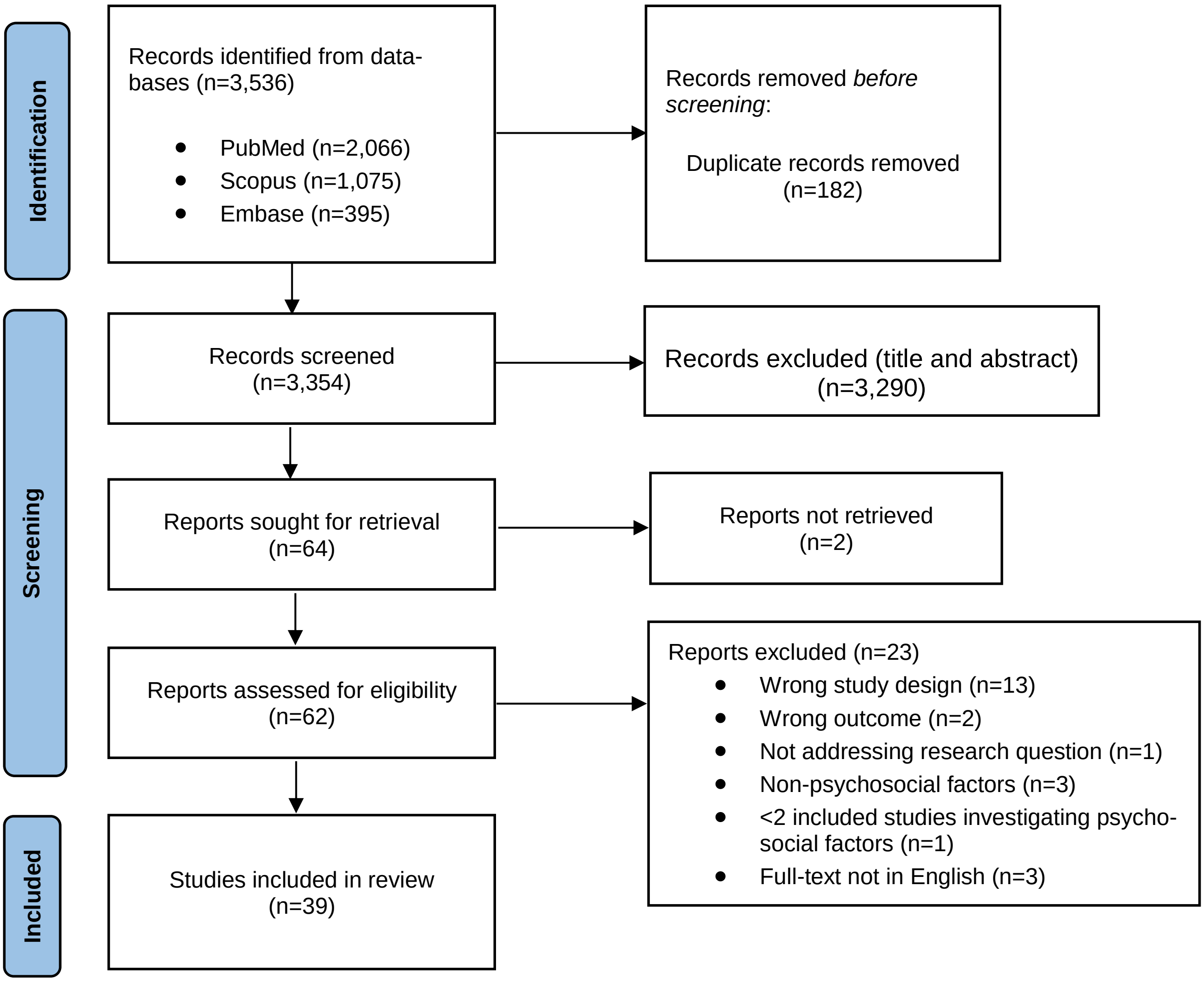

Table 7. Characteristics of included studies in the umbrella review on psychosocial risk factors. (1 of 5)

Authors (Year of publication)	Study Origin	Study Design	Objective/aim of the research	Included studies			Participants			Factors			Results
				Nr. of studies included	Type of studies included	Country of origin of included studies	Sample size (N)	Characteristics	Cancer type	Psychological factors	Social factors	Other behavioural factors	
Ahn et al. (2016)	South Korea	MA	Analyze the effect of depression on subsequent risk of cancer	9	6 nested case-control studies, 2 retrospective cohort studies, and 1 prospective cohort study	International (n=1), Taiwan (n=2), UK (n=2), USA (n= 2), Denmark (n=1), Australia (n=1)	386,552	Patients with depression diagnosis	Overall, breast, lung, CRC, liver, prostate, skin, brain, oral cavity, hematologic	Depression	N/A	N/A	Patients with depressive disorder were at increased risk for cancer (OR: 1.26; 95% CI: 1.06–1.50; I2=96.4%), specifically lung cancer (OR: 1.47; 95% CI: 1.26-1.72), OCC (OR: 1.75; 95% CI: 1.22-2.51), and hematologic malignancies (OR: 1.14; 95% CI: 1.02-1.27). However, a significant effect was observed only in low-quality studies (OR, 1.31; 95% CI: 1.05–1.63), and not in high-quality studies.
Akinyemiju et al. (2015)	USA	SRMA	Investigate the associations between breast cancer risk and features of the residential environment	27	23 cross-selectional, 2 case-control, 2 longitudinal study	USA (n=20), Canada/USA (n=1), Candada (n=2), UK (n=2), Australia (n=1), Italy (n=1)	>2,215,182	Participants ≥ 15; cases: 2,037,724	Breast	N/A	ABR constructs (i.e., indicators of SES such as education, income, poverty, occupational class, urbanization, and composite SES)	N/A	Positive associations were found between breast cancer incidence and urbanization (pooled RR for urban vs. rural: 1.09, 95% CI: 1.01, 1.19; I^2 =95.4%), ABR income (pooled RR for highest vs. lowest: 1.17, 95% CI: 1.15, 1.19), and ABR composite SES (pooled RR for highest vs. lowest: 1.25, 95% CI: 1.08, 1.44; I^2 =98.7%).
Bahri et al. (2018)	Iran	SRMA	Investigate the relation between stressful life events and breast cancer	11	11 cohort studies	USA (n=2), Finland (n=2), Australia (n=1) United Kingdom (n=2) Denmark (n= 2), Sweden (n=2)	498,737	Women ≥ 16; follow-up range: 1-40 years	Breast cancer	Stressful life events (i.e., maternal death in childhood, stress of daily activities, life stressors, stressful life experiences, death of cohabiting partner, parental death during early adulthood)	N/A	N/A	History of stressful life events slightly increases the risk of breast cancer (pooled RR: 1.11; 95% CI: 1.03-1.19; I2: 53%).
Basten et al. (2023)	Netherlands	MA	Examine interaction and effect modification of psychosocial factors and health behaviors/behavior-related factors in their association with incident cancer	18	18 cohort studies	N/A	437,827	36,961 cancer incidences; mean age range at baseline: 28-76 years; percentage of females range: 25% -100%; maximum follow-up time range: 6-39 years	Overall, breast, CRC, lung, prostate, smoking-related, and alcohol-related cancers	Depression, anxiety, recent loss event, general distress, and neuroticism	Perceived social support, relationship status	Smoking, alcohol use, physical activity, sedentary behavior, sleep quality, sleep duration	Lower perceived social support amplified the impact of cigarette smoking on overall cancer (RERI: 0.03, 95% CI: 0.01-0.05; AP: 3%, 95% CI: 1%-4%; multiplicative effect: HR: 1.03, 95% CI: 1.01-1.04) and lung cancer incidence (RERI: 0.05, 95% CI: 0.01-0.09; AP: 3%, 95% CI: 0%-5%; multiplicative effect: HR: 1.01, 95% CI: 0.98-1.04). An anxiety diagnosis increased the effect of alcohol consumption on alcohol-related cancer incidence (RERI: 0.14, 95% CI: 0.00-0.28; AP: 12%, 95% CI: 1%-22%; multiplicative effect: HR: 1.14, 95% CI: 1.01-1.28), higher depressive symptoms enhanced the impact of BMI on colorectal cancer incidence (RERI: 0.04, 95% CI: 0.001-0.08; AP: 4%, 95% CI: 0.03%-7%; multiplicative effect: HR: 1.04, 95% CI: 1.001-1.08). Depression symptoms combined with pack years (RERI: 0.04, 95% CI: 0.00-0.08; AP: 2%, 95% CI: 0%-4%; HR: 0.98, 95% CI: 0.96-1.00) and anxiety diagnosis combined with pack years (RERI: 0.22, 95% CI: 0.02-0.43; AP: 9%, 95% CI: 2%-17%; HR: 0.97, 95% CI: 0.88-1.05) showed increased lung cancer incidence.
Bellis et al. (2019)	UK	SRMA	Calculate the proportions of causes of ill health (including cancer) attributable to one or multiple ACEs	6	2 cohort, 4 cross-sectional studies	USA (n=2), UK (n=3), Ireland (n=1)	35,965	Adults ≥ 18 from Europe (n=21,593) and from North America (n=14,372) not at a known high risk of ACEs	Overall incidence	ACEs	N/A	N/A	ACEs were associated with an increased risk of cancer, showing a higher risk for individuals with one or more ACEs. Specifically, the risk was greater for those with two or more ACEs (Europe = pooled RR: 1.58 [95% CI: 1.32-1.91]); North America = pooled RR: 1.25 [95% CI: 1.10-1.43]) compared to those with just one ACE (Europe = pooled RR: 1.08 [95% CI:0.89-1.30]); North America = pooled RR: 1.10 [95% CI: 0.95-1.28]).
Bennett et al. (2015)	UK	SRMA	Provide a systematic review of lifestyle factors and SIA risk	3	1 prospective cohort, 2 population based case-control studies	USA (n=2), Denmark (n=1)	502,222	Cases (n=199), controls/cohort size (n=502,023)	SIA	N/A	Socio-economic status (education and occupation)	N/A	No significant association between education and SIA carciogenesis was found. Several occupations were reported to carry significant elevated SIA in one study, such as men employed as building caretakers and welders, and women employed as housekeepers, general farm laborers, dockers, dry cleaners or launderers, and textile workers. Direct dose–response relationships were noted for the duration of employment and SIA risk.
Brown et al. (2018)	Barbados	SRMA	Determine the distribution, by known social determinants of health, of the frequency of prostate cancer among Caribbean populations	10	8 case-control, 2 registry-based studies	Cuba (n=2), Jamaica (n=3), Trinidad&Tobago (n=1), Guadalupe (n=1), Barbados (n=1), Puerto Rico (n=2)	>4,912	N/A	Prostate	N/A	Education, occupation, SEP	N/A	Increased frequency of prostate cancer was found among men with less formal education (OR: 1.60; 95% CI: 1.18–2.19), and men with higher SEP (OR: 1.12, 95% CI 1.04–1.21).

Table 7. *Continued*. (2 of 5)

Authors (Year of publication)	Study Origin	Study Design	Objective/aim of the research	Included studies			Participants			Factors			Results
				Nr. of studies included	Type of studies included	Country of origin of included studies	Sample size (N)	Characteristics	Cancer type	Psychological factors	Social factors	Other behavioural factors	
Brown et al. (2017)	Barbados	SR	Determine the distribution, by known social determinants of health, of the risk factors and frequency of breast cancer among female populations living in the Caribbean	9	5 registry-based, 2 cross-sectional, 2 case-control	Cuba (n=3), Trinidad&Tobago (n=1), Puerto Rico (n=2), Barbados (n=1), Jamaica (n=1), Suriname (n=1)	>5,502	N/A	Breast	N/A	Education, occupation, residence	N/A	Only in Puerto Rico a higher likelihood of being diagnosed with breast cancer was found in those with only primary and secondary eduction compared to women with higher education. No associations emerged with respect to occupation and residence.
Carnegie et al. (2022)	UK	SR	Investigate the relationship between population density and non-communicable disease outcomes (including cancer incidence and risk)	7	N/A	Western countries	N/A	Residents in Western developed countries	Colorectal, gynaecological, breast, stomach, liver, oesophageal, pancreatic, head and neck, kidney, bladder, skin	N/A	Population density	N/A	Population density correlated with (1) breast cancer rates, (2) liver cancer only in women, (3) lung cancer. Monotonic association in white women and non-monotonic association in black and white men for OCC. Population density was also positively correlated with increased head and neck cancer, and stomach cancer only in white men. Significant risk for non-melanoma skin cancer was found in urban areas for both sexes, and a higher incidence of melanoma skin cancer was found in areas with high population density and high SES.
Catalá-López et al. (2019)	Spain	SRMA	Evaluate the association of anorexia nervosa with the risk of developing cancer.	6	5 retrospective, 1 prospective	Denmark (n=1), United States (n=2), Sweden (n=3), Denmark/Finland/Sweden (n=1)	42,394 (range: 275-24,332)	Patiens with AN; proportion of female participants varied from 60.5% to 100%; cancer cases (n=559) ranging from 2 to 389; follow-up period range = 5.4-15.2 years	Breast, malignant skin melanoma, other skin cancer, lymphoid/hematopoietic, brain and CNS, lung, colorectal, thyroid, cervix, esophagus, stomach, ovary, liver, pancreas, uterus, kidney, gallbladder, lip and oral cavity, bladder, bone, prostate, testicular	Anorexia nervosa	N/A	N/A	No overall increased risk of cancer in individuals with anorexia nervosa compared to the general population was found, with specific decreased risk for breast cancer (RR: 0.60; 95% CI: 0.50-0.80) but increased risk for lung (RR: 1.50; 95% CI: 1.06-2.12) and esophageal cancers (RR: 6.10; 95% CI: 2.30-16.18). An increased risk of smoking-related cancer incidence was observed in women with anorexia nervosa (RR: 1.59; 95% CI: 1.17-2.16; I^2=58%). Anorexia nervosa was associated with decreased risk of developing cancer occurring in hormone-sensitive tissues compared with those without anorexia nervosa or the general population (RR: 0.69; 95% CI: 0.55-0.87).
Chen et al. (2023)	China	MA	Evaluate the relationship between EA and OCPC	36	36 case-control studies	America (n=16); Brazil (n=3), China (n=3), Cuba (n=1), EU (n=1), France (n=1), India (n=5), Italy (n=4), Korea (n=1), Latin America (n=1)	105,229	Cases/OCPC (n=67,326) and controls/non-OCPC (n=37,903); adults ≥ 18	OCPC	N/A	EA	N/A	EA was negatively associated with OCPC risk (pooled OR: 0.439, CI: 0.383–0.503). A negative association between EA and OCC was also found (pooled OR: 0.425, 95% CI: 0.345–0.549). The meta-analysis revealed a significant heterogeneity (I^2=92.7%).
Conway et al. (2008)	USA, Italy	SRMA	Assess the association between SES and OC incidence risk	41	41 case-control studies	N/A	49,196	15,344 individuals with OC and 33,852 controls	Oral	N/A	SES (EA, occupational social class, income)	N/A	Higher risk for developing OC was found for those with low EA (pooled OR: 1.85; 95% CI: 1.60-2.15), those with low occupational social class (pooled OR: 1.84, 95% CI:1.47-2.31) and those with low income (pooled OR: 2.41; CI: 1.59-3.65) compared to those who were in high SES strata.
Coughlin et al. (2020)	USA	SR	Examine the relationship between social determinantts and colorectal cancer incidence	2	2 cohort studies	Japan (n=1), Denmark (n=1)	52,700	44,152 individuals from Japan, 8,548 individuals at risk for CRC	CRC	N/A	Social support	N/A	One study found no association between social support and CRC risk, while the other one only in men (HR in the highest social support group vs. lowest social support group: 1.48; 95% CI: 1.06, 2.05).
Dong & Qin (2019)	Japan, China	MA	Examine the association between education level and breast cancer incidence	18	18 ohort studies	USA (n=5), Netherlands (n=1), Norway/Sweden (n=1), Denmark (n=3), Japan (n=2), Sweden (n=2), Ittaly (n=1), Europe (n=1), Norway (n=1), Israel (n=1)	>10,225,293 (range: 1,716-4,335,484)	Women; 194,654 cases (range: 122-76,152); follow-up period range: 3-44 years	Breast	N/A	Education level	Alcohol use and physical activity level	Higher education levels are associated with an increased risk of developing breast cancer (pooled RR: 1.22 [95% CI: 1.14-1.30]). However, in the nine studies that adjusted for alcohol use, the association is attenuated and no longer significant (pooled RR: 1.07 [95% CI: 0.99-1.14]). Considerable evidence of heterogeneity between studies was observed (I^2=84.7%).
Duijts et al. (2003)	UK	MA	Identify the relationship between stressful life events and breast cancer risk	27	10 retrospective case-control studies, 4 prospective case-control studies, 9 limited prospective cohort studies and 4 prospective cohort studies	UK (n=9), Australia (n=2), USA (n=4), France (n=2), Norway (n=1), Germany (n=4), Finland (n=2), Croatia (n=1), Denmark (n=2)	>7,666	Total number of cases across all studies was 7,666 (mean age at diagnosis: 53.8, range: 45–72 years).	Breast	Stressful life events, death of a close family member, change in marital, financial status and in environmental status	N/A	N/A	Only the categories stressful life events (OR = 1.77, 95% CI 1.31–2.40), death of spouse (OR = 1.37, 95% CI 1.10–1.71) and death of relative or friend (OR = 1.35, 95% CI 1.09–1.68) showed a statistically significant effect. The results of this meta-analysis do not support an overall association between stressful life events and breast cancer risk.
Ge et al. (2022)	China	SRMA	Investigate association and causality between schizophrenia and prostate cancer risk	13	4 prospective studies and 9 retrospective studies	US (n=1), Europe (n=9), Oceania (n=1), Asia (n=2) [United States (n=1), Denmark (n=2), Australia (n=1), Finland (n=1), Israel (n=2), UK (n=2), China (n=2), Sweden (n=2)]	218,076	Male patients diagnosed with schizophrenia (n=208,076); prostate cancer cases (n=1,784); follow-up period range = 7-39 years	Prostate	Schizophrenia	N/A	N/A	Schizophrenia was related to a significantly reduced risk of prostate cancer (SIR: 0.610; 95% CI: 0.500–0.740). The relationship between schizophrenia and a decreased prostate cancer incidence was specifically apparent in studies in which schizophrenia pre-occurring prostate cancer were excluded (SIR: 0.560; 95% CI: 0.420–0.760). A decreased risk of prostate cancer was found in patients from Europe (SIR: 0.60; 95% CI: 0.51–0.70). Heterogeneity was significant (I^2=83.3%).

Table 7. *Continued*. (3 of 5)

Authors (Year of publication)	Study Origin	Study Design	Objective/aim of the research	Included studies			Participants			Factors			Results
				Nr. of studies included	Type of studies included	Country of origin of included studies	Sample size (N)	Characteristics	Cancer type	Psychological factors	Social factors	Other behavioural factors	
Geng et al. (2023)	China	MA	Evaluate whether psychological factors increases the incidence of ovarian cancer.	4	3 cohort studies, 1 case-control	N/A	240,94	Cases: 42,482, controls: 198,458; follow-up range: 6-26 years	Ovarian	PTSD, depression	Berkman-Syme Social Network Index, marital status (widowhood), social support availability of social integration, and social support availability of attachment	N/A	Psychological factors increase the risk of ovarian cancer (ES: 1.25; 95% CI: 1.01–1.50; I2=66.4%). This result was confirmed in the cohort study subgroup (ES: 1.37; 95% CI: 1.20-1.53), but not in the case-control study subgroup (ES: 0.84; 95% CI: 0.70-0.98).
Heikkila Et al. (2013)	European countries	MA	Investigate whether work related stress, measured and defined as job strain, is associated with the overall risk of cancer and the risk of colorectal, lung, breast, or prostate cancers	12	Cohort studies	Finland (n=2), France (n=1), Netherlands(n=4), Sweden (n=2), Denmark (n=4),	116,056	Cancer cases (n=5765): colorectal cancer (n=522), lung cancer (n=374), breast cancer (n=1,010), prostate cancer (n=865). Age Range: 17-70.	Colon, lung, breast and prostate	Work stress (job strain)	N/A	Smoking and alcohol behavior	Job strain (versus no strain) was not associated with the overall risk of cancer, CRC, lung, breast, or prostate cancers.
Holman et al. (2016)	UK	SR	Summarize the literature on associations between ACEs and risk of cancer in adulthood	12	Prospective cohort (n=5), case-control (n=1); cross-sectional (n=6)	United States (n=7) , Great Britain (n=2), Canada (n=1) Finland (n=1), Saudi Arabia (n=1)	119,100	Participants ≥ 12	Any, breast, lung, cervical	ACEs (e.g., abuse victimization, neglet, household challenges, and other types of early adversity or trauma)	N/A	N/A	ACEs were associated with an increased risk of cancer in adulthood. Of the different types of ACEs examined, physical and psychological abuse victimization was more frequently associated with adult cancer risk. Concerning specific cancer types, ACEs were associated with lung cancer, but not with breast cancer. There is lack of consistency in findings regarding cervical cancer.
Hu et al. (2021)	China, Malawi	SRMA	Explore the effect of the number and specific subtypes of ACEs before the age of 18 on the risk of cancer in adulthood	18	11 cross-sectional studies, 6 prospective cohort studies and 1 case-control study	United States (n=8), Canada (n=3), Finland (n=1), UK (n=3), Saudi Arabia (n=1), Australia (n=1), Japan/Finland (n=1)	406,21	Adults ≥ 18	Any, cervical , lung, breast, any except skin cancer	ACEs (6 specific subtypes: physical abuse, eposed to intimate partner violence, household alcohol abuse, household financial difficulties, parents divorced)	N/A	N/A	Being exposed to one or more negative events during childhood is associated with higher risk of cancer (OR: 1.34, 95% CI: 1.17, 1.54; I^2=62.00 %). Individuals with 2 or 3 kinds of ACEs (OR: 1.35, 95% CI:1.12,1.62) or at least 4 ACEs (OR: 2.17, 95% CI: 1.76,2.68) were at increased risk of cancer when compared with individuals with one ACE (OR: 1.06; 95% CI: 0.91-1.23). Of the different types of ACEs examined, physical abuse (pooled OR: 1.23, 95% CI:1.05,1.43; I^2=65%) and sexual abuse (pooled OR: 1.26, 95% CI:1.02,1.56; I^2=74%), as well as exposure to intimate partner violence (pooled OR: 1.26, 95 % CI: 1.12,1.41) and household financial difficulties (pooled OR: 1.16, 95% CI:1.00,1.33) were associated with the risk of any cancer. There was also a significant weak association between household alcohol abuse (OR: 1.09, 95% CI: 0.93-1.28) and parents divorce (OR: 1.06, 95% CI: 0.94-1.19) with cancer occurrence in adulthood.
Jia et al. (2017)	China	SRMA	Assess the association between depression and cancer risk and clarify its potential extent	25	25 prospective studies	USA (n = 11), the UK (n = 2), Netherlands (n = 2), Taiwan (n = 3), Denmark (n = 1), Korea (n = 1), France (n = 1), Finland (n = 2), and Australia (n = 1), International study (n = 1)	1,469,179 (range: 1,529-,601,775)	Incident cases of cancer (n=89,716; range: 39-57,604); follow-up time: 5-34 years	Overall, breast, liver, lung, prostate, esophagus, stomach, colon, skin, stomach, cervical, endometrial, ovarian, epithyelial, lymphoid and hematopoietic, smoking-related, brain, uterus, vaginal, colorectal, hepatocellular carcinoma, oral, gastrointestinal, respiratory, genitourinary	Depression	N/A	N/A	An association between depression and overall cancer risk was found (RR: 1.15, 95% CI: 1.09-1.22, I^2 = 60.8%), as well as with liver cancer (RR: 1.209; 5% CI: 1.01-1.43) and lung cancer (RR: 1.33; 95% CI: 1.04-1.72; I^2=90.5%). No significant associations were found for breast, prostate, or colorectal/colon cancer. Subgroup analysis of studies in North America resulted in a significant summary relative risk (RR: 1.28, 95% CI: 1.14-1.44).
Jokela et al. (2014)	Finland, UK	MA	Examine whether personality traits of the Five Factor Model are associated with the incidence of cancer.	6	6 prospective cohort studies	United States, United Kingdom, Australia	42,843	55.6% women; mean age: 52.2 years, incident cancer cases (n=2,156)	Any, lung, colon, breast, prostate, skin, and leukaemia/lymphoma	Extraversion, neuroticism, agreeableness, conscientiousness, openness to experience	N/A	Smoking, alcohol consumption, physical activity	None of the personality traits of the Five Factor Model were associated with overall risk of cancer incidence or with six site-specific cancers (lung, breast, colorectal, prostate and skin cancers, or leukaemia/lymphoma). The null findings were replicated when the associations were adjusted for risk factors including smoking, alcohol consumption, and physical activity.
Kamsa-Ard et al. (2018)	Thailand	SRMA	Investigate the risk factors for cholangiocarcinoma in Thailand	4	4 case-control studies	Thailand (n=4)	2,372	N/A	CCA	N/A	EA	N/A	Individuals with higher EA had lower risk of developing CCA compared to those with only primary school education (pooled OR: 0.68; 95% CI: 0.51-0.93).

Table 7. *Continued*. (4 of 5)

Authors (Year of publication)	Study Origin	Study Design	Objective/aim of the research	Included studies			Participants			Factors			Results
				Nr. of studies included	Type of studies included	Country of origin of included studies	Sample size (N)	Characteristics	Cancer type	Psychological factors	Social factors	Other behavioural factors	
Kruk et al. (2019)	Poland	SR	Assess the relationship between psychological stress and the risk of cancer	24	Case-control (n=13), prospective cohort (n=10), prospective cross-sectional (n=1)	Poland (n=1); Taiwan (n=2), China (n=2), Japan (n=3), UK (n=2), Turkey (n=1), Australia (n=1), USA (n=2) Italy (n=1), Korea (n=2), Canada (n=2), France (n=1), Iran (n=1), Denmark/Sweden (n=1), Sweden (n=1), International (n=1), Denmark (n=1)	1,083,707	Breast (n=144,9003; 6,203 cases, 122,600 controls), other cancer types (n=938,804; 100,418 cases and 776,594 controls)	Breast, brain, pancreas, colon, rectum, stomach, prostate, lung, cervical, bladder, CNS, leukemia	Stressful/severe life events (e.g., death of a close family member, personal injury, divorce/separation), anxiety, depression, avoidant coping strategy	Social support perception	Smoking behavior, alcohol use	In seven observational studies, severe life events, anxiety, depression, insufficient social support perception, or avoiding coping strategy were significantly associated with breast cancer risk. For other specific types of cancer, 11 studies reported increased risk factors for stressful life events.
Lei et al. (2021)	China	SRMA	Systematically evaluate the effect size of psychosocial risk factors for esophageal cancer (EC) in a Chinese cohort	27	27 case-control studies	China (n=27)	14,420	6,951 cases and 7,469 controls	EC	Psychological trauma, Type A behavior, depression, melancholy, always in sulks, outgoing personality, and irritable personality	Interpersonal relationships	Smoking behavior, alcohol use	Higher risk of EC was found among individuals with psychological trauma (OR: 2.36, 95% CI: 1.71–3.26), Type A behavior (OR: 1.40, 95% CI: 1.17–1.67), depression (OR: 4.00, 95% CI: 2.44–6.55), melancholy (OR: 2.06, 95% CI: 1.32–3.20), always in sulks (OR: 2.49, 95% CI: 1.21–5.12), and irritable personality (OR: 2.13, 95% CI: 1.58–2.89). A lower EC risk was found in the individuals with good interpersonal relationship (OR: 0.35, 95% CI: 0.17–0.70) and outgoing personality (OR: 0.39, 95% CI: 0.19–0.78).
Li et al. (2021)	Canada	SR	Evaluate the evidence on the association of SES and melanoma incidence in Canada	6	4 cohort studies, 2 case-control studies	Canada (n=6)	243,871	N/A	Melanoma	N/A	SES (occupation, income) and residence (urban vs rural)	N/A	High SES was associated with increased melanoma incidence. Results concening urban vs rural residence on melanoma incidence were inconsistent.
Lin et al. (2013)	China	MA	Assess the relationship between striking life events and primary breast cancer incidence in women	7	3 cohort and 4 case-control studies	USA (n=2), England (n=1), Australia (n=1), Poland (n=1), Sweden (n=1), Finland (n=1)	99,870	Participants aged ≥ 20	Breast	Striking life events	N/A	N/A	Women with striking life events were at greater risk of developing breast cancer (pooled OR: 1.51; 95% CI: 1.15 - 1.97; I2=93%), especially those with severe striking life events (pooled OR: 2.07; 95% CI 1.06 - 4.03; ; I2 = 96%).
Manser & Bauerfeind (2014)	Switzerland	SR	Analyse the impact of socioeconomic status on colorectal cancer incidence	21	N/A	United States/Canada (n=1), United States (n=5), Denmark (n=1) , Finland (n=1), Norway (n=1), Sweden (n=1), Italy (n=3), Netherlands (n=1), Europe (n=1), Great Britain (n=1), South Korea (n=2), Australia (n=2), and Puerto Rico (n=1).	>248,608	N/A	CRC, colon, rectal	N/A	SES (measured by education, income, occupation)	N/A	The review found significant variability in study results regarding the impact of socioeconomic status (SES) on colorectal cancer (CRC) risk. Some studies indicated reduced risk among low SES individuals, while others showed increased risk. US studies generally linked low SES to higher colon cancer risk, while European studies often found reduced or non-significant risk.
Mund, Lüdtke & Neyer (2012)	Germany	MA	Investigate the relation between stressful life events and breast cancer	10	N/A	Denmark (n=3), Israel (n=2), Netherlands (n=2), Belgium (n=2), Canada (n=1), Spain (n=1),USA (n=3)	2,015	95.83% females	Overall	Repressive coping	N/A	N/A	Repressive coping is associated with cancer when assessed after diagnosis (OR: 1.51; 95% CI: 1.09-2.08, with significant heterogeneity), but not when assesed before diagnosis.
Parikh et al. (2003)	France	MA	Identify all previously reported case-control studies of cervical cancer or dysplasia and screen them for information on socio-economic characteristics, and investigate the relationship between cervical cancer and socio-demographic characteristics separately for stage of disease, geographical region, age and histological type.	57	57 case-control studies	N/A	N/A	Women	Cervical	N/A	Social class	N/A	Approximately twice the risk of invasive cervical cancer was found in low vs high social class categories (OR: 1.97; 95% CI: 1.80-2.15), wheares an increased risk of approximately 60% for dysplasia (including carcinoma in situ) and cancer (OR: 1,58; 95% CI: 1.41-1,78). No clear differences were observed between squamous cell carcinoma and adenocarcinoma. Significant heterogeneity was found.
Pereira et al. (2022)	Portugal	SR	Study the connection between psychological factors (trauma, grief, and depression) and the risk of breast and lung cancer.	26	25 cohort and 1 case-control studies	Canada (n=1), Denmark (n=2), Finland (n=4), France (n=2), Iran (n=1), South Korea (n=1), Netherlands (n=1), Taiwan (n=2), United Kingdom (n=2), United States (n=10)	2,554,762 (range: 115-1,220,697)	Males (n=943,056); 12,962 cases of trauma, 1,667 cases of grief, 694,537 cases of grief	Breast, lung, both	Trauma, grief, and depression	N/A	N/A	5 out of 8 studies found a significant association between depression and higher risk of lung cancer. Only 5 out of 20 studies found a significant higher risk of breast cancer in association with depression, 1 out of 2 with unsolved recent grief, and 3 out of 5 with trauma. The most significant adverse life events/traumas reported to be linked to breast cancer refer to death of a close relative, divorce/separation, death of a spouse, death of a close friend, and maternal death in childhood was also reported.

Table 7. *Continued*. (5 of 5)

Authors (Year of publication)	Study Origin	Study Design	Objective/aim of the research	Included studies			Participants			Factors			Results
				Nr. of studies included	Type of studies included	Country of origin of included studies	Sample size (N)	Characteristics	Cancer type	Psychological factors	Social factors	Other behavioural factors	
Santos et al. (2009)	Brazil	SRMA	Search for evidence of an association between stressful life events and primary breast cancer incidence in women	8	6 case-control studies, 2 cohort studies	Denmark (n=1), Norway (n=1), England (n=1), Australia (n=2), United Stated (1), Sweden (n=1), Finland (n=1)	66,612	Women ≥ 18	Breast	Divorce, widowhood, self-rated intensity/frequency of stressful events	N/A	N/A	No association between widowhood and divorce with breast cancer was found. High-intensity self-rated stress showed borderline association with the development of breast cancer (RR: 1.73; 95% CI: 0.98-3.05; p=0.059). The heterogeneity was significant for widowhood, divorce, and self-rated stress.
Soffian et al. (2021)	Malaysia	SR	Identify and synthesise clustering patterns of CRC incidence, specifically related to the associated determinants.	12	7 cross-sectional studies, 2 retrospective studies, and 3 ecological studies	Canada (n=1), United States (n=3), France (n=1), Portugal (n=1), Iran (n=6)	>249,227	N/A	CRC	Housing violations and domestic violence	Employment status, health costs, median household income level, healthcare coverage/accessibility, urbanicity, dirty streets, tree coverage	N/A	The incidence of CRC was found to be higher in areas with several factors: high accessibility to healthcare facilities, urban locations, dirty streets, low tree coverage, higher healthcare costs, unemployment, housing violations, and domestic violence. Higher median household income was associated with lower CRC incidence.
Sun et al. (2015)	China	SRMA	Describe the association between depression and risk of breast cancer	11	11 cohort studies	USA (n=3), Taiwan (n=2), Netherlands (n=2), France (n=1), UK (n=1), Denmark (n=1), Finland (n=1)	182,241	Cases (n=2,353); follow-up period range: 5-38 years	Breast	Depression	N/A	Smoking, alcohol consumption	Depression was not associated with breast cancer risk (I^2=67.2%). The association was not present even when adjusting for smoking and alcohol consumption (I^2=86.20%).
Uthman et al. (2013)	Sweden	MA	Identify all studies that examined gastric cancer incidence in relation to SEP and perform a meta-analysis	36	23 case-control studies, 13 cohort studies	N/A	N/A	N/A	Gastric	N/A	SEP (education, occupation, income)	N/A	Increased risk of gastric cancer was found among the lowest SEP categories in education (pooled RII:2.97; 95% CI: 1.93-4.58; I2=98.7%), occupation (pooled RII: 4.33; 95% CI: 2.57-7.29) and combined SEP (pooled RII: 2.64; 95% CI: 1.056.63; I2=66.4%) compared with the highest SEP categories. The association between incidence of gastric cancer and level of income was not statistically significant.
Van Tuijl et al. (2023)	Netherlands	MA	Provide a stronger basis for addressing the associations between depression, anxiety, and the incidence of various cancer types (overall, breast, lung, prostate, colorectal, alcohol-related, and smoking-related cancers)	18	Prospective cohort studies	Netherlands (n=10); Norway, UK, Canada (n=8)	319,613	Cancer incidences (n=25,803); mean age range: 27.6-75.7; follow-up period range: 8-24 years	Lung, colorectal, prostate, smoking-related, alcohol-related	Depression, anxiety	N/A	Smoking behavior, alcohol use, sedentary behaviour	Depression and anxiety were associated with the incidence of lung cancer (HRs: 1.12–1.60) and smoking-related cancers (HRs: 1.06–1.24), but not with overall, breast, prostate, colorectal, and alcohol-related cancers. These associations were substantially attenuated when additionally adjusting for covariates including smoking and alcohol use, but not when including sedentary behaviour.
Wang et al. (2020)	China	SRMA	Investigate the associations between depresion and anxiety and the risks of cancer incidence, clarify whether clinically diagnosed depression and anxiety disorrders and psychological distress symptoms have different impacts on cancer, and explore the association of depression and anxiety with site-specific cancer incidence.	21	Follow-up (n=16), data linkage (n=5)	UK (n=3), USA (n=8), Korea (n=1), China (n=3), Denmark (n=1), Australia (n=1), Finland (n=1), France (n=1), International (n=2)	2,284,226	Participants ≥ 15; mean follow-up range: 4.34-35 years	Mixed	Depression, anxiety, psychological distress (i.e., symptoms of depression and anxiety)	N/A	N/A	Depression and anxiety were associated with a significantly increased risk of all-sites combined cancer incidence (adjusted RR: 1.13, 95% CI: 1.06–1.19; I2=84.2%). Clinically diagnosed depression and anxiety disorders were associated with an increased cancer risk (RR: 1.15, 95% CI: 1.07–1.24), while psychological distress was not (1.09, 1.00–1.18). Significant associations were only observed in lung cancer (RR: 1.41, 95% CI: 1.17–1.69), OCC (RR: 1.47, 95% CI: 1.39–1.55), prostate cancer (RR: 1.37, 95% CI: 1.01–1.86), and skin cancer (RR: 1.09, 95% CI: 1.01–1.18).
Williams et al. (2018)	UK	SR	Map the literature on evidence from low- and lower-middle-income countries on the socioeconomic status gradient of non-communicable diseases, including cancer.	6	4 control-case, 2 cross-sectional	Tanzania (n=1), Uganda (n=1), Morocco (n=1), India (n=2), Vietnam (n=1)	7,381	Residents of low- and lower-middle-income countries	Breast, non-Hodgkin lymphoma, cervical, hepatocellular	N/A	Education, income, SES as an aggregated measure/some other measure of wealth	N/A	Breast cancer was associated with higher property levels (property index) and low socioeconomic status (SES). Non-Hodgkin lymphoma was linked to higher education levels. Cervical cancer was prevalent among individuals with low SES, illiteracy, and lower income. Hepatocellular carcinoma was associated with higher income.
Yang et al. (2018)	China	MA	Assess the association between work stress and the risk of cancer	9	Cohort studies (n=4); case-control studies (n=5)	Sweden (n=2), Europe (n=1), Denmark (n=1), United States and Denmark (n=1), Poland (n=1), French (n=1), Canada (n=2)	281,290	9,090 cases (lung: n =1,145, colorectal: n = 1,138, prostate: n = 2,985, breast: n = 1,409, esophagus: n = 688, ovarian: n = 396, bladder: n = 439, gastric: n = 22, non-hodgkin lymphoma: n = 197, kidney: n = 158, melanoma: n = 94, pancreas: n = 94, brain: n = 67, hormone-related: n = 36, virus-related: n = 6, and digestive cancer: n = 10)	Overall, lung, colorectal, prostate, breast, esophagus, ovarian, bladder, gastric, non-Hodgkin lymphoma, kidney, melanoma, pancreas, brain, hormone-related, virus-related, and digestive cancer	Work stress (job strain)	N/A	Smoking, drinking, physical acticity	Higher risk for overall cancer was found in high work stress group vs no strain group (multivariable adjusted RR: 1.17; 95% CI: 1.09-1.25). Specifically, the increased risk was statistically significant for 3 cancer sites: lung cancer (RR: 1.24; 95% CI: 1.02–1.49), CRC (RR: 1.36; 95% CI: 1.16–1.59), EC (RR: 2.12; 95% CI: 1.30–3.47). The association between work-related lung cancer and CRC with work-related stress was also evident when adjusting for smoking, drinking, and physical cactivity, and was more pronounced in men (lung cancer: RR: 1.33; 95% CI: 1.01–1.75; CRC: RR: 1.51; 95% CI: 1.23–1.86). There was no statistically significant association between work stress and prostate, breast, or ovarian cancers. One study found a statistically significant association between work stress and the risk of bladder (RR: 1.37; 95% CI: 1.03-1.81) and stomach (RR: 1.53; 95% CI: 1.08-2.15) cancer. There was a higher risk of lung cancer in the case-control studies (pooled RR: 1.33; 95% CI: 1.01–1.75) than in cohort studies (pooled RR: 1.16; 95% CI: 0.89–1.50). Similarly, the increased risk of CRC was more pronounced in the case–control studies than in the cohort studies (pooled RR: 1.51; 95% CI: 1.23–1.86) than in cohort studies (pooled RR 1.16; 95% CI: 0.90–1.48) in the cohort studies.

Abbreviations. ABR = area-based residential; ACE = Adverse Childhood Experience; AN = Anorexia Nervosa; BMI = Body Mass Index; CCA = cholangiocarcinoma; CI = Confidence Interval; CNS = Central Nervous System; CRC = Colorectal Cancer; EA = Educational Attainment; EC = Esophageal Cancer; ES: effect-size; HR = Hazard Ratio; MA = Meta-analysis; MR = Mendelian Randomization; N/A = Not Applicable; OC = oral cancer; OCC = Oral cavity cancer; OCPC = Oral and oropharyngeal cancer; OR = Odds Ratio; OSC = occupational social class; PTSD: post-traumatic stress disorder; RR = Relative Risk; SEP = socio-economic position; SES = Socio-economic Status; SIA = Small Intestine Adenocarcinoma; SIR = standardized incidence ratio; SR = Systematic Review; SRMA = Systematic Review and Meta-analysis.

4.3.3. Results from the selected studies

Given the high number and heterogeneity of the measured variables, we have decided to group the results into two categories for easier comparison: psychological factors and cancer (paragraph 4.3.3.1) and social factors and cancer (paragraph 4.3.3.2). Only one study was not categorized under any specific category as it found an increased risk of ovarian cancer in association with psychosocial factors - such as post-traumatic stress disorder (PTSD), depression, and social support - without differentiating results for these variables but considering them collectively (Geng et al., 2023). Therefore, it is not particularly informative for the iBeChange project and will not be discussed below.

4.3.3.1. *Psychological factors and cancer*

The results related to the relationship between psychological factors and cancer have been further subdivided into macro-areas based on the variables considered by the studies included in this umbrella review. Specifically, we have divided the psychological factors into the following areas: (1) stress-related factors and coping strategies, (2) emotional factors, (3) personality, and (4) psychiatric diagnoses.

(1) Stress-related factors and coping strategies

Stress-related factors refer to variables or conditions that significantly contribute to an individual's experience of stress, encompassing adverse life experiences, environmental conditions, and personal situations capable of inducing significant psychological stress. We included in this category Adverse Childhood Experiences (ACEs), psychological trauma and stressful life events (e.g., divorce and widowhood, grief, work-related stress, etc.), since these variables can contribute to the overall stress burden. Additionally, coping strategies have been included in this paragraph since they refer to mechanisms for managing and dealing with stress.

Adverse Childhood Experiences (ACEs). Three studies explored the relationship between Adverse Childhood Experiences (ACEs) and cancer onset. Bellis et al. (2019) conducted a systematic review and meta-analysis including 6 studies with a total sample size of 35,965 participants, where ACEs were defined broadly to include child maltreatment, interparental violence, and parental substance use. The study found that experiencing multiple ACEs significantly increased the risk of developing cancer later in life, with individuals having two or more ACEs being at higher risk compared to those with only one ACE. Similar results were obtained by Hu et al. (2021), which also performed a systematic review and meta-analysis, incorporating 18 studies with a total sample size of 406,210 participants, also considering ACE subtypes. Physical and sexual abuse, exposure to intimate partner violence, and household financial difficulties were particularly linked to an increased cancer risk. Additionally, there was a weak but significant association between household alcohol abuse and parental divorce with cancer occurrence in adulthood (Hu et al., 2021). Coherently, Holman et al. (2016) in their systematic review found that physical and psychological abuse during childhood were particularly strong predictors of adult cancer risk. However, the study found no significant link between ACEs and breast cancer, but a strong association with lung cancer risk.

Psychological trauma and stressful life events. The systematic review conducted by Pereira et al. (2022) found that trauma (evaluated in terms of adverse life events and/or post-traumatic stress disorder) is associated with an increased risk of breast cancer. Specifically, out of 5 studies that examined trauma, 3 found a significant association. The most significant adverse life events or traumas reported include death of a close relative, divorce or separation, death of a spouse, death of a close friend, maternal death in childhood. Santos et al. (2009) conducted a systematic review and meta-analysis including 8 studies with a total sample size of 66,612 women. The stressful life events examined included divorce, widowhood, and self-rated intensity or frequency of stressful events (regardless of the situation that caused it). The meta-analysis found no significant association between widowhood or divorce and breast cancer. However, high-intensity self-rated stress showed a borderline association with the development of breast cancer. Furthermore, the meta-analysis conducted by Duijts et al. (2003) indicated that stressful life events, death of a spouse, and death of relative or friend showed a statistically significant effect on breast cancer risk. However, a systematic review conducted by Kruk et al. (2019) assessing the relationship between psychological stress and the risk of cancer indicated that severe and stressful life events - such as the death of a close family member or personal injury - and divorce/separation, were significantly associated with breast cancer risk. Coherently, two other studies found associations between stressful life events and breast cancer. Specifically, Bahri et al. (2018) conducted a meta-analysis on 11 cohort studies involving 498,737 participants, finding that history of stressful life events (such as maternal death in childhood, stress of daily activities, life stressors, stressful life experiences, death of cohabiting partner, parental death during early adulthood) slightly increases the risk of breast cancer. Similarly, Lin et al. (2013) in their meta-analyses found that women with striking life events were at greater risk of developing breast cancer, especially those with severe striking life events. Concerning other types of cancers, Lei et al. (2021) in their meta-analysis underlined those individuals with a history of psychological trauma had a higher risk of esophageal cancer (EC), and the systematic review conducted by Soffian et al. (2021) found that the incidence of CRC was higher in areas with higher rates of housing violations and domestic violence.

Work stress. Only 2 studies evaluated the relationship between work stress (specifically, job strain) and cancer risk. Heikkilä et al. (2013) conducted a meta-analysis involving 116,056 individuals finding no evidence linking work stress to the overall risk of cancer, including colorectal, lung, breast, and prostate cancers. On the other hand, Yang et al. (2018), in their meta-analysis of 9 studies involving a total of 281,290 participants and 9,090 cancer cases, found a higher risk for overall cancer in people reporting high levels of work stress. Specifically, the increased risk was statistically significant for lung cancer, CRC, and EC. The association between lung cancer and CRC with work-related stress was also evident when adjusting for smoking, drinking, and physical activity. However, no statistically significant association was found between work stress and prostate, breast, or ovarian cancers.

Coping strategies. A meta-analysis conducted by Mund, Lüdtke & Neyer (2012) investigated repressive coping in relation to cancer onset, encompassing 10 studies and 2,015 participants. For individuals with repressive coping strategies (defined as avoiding or denying stressors and emotions), the risk of a cancer diagnosis was found to be increased by 51%. However, it is to note that only 2 out of the 10 studies included in the meta-analysis assessed repressive coping before diagnosis, and no significant effect was found. Therefore, the authors suggested that repressive coping might be a consequence of a cancer diagnosis rather than a risk factor for developing cancer. However, Kruk et al. (2019), in their systematic review, found that avoidant coping strategies were significantly associated with breast cancer risk.

(2) Emotional factors

Emotional factors refer to psychological states or conditions that significantly influence an individual's emotions and overall mental well-being. Therefore, we included into this category depression and anxiety, as they significantly affect mood, emotional responses, and daily functioning.

Depression. Eight studies examined the relationship between depression (evaluated both in terms of clinical diagnosis and reported symptoms) and cancer. Ahn et al. (2016), in their meta-analysis of 9 studies covering a total of 386,552 patients diagnosed with depression, found that individuals with depressive disorder are at increased risk for cancer, specifically lung cancer, oral cavity cancer (OCC), and hematologic malignancies, even though these associations were evident only in low-quality studies. Similarly, Pereira et al. (2019) found a significant association between lung cancer risk and depression in 5 out of 8 studies, whereas for breast cancer only 5 out of 20 studies found such an association. Jia et al. (2017) conducted a systematic review and meta-analysis of 25 prospective studies, encompassing 1,469,179 participants and 89,716 incident cancer cases. The analysis found a significant association between depression and overall cancer risk, particularly for liver and lung cancer, but no significant associations were observed for breast, prostate, and colorectal/colon cancers. Sun et al. (2015) conducted a systematic review and meta-analysis of 11 cohort studies, including 182,241 participants and 2,353 cases of breast cancer. The analysis found no significant association between depression and increased risk of breast cancer. Coherently, Van Tuijl et al. (2023) conducted a meta-analysis including 18 prospective cohort studies, with a total sample size of 319,613 participants and 25,803 cancer incidences. The results showed no associations between depression and overall, breast, prostate, CRC, and alcohol-related cancers. On the contrary, the study conducted by Kruk et al. (2019) reported significant association between depression and breast cancer risk. However, depression was associated with the incidence of lung cancer and smoking-related cancers in the meta-analysis performed by Van Tuijl et al. 2023, even if these associations were substantially attenuated when adjusting for covariates including smoking and alcohol use. Consistently with these findings, Basten et al. (2023) found that depression symptoms significantly increase the effect of smoking on lung cancer incidence.

In the meta-analysis conducted by Lei et al. (2021), individuals with depression had a higher risk of EC. An additional result of their study that is worth mentioning is that five studies investigated the association between melancholy (i.e., a persistent state of sadness) and EC risk, finding that individuals with melancholy had a higher risk of EC.

Anxiety. Similarly to what has been observed with respect to depression, the studies by Van Tuijl (2023) and Kruk et al. (2019) show conflicting results: the former found no association between anxiety and overall, breast, prostate, colorectal, and alcohol-related cancers, whereas the latter showed a significant association between depression and breast cancer risk. However, anxiety was associated with the incidence of lung cancer and smoking-related cancers (Van Tuijl, 2023). Furthermore, Basten et al. (2019) found that an anxiety diagnosis amplified the effect of alcohol consumption on alcohol-related cancer incidence, although this effect was not significant in the fully adjusted model. Additionally, they discovered that an anxiety diagnosis combined with smoking (specifically, packs years) was associated with an increased incidence of lung cancer.

General distress. The study conducted by Wang et al. (2020) evaluated the association between psychological distress (defined as the presence of depression and anxiety symptoms and diagnosis) with the risk of cancer. They found that both depression and anxiety symptoms were associated with a significantly increased risk of all-sites combined cancer incidence. This association was particularly evident for clinically diagnosed depression and anxiety disorders, with significant associations observed for lung cancer, prostate cancer, and skin cancer.

(3) Personality

Jokela et al. (2014) conducted an individual-participant meta-analysis including six prospective cohort studies, with a total sample size of 42,843 participants and 2,156 incident cancer cases. The findings showed that none of the personality traits from the Five Factor Model (McCrae & John, 1992) – i.e., openness, conscientiousness, extraversion, agreeableness, and neuroticism – were associated with the overall risk of cancer incidence or with any of the six site-specific cancers (lung, colon, breast, prostate, skin, and leukemia/lymphoma). Furthermore, Basten et al. (2023) found no significant interaction for neuroticism with health behaviours on cancer onset. Nonetheless, the systematic review and meta-analysis conducted by Lei et al. (2021) highlights a relationship between personality traits and EC risk. Specifically, they found that individuals with type A behaviour (i.e., irritable personality, and always in sulks) had a higher risk of EC. Conversely, people with outgoing personality showed a lower risk of developing EC.

(4) Psychiatric Diagnoses

Only two studies evaluated the relationship between a psychiatric diagnosis and cancer risk. Ge et al. (2022) conducted a systematic review and meta-analysis including 13 studies, with a total sample size of 218,076 male patients diagnosed with schizophrenia, including 1,784 prostate cancer cases. The findings from the meta-analysis indicated that schizophrenia was related to a significantly reduced risk of prostate cancer. However, a Mendelian Randomisation (MR) analysis was also performed but did not find an association between prostate cancer and schizophrenia. The contrasting results might be due to confounding factors such as hormone levels, smoking, obesity, diet, and sedentary behaviour, which were not fully adjusted for in the included studies. Catalá-López et al. (2019) conducted a systematic review and meta-analysis to evaluate the association of anorexia nervosa (AN) with the risk of developing cancer. The study included six cohort studies, with a total sample size of 42,394 patients with AN. The analysis revealed no overall increased risk of cancer in individuals with AN compared to the general population. Nevertheless, a specific decreased risk was found for breast cancer, while an increased risk was observed for lung cancer and EC.

4.3.3.2. Social factors and cancer

In this context, social variables refer to factors related to the characteristics and conditions of society and the social environment that influence individuals' life experiences, social interactions, access to resources, behaviours, and psychological well-being. Conversely, we did not include socio-demographic factors such as age, sex, and ethnicity in this category. While these factors are important for understanding demographic characteristics and social dynamics, they do not directly influence psychological and social well-being through specific mechanisms, since they also substantially involve biological processes. Therefore, as for psychological factors, the results related to the relationship between social factors and cancer have been subdivided into the following macro-areas based on the variables considered by the studies included in this umbrella review: (1) socio-economic status (SES), (2) urbanicity, and (3) social support.

(1) Socio-economic status

Socio-economic status (SES) refers to an individual's or group's social and economic position in society, typically measured by education, income, and employment/occupation. Therefore, all studies that measured these variables, also considering those referring to them in terms of socio-economic position (SEP), have been included in this category.

<u>*Education*</u>. Chen et al. (2023) conducted a meta-analysis examining the link between educational attainment (EA) and the risk of oral and oropharyngeal cancer (OCPC). The study included 36 case-control studies with a total sample size of 105,229. The findings demonstrated a significant negative association between higher EA and the risk of OCPC, confirmed by a MR analysis that accounted for mediators like the number of sexual partners, smoking, and alcohol consumption. In contrast, studies on breast cancer present differing results. Dong & Qin (2019) conducted a meta-analysis of 18 cohort studies involving over 10.2 million women, finding that higher education levels were associated with an increased risk of developing breast cancer. However, this association diminished when adjusting for alcohol use. Brown et al. (2017), focusing on Caribbean populations, reported that in Puerto Rico, women with only primary and secondary education had a higher likelihood of being diagnosed with breast cancer compared to those with higher education. For non-Hodgkin lymphoma and cervical cancer, Williams et al. (2018) analyzed data from seven studies involving 7,637 participants in low- and

lower-middle-income countries. They found that non-Hodgkin lymphoma was associated with higher education levels, while cervical cancer was more prevalent among individuals with illiteracy. Regarding stomach and liver cancers, Uthman et al. (2013) examined the relationship between socioeconomic position (SEP) indicators and gastric cancer risk in a meta-analysis of 36 studies, reporting an increased risk among individuals with lower education. Bennet et al. (2015), in a systematic review including 502,222 participants, found no significant association between education and small intestine adenocarcinoma (SIA) carcinogenesis. Kamsa-Ard et al. (2018) investigated cholangiocarcinoma (CCA) risk factors in Thailand, including four case-control studies with 2,372 participants, and found that higher EA was linked to a lower risk of developing CCA. Lastly, Brown et al. (2018) explored prostate cancer risk factors in the Caribbean, reporting that men with less formal education had an increased frequency of prostate cancer.

Income. Four of the studies that evaluated education as an indicator of SES also investigated income. Williams et al. (2018) found that cervical cancer was more prevalent among individuals with lower income, while hepatocellular carcinoma was associated with higher income levels. Similarly, Akinyemiju et al. (2015) included 27 studies in their meta-analysis with over 2.2 million participants and reported positive associations between breast cancer incidence and income, with higher income levels correlating with increased risk. In contrast, Conway et al. (2008) identified a higher risk for developing oral cancer (OC) among those with low income, highlighting the adverse impact of low SES on oral cancer risk. Conversely, Uthman et al. (2013) found no statistically significant association between the incidence of gastric cancer and the level of income. Additionally, the systematic review conducted by Soffian et al. (2021) found that higher median household income was associated with lower CRC incidence.

Occupation. Several studies also evaluated occupation and employment as indicators of SES. Soffian et al. (2021) reported that CRC incidence was higher in areas with higher unemployment, while Bennett et al. (2015) found that certain occupations were associated with a significantly elevated risk of small intestinal adenocarcinoma (SIA). Specifically, men employed as building caretakers and welders, and women employed as housekeepers, general farm labourers, dockers, dry cleaners or launderers, and textile workers, were at higher risk. For oral cancer (OC), Conway et al. (2008) identified a higher risk for developing OC among individuals with low occupational social class, emphasizing the impact of lower occupational status on cancer risk. Similarly, Uthman et al. (2013) found an increased risk of gastric cancer among the lowest socioeconomic position (SEP) categories in occupation, reinforcing the association between lower occupational status and higher cancer incidence. In contrast, Brown et al. (2017) found no associations between occupation and breast cancer incidence in the Caribbean, suggesting that occupational factors may not play a significant role in breast cancer risk in that region.

SES/SEP. SES and SEP were also evaluated as aggregated measures of education, income, occupation or some other measure of wealth in different studies. For breast cancer, Williams et al. (2018) found a complex association where both higher property levels and low SES were linked to increased risk. Akinyemiju et al. (2015) supported this finding, reporting positive associations between breast cancer incidence and composite SES, with higher SES correlating with increased risk. Cervical cancer showed a consistent pattern related to low SES: Williams et al. (2018) observed a higher prevalence among individuals with low SES, and Parikh et al. (2003) conducted a meta-analysis including 57 case-control studies, revealing that women of lower social class had approximately twice the risk of invasive cervical cancer compared to those of higher social class, along with a 60% increased risk for dysplasia and cancer. In the case of colorectal cancer (CRC), the findings are more variable. Manser & Bauerfeind (2014) reviewed studies on SES and CRC incidence, noting significant variability: some studies indicated a reduced risk among low SES individuals, while others showed an increased risk. Additionally, Soffian et al. (2021) found that CRC incidence was higher in areas with higher healthcare costs, indirectly suggesting a possible link to higher SES. For other types of cancer, results also varied. Brown et al. (2018) found an increased frequency of prostate cancer among men with higher SEP. Li et al. (2021) reported that high SES was associated with increased melanoma incidence. Conversely, Uthman et al. (2013) found an increased risk of gastric cancer among individuals in the lowest SEP categories compared to those in the highest.

(2) Urbanicity

Urbanicity encompasses the characteristics and conditions of urban living, affecting residents' quality of life and health outcomes through various social, economic, and environmental factors. Therefore, we included in this category variables such as population density, healthcare coverage/accessibility, dirty streets, tree coverage, and neighbourhood disadvantage. Three studies investigated these aspects. Soffian et al. (2021) found that CRC incidence was higher in areas with high accessibility to healthcare facilities, urban locations, dirty streets, low tree coverage. Carnegie et al. (2022) conducted a systematic review investigating the relationship between population density and non-communicable disease outcomes such as cancer. Key findings showed that population density correlated with (1) breast cancer rates, (2) liver cancer only in women, (3) lung cancer. Population density was also positively correlated with increased head and neck cancer, and stomach cancer only in white men. Significant risk for non-melanoma skin cancer was found in urban areas, and a higher incidence of melanoma skin cancer was found in areas with high population density. Finally, Akinyemju et al. (2015) found positive associations between urbanization and residential area with breast cancer risk. Specifically, people living in urban areas and areas with higher SES have higher risk of developing breast cancer. However, the systematic review conducted by Li et al. (2021) found inconsistent results concerning melanoma incidence and urban or rural residence in Canada, and no associations were found between residence and breast cancer risk in the Caribbean (Brown et al., 2017).

(3) Social support

Social support can be defined as the assistance and support provided by individuals and organizations, which has a positive impact on physical health, mental health, and overall well-being. In the meta-analysis by Lei et al. (2021), four studies examined the association between interpersonal relationships with esophageal cancer (EC) risk, including 775 cases and 878 controls. The results indicated that individuals with good interpersonal relationships had a lower risk of EC. Similarly, Kruk et al. (2019) in their systematic review found that the perception of insufficient social support is associated with an increased risk of breast cancer. Furthermore, Basten et al. (2023) found that lower perceived social support amplified the impact of cigarette smoking on overall cancer. However, in the systematic review conducted by Coughlin (2020), only two studies evaluated the association between social support and cancer incidence, with one study showing no association and the other one indicating higher CRC risk only in men with higher social support.

4.4. Theoretical framework for iBeChange platform development

The studies included in this umbrella review examined a wide range of psychosocial variables and cancer types, leading to a highly diverse synthesis of evidence. Additionally, several meta-analyses showed heterogeneity greater than 50%, which the authors generally attributed to differences in confounder adjustments, varying study designs, and inconsistent definitions and measurements of the investigated constructs. Despite this variability, these results still offer valuable insights into the psychosocial areas worth considering for the development of the iBeChange platform, which will be discussed below.

4.4.1. Psychological factors

Regarding stress-related factors, the correlation with cancer onset is clear. All three studies evaluating ACEs found an increased risk of cancer in general (Bellis et al., 2019; Hu et al., 2021; Holman et al., 2016), though one did not find this for breast cancer but for lung cancer instead (Holman et al., 2016). In studies assessing psychological trauma and stressful life events, correlations emerged with increased risk of EC cancer (Lei et al., 2021), breast cancer (Pereira et al., 2022; Santos et al., 2009; Duijts et al., 2003; Kruk et al., 2019; Bahri et al., 2018, Lin et al., 2013), and CRC (Soffian et al., 2021). However, not all categories of stress showed significant associations with cancer risk. Indeed, results regarding work-related stress are not as definitive: only Yang et al. (2018) report an association between job strain and CRC and lung cancer risk, which was not found by Heikkilä et al. (2013). Nonetheless, both studies concur that work stress is not associated with breast and prostate cancer risk.

In light of these findings and considering especially the results related to breast, CRC, and lung cancers, which will be the focus of the iBeChange project, it is appropriate to evaluate psychological stress-related factors. Specifically, during the initial risk assessment the presence of ACEs and stressful life events could be investigated, and then levels of stress could be monitored over time and adequately addressed through the iBeChange platform. However, it is important to note that assessing ACEs and past stressful life events within this project presents ethical and practical challenges that warrant further discussion. Firstly, this is a highly sensitive topic, and participants will be required to self-report their experiences. Currently, there is no provision for participants to discuss their feelings or concerns with an iBeChange professional immediately after the assessment, which may leave them without necessary support. Moreover, we aim to communicate a health habit score to motivate participants to make daily changes in their habits to reduce cancer risk and monitor their progress. While doing this, we have to unsure that in communicating the presonalized feedback ACEs and past stressful will not be directly addressed. Communicating this could be problematic, particularly since participants cannot change their past experiences. Given these considerations, it is crucial to carefully evaluate whether to incorporate these variables in the initial assessment and, if so, to determine the best possible approach.

Concerning coping strategies, only the systematic review by Kruk et al. (2019) concluded that avoidant coping is associated with breast cancer risk. Therefore, care must be taken when deciding whether to assess avoidant coping in the iBeChange project, to avoid overburdening participants. However, considering that coping strategies are actionable constructs that participants can work on, evidence-based healthy coping strategies can be included as a recommendation/intervention when psychological distress is detected.

Regarding emotional aspects, depression has been associated with an increased risk of EC cancer (Lei et al., 2021), liver cancer (Pereira et al., 2022), lung cancer (Pereira et al., 2022; Ahn et al., 2016; Van Tuijl et al., 2023), smoking-related cancers (Van Tuijl et al., 2023), and OCC and hematological malignancies (Ahn et al., 2016). Additionally, anxiety has been associated with an increased risk of lung cancer and smoking-related cancers (Van Tuijl et al., 2023). The results for breast cancer are not consistent, with a systematic review finding an association between anxiety and breast cancer

(Kruk et al., 2019), while a meta-analysis did not (Van Tuijl et al., 2023). Furthermore, both depression and anxiety seem to amplify the effect of smoking on lung cancer incidence, and anxiety seem to amplify the effect of alcohol consumption on alcohol-related cancer incidence (Basten et al., 2019). Therefore, both depression and anxiety should be taken into account in the iBeChange project and appropriately evaluated, as they both show to have an impact on cancer onset when considered together (Wang et al., 2020) and independently. Moreover, given the iBeChange project's focus on behaviour change including unhealthy behaviour such as smoking habits and alcohol consumption, we suggest considering both depression and anxiety as variables to assess, monitor and target through the iBeChange platform.

Considering personality traits, it is not worthwhile to consider the Big Five Model traits (i.e., openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism), as they have not been associated with an increased risk of cancer (Jokela et al., 2014) nor does neuroticism seem to interact with health behaviours in relation to cancer onset (Basten et al., 2023). However, it may be beneficial to consider traits such as irritability, outgoingness, type A behaviour, and a tendency to sulk. Indeed, irritability, type A behaviour, and always being in sulks have been associated with an increased risk of EC, while outgoing personality has been associated with a decreased risk of EC (Lei et al., 2021). On the other hand, this should be further discussed since personality traits are very complex constructs that usually require long questionnaires to be assessed. Since these traits cannot be changed, it may not be useful to assess them in the iBeChange study, unlike focusing on constructs for which we can provide skills or resources to improve.

The results related to psychiatric diagnoses do not provide a clear indication for the iBeChange platform and need further discussion. On the one hand, the meta-analysis conducted by Ge et al., (2022) showed that schizophrenia is associated with a reduced risk of prostate cancer, even though these results were not replicated in the MR analysis. On the other hand, anorexia is not associated with an increased overall cancer risk but has been linked to a decreased risk of breast cancer and an increased risk of lung and EC (Català-Lopez et al., 2019). These findings are not particularly informative for the iBeChange project, and schizophrenia should rather be considered an exclusion criterion for participation rather than a variable to consider for risk assessment, since such a diagnosis might hinder effective user engagement and significantly confound data collection and results. Anorexia could be considered in the initial risk assessment, but it is also important to note that the iBeChange platform will include a health pillar on nutrition, so this aspect needs to be further discussed among clinical partners.

4.4.2. Social factors

Overall, studies analyzing socio-economic status variables (education, income, and/or occupation/employment status) generally report that low SES measures are associated with a higher risk of cancer. Indeed, most studies found an association between lower levels of education and increased risk of different types of cancer (Chen et al., 2023; Conway et al., 2008; Uthman et al., 2013; Kamsa-Ard et al., 2018; Brown et al., 2018). Coherently, most studies found an increased risk of cancer in areas with higher unemployment rates (Soffian et al., 2021) and in lower occupational classes (Bennett et al., 2015; Conway et al., 2008; Uthman et al., 2013). Additionally, the risk of some types of cancer appears to be increased by lower income (Williams et al., 2018; Conway et al., 2008; Soffian et al., 2021). However, higher SES was consistently associated with increased risk of breast cancer across different studies (Dong & Qin, 2019; Akinyemju et al., 2015; Conway et al., 2008). Thus, it may be beneficial for the iBeChange project to evaluate SES variables during the initial risk assessment phase, as higher SES might serve as a protective factor against cancer development, with the exception of breast cancer, where it appears to be a risk factor instead. Although these factors cannot be addressed and changed through the iBeChange project, this information can be easily collected and can be valuable for tailoring recommendations, especially according to participants' educational background.

Concerning urbanicity, living in urban areas is associated with higher risk of cancer (Carnegie et al., 2022), including CRC (Soffian et al., 2021), breast cancer (Akinyemju et al., 2015; Carnegie et al., 2022) and lung cancer (Carnegie et al., 2022). Therefore, it may be beneficial to consider the residence of study participants during the initial assessment to evaluate their level of risk. Social support is also an important variable to consider within the iBeChange platform, even if one study did not find evident association between social support and cancer incidence (Coughlin, 2020). However, associations were found between good interpersonal relationships and reduced EC risk (Lei et al., 2021), and between the perception of insufficient support and increased breast cancer risk (Kruk et al., 2019). Furthermore, lower perceived social support seems to amplify the impact of cigarette smoking on overall cancer (Basten et al., 2023). In light of the evidence emerging from this review, the psychosocial aspects that should be considered within the iBeChange project are summarised in Table 8.

Table 8. Variables to consider for assessment and monitoring of psychosocial factors within the iBeChange project.

Psychological factors	Social factors
Stress-related factors ▪ Stressful life events ▪ Avoidant coping strategies	Socio-economic status ▪ Income ▪ Education ▪ Employment/occupation
Emotional aspects ▪ Depression ▪ Anxiety	Social support
Personality ▪ Irritable personality ▪ Type A behaviour ▪ Always being in sulks ▪ Outgoing personality	Urbanicity (e.g., residence)

5. Wearable devices for the assessment of the psychosocial risk factors

One of the key aspects of the iBeChange project is the inclusion of a subsample of participants who will wear wearable devices in the prospective studies - i.e., pilot study and randomized controlled trial (RCT) (**Task 5.4.** Pilot study and data management; **Task 5.5** Wearables study and data management; **Task 5.8** Multicentre clinical trial and data management), assessing the feasibility and effectiveness of the iBeChange platform respectively. Wearable technology has significantly transformed contemporary life, including psychological assessment. Traditional methods for psychological assessment often rely on self-reported data, such as questionnaires and surveys. However, these methods are limited by their subjective nature, meaning they depend heavily on an individual's perception, memory, and honesty, which can introduce biases and inaccuracies (Shiffman, Stone & Hufford 2008). In contrast, wearable devices such as smart watches, fitness trackers, and specialized health monitors provide a non-invasive, continuous method for gathering a wide range of physiological and behavioural data objectively (Piwek et al., 2016). More in detail, these devices allow to shape a more comprehensive, dynamic, and ongoing picture of an individual's psychological state by measuring physiological aspects and enabling the passive collection of real-time data without disrupting daily routines. Furthermore, using wearable devices allows for accurate data collection and delivery of timely interventions, being crucial for effective mental health management. Moreover, wearable devices can enhance patient engagement and compliance, as many individuals find these devices empowering and self-awareness-enhancing (Patel, Ash & Vopp, 2015). Therefore, to identify the most suitable wearable devices and features to be monitored for this project, we conducted a non-systematic literature review to determine which devices allow for non-intrusive and passive monitoring of the psychosocial variables identified in our umbrella review. These wearable devices will provide continuous, real-time data, significantly enriching our data collection and strengthening the validity and reliability of our findings. Integrating these devices with traditional methods will allow for a more accurate monitoring and delivery of personalized interventions within the iBeChange platform.

5.1. Methods

A non-systematic literature review was performed by using PubMed and Google Scholar and the following terms: "wearable device", "mental health", "assessment". Subsequently, we conducted a more targeted search by combining the terms "wearable device" and "assessment" along with each psychosocial variable identified in our umbrella review that resulted associated with cancer onset. Specifically, with respect to psychological variables, we focused on stress, anxiety, depression, and personality. The literarature search was concluded once data saturation was reached. Finally, the grey literature was examined.

5.2. Results

Psychological variables

Mental health. The research conducted showed that wearable sensors are increasingly significant in monitoring mental health, detecting bodily responses associated with psychological stress, anxiety, and depression. Typically worn on the wrist, chest, or head, these devices gather physiological data such as EEG, heart rate (HR), heart rate variability (HRV), galvanic skin response (GSR), blood pressure (BP), body temperature, and respiratory rate. Studies suggest that wearable sensors, such as smart sensors, effectively detect subtle stress-induced changes in the body, including insomnia, headaches, rapid heartbeat, and muscle tension. For instance, Jovanov et al. (2003) indicated that these devices could collect data on HRV, EEG, GSR, skin temperature (ST), BP, sleep patterns and blood oxygen saturation (SpO2). Similarly, Sano et al. (2022) explored the interplay between academic performance, sleep quality, stress perception, and mental health in college students using devices like Fitbit Charge, Garmin Vivosmart, and Empatica E4. Their findings confirmed that wearables could correctly monitor stress.

Despite the promising capabilities of AI-based wearable devices in capturing physiological signals for mental health detection, research on using speech and behavioural signals remains limited. Gedam et al. (2021) emphasized that HRV, EEG, ST, and GSR are critical indicators for mental health monitoring, providing a foundation for developing more effective devices. Longo et al. (2022) further demonstrated that integrating classic wearable devices with advanced sensors and machine learning algorithms, such as Support Vector Machines (SVMs), k-nearest neighbor (KNN) algorithms, random forests (RF), artificial neural networks (ANNs), logistic regression (LR), decision trees (DTs), Bayesian networks (BNs), linear discriminant analysis (LDA), and principal component analysis (PCA), enhances the accuracy of psychological variable monitoring, especially stress. They highlighted SVMs as the most frequently used algorithm for mental health detection. Additionally, Corcoran et al. (2018) discussed how advancements in artificial intelligence, particularly natural language processing, allow for the precise prediction of mental illnesses by identifying linguistic patterns indicative of mental health issues. Their study found that machine learning classifiers could predict psychotic episodes with an 83% accuracy rate based on speech patterns. The reviewed studies (see Table 9) underscore the potential of wearable sensors in mental health monitoring, while also identifying significant gaps, especially in the areas of detailed machine learning methodologies and signal classification. The research predominantly focuses on stress, anxiety, and depression, but issues like user compliance and the limitations of single-category signal collection reduce accuracy. Therefore, integrating data from self-reports and wearables could enable clinicians to better identify predictors of psychological pathology development, enhancing the accuracy of mental health screening.

Table 9. Summary of Devices and Measured Variables for Mental Health.

Study	Device/Wearables	Measured Variables
Jovanov et al. (2003)	Smart Sensors	HRV, EEG, GSR, ST, BVP, Sleep Patterns, SpO2
Sano et al. (2022)	Fitbit Charge, Garmin Vivosmart, Empatica E4	Academic Performance, Sleep Quality, Stress Perception, Mental Health
Gedam et al. (2021)	Wearable Sensors	HRV, EEG, ST, GSR
Longo et al. (2022)	Wearable Devices with Advanced Sensors	HRV, EEG, ST, GSR, Integrated with ML Algorithms
Corcoran et al. (2018)	Wearable Sensors with NLP	Speech Patterns, Mental Illness

Notes. Blood Volume Pulse (BVP), Electroencephalography (EEG), Electromyography (EMG), Galvanic Skin Response (GSR), Heart Rate Variability (HRV), Blood Oxygen Saturation (SpO2), Skin Temperature (ST).

Stress and wearable devices. Numerous studies in physiological stress sensing have utilized a range of wearable sensors. For instance, electrocardiography (ECG) sensors were used while other studies (Gedam et al., 2021) employed electrodermal activity (EDA) sensors, inductive respiration (RIP) sensors, blood volume pulse (BVP) finger clip sensors, and electromyography (EMG) sensors. Devices like the Fitbit Sense, Empatica E4, and Shimmer GSR3+ have been tested in various conditions, including laboratory-induced stress, controlled real-life activities (e.g., driving, call centers, sleeping), and free-living environments. Commonly measured physiological parameters include EDA, heart rate (HR), and heart rate variability (HRV), frequently used in well-being and affect studies. Specific studies illustrate the effectiveness of wearable devices in stress monitoring, Can et al. (2019) used Samsung Gear S and S2 to measure HRV and diastolic velocity, achieving 92.19% accuracy with a multi-layer perceptron algorithm. Betti et al. (2017) utilized an LG smartwatch and Empatica E4 wristband, combining sensors like an accelerometer (ACC), GSR, HRV, ECG, and EEG, achieving 86% accuracy. Egilmez et al. (2018) employed a mobile EEG headset and a chest belt to measure EEG, HRV, achieving an F-value of 88.8% in pressure detection. Similarly, Gjoreski et al. (2019) combined a smart shirt with the Empatica wristband to monitor HR, BVP, IBI, and ST, achieving 95% accuracy in detecting stress events over 55 days. Ahn et al. (2019) used head-mounted electrodes to measure HRV, GSR, and SpO2, achieving 87.5% accuracy with SVM technology and cross-validation of EEG and HRV features. Wu et al. (2019) utilized multiple devices, including the Empatica E4 wristband and chest-worn sensors like BVP, ST, ACC, ECG, RR, EMG, and EDA, achieving 97% accuracy in stress level prediction. Jesmin et al. (2020) employed the Empatica E4 wristband to measure HRV, GSR, and ECG, demonstrating the effectiveness of multi-sensor data fusion with artificial neural networks. Silva et al. (2020) used a smartwatch to measure HRV, applying PCA, LDA, and LR models, achieving 85.3% accuracy. Kim et al. (2020) utilized the Empatica E4 wristband to measure GSR, achieving 94.55% accuracy in 10-fold cross-validation. Finally, Han et al. (2020) used a smart wristband to measure GSR and ECG, achieving 81.82% accuracy in daily stress assessment. Recent research highlights various algorithms and machine learning techniques employed in stress detection systems, which can help in early identification of this distress in individuals. For example, Kim et al. reviewed health sensing devices from 2017 to 2022, covering data collection and analysis methods, including supplementary data to enhance stress detection. Overall studies retrieved (see Table 10) demonstrate that the integration of wearable devices in stress monitoring showcases significant advancements in physiological stress sensing. Numerous studies have demonstrated the effectiveness of various sensors, such as ECG, EDA, RIP, BVP, and EMG, in diverse environments ranging from controlled laboratory settings to real-life and free-living conditions. Devices like the Fitbit Sense, Empatica E4, and Shimmer GSR3+ have shown high accuracy rates in detecting stress through physiological parameters like EDA, HR, and HRV. Machine learning algorithms and data fusion techniques further enhance the precision of stress detection, as evidenced by high accuracy rates achieved in multiple studies. This body of research underscores the potential of wearable sensors combined with advanced data analytics to provide reliable and early identification of stress, paving the way for more effective mental health interventions and personalized healthcare solutions.

Table 10. Summary of Devices and Measured Variables for Stress.

Study	Device/Wearable	Measured Variables
Can et al. (2019)	Samsung Gear S, S2	HRV, Diastolic Velocity
Betti et al. (2017)	LG Smartwatch, Empatica E4	ACC, GSR, HRV, ECG, EEG
Egilmez et al. (2018)	Mobile EEG Headset, Chest Belt	EEG, HRV
Gjoreski et al. (2019)	Smart Shirt, Empatica Wristband	HR, BVP, IBI, ST
Ahn et al. (2019)	Head-mounted Electrodes	HRV, GSR, SpO2
Wu et al. (2019)	Empatica E4, Chest-worn Sensors	BVP, ST, ACC, ECG, RR, EMG, EDA
Jesmin et al. (2020)	Empatica E4	HRV, GSR, ECG
Silva et al. (2020)	Smartwatch	HRV
Kim et al. (2020)	Empatica E4	GSR
Han et al. (2020)	Smart Wristband	GSR, ECG

Notes. Accelerometer (ACC), Blood Volume Pulse (BVP), Electrodermal Activity (EDA), ECG: Electrocardiography (ECG), Electroencephalography (EEG), Electromyography (EMG), Galvanic Skin Response (GSR), Heart Rate (HR), Heart Rate Variability (HRV), Inter-Beat Interval (IBI), Blood Oxygen Saturation (SpO2), Skin Temperature (ST).

***Emotional variables: anxiety and depression*.** Wearable devices are increasingly employed in interventions aimed at enhancing the well-being of individuals with anxiety disorders (AD) and depression. The advent of wearables such as electrocardiogram (ECG) smartwatches, belts, and mobile apps has provided new methods for influencing decisions and behaviours related to mental health. For example, depression, a major emotional condition, can now be effectively monitored using these devices. Hickey et al. (2021) conducted a systematic review on the use of smart devices and wearable technologies to detect and monitor mental health conditions. Their findings highlighted that HRV and sleep patterns can identify symptoms of anxiety and depression. Specifically, devices such as the Fitbit Sense, Moodbeam, Fitbit Charge, Oura Ring, and WHOOP Strap were found to be valuable in examining these predictive factors, aiding in the early detection and management of anxiety and depression. Ahmed et al. (2023) performed a scoping review, discovering that smart bands were used in 32% of the studies and smartwatches in 29%. Actigraphy brands were the most common commercial devices, appearing in 15% of the studies, while smart glasses were used in only 7%. Other devices like smart belts, smart necklaces, and smart clips were each used in 3% of the studies. Uncommon devices mentioned only once included smart rings, human performance electrodes, skin conductance biofeedback devices, and wearable near-infrared spectroscopy (NIRS). Overall, wrist-worn devices (71%) were far more prevalent than those worn on other body parts: waist, head, chest, suit, neck, finger, or elsewhere, which collectively made up the remaining 20%. The study noted that Fitbit (16%) was the most common brand, followed by Actiwatch and Empatica (12%). Smartphones (45%) were the most frequently used gateways for data storage or further processing, followed by computers (10%) and online websites (3%).

Physiological characteristics of anxiety include increased autonomic nervous system activity, which leads to elevated heart rate (HR), reduced HRV, higher blood pressure, and altered respiration (Jung & Chung, 2013). HRV, an important marker of psychological well-being (Chalmers et al., 2014), along with electrophysiological signals like muscular activity, galvanic skin response, and brain activity, can help identify signs of anxiety (Massot et al., 2012). Several studies have shown a correlation between HRV and stress or anxiety (Chalmers et al., 2014). Depending on the device, wearables can measure one or several of these anxiety symptoms. For instance, biofeedback (Goessl et al., 2017) provides users with information about somatic states, enhancing self-regulation and self-awareness, and enabling individuals to manage physiological functions and reduce negative emotions. Depending on the device, biofeedback can provide information about ST, HR, muscle potential, HRV, EDA, and respiration (Schoenberg & David, 2014). For example, a smart patch used by Chung et al. (2021) provides feedback through vibrations in cases of decreased HRV, which correlates with increased anxiety, and guides the user's breathing to promote relaxation and reduce anxiety. Another study by Evmenova et al. (2019) demonstrated that wearables could support adolescents during anxious moments by delivering short prompting messages to enhance self-regulation. This continuous monitoring facilitates early detection and intervention. Hickey et al. (2021) further emphasized the significance of HRV and skin conductance in assessing anxiety levels. Wearables like the Apple Watch, Fitbit Sense, and Empatica E4 were identified as effective tools for capturing these signals and providing continuous monitoring to manage anxiety. Additionally, wearable EEG devices such as the Emotiv Insight have shown promise in detecting depressive episodes by monitoring brain wave patterns, offering real-time data on mental health. These devices can detect abnormal brain activity indicative of worsening symptoms, allowing for timely interventions and potentially improving treatment outcomes for individuals with these conditions.

Personality. No study assessing the personality characteristics emerged in the umbrella review (i.e., irritable personality, type A behaviour, always being in sulks, outgoing personality) and wearable devices was found. Indeed, although some studies suggest different suitable methods for studying physiological correlates of personality traits – such as EEG, ECG, electrodermal assessment and myography (e.g., facial electromyography and electrooculography) (Wrzus & Mehl, 2015) and EEG, GSR, and photoplethysmogram (PPG) (Butt, Arsalan & Majid, 2020) – Ihsan & Furnham (2018) highlighted in their review that research on the topic is currently limited.

Social variables

Our research did not yield informative results regarding social variables. Indeed, socioeconomic status (SES) is a complex measure that typically includes variables such as income, education, and occupation, and therefore cannot be directly measured by physical or physiological correlates through wearable devices. Similarly, while wearables can assess social interactions (Baronti et al., 2020; Hänsel et al., 2018), they cannot measure social support itself, as it lacks specific physical or physiological correlates that can be quantified. No significant results emerged concerning

6. Conclusions

Results reported in the current **D2.1** allowed to identify lifestyle, behavioural, and psychosocial factors associated with cancer onset, as well as digital devices and wearables for passive monitoring of these factors. Based on these findings, the next steps will be as follows:

- **Defining PROMs for the iBeChange Platform**: discussion among clinical partners will enable to identify the proper psychological and behavioural variables that should be evaluated and included in the iBeChange Platform, and to evaluate and select the most appropriate measurement tools for these variables (PROMs), as underlined in **Task 2.5** (T2.5: PROM, lifestyle, and psychosocial factors collection).
- **Contributing to the identification of non-intrusive monitoring devices**: the results will be shared with our technical partners. This collaboration will enable us to gather input regarding the variables that can be effectively measured through wearable devices, ensuring passive and non-intrusive monitoring of psychological and behavioural variables, as outlined in **Task 3.3** (T3.3: Smart, non-intrusive & trustworthy strategies to gather user information).
- **Scientific dissemination of the results**: according to the publications and authorship guidelines of the iBeChange Project, we will begin drafting a set of manuscripts to document and publish the results. This step is crucial for disseminating our findings to the broader scientific community and contributing to the existing body of knowledge. These steps will ensure that we continue to build on the momentum of our current work and facilitate the seamless integration of our findings into practical applications.

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Version history

Version	Description	Date completed
v1.0	First upload	31/07/2024