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A systematic literature review on obesity: Understanding the causes & consequences of obesity and reviewing various machine learning approaches used to predict obesity

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ABSTRACT

Obesity is considered a principal public health concern and ranked as the fifth foremost reason for death globally. Overweight and obesity are one of the main lifestyle illnesses that leads to further health concerns and contributes to numerous chronic diseases, including cancers, diabetes, metabolic syndrome, and cardiovascular diseases. The World Health Organization also predicted that 30% of death in the world will be initiated with lifestyle diseases in 2030 and can be stopped through the suitable identification and addressing of associated risk factors and behavioral involvement policies. Thus, detecting and diagnosing obesity as early as possible is crucial. Therefore, the machine learning approach is a promising solution to early predictions of obesity and the risk of overweight because it can offer quick, immediate, and accurate identification of risk factors and condition likelihoods. The present study conducted a systematic literature review to examine obesity research and machine learning techniques for the prevention and treatment of obesity from 2010 to 2020. Accordingly, 93 papers are identified from the review articles as primary studies from an initial pool of over 700 papers addressing obesity. Consequently, this study initially recognized the significant potential factors that influence and cause adult obesity. Next, the main diseases and health consequences of obesity and overweight are investigated. Ultimately, this study recognized the machine learning methods that can be used for the prediction of obesity. Finally, this study seeks to support decision-makers looking to understand the impact of obesity on health in the general population and identify outcomes that can be used to guide health authorities and public health to further mitigate threats and effectively guide obese people globally.

1. Introduction

Obesity and its attendant conditions have become major health problems worldwide, and obesity is currently ranked as the fifth most common leading cause of death globally. The World Health Organization (WHO) defines obesity as an "abnormal or excessive fat accumulation that may impair health," further clarifying that "the fundamental cause of obesity and overweight is an energy imbalance between calories consumed and calories expended" [1,2]. The unit of "Body Mass Index" (BMI), which is measured by calculating [(weight in *kg*)/(height in m^2)], is a simple index intended to classify adults into one of three categories: "underweight," "overweight," or "obese." Though initially developed in the 1830s by a Belgian mathematician and sociologist, BMI is still widely used as a measurement of obesity and obesity rates. For instance, the WHO [3], often classifies adult obesity using certain BMI cutoffs (Table 1). This WHO classification is beneficial in distinguishing individuals who may be at increased risk of morbidity and mortality due to obesity. Over the last two decades, the rates of obesity (calculated as adults having BMI over 30 kg/m^2) have rapidly increased across the developing world. Researchers have estimated that numbers reached

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Table 1
BMI classification of adult weights based on WHO schema (*BMI = weight in kg/ height in meters*^{2}).

Classification	BMI (kg/m^2)	Risk of co-morbidities
B2.5 Underweight	<18.5	Low (but risk of other clinical problems increased)
Normal weight	18.5–24.9	Average
Overweight	25.0–29.9	Mildly increased
Obese	≥30	
Obese I	30.0–34.9	Moderate
Obese II	35.0–39.9	Severe
Obese III	≥40	Very severe

641 million obese adults in 2014 compared to only 105 million in 1975 [4], thus showing an alarming increase [5]. Multiple studies have demonstrated that obesity is not a simple problem but a complex health issue stemming from a combination of individual factors (genetics, learned behaviors) and substantial causes (unhealthy societal or cultural eating habits, food deserts) [6,7]. Most researchers also agree that obesity is an "acquired" disease that, heavily depends on lifestyle factors (i.e., personal choices), such as low rates of physical activity and chronic overeating, despite its genetic and epigenetic influences. Researchers have also noted that various forms of obesity, including abdominal obesity, are related to increased risk of several chronic conditions and diseases, which include asthma, cancer, diabetes, hypercholesterolemia, and, cardiovascular diseases [8,9]. Thus, while obesity is undoubtedly a condition, it also exacerbates pre-existing conditions and instigates new ones [10]. More specifically, Bischoff et al. [11] maintained that obesity can affect nearly every organ system, from the cardiovascular (CV) system to the endocrine system, central nervous system, and the gastrointestinal (GI) system. In addition, obesity is associated with the growing prevalence of several CV conditions, from hypertension and coronary heart disease (CHD) to atrial fibrillation (AF) and even total heart failure [12].

Some genetic and lifestyle factors affect an individual's likelihood of adult obesity; thus, the significant clusters of obesity observed in specific geographical regions and contexts also signal the impact of socioeconomic and environmental factors in "obesogenic" environments [13]. Understanding the causes and determinants of obesity is a critical step toward creating effective policy and developing workable prevention programs due to the aforementioned additional complications. Efforts will not succeed without detailed, science-based understandings of the risk factors for obesity and the numerous links among these factors.

Although several studies have concentrated on overweight and obesity, systematic literature reviews (SLRs) and similar overviews that outline the potential parameters influencing and causing adult obesity are still needed. Similarly, SLRs are necessary to identify overlaps between studies of obesity and research methods such as machine learning (ML). Limited studies have investigated how ML techniques can predict adult obesity. however, groundbreaking work in any effective, systematic manner has not been presented to date. Therefore, this SLR systematically investigates the causes of adult obesity and the current and emerging research in this investigation. As briefly proposed above, this SLR is intended to support practitioners and decision-makers by helping them take useful information from the existing literature. Therefore, this study will support mergers among cutting-edge research, medical knowledge, and policy makers to propose new evidence-based approaches and solutions regarding adult obesity. The major contributions of this SLR include the following:

- To identify existing potential parameters that influence and cause adult obesity.
- To investigate major diseases, conditions, and other negative health effects related to adult obesity and overweightness.
- To identify the ML techniques currently used in the automatic prediction and/or identification of adult obesity.

The remainder of this paper is organized as follows. Section 2 discusses related works from across the current scientific literature. Section 3 describes the proposed methodology for an SLR process related to obesity, and the overall process of the project. Section 4 presents the results and discussions, while Section 5 discusses future directions and applications of this work. Table 2 displays the list of acronyms used in this study.

2. Related research works

Obesity is commonly recognized as a critical public health issue and has drawn significant interest across the health sciences. In addition to original research using traditional scientific methods, studies in this area have discussed prevention, treatment, and quality of life for those living with obesity, often through SLRs and novel methods, such as ML. This section summarizes several related studies in preparation for comparisons with the current work and offers an overview of the current literature addressing obesity from several perspectives.

Simmonds et al. [14] conducted a systematic review later combined with meta-analysis to examine whether BMI and similar measures used to calculate childhood obesity could also predict adult obesity. Their review supported the conclusion that teenage obesity is a notable public health crisis because, it often continues into adulthood. Accordingly, acting to reduce teen obesity can also reduce adult obesity. Early action is one of the most suitable approaches because once children have become overweight, this trend often persists through their adolescence and adulthood.

More recently, de Siqueira et al. [15] presented a survey that evaluated potential relationships between obesity and COVID-19, as traced through increased hospitalization rates, poor diagnosis and recovery outcomes, and high death rates. This survey identified and validated associations between high BMI (that is, significantly higher than 30 kg/msup2) and poor COVID-19 outcomes. The researchers also discerned a high severity of clinical COVID-19 and a considerable

Table 2
List of abbreviations and acronyms.

Acronym	Description	Acronym	Description
WHO	World Health Organization	LR	Logistic Regression
ML	Machine Learning	NB	Naive Bayes
SLR	Systematic Literature Review	ANNs	Artificial Neural Networks
BMI	Body Mass Index	RNN	Recurrent Neural Network
CV	Cardiovascular	GB	Gradient Boosting
GI	Gastrointestinal	GFA	Group Factor Analysis
CHD	Coronary Heart Disease	AD	Alzheimer's Disease
AF	Atrial Fibrillation	PD	Parkinson's Disease
QA	Quality Assessment	BPH	Benign Prostate Hyperplasia
RQ	Research Questions	PCa	Prostate Cancer
AI	Artificial Intelligence	RA	Rheumatoid Arthritis
MLFFNN	Multi-Layer Perceptron Feed-Forward Artificial Neural Networks	SLE	Systemic Lupus Erythematosus
MCS	Millennium Cohort Study	IBD	Inflammatory Bowel Disease
SVM	Support Vector Machine Regression Model	MS	Multiple Sclerosis
DT	Decision Tree	T1D	Type-1 Diabetes
RGIFE	Ranked Guided Iterative Feature Elimination	TAI	Thyroid Autoimmunity
DCNN	Deep Convolutional Neural Networks	HT	Hashimoto Thyroiditis
KNN	K-Nearest Neighbors	RF	Random Forest

prevalence of ICU and general hospitalizations in patients with high BMI. Overall, researchers concluded that obesity was an adverse determinant for COVID-19. Specifically, high BMI led to worse outcomes.

Ananthakumar et al. [16] also presented a survey evaluating patient responses to consultations regarding extra weight. Their research also evaluated the role of physician weight in framing the responses and how the observed significance of extra body weight to specific health situations shaped those responses. Moreover, this survey developed a theoretical understanding of common motivations behind such reactions. This review concluded that patients could be anticipated to answer honestly to clinicians inquiring into current attempts to lose weight. These findings indicated that, weight loss investigations were also successful when they involved a trusted clinician who took time to enumerate the advantages of weight loss in a non-judgmental way.

Felso et al. [17] also presented an SLR studying associations between duration of sleep and childhood obesity. They also examined the physiological and pathophysiological mechanisms that might underlie this connection. Their work found that sleep duration affects weight increase in children, despite the unknown precise mechanisms. Their findings also confirmed that additional factors, such as a sedentary lifestyle, unhealthy diet, and insulin resistance, can all predispose children to poor sleep, and by extension, to unhealthy weight gains as well. Felso et al. [17] also reported that the role of other supposed mediators (ghrelin, screen time, and leptin levels) remains uncertain. Overall, most of the literature on obesity focus on exploring the potential parameters that cause, impact, and/or worsen obesity in adults considering the representative samples. ML techniques have also been used in several health applications, including disease recognition, over the last several years. However, only limited research has focused on associations between ML approaches and obesity. Moreover, understanding the potential association of obesity and its chronic diseases with severe outcomes is vital but still often neglected in previous studies.

The present SLR aims to address these gaps through the following:

- Locating the most significant works related to obesity, their causes, and their risk factors.
- Identifying the ML techniques used most often and productively to predict obesity.
- Surveying associations between obesity and other risks, conditions, and diseases.

3. Research methods

A systematic literature review (SLR) describes a coordinated, system-based means of devising relevant research questions, defining important keywords, and finally collating collected research in an accessible, systematic way [18–20]. An SLR will analyze a particular problem broadly and offer alternative methods for investigating the issue comprehensively, as further demonstrated below. The next sub-sections demonstrate the research methodology and the SLR protocol used to conduct this study.

3.1. Review protocol

This study follows the standards introduced by Kitchenham and Charters [18], and also uses Jula [21] who maintained that the SLR method comprises the following three phases: (1) planning the SLR, (2) conducting the research for the SLR, and (3) reporting the outcomes of the SLR. Each of the three main steps also includes the following particular tasks: proposing the driving research questions, developing the review protocol, describing the “inclusion and exclusion” criteria, selecting a viable search strategy, developing the resulting study process, and planning for quality assessment (QA), data extraction, and synthesis of findings. Subsequent sections of this paper describe the proposed approach to these steps comprehensively. Meanwhile, Fig. 1 displays the steps of conducting an SLR, while the overall recommended research protocol and its processes are outlined in Fig. 2.

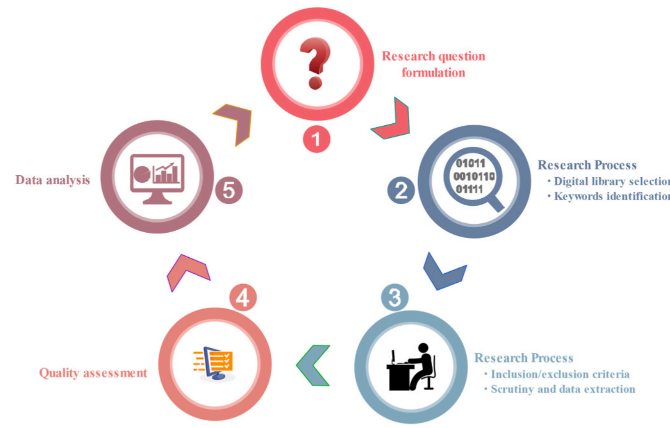

Fig. 1. Research process.

3.2. Identifying research questions

The following research questions (RQ) were formulated for this particular study.

RQ1 What are the factors that potentially influence and/or cause adult obesity?
RQ2 What are the most important applied ML techniques currently used for predicting obesity issues?
RQ3 What are the major medical conditions and diseases associated with obesity, based on the current literature?

3.3. Search strategy

In the current work, a “backward and forward” search approach was first applied to determine the reference of the chosen studies. The Google Scholar search engine was utilized to “go forward” and obtain the articles mentioned within selected initial reviews [22]. This search strategy is significant due to its data extraction capability from particular articles, and aiding researchers in locating as many related papers as possible.

Thus, select databases and libraries were utilized to locate the most relevant articles to the formulated research questions. The selected keywords are as follows:

- “Obesity” OR “Overweight” AND” “Factors” OR “Parameters”;
- “Obesity” OR “Overweight” AND” Machine learning techniques”;
- “Obesity” OR “Overweight” AND “Disorders” OR “Diseases”.

The following online databases were included in the search strategy, limiting results to a range of 10 years (from September 2010 to September 2020):

- Science Direct
- Springer Link
- IEEE Explorer
- Taylor and Francis Online
- ACM Digital Library
- MDPI
- NCBI

A manual search was then conducted after the initial automated search. Watson and Webster [23] maintained that a “forward and backward” search approach can be used to trace locations for the references cited in primary studies. This manual step was adopted

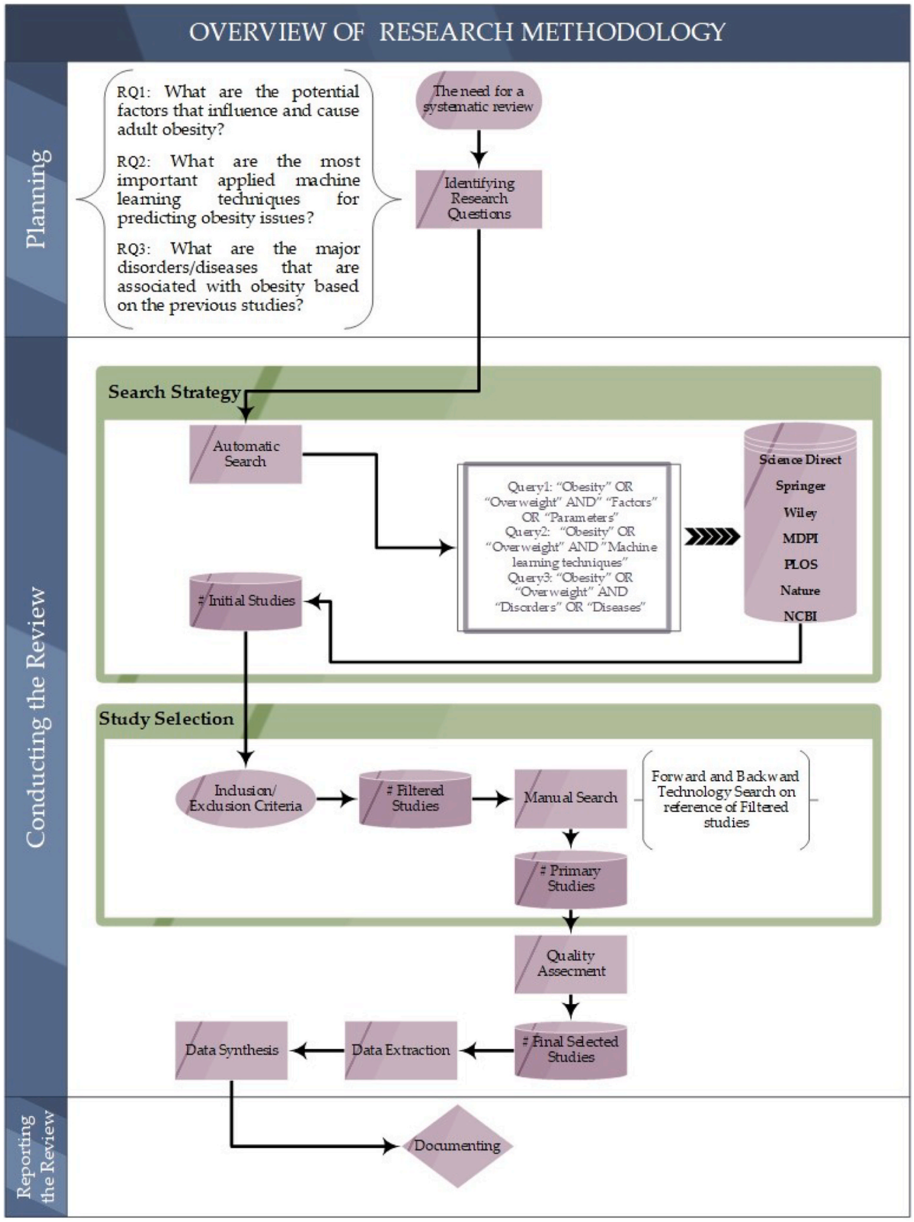

Fig. 2. Review protocol.

following the initial search to ensure the systematicity, comprehensiveness, and completeness of this SLR. Mendeley, an industry-standard reference management tool, was then employed to arrange and classify the selected articles, including the retainment of all research results and the elimination of duplicates.

3.4. Inclusion and exclusion criteria

Next, inclusion (characteristics that qualify subjects for inclusion) and exclusion (characteristics that disqualify subjects from inclusion) criteria were identified to ensure the relationship of the located articles to the subject of this research work.

First, abstracts were read closely to decide whether they addressed subjects, approaches, or other information that fit the scope of the current SLR. Second, each article was reviewed considering specific inclusion and exclusion criteria to determine whether or not to retain them.

Only articles published in English, on the subject of obesity, within a specific period (January 2010–October 2020) were ultimately selected for this particular review. Table 3 summarizes the specific inclusion and exclusion criteria utilized in this research.

Table 3
Inclusion and exclusion criteria.

Criteria	Principle
Inclusion	Studies published within a particular time period (Jan. 2010–Oct. 2020)
	Studies written in English
	Studies that were complete
	Studies related to the defined research questions
Exclusion	Duplicated studies
	Studies in languages other than English
	Studies whose work was irrelevant to the research questions of the current study

3.5. Study selection process

The selection process mainly aims to identify relevant articles. A total of 738 articles were initially obtained from automatic searches based on the keywords defined above. The results were narrowed to only 296 articles after eliminating repeated articles using the reference management tool Mendeley. Inclusion and exclusion criteria were then utilized to review the abstract and conclusion of each study, which removed 167 articles from consideration. Any irrelevant articles to the research questions were also removed in accordance with guidelines of Kitchenham and Charters [24].

Exclusion criteria were then applied to the full articles, using full-text scanning to determine whether articles with abstracts and conclusions that initially meet the inclusion criteria were still fit. Manual searches at the reference page level of individual articles also used to identify any articles that might have been missed with initial searches. This manual search further obtained 8 studies, while the scans eliminated over 30. A total of 137 primary studies were considered after the completion of the aforementioned step. The final step was to implement quality assessment (QA) measures, which eliminated 44 additional papers, retaining a total of 110 articles as the primary studies of the SLR. (For reference, the bibliographic information of all included works is listed in Table in the Appendix).

3.6. Quality assessment

QA criteria help researchers answer pre-determined research questions and ensure that the purposes of the study are met [25]. The following criteria were used for the QA process:

- QA1 Are the topics presented in each article associated with the review subject?
- QA2 Is the methodology of the study described precisely in each article?
- QA3 Is the data gathering process of the researchers explained in each article?
- QA4 Are the data analysis method of the researchers illustrated in each article?

The four QA criteria were then used to further assess the quality, applicability, credibility, and suitability of the 110 articles selected in previous steps.

The four-question QA schema was suggested by Nidhra et al. [26], who used such questions to assign each collected article one of three levels of quality (high, medium, low). Herein, the level of quality assigned to each article depends on the sum of the calculated consequences for all QA criteria. Studies that meet all criteria will be awarded a score of 2, those that moderately satisfy criteria will be awarded a score of 1, and, studies that do not satisfy any criteria will be awarded a score of 0. Overall, studies that received a score of 5 or higher on this scale were of high quality, while those with a score of 4 were rated average. Meanwhile, studies that received scores lower than 4 were of low quality and eliminated from consideration in this SLR. A total of 44 further articles were excluded.

3.7. Extraction and synthesis of data

Data extraction was performed to obtain relevant information from each article to be included in the SLR. The reference management tool Mendeley and Microsoft Excel spreadsheets were utilized to collate and compare important information.

This process began with the creation of a form to manage the extracted data, in the form of columns for several relevant items from each of the 93 studies to be included. The created columns were allocated to the extracted data, which included ID, year of publication, and ML method(s) or approach(es) of each study. Table 4 presents the full data extraction form used for the 93 studies.

3.7.1. Temporal view of publication

As specified in Section 2.4, this study focused on articles published between January 2010 and October 2020. The distribution of articles published within this period is demonstrated in Fig. 3, which shows that their prevalence has steadily risen since 2011. Other notable milestones include the most significant number of papers in a single year, which was 2017 with 19 published articles, followed by 2020 with 15 published studies. This trend reveals the increase in investigations on obesity over time, particularly in the last decade.

In a follow-up to this first temporal view, Google searches for the terms "Obesity" and then "Machine learning," were also ran to determine their use during a comparable time period (from 1 January 2010 through 18 November 2020). This approach was conducted to discern whether Google searches would also reflect the observed increase with the publishing rate discussed above. A match herein would further highlight the current interest in and importance of this combined research domain.

Therefore, the Google Trends tool (Trend, 2020) was used to target the two keywords: "Obesity" and "Machine learning." As demonstrated in Fig. 4, the increasing prevalence of search queries in this area suggests that most users were more interested in "Machine learning" than "Obesity."

Table 4
Data extracted from the primary studies included.

Extracted data	Description
Study ID	Unique number assigned to each study protocol
Paper Title	Title of each study, as presented in the article
Year	Year of publication for each article
Research topic	Description of what each study addressed
Country	Countries addressed by each study
Method	ML technique(s) used in each study
Causing factors	Causes and factors that often lead to obesity, as mentioned and/or addressed in each study
Disease	Major disease related with obesity and overweightness, as mentioned and/or addressed in each study

4. Research questions results

RQ1: What are the potential factors that influence and cause adult obesity?

High BMI in adults (specifically, ($\geq$25 kg/m^2) has been shown to complicate, or even lead to, high occurrences of cardiovascular diseases, conditions, and issues, as well as rising mortality rates [27]. Thus, understanding the common causes of obesity and excessive weight gain is crucial because this will enable the development of approaches and even policies that could help curb this global epidemic [5]. Current research has already identified or verified certain unhealthy habits, including

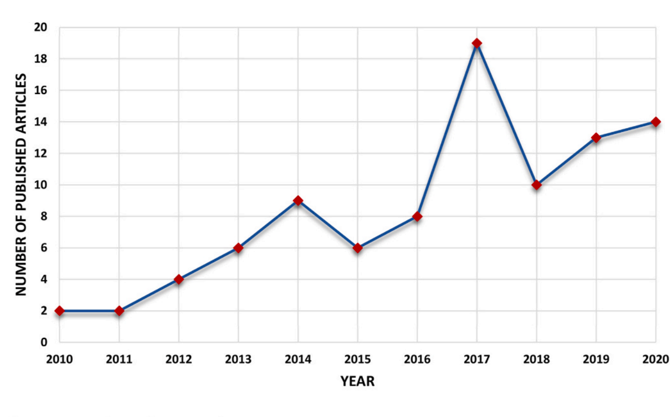

Fig. 3. Temporal view of primary studies.

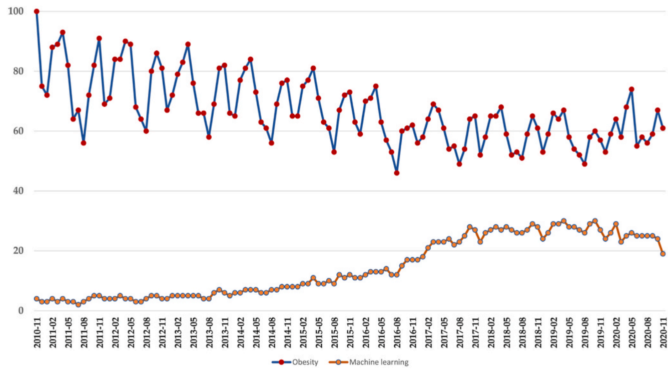

Fig. 4. Number of Google results for the terms "obesity" and "machine learning".

excess drinking, smoking, insufficient exercise, and overeating, as direct causes of obesity and other chronic illnesses [28].

However, obesity also has multiple impacting factors. Table 5 depicts some of the influential factors that determine adult overweightness or obesity, as reported by previous researchers. For instance, Ishida et al. [29] conducted a study showing the following: (1) those who are not in good health tend to be lean; (2) middle-aged people, those who eat irregularly, and those with low standards of living are often overweight; and finally, (3) the middle-aged, those suffering from stress and depression, those with low life satisfaction, and those who bring in low annual household incomes are often obese.

Several studies have also indicated infrequency or lack of exercise and individual education levels as determining factors of obesity [29–34]. Further study by Kadouh and Acosta [5,35] have also shown that obesity may be similar to a heterogeneous chronic condition, in which numerous factors interact, producing an energy imbalance that leads to increased body weight. Thus, biological, environmental, and behavioral factors are all determinants of obesity. Accordingly, differences in the prevalence of obesity among different population groups could be influenced by various behavioral and environmental factors, predominantly increasing caloric consumption and reduced physical activity [36,37]. Fig. 5 also illustrates factors that often lead to obesity.

Another study conducted by Cheng et al. [38] revealed that significant predictors of adult obesity, particularly around the age of 55 (women and men), include maternal smoking during pregnancy, childhood neurological functions, educational qualifications, trait conscientiousness, and physical exercise. An earlier study by Cheng and Furnham [30] also identified many of the same traits and maintained that each was significantly, but also independently, associated with chances of adult obesity.

RQ2 *What are the most important applied ML techniques for predicting obesity issues?*

Researchers have drawn from various techniques to build predictive and prognostic models for biomedical applications. In addition to the logistic and Cox regression models that are most often utilized [39], ML techniques have generally shown promising potential [40]. In particular, when used as an algorithmic framework, ML can provide insight into data collections, facilitate the development of inferences, and even derive knowledge from findings. Therefore, ML approaches have already been applied across for a variety of prognostic and diagnostic purposes [41]. ML algorithms have also been applied across various health and healthcare domains to predict the development or presence of particular health conditions based on pre-determined characteristics [42]. ML has also been particularly utilized in obesity research [43–46]. However, some researchers caution that ML describes a wide-ranging variety of techniques, which can be characterized only broadly depending on whether their learning phases are supervised (i.e., whether a specific

Table 5
Potential factors that influence and/or cause obesity.

Author (s)	Factor(s)
Cheng [38]	•Maternal smoking •Neurological functioning •Physical exercise •Personality and/or intelligence
Choukem et al. [31]	•Physical inactivity •Lacking and/or imbalanced diet •Socio-economic status (past or present) •Diabetes and/or glucose intolerance •Gender •High maternal BMI •Maternal level of education •High birth weight •Metabolic syndrome •Hypertension •Dyslipidemia
Ishida et al. [29]	•Education level •Eating meals at regular times •Length of sleep time •Frequency of physical exercise •Intensity of stress and/or depression •Annual household income •Subjective satisfaction with daily life •Subjective satisfaction with personal health
Keramat et al. [49]	**Lifestyle factors** •Consumption of fruits and vegetables •Excess drinking or alcohol consumption, past or present •Lacking or insufficient physical activity **Health factors** •Psychological distress **Socio-demographic factors** •Age •Sex •Marital status •Education •Labor force status •Ethnicity •Remoteness
Pinto Pereira et al. [50]	•Physical functioning
Sun et al. [37]	**Socio-economic status** •Poverty •Unemployment **Behavioral factors** •Sugary drinks consumption •Fruits and vegetable consumption **Built environment** •Prevalence of physical activity •Supermarket accessibility
Sun et al. [37]	**Personal lifestyle drivers** •Unhealthful diet •Lack of physical activity •Family reasons •Perceived stress of work •Irregular life **Societal drivers** •Prevalence of fast food •Transport and/or new technology •Lack of facilities •Misleading ads related to health and/or consumption
Sun et al. [51]	**Sociodemographic characteristics** •Demographics of age •Demographics of ethnicity •Individual and collective education levels •Relative living status •Annual household income, as calculated per capita **Individual behavioral factors** •Current habits and/or history of smoking •Current habits and/or history of excessive drinking •Current habits and/or history of regular, excessive red meat intake
Al-Raddadi et al. [52]	•Smoking status •Ethnicity •Physical activity

(*continued on next page*)

Table 5 (*continued*)

Author (s)	Factor(s)
Tulp et al. [53]	•Smoking •Alcohol consumption •Soft drink consumption
Gomez-Llorente et al. [32]	•Low physical activity •Over nutrition •Genetic factors
Hu et al. [8]	•Smoking habit •Alcohol consumption
Kadouh & Acosta [5]	**Biological factors** •Genetics of obesity •Brain-gut axis, including gut microbiome •Prenatal determinants •Experience of pregnancy or current pregnancy •Menopause •Neuroendocrine conditions •Use of medications •Presence of physical disability and/or disabilities •Presence of viruses **Environmental factors** •"Obesogenic environment" •Surrounding society and culture(s) •Chemicals present in current and/or childhood environment **Behavioral factors** •Frequent caloric intake and/or continuous eating patterns •Sedentary lifestyle and/or physical inactivity •Insufficient or deficient sleep •Past or present smoking habits
Lecube et al. [54]	•Physical activity •Nutritional habits •Consumption of unhealthy beverages, either soft drinks or alcohol •Consumption of alcohol (e.g., wine, beer, and/or other options with high alcohol content) •Sleep pattern •Difficulties following healthy diet
Nikookar et al. [55]	•History of parental obesity •Individual childhood obesity •Menopause •Energy intake •Over-large serving sizes for particular foods, including grains (bread & cereal), meat, and fats •Physical activity •Sleep duration
Yang et al. [56]	•Social isolation •Current cigarette smoker •Physically inactive •Consumption of fast food on regular basis •Excess consumption ("abuse") of alcohol •Use of illicit drugs
Wang et al. [57]	•Smoking •Drinking •Diet •Sleep (measured as hours per night)
Cois and Day [58]	•Smoking •Use of alcohol •Exercise frequency
Sartorius et al. [36]	**Individual Factors** •Genetic factors (e.g., sex, ethnicity) •Socio-economic factors (e.g., income and education) •Depression **Social Factors** •Family influences (e.g., marriage) •Peer influences **Lifestyle/Behavioral** •Food consumption (e.g., energy intake) •Physical activity **Environmental Factors** •Community characteristics (e.g., rural urban, access to unhealthy food options, crime) •Economic (e.g., cost, price, trade) •State policies •Marketing
Shi et al. [59]	•Alcohol consumption •Cigarette smoking •Hours of sleep (per night/sleeping period) •Free-time exercise
Ang et al. [60]	•Genetic influences •Ethnic differences •Gestational weight and/or intrauterine factors •Diet •Socio-economic status •Level of physical activity •Sleep •Parental determinants
Bressan et al. [61]	•Assortative mating (e.g., with similar phenotypes) •Parental traits (e.g., age and education at subject birth and during childhood) •Body image and/or perceptions thereof •Sleep habits and/or conditions •Degree of physical activity/evidence of sedentary lifestyle •Levels of alcohol consumption
Cheng and Furnham [30]	•Educational level and/or qualifications •Specific traits (e.g., extraversion, conscientiousness) •Past or present psychological distress •Lacking or insufficient physical activity and exercise
Michels et al. [30]	•Chronic stress •Diet •Sleep •Physical activity

Fig. 5. Factors often leading to adult overweightness/obesity.

algorithm uses outcome data for training). Supervised ML methods include classifiers, while unsupervised ones include clustering and semi-supervised methods include options such as label propagation [47].

Even before the proliferation of ML techniques, other so-called expert systems (such as early attempts with artificial intelligence, or AI) had been utilized in the analysis of medical images and scans or even the detection of certain medical or physiological abnormalities [42]. However, ML represents a powerful new set of fine-tuned algorithms with a considerable collective capability to learn, adapt, predict, and analyze data, which can all introduce unprecedented precision to obesity predictions, among other conditions [44]. Therefore, ML has been applied to questions and problems in obesity-based research with increasing frequency.

This study identified the ML techniques used from the overall list of selected articles and the risk factors considering obesity (Table 6). For example, Singh and Tawfik [42] investigated numerous multivariate regression algorithms and multi-layer perceptron feed forward artificial neural networks (MLFFNN) on a dataset obtained from a millennium cohort study (MCS) and acquired over 93.4% accuracy in their attempts to predict teenage BMI from existing BMI values. These results are encouraging, particularly their achievement of prediction accuracy over 90%.

Table 6
Potential factors that influence and/or cause obesity.

Author (s)	Machine Learning technique (s)	Risk Factor(s)
Singh & Tawfik [42]	Multi-layer perceptron feed forward artificial neural networks (MLFFNN)	Body Mass Index (BMI)
Uçar et al. [48]	MLFFNN, Support Vector Machine (SVM) and Decision Tree Regression (DT)	Body Fat Percentage (BFP)
Dugan et al. [44]	Random Tree (RF), J48, ID3, Naïve Bayes NB), and Bayes trained	Prediction of obesity
Fergus et al. [89]	Artificial Neural Networks (ANN)	BMI
Lingren et al. [62]	Rule-based and ML-based algorithms	Prediction of obesity
Fernández-Navarro et al. [63]	Decision Trees (DT)	Fatty acids
Lazzarini et al. [64]	Ranked Guided Iterative Feature Elimination (RGIFE)	Knee osteoarthritis
Pouladzadeh et al. [65]	Deep convolutional neural networks (CNN)	Food and energy Intake for combatting obesity
Farran et al. [66]	Logistic Regression (LR), K-nearest Neighbors (K-NN), and Support Vector Machines (SVM)	BMI and type 2 diabetes
Selya & Anshutz [47]	SVM	Dietary and physical activity
Jindal et al. [67]	RF	BMI
Pleuss et al. [90]	ML and 3D image processing	BMI, Waist Circumference (WC), or Hip Circumference (HC)
Dunstan et al. [68]	SVM, RF and Extreme Gradient Boosting	Prediction of obesity
Gupta et al. [91]	Recurrent Neural Network (RNN) architecture with Long Short-term Memory (LSTM)	BMI
Taghiyev et al. [69]	DT and LR	Causes of obesity
Machorro-Cano et al. [70]	J48 algorithm	Prediction, prevention, and detection of obesity
de Moura Carvalho et al. [92]	DT	Tackling obesity
Gerl et al. [93]	Lasso Model	BMI, WC, waist-hip ratio (WHR), and BFP
Montañez et al. [94]	Gradient Boosting (GB), Generalized Linear Model, Regression Trees (RT), KNN, SVM, RF, and MLFFNN	Prediction of obesity
Wiechmann et al. [95]	C4.5	Diagnosis of obesity
Pang et al. [96]	XGBoost model predictions	Prediction of obesity
Pereira et al. [97]	Logistic Regression (LR), NB, DT, KNN, RF, and AdaBoost	Prediction of obesity
Rajput et al. [98]	DL	Prediction of obesity
Kibble et al. [99]	Group factor analysis (GFA)	Prediction of obesity
Scheinker et al. [100]	GB and multivariate LR	BMI
Zheng & Ruggiero [101]	DT, Weighted KNN, and ANN	Prediction of obesity
Wang et al. [102]	SVM, KNN, and DT	Prediction of obesity

Uçar et al. [48] estimated individual percentages of body fat using hybrid machine learning algorithms, such as MLFFNN, support vector machine regression model (SVM), and decision tree (DT) regression. This study also used real data sets, which comprised 13 anthropometric measurements of actual individuals.

Herein, estimations could be made with a correlation value of R = 0.79 regarding any single data set from among the 13 anthropometric measurements. These results demonstrate that a developed ML system could also be used in practice to estimate body fat percentages accurately.

Dugan et al. [44] conducted a study that used ML techniques for the prediction of early childhood obesity. This study applied six different machine learning approaches (random tree, random forest, J48, ID3, Naïve Bayes, and Bayes trained) and collected data through a pediatric clinical decision support system called CHICA. The results of this study after training and evaluation showed that the ID3 model trained using this CHICA dataset offered the best overall performance: 85% accuracy and 89% sensitivity.

Lingren et al. [62] developed their rule- and ML-based algorithms to identify children with severe, early-onset obesity accurately. Their results revealed that the rule-based algorithm offered optimal performance, yielding 0.895 (CCHMC) and 0.770 (BCH).

Fernández-Navarro et al. [63] investigated obesity-driven interactions between "serum free" fatty acids and fecal microbiota using an ML algorithm. Classifications were managed using DTs, which drove the performance of statistical analyses and the identification of predictive factors for obesity. They found that Serum eicosatetraenoic and gender are the most significant variables identified, with 100% and 80% significance, respectively. Lazzarini et al. [64] applied an ML approach to their identification of new biomarkers for tracking the development of knee-based osteoarthritis in overweight and obese women. Ranked guided iterative feature elimination (RGIFE), which is an ML heuristic, was applied to select biomarkers that demonstrated high predictive power. The models of Lazzarini et al. [64] also offered high performance (AUC >0.7) despite using relatively few variables.

Multiple researchers have also shown that, overweightness and obesity are outcomes of energy imbalances in the human body. Many common treatments, such as special diets, balanced caloric intake, and enhanced activity, are intended to treat such imbalances. Pouladzadeh et al. [65] applied deep convolutional neural networks (DCNN) in an attempt to classify over 10,000 high-resolution images of food. The results obtained showed 99% accuracy in recognizing single portions of food, which is close to appropriate portions for those attempting to combat and/or avoid high BMI.

Farran et al. [66] performed a study predicting future risks of type 2 diabetes among the Kuwait population by using three models based on three techniques: LR, k-nearest neighbors (k-NN), and SVMs with five-fold cross-validation. Their techniques outperformed most other commonly used methods, LR and otherwise.

Jindal et al. [67] employed the ensemble prediction model to propose an ensemble ML approach for predicting obesity based on four main determinants: age, height, weight, and BMI. They utilized Random Forest (RF), generalized linear model, and partial least square, and ultimately, the average predicted values were 89.68% accurate.

Dunstan et al. [68] implemented three different ML algorithms (SVM, RF and extreme gradient boosting) for nonlinear regression in predicting obesity at the national level. Their method was validated considering its absolute prediction error and the proportion of surveyed countries, in which the prevalence of obesity was predicted satisfactorily. Their study forecasted that flours and baked goods, dairy-product cheeses, and sugar-sweetened carbonated drinks were the food categories that most closely and accurately predicted the prevalence of obesity.

Taghiyev et al. [69] developed a two-stage classification model using DT and logistic regression (LR) to identify effectively the causes of obesity among females aged 18 years and above in the region of Turkey. Their proposed hybrid system achieves 91.4% accuracy, which is better than other classifiers (i.e., 4.6% and 2.3% higher than the performance of LR and DT, respectively).

Machorro-Cano et al. [70] offered PISIoT, which was an ML- and IoT-based smart health platform intended to prevent, detect, and treat obesity. They applied the Weka API and J48 ML algorithms to identify critical variables regarding obesity and classify patients. Their investigation also presented a case study regarding the prevention of myocardial infarction in obese elderly patients through the monitoring of biomedical variables to validate the proposed PISIoT platform.

The existing applications of ML techniques to predict instances of obesity are presented in Fig. 6. This figure shows that ML techniques were categorized in accordance with single and hybrid methods.

These results demonstrate that the artificial neural networks (ANNs) approach was the most often used method in previous studies. ANNs are related to ML methods [42]. ANNs can solve several types of multi-variate, nonlinear problems when presented with the appropriate training algorithm and useful amounts of data [71]. Different ANNs have also been employed to predict the presence of disease and solve other complex problems, though only those based on a set of known parameters. The ANN architecture entails at least three layers: one for input, one hidden (though this can also include sub-layers), and one for output [72]. Every layer includes multiple nodes responsible for transmitting important information between layers despite the impossibility of neither lateral nor feedback connection [73]. ANNs have attracted considerable interest over the last decade due to, their use as predictive models and for their possibilities regarding pattern recognition.

RQ3: What are the major disorders/diseases associated with obesity based on the work of previous studies?

The medical consequences of adult obesity are numerous and complex. One of the most concerning is the prevalence of obesity as a public health crisis. Another is that obesity increases the risks of individuals for other primary lifestyle diseases, which include coronary heart disease, hypertension and stroke, type 2 diabetes (mellitus), sleep apnea, and osteoarthritis [74]. Table 7 offers a summary of known obesity-related diseases and conditions.

- **Neurodegenerative diseases**

Neurodegenerative diseases or disorders in which the central or peripheral nervous system degenerates progressively, are another growing public health concern. The data from various studies have revealed a worldwide increase in co-occurrences of neurodegenerative diseases and obesity [75]. Moreover, evidence suggests correlations between adult obesity and patients' development of specific neurodegenerative diseases such as Alzheimer's disease (AD) and Parkinson's disease (PD), due to the correlating factor of type 2 diabetes mellitus [76]. Dementia, which has correctly been characterized as a chief cause of cognitive function impairment in older adults, may also be linked to these factors [77]. Mazon et al. [78] examined associations among various neurodegenerative diseases, focusing on AD, PD, and individual metabolic changes. Their results showed that adult obesity can kickstart the development of neurodegenerative diseases, while diet-induced metabolic dysfunctions can aggravate existing conditions. Profenno et al. [79] confirmed that adult obesity and diabetes increase the risk of patients for AD. Midlife and in old age, increased risks for AD are consistent with AD pathogenesis, beginning several years before the clinical onset of the condition.

- **Cardiovascular disease**

Obesity takes a considerable toll on the human cardiovascular (CV) system. In particular, adult obesity tends to worsen several key risk factors. Factors and conditions, such as hypertension, coronary heart disease, atrial fibrillation, and outright heart failure, are all exacerbated in patients with obesity as a pre-existing condition [80–82].

- **Prostate diseases**

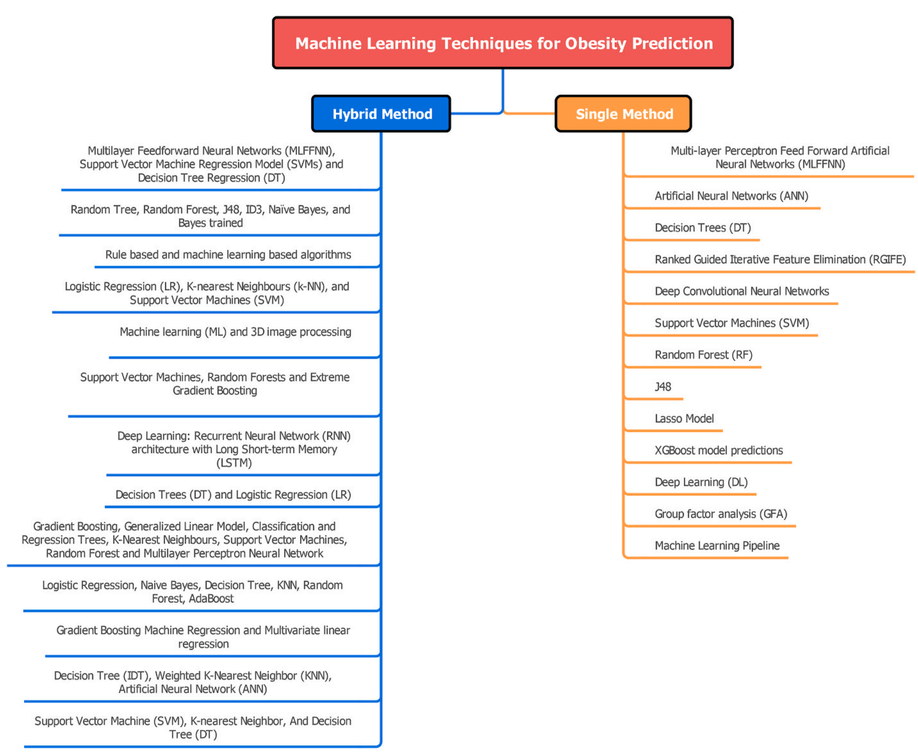

Fig. 6. ML techniques for obesity prediction.

Table 7
Major diseases that are associated with obesity in the previous studies.

	Cardiovasculardiseases(CVDs)	*Neurodegenerativediseases*	*Prostatediseases*	*Respiratorydiseases*	*Autoimmunediseases*	*Phenotypes*	*Diabetes*	*Oraldiseases*	*Non − communicablediseases*	*Hyper − Tension*	*Cancer*	*MusculoskeletalDisorders*	*MentalDisorders*	*DigestiveDiseases*	*Pneumonia*	*Metabolicsyndrome*	*Carcinogenesisandinfertility*	*Other*
[110]	✓																	
[78]		✓																
[79]		✓																
[82]	✓																	
[81]	✓																	
[84]			✓															
[128]		✓																
[12]	✓																	
[120]	✓																	
[85]				✓														
[12]	✓																	
[86]					✓													
[119]	✓					✓	✓											
[80]	✓																	
[129]								✓										
[88]									✓									
[106]	✓						✓			✓	✓	✓						
[122]							✓											
[104]	✓			✓			✓			✓	✓	✓						
[121]	✓			✓			✓				✓							
[124]	✓			✓			✓			✓	✓	✓	✓	✓				✓
[109]															✓			
[125]	✓						✓											
[114]	✓	✓			✓		✓											
[123]							✓				✓							
[130]									✓									
[131]									✓									
[132]					✓													
[133]														✓				
[111]	✓						✓				✓							
[118]	✓						✓									✓	✓	
[134]				✓														
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[135]									✓									
[136]									✓									
[117]	✓																	
[115]	✓																	
[113]																✓		
[126]							✓											
[137]													✓					
[138]													✓					
[137]													✓					
[139]													✓					

Prostatitis, or inflammation of the prostate in men, is a common but poorly-defined medical condition. Its many causes and different durations also lead to a lack of uniform diagnostic criteria and clear approaches to treatment. However, prostatitis can be found in 10%–14% of men, regardless of age, socioeconomic status, or racial and ethnic origin, and nearly 50% of men will experience this condition at some point in their lives [83]. Parikesit et al. [84] also found that obesity is a risk factor for various versions of prostate diseases, including benign prostate hyperplasia (BPH) and prostate cancer (PCa).

- **Respiratory diseases**

Respiratory systems and respiratory diseases are also adversely impacted by obesity. Obesity can worsen existing conditions or trigger new ones. More specifically, several common respiratory problems, such as asthma and obstructive sleep apnea, are more prevalent in obese children than in peers with healthy weights [85].

- **Autoimmunity**

Researchers have also sought further knowledge regarding relationships between adult obesity and autoimmunity disorders. Studies have already indicated to the possibility that this confluence is impacted by a combination of environmental factors. Of the ones already considered, strong evidence points toward the adverse impact of obesity on many immune-mediated conditions because they develop and worsen. These conditions include rheumatoid arthritis (RA), systemic lupus erythematosus (SLE), inflammatory bowel disease (IBD), multiple sclerosis (MS), type-1 diabetes (T1D), and thyroid auto-immunity (TAI), especially Hashimoto thyroiditis (HT) [86].

- **Autoimmunity**

Non-communicable diseases (NCD) are another type of condition adversely impacted by obesity, particularly the earlier identified cardiovascular conditions as well as type 2 diabetes, osteoarthritis, and some categories of cancer. In the Middle East specifically, NCDs are the foremost cause of mortality, accounting for 60% of all deaths annually [87]. Kilpi et al. [88] examined trends and predictions regarding obesity in nine countries across the Middle East and, found high and increasing obesity rates in men and women for most of the studied countries studied. They recommended that diagnoses of strokes and type 2 diabetes would be decreased with even minor reductions in collective levels of obesity.

- **Diabetes**

Overweightness and obesity are also well-documented as increasing the risk of diabetes, particularly type 2 diabetes mellitus [103]. de Oliveira et al. [104] confirmed that diabetes occurs with high incidence in obese patients. aTbares2017health [105] indicated that diabetes followed obesity in 2015 as the second leading cause of BMI related deaths, contributing to 0.6 million mortalities worldwide. Similarly, Lette et al. [106] calculated that healthcare costs attributable to overweight-related diseases could account for as much as 26% of spending, with main contributors to this number being diabetes, followed by endometrial cancer and then osteoarthritis.

- **Pneumonia**

Obesity increases mortality rates for many disorders and the susceptibility of patients to various everyday infections [107]. The mechanisms that could be underlying this connection are not yet clear. Thus, these mechanisms could be related to deregulation of the immune system, and by extension, to co-morbidities either caused or exacerbated by obesity [108]. For instance, Atamna et al. [109] found connections between obesity and short-term mortality among patients hospitalized with pneumonia. However, these connections had minimal to no impact on mortality considering many other types of infections.

Table 7 and Fig. 7 reveal that obesity demonstrated several connections to other types of diseases. Numerous studies included in this SLR have discussed the adverse effects of obesity on various cardiovascular conditions and diseases [80–82,104,106,110–121]. For instance, patients who were overweight or obese displayed a higher incidence of cardiovascular diseases of almost every kind compared with those patients with normal BMIs and weights [117]. Thus, the research suggests that CVD preventive strategies should also target obesity, and these strategies must be circulated widely to address underlying conditions at the popular level. Researchers conclude that this kind of preventive approach would reduce not only workplace issues, such as employee insurance rates and absenteeism for medical leave, but also large social issues, including medical costs (hospital stays, treatments, and drugs) that currently burden numerous healthcare systems worldwide.

The twin epidemics of obesity and diabetes have combined to form a major global health crisis. Several studies collected herein indicate that, diabetes was also one of the most commonly-considered comorbidities of obesity [104,106,111,114,118,119,121–126]. In a related vector, researchers also estimated that as much as 90% of type 2 diabetes can be attributed to high BMI or excessive weight of patients [126].

5. Discussion and conclusion

Obesity is a preventable but all-too-common health condition that has recently developed into a global epidemic, impacting public health at multiple levels. This SLR and the collected primary works reveal that several studies have determined that adult obesity and even being overweight are unmistakably associated with various co-morbidities, which include CVD, cancers, and various chronic conditions. As an initial approach to the studies already conducted in this area, the current SLR has presented an outline of recently published articles related to obesity or being overweight, particularly in connection to ML methods, for diagnosis and/or prevention. Herein, a systematic approach was used to explore three defined research questions using articles that fit several criteria and were evaluated using systematic methods.

The outlined results herein indicate that many factors cause and

Fig. 7. Specific types of diseases related to obesity.

exacerbate overweightness and obesity, particularly among adults. This SLR determined that certain factors are often considered crucial parameters and leading factors of obesity. This study then reviewed ML techniques used to predict obesity. This review indicated that ML is currently continuously used in researching obesity. However, this SLR also reveals that only limited research has reported using ML specifically for detecting obesity. This aspect remains a promising research area because ML techniques can provide far more robust rates of prediction accuracy than those achieved using simple techniques, including statistical methods, such as linear regression. Uçar et al. [48] indicated that, ML methods are also preferable for performance alone. The use of general equations to estimate body fat percentages is already a major indicator of the effective performance of ML in this area.

Next, specific ML approaches can be categorized as either single or hybrid method based on the trends identified in this SLR. As of this writing, the ANN approach is the most often applied ML method in the existing literature. Finally, this SLR also reviewed certain types of diseases related to obesity. The results confirmed that obesity is a healthcare concern and epidemic worldwide and is also well documented as a risk for increasing rates of various other conditions.

Therefore, obesity deserves serious consideration and attention from policymakers, healthcare providers, and researchers alike. Obesity prevention must be multifaceted and should actively involve stakeholders at different levels. From potential areas of policy to the development and implementation of these policies, approaches should account for people's home environments and broad, society-level views of socioeconomic environments. However, many barriers that prevent strategizing on the level of policy alone may be encountered. Instead, the reduction and prevention of obesity will considerably depend on individual lifestyle changes. In this case, further research on motivations for individual and societal behavioral changes is crucial.

6. Clinical implications of the study

An important clinical implication of the findings is the identification of ML techniques that are most often used successfully in prior studies. ML techniques provide substantially more robust prediction accuracy rather than using simple techniques, such as linear regression, or other statistical methods. Overall, ML techniques, such as neural network, DT, RF, and Deep Learning, are some of the most effective approaches enabling the early detection and clinical management of obesity.

7. Limitations of the study

First, this study included peer-reviewed journal papers and excluded conference articles, books, and unpublished full-text papers, which both follow best practices in academic publishing but could have also limited its access to other research and results. However, this decision is attributed to the expected report on validated findings by peer-reviewed journal papers, which also have the most significant influence on the field [127]. The second limitation is the restricted search for articles to only six online databases: i.e., Science Direct, SpringerLink, IEEE Explorer, Taylor and Francis Online, ACM Digital Library, MDPI, and NCBI. Nevertheless, these databases were selected because they are among the most extensively-used in the world [46], and each one indexes journals and articles from any discipline associated with the review, namely medicine, engineering, and computer science. Thus, articles published in these fields, as well as those in healthcare, discipline associated.

Additionally, locating all published research during the 10 years under investigation cannot be guaranteed with the growing amount of research on obesity. This comprehensive exploration still illustrates the current status of research on obesity using ML methods. However, future studies should consider substantially expanded approaches, such as additional databases or consideration of conceptualized and unpublished research and peer-reviewed scholarship.

Finally, this study only introduced and reviewed ML techniques because they are used for obesity prediction. Therefore, future work should evaluate the robustness and weaknesses of each technique used in this area.

8. Further work

The present study is intended as a step toward effectively understanding obesity and its identification, investigation, and treatment. The collected findings are promising, but additional research is required to increase understanding of this disease. For instance, one of the primary objectives of this study was to uncover the ML techniques already often applied to predict obesity. Therefore, future researchers should test each ML algorithm for accuracy and robustness when attempting to expand the research in this field. Moreover, this study briefly examined the most influential factors that cause or worsen obesity. However, this complex area demands additional further research, particularly because it could also refocus the other influential factors that have already been determined to result in obesity. Finally, future work should continue to focus on developing effective and safe interventions to combat the spread of obesity and related health risks, conditions, and diseases.

Declaration of competing interest

'None Declared'.

Acknowledgements

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Appendix. Primary studies

Table Appendix: Primary studies

Study ID	Study Title	Authors
S1	"Factors Affecting Adult Overweight and Obesity in Urban China"	Ishida et al. [29]
S2	"Obesogenic environmental factors of adult obesity in China: a nationally representative cross-sectional study"	Zhang et al. [13]
S3	"Prevalence of overweight, obesity, abdominal obesity and obesity-related risk factors in southern China"	Hu et al. [8]
S4	"Children's Body composition and Stress–the ChiBS study: aims, design, methods, population and participation characteristics"	Michels et al. [140]
S5	"Phytocompounds as potential agents to treat obesity-cardiovascular ailments"	Meriga et al. [33]
S6	"Obesity and asthma: a missing link"	Gomez-Llorente et al. [32]
S7	"Social components of the obesity epidemic"	Bressan et al. [61]
S8	"Multifactorial influences of childhood obesity"	Ang et al. [60]
S9	"Current paradigms in the etiology of obesity"	Kadouh, H.C. and Acosta, A [5].

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Table Appendix: Primary studies

Study ID	Study Title	Authors
S10	"Overweight/obesity and associated cardiovascular risk factors in sub-Saharan African children and adolescents: a scoping review"	Choukem et al. [31]
S11	"Determinants of obesity and associated population attributability, South Africa: Empirical evidence from a national panel survey"	Sartorius et al. [36]
S12	"Biomedical, psychological, environmental and behavioural factors associated with adult obesity in a nationally representative sample"	Cheng et al. [38]
S13	"Impact of Disadvantaged Neighborhoods and Lifestyle Factors on Adult Obesity: Evidence From a 5-Year Cohort Study in Australia"	Keramat et al. [49]
S14	"Estimating neighborhood-level prevalence of adult obesity by socio-economic, behavioral and built environment factors in New York City"	Sun, Y. et al. [37]
S15	"Obesity as a self-regulated epidemic: coverage of obesity in Chinese newspapers"	Sun, S. et al. [51]
S16	"Adult obesity and mid-life physical functioning in two British birth cohorts: investigating the mediating role of physical inactivity"	Pinto Pereira et al. [50]
S17	"Factors Accounting for Obesity and Its Perception among the Adult Spanish Population: Data from 1,000 Computer-Assisted Telephone Interviews"	Lecube et al. [54]
S18	"The prevalence of adult obesity in Africa: A meta-analysis"	Tulp et al. [53]
S19	"Obesity trends and risk factors in the South African adult population"	Cois and Day [58]
S20	"Young adult risk factors for cancer: obesity, inflammation, and sociobehavioral mechanisms"	Yang et al. [56]
S21	"Prevalence of overweight and obesity and some associated factors among adult residents of northeast China: a cross-sectional study"	Wang et al. [57]
S22	"Factors Associated with Obesity: A Case–Control Study of Young Adult Singaporean Males"	Shi et al. [59]
S23	"The prevalence of obesity and overweight, associated demographic and lifestyle factors, and health status in the adult population of Jeddah, Saudi Arabia"	Al-Raddadi et al. [52]
S24	"Overweight, Obesity, and Its Associated Factors in Adult Women Referring to Health Centers in Shiraz in 2013–2014″	Nikookar et al. [55]
S25	"Personality traits, education, physical exercise, and childhood neurological function as independent predictors of adult obesity"	Cheng and Furnham [30]
S26	"A Machine Learning Approach for Predicting Weight Gain Risks in Young Adults"	Singh and Tawfik [42]
S27	"Estimation of body fat percentage using hybrid machine learning algorithms"	Uçar et al. [48]
S28	"Machine learning techniques for prediction of early childhood obesity"	Dugan et al. [44]
S29	"A machine learning approach to measure and monitor physical activity in children to help fight overweight and obesity"	Fergus et al. [89]
S30	"Developing an algorithm to detect early childhood obesity in two tertiary pediatric medical centers"	Lingren et al. [62]
S31	"Exploring the interactions between serum free fatty acids and fecal microbiota in obesity through a machine learning algorithm"	Fernández-Navarro et al. [63]
S32	"A machine learning approach for the identification of new biomarkers for knee osteoarthritis development in overweight and obese women"	Lazzarini et al. [64]
S33	"Food calorie measurement using deep learning neural network"	Pouladzadeh et al. [65]
S34	"Use of Non-invasive Parameters and Machine-Learning Algorithms for Predicting Future Risk of Type 2 Diabetes: A Retrospective Cohort Study of Health Data from Kuwait"	Farran et al. [66]
S35	"Machine Learning for the Classification of Obesity from Dietary and Physical Activity Patterns, Advanced Data Analytics in Health"	Selya and Anshutz [47]
S36	"Obesity prediction using ensemble machine learning approaches, Recent Findings in Intelligent Computing Techniques"	Jindal et al. [67]
S37	"A machine learning approach relating 3D body scans to body composition in humans"	Pleuss et al. [90]
S38	"Predicting nationwide obesity from food sales using machine learning"	Dunstan et al. [68]
S39	"Obesity Prediction with EHR Data: A deep learning approach with interpretable elements"	Gupta et al. [91]
S40	"A Hybrid Approach Based on Machine Learning to Identify the Causes of Obesity"	Taghiyev et al. [69]
S41	"PISIoT: A machine learning and IoT-based smart health platform for overweight and obesity control"	Machorro-Cano et al. [70, 70]
S42	"Using Machine Learning for Evaluating the Quality of Exercises in a Mobile Exergame for Tackling Obesity in Children"	de Moura Carvalho et al. [92]
S43	"Machine learning of human plasma lipidomes for obesity estimation in a large population cohort"	Gerl et al. [93]
S44	"Machine learning approaches for the prediction of obesity using publicly available genetic profiles"	Montañez et al. [94]
S45	"Identifying discriminative attributes to gain insights regarding child obesity in hispanic preschoolers using machine learning techniques"	Wiechmann et al. [95]
S46	"Understanding Early Childhood Obesity via Interpretation of Machine Learning Model Predictions"	Pang et al. [96]
S47	"Obesity Related Disease Prediction from Healthcare Communities Using Machine Learning"	Pereira et al. [97]
S48	"Obesity and Co-Morbidity Detection in Clinical Text Using Deep Learning and Machine Learning Techniques"	Rajput et al. [98]
S49	"An integrative machine learning approach to discovering multi-level molecular mechanisms of obesity using data from monozygotic twin pairs"	Kibble et al. [99]
S50	"Identification of Factors Associated with Variation in US County-Level Obesity Prevalence Rates Using Epidemiologic vs Machine Learning Models"	Scheinker et al. [100]
S51	"A review of machine learning in obesity"	DeGregory et al. [141]
S52	"Using machine learning to predict obesity in high school students"	Zheng and Ruggiero [101]
S53	"Machine Learning-Based Method for Obesity Risk Evaluation Using Single-Nucleotide Polymorphisms Derived from Next-Generation Sequencing"	Wang et al. [102]
S54	"Clinical relevance of adipokines"	Blüher and journal [110]
S55	"The impact of obesity on neurodegenerative diseases"	Mazon et al. [78]
S56	"Meta-analysis of Alzheimer's disease risk with obesity, diabetes, and related disorders"	Profenno et al. [79]
S57	"Obesity and prevalence of cardiovascular diseases and prognosis—the obesity paradox updated"	Lavie et al. [82]
S58	"An overview and update on obesity and the obesity paradox in cardiovascular diseases"	Elagizi et al. [81]
S59	"The impact of obesity towards prostate diseases"	Parikesit et al. [84]
S60	"Astrocytes and endoplasmic reticulum stress: A bridge between obesity and neurodegenerative diseases"	Martin-Jimenez et al. [128]
S61	"Impact of obesity and the obesity paradox on prevalence and prognosis in heart failure"	Lavie et al. [116]
S62	"Obesity phenotypes and their paradoxical association with cardiovascular diseases"	Vecchié et al. [120]
S63	"Obesity and common respiratory diseases in children"	Xanthopoulos and Tapia [85]
S64	"Obesity and cardiovascular diseases: implications regarding fitness, fatness, and severity in the obesity paradox"	Lavie et al. [12]
S65	"Obesity in autoimmune diseases: not a passive bystander"	Versini et al. [86]
S66	"Obesity phenotypes, diabetes, and cardiovascular diseases"	Piché et al. [119]
S67	"Association of central obesity with the incidence of cardiovascular diseases and risk factors"	Barroso et al. [80]
S68	"Relationship between obesity and oral diseases"	Sede and Ehizele [129]
S69	"Alarming predictions for obesity and non-communicable diseases in the Middle East"	Kilpi et al. [88]
S70	"Health care costs attributable to overweight calculated in a standardized way for three European countries"	Lette et al. [106]

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Table Appendix: Primary studies

Study ID	Study Title	Authors
S71	"Obesity, lifestyle risk-factors, and health service outcomes among healthy middle-aged adults in Canada"	Alter et al. [122]
S72	"Direct healthcare cost of obesity in Brazil: an application of the cost-of-illness method from the perspective of the public health system in 2011"	de Oliveira et al. [104]
S73	"The burden of overweight and obesity on long-term care and Medicaid financing"	Yang and Zhang [121]
S74	"Economic costs of obesity in Thailand: a retrospective cost-of-illness study"	Pitayatienanan et al. [124]
S75	"How obesity impacts outcomes of infectious diseases"	Atamna et al. [109]
S76	"Obesity, diabetes, and cardiovascular diseases: a compendium"	Scherer and Hill [125]
S77	"Obesity: how much does it matter for female pelvicorgan prolapse?"	Young et al. [9]
S78	"How western diet and lifestyle drive the pandemic of obesity and civilization diseases"	Kopp et al. [114]
S79	"Obesity, Metabolism, 2014. Diabetes and cancer: two diseases with obesity as a common risk factor"	Garg et al. [123]
S80	"Overweight, obesity and related non-communicable diseases in Asian Indian girls and women"	Chopra et al. [130]
S81	"New national data show alarming increase in obesity and noncommunicable chronic diseases in China"	Wang et al. [131]
S82	"Obesity as a risk and severity factor in rheumatic diseases (autoimmune chronic inflammatory diseases)"	Gremese et al. [132]
S83	"Obesity-related digestive diseases and their pathophysiology"	Nam and liver [133]
S84	"An integrated framework for the prevention and treatment of obesity and its related chronic diseases"	Dietz et al. [111]
S85	"Endocrine disruptors leading to obesity and related diseases"	Petrakis et al. [118]
S86	"Obesity and respiratory diseases"	Zammit et al. [134]
S87	"Stress and obesity as risk factors in cardiovascular diseases: a neuroimmune perspective"	Ippoliti et al. [112]
S88	"The prevalence and trends of overweight, obesity and nutrition-related non-communicable diseases in the Arabian Gulf States"	Ng et al. [135]
S89	"High rates of obesity and non-communicable diseases predicted across Latin America"	Webber et al. [136]
S90	"Management of cardiovascular diseases in patients with obesity"	Lavie et al. [117]
S91	"Obesity and the "obesity paradox" in cardiovascular diseases"	Lavie et al. [115]
S92	"The association of periodontal diseases with metabolic syndrome and obesity"	Jepsen et al. [113]
S93	"Obesity and diabetes: an update"	Verma et al. [126]

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