

# The Complex Relationship Between Technology and Obesity

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Obesity is a crucial global health concern, with its prevalence continuously increasing, particularly in the United States. The rise of technology has introduced new opportunities and challenges in the battle against obesity. While technology offers tools for weight management and intervention, it also contributes to sedentary behaviors, disrupted sleep patterns, unhealthy eating habits, and influences body image perceptions through social media and online advertising. To address this complex issue, it is essential to understand the multifaceted relationship between technology and obesity. This review examines the impact of technology on obesity, revealing a nuanced relationship with both positive and negative consequences. On the positive side, technology presents innovative solutions such as e-Health and m-Health applications that enhance weight management interventions, mathematical models for personalized guidance, and virtual reality for immersive experiences and therapy. These tools empower individuals to make healthier choices and engage in effective weight management. However, technology also contributes to obesity-related challenges. Sedentary behaviors induced by excessive screen time, inadequate sleep due to technology use, and the convenience of food delivery apps all lead to unhealthy eating habits and weight gain. Furthermore, social media and online advertising influence body image perceptions, potentially contributing to eating disorders and poor dietary choices, especially among young individuals. Technology is an incredibly powerful resource being used in the fight against obesity, providing options that can revolutionize detection and treatment. To harness its potential to the maximum, its implementation must be used in a way that minimizes the adverse effects, such as sedentary behaviors, sleep disruptions, and unhealthy eating habits. However tricky, achieving a balance between leveraging technology's benefits while avoiding its drawbacks is essential. Further research should focus on long-term impacts, policy approaches, interdisciplinary collaboration, and the evolving role of technology in obesity prevention and treatment. Ultimately, a holistic approach is needed to make the most of the power of technology while combating the multifaceted causes of obesity.

## Introduction

Body mass index (BMI) is a measurement used to identify obesity in an individual. BMI is calculated by the weight (kg) divided by the height (m) squared of the individual. In adults, a BMI ranging from 25.0-29.9kg/m<sup>2</sup> is categorized as overweight while a BMI of 30kg/m<sup>2</sup> and over is known to be obese. For children from 2-18, a percentile scale based on the child's sex and age is mainly used as opposed to BMI<sup>1</sup>.

In the current era, technology is ubiquitous; however, the time spent on these devices can take away from the time spent on physical activity; as the US population continues to grow, the rates of obesity grow as well. Indeed, the percentage of obese Americans has more than doubled since 1980<sup>2</sup>. It is estimated now that in US adults, over 42% are obese while 30.7% are overweight. 19.3% of children are obese and 16.1% are overweight<sup>3</sup>. It is predicted that if these numbers continue their upward trend, about half of the men and women in the U.S. will be obese by 2030<sup>2</sup>. One of the factors that these stunning percentages can likely be attributed to is the lack of physical activity, a contributing factor of this being the rise in technology.

This review will discuss the current positive and negative

effects of technology relating to obesity. It will also dive into potential technological solutions and preventative measures to reduce the risk of obesity and its negative consequences.

Classification	BMI (kg/ m <sup>2</sup> )	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

**Table 1** BMI classification of adult weights based on WHO schema (BMI = weight in kg/height in meters<sup>2</sup>)<sup>4</sup>.

## Positives

The increased use of technology in society today has numerous benefits for individuals struggling with obesity. This includes the increasing use and development of eHealth and mHealth in mobile applications, web-based applications, wearable tech-

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nology, and virtual reality. Weight management intervention programs adopt many of technology's benefits for maximized effectiveness in their programs.

### Effective Approaches for Weight Management

Weight management intervention programs are a beneficial tool for those who need assistance in controlling their weight. The development of technology has especially aided in the effectiveness of weight management intervention programs. Three of the most efficacious programs are the Diabetes Prevention Program (DPP), Look AHEAD, and Pounds Lost, all programs administered by the National Institute of Health. Within these three programs, the main aspects that contribute to their effectiveness are their (1) behavior change component, (2) self-monitoring of individual data, and (3) personalized recommendations and feedback<sup>5</sup>.

Behavior therapy is essentially the approach of providing necessary techniques to change individuals' eating, activity, and thinking patterns that may contribute to their excessive weight. However, most weight management programs only work for the short-term period in which the individual is a part of the program. After it ends, the individual tends to regain the weight they just lost. To combat this issue, many effective programs utilize wellness coaches that provide personalized feedback to cultivate permanent behavior change. This addition has proven to result in greater weight loss in comparison to more traditional methods. This issue paves the way for the use of online platforms that can reach many more individuals at once<sup>5</sup>.

In addition, the use of mathematical models has the potential to be a crucial aspect of obesity prevention. For personalized recommendations, more specific directions for the individuals are extremely helpful, so these directions can be taken from data from these mathematical models. They are created using the most comprehensive datasets of individuals already enrolled in intervention programs. One model developed by Robert S. Lasater and James K. Starling of Louisiana State University was created from the energy balance equation based on the first law of thermodynamics, stating that the rate of energy stored/lost ( $ES$ ) is equal to the difference of rate of energy intake ( $EI$ ) and the rate of energy expended ( $EE$ ),  $ES = EI - EE$ <sup>6</sup>. This equation was combined with another equation, that the total energy expenditure is the sum of the resting metabolic rate voluntary physical activity ( $PA$ ), dietary-induced thermogenesis ( $DIT$ ), and spontaneous physical activity ( $SPA$ ),  $EE = EMR + PA + DIT + SPA$ . These equations were combined to form an ordinary differential equation system that can predict weight changes over time, given initial conditions and parameter values. As shown in Figure 1, demographical and physiological characteristics may be inputted, and a predicted curve that estimates the total weight change is computed. The projections generated by these models are used in intervention to guide adherence to the long-term

project. There are 3 clear benefits to the use of these models: (1) these models can give users motivation to achieve their goals and develop greater commitment to the program; (2) individuals may be more likely to achieve weight loss as realistic dietary measures can be set to achieve a target weight; (3) individuals can learn to read the curve and self-input their weight, so self-monitoring can be improved for the individual and interventionist to see their progress<sup>5</sup>.

### The Negative Influence of Technology on Obesity

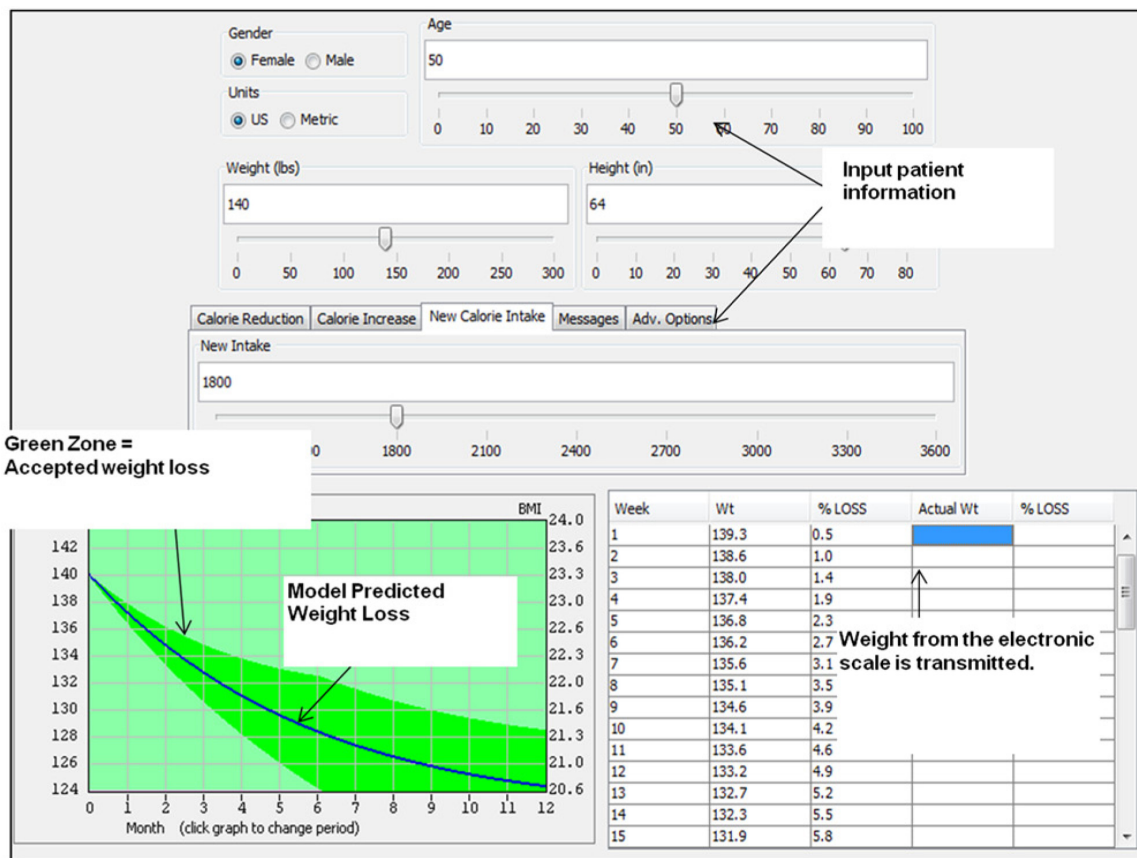
Although the use of technology provides widespread benefits in the prevention of obesity, there are also numerous drawbacks that continue to increase the U.S. population of obesity. Technology promotes a very sedentary lifestyle which leads to consequences such as lack of sleep, decreased physical activity, and unhealthy eating habits.

#### Decreased Physical Activity

The increase in sedentary behaviors such as watching television and computer games has a negative influence on energy levels for physical activity. However, validation and confirmation of self-reported sedentary behavior are very minimal. In a nationally representative study, it was found that weekly hours of screen time during adolescence independently and significantly directly predicted obesity in early adulthood<sup>7</sup>. In contrast, fewer weekly hours of screen time decreased the odds of obesity by over 40% among females and over 20% among males. It was also concluded in this study that screen time among adolescents needs to be reduced in order to lessen the population's obesity. It is further concluded that physical activity levels during adolescence are an important factor in establishing lifelong weight management habits<sup>7</sup>.

#### Lack of Sleep

Not only are environmental and behavioral changes such as dietary habits and reduced physical activity responsible for weight gain but decreased duration of sleep also is an important factor. Growing evidence suggests that technological advancements affect human functioning through their harmful effects on sleep quality, quantity, and timing<sup>8</sup>. Behavioral lifestyle factors that are correlated with poor sleep include weight gain, insufficient physical exercise, and substances such as caffeine, alcohol, and nicotine. So, not only can the use of technology directly lead to poor sleep, but technology can lead to insufficient physical activity as discussed further above, which can then lead to lack of sleep. It can also lead to exposure to substances through appealing advertisements of substances like caffeine, alcohol, and nicotine.



**Fig. 1** Example of a mathematical model used for obesity treatment. Individual-specific parameters such as age, gender, height, and weight can be inputted to generate graphs and tables that show the predicted trajectory of weight change<sup>5</sup>.

Modern lifestyle factors such as television and computers encourage later bedtimes and nighttime use of these screens. Screens emit a bright light to the eyes that suppress the release of melatonin from the body, which impacts the individual’s circadian rhythm, especially if exposure is during the nighttime. Times exposure to bright light can both delay and create an advance in the timing of circadian rhythms. These lights can also have immediate effects on physiological and behavioral measures. Electronic media exposure—especially those with a media device in the bedroom—in children and adolescents was correlated with later bedtimes and shorter sleep durations<sup>8</sup>.

Studies have investigated sleep as a cause and a consequence of weight gain. Shorter sleep was associated with higher measures of obesity in terms of BMI, waist circumference, and body fat percentage. Shorter sleepers tended to have more sedentary behaviors, watching more television and having an unhealthier diet than adequate sleepers ( 8 hours per night). Mechanisms explaining the relationship between sleep duration and obesity have been investigated. Studies have shown that in sleep loss, the regulation of hormones leptin and ghrelin, which signal satiety and appetite respectively, is interrupted, resulting in greater

levels of hunger and appetite<sup>8</sup>. It has also been proposed that increased rates of television viewing led to less sleep, which then leads to greater levels of hunger and a decreased metabolic rate, resulting in obesity<sup>8</sup>.

### Poor Eating Habits

The increased prominence of technology has caused explorations into making food more convenient in our society. However, these modern forms of food delivery have made unhealthy foods easily accessible and have caused an unhealthy shift in the eating habits of Americans<sup>9</sup>. On top of that, the tendency to watch screens while eating can cause mindless overeating, leading to weight gain<sup>10</sup>.

### Convenience of Food Delivery Apps

In almost every area in the U.S., digital food ordering can be done directly with a restaurant app or third-party food service, with GrubHub and Uber Eats being the most popular<sup>9</sup>. Digital orders, either through mobile apps, the Internet, or text

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messages, have increased by 23% over the past 4 years resulting in a \$26.8 billion dollar industry<sup>9</sup>. About two-thirds of American consumers who use a food-delivery service (GrubHub, UberEats, DoorDash), reported that food delivery was their preferred method of getting dinner. Though services like these allow the convenience of receiving food from a diversity of restaurant chains, reports highlight that America's top ordered food choices were cheeseburgers and fries, pizzas, nachos, cheesecakes, pork ribs, etc., demonstrating the calorie-dense options were the most popular selections to be delivered<sup>9</sup>. The frequency of eating food from outside of home is positively associated with a high BMI. The increased fast food portion sizes, calorie levels, and sodium levels over the past 30 years worsen the potential issue that these food delivery services may present to the ongoing obesity epidemic<sup>9</sup>.

### **Mindless Eating**

Recent technological developments have caused many people to develop a habit of eating and drinking while simultaneously being immersed in their televisions, computers, tablets, or smartphones. This mindless or distracted eating has become increasingly relevant in understanding obesity-related eating patterns and behaviors.

Recent studies suggest that distracted eating causes increased food consumption. Several recent experiments have demonstrated that this type of distracted eating can lead to reduced taste perception<sup>11,12</sup> and cause an increase in immediate and later food intake<sup>13</sup>. One of these studies was a neuroimaging experiment, which found that when individuals tasted a milkshake under cognitive stress (distraction), lower connectivity between the brain areas involved in primary taste processing (insula) and higher order processing (orbitofrontal cortex) is shown than when the milkshake was consumed under a normal cognitive state<sup>14</sup>; this proposes that distracting factors during food consumption can alter humans' perceptions of taste<sup>10</sup>. In addition, regular distracted consumption may lead to frequent overconsumption, leading to an increase in weight. In separate studies, it was found that higher levels of television use were associated with greater intakes of energy, fat, sweets, salty snacks, carbonated drinks, and lower intakes of fruit and vegetables<sup>15</sup>. In summary, eating while distracted can cause long-term health implications through overeating, and, in turn, body weight increase<sup>10</sup>.

### **Social Media Influence and Advertising**

Although the use of social media is designed to promote social connection and interaction, many users engage in passive utilization, when they rarely interact with others' content. From this passive utilization, no interpersonal connections are created which builds the conditions for isolation and social compari-

son which can heavily influence personal well-being. These examples can lead to dissatisfaction in self-perception, resulting in dramatic efforts to "improve" themselves, which are typical symptoms of some eating disorders. The use of social media is significantly linked to body image concerns and the possible development of eating disorders. The duration spent on social media relating to self-image and eating behaviors was correlated with a decreased perception of self-body image and an increase in problematic eating behaviors<sup>15</sup>.

Advertising is a form of online media widely considered to encourage unhealthy consumption. Foods that are featured on television and in online media in general are usually low-nutrient drinks, such as coffee and alcohol, and snacks, such as sweets, or salty snacks. In a study reviewing the past 30 years of journal articles, it was concluded that children exposed to advertisements tend to choose advertised food products at much greater rates than foods not exposed to through advertising<sup>15</sup>.

## **Other Uses of Technology in Weight Management**

### **Uses of eHealth and mHealth**

The broad field of digital health care can generally be separated into two categories: electronic health (eHealth) and mobile health (mHealth) which is thought to be a subset of eHealth. eHealth can be defined by the World Health Organization (WHO) as the use of information and communication technologies for health<sup>16</sup>. The most prominent forms of eHealth are electronic health records (EHRs) and personal health records (PHRs). EHRs are made up of an individual's health information compiled within or across different organizations. EHRs allowed clinical records to be accessed across multiple locations on computers instead of a single piece of paper. PHRs are health information records maintained by individuals. They can be an extremely effective way of storing health information and sharing it with healthcare providers. These uses of technology have revolutionized the communication of healthcare information among individuals and organizations. This is just an example of the wide variety of tools available through eHealth. mHealth on the other hand is the "medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants (PDAs), and other wireless devices"<sup>16</sup>. mHealth is becoming especially ubiquitous due to the prevalence of mobile devices and technology<sup>16</sup>.

### **Mobile Applications**

Provided that 85% of Americans own a smartphone<sup>17</sup>, mHealth applications have been on the rise to increase access to healthcare, intervention cost-effectiveness, and participation. As of 2022, over 350,000 mobile healthcare apps were globally available, with consumer health and fitness being the most popular.

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In addition, combining mobile health apps with wearable sensors gives individuals a thorough understanding of their health-related information. These mobile apps and wearable can be used to monitor heart rate, blood pressure, and diabetes<sup>18</sup>.

Mobile applications for weight management can provide countless benefits to the user. They often have features like self-monitoring of diet and physical activity, goal setting, feedback, and reminders to input personal recorded data. These apps also include a wide variety of information that is needed to live a healthy lifestyle, such as dietary intake, the importance of different food groups, physical exercise, recipes, and everyday tips to manage weight. A helpful aspect for social engagement is used in some applications such as BodySpace, which includes a social media platform within the app that allows users to “follow” others who are at similar stages to themselves. As a result, users experience reduced feelings of isolation that some may have at the start of a weight-loss journey and instead provide them with a sense of connectedness with those around them. In addition, there is an “inspirational” feature which is used to follow someone else they found inspirational. These aspects can instill a deeper feeling of motivation that an app itself simply can’t give, a person-to-person connection. Additionally, mobile applications offer real time healthcare to individuals. For example, the Monica application, a phone-based reporting and automated feedback system in which the user monitors their blood pressure, glucose, levels, weight, and physical activity, observes trends in this data and provides suggestions for behavior change<sup>19</sup>. Furthermore, in a pilot study performed by Ross and Wing, self-monitoring technology that includes tracks caloric intake, weight, and physical activity, has been proven to improve adherence to weight loss compared with some of the more traditional self-monitoring tools<sup>20</sup>. In this study, participants were provided with real-time technology, including a Fitbit Zip activity monitor and a Fitbit Aria smart scale, and tracked their caloric intake using the Fitbit smartphone app. The key aspects of this technology gave participants the ability to receive feedback continually, so that they were able to see their calorie totals updated live and could see graphs of their caloric intake, physical activity, and weight over time. Overall, participants who used these smartphone applications reported better long-term eating habits and weight management following application use<sup>18</sup>.

Despite the numerous benefits mobile applications have, they also have some drawbacks. With mHealth applications being a relatively new area, there are some worries regarding their data accuracy and privacy. Many of these weight management applications are created with little to no input from experts, for example, regarding the impacts of diet and physical activity. This can lead to inaccurate and unreliable information that could lead to frustrated users who don’t see any progress despite following the guidance of the app. In addition, a study assessing the important components of weight management applications

came up with twenty components that are essential in leading to a successful application: “weight-loss goal, dietary goal, calorie balance, physical activity goal, exercise safety, benefits of a healthy diet and physical activity, food pyramid, stimulus control, portion control, lifestyle activity, target heartrate, problem solving, stress reduction, relapse prevention, negative thinking, social cues, developing a regular pattern of eating, time management, and nutritional label reading”<sup>18</sup>. However, on average, only 18.8% of these strategies were found in a thorough search of 30 applications for weight loss. In a study by Solbrig et al., people reported difficulty in self-managing their weight on the application and lacked motivation resulting from a lack of time or energy, inadequate results or boredom, and submitting to other temptations<sup>21</sup>. The authors concluded that the most challenging issue was a lack of motivation. They also found an inconsistency between the help provided by the weight loss applications (information and self-monitoring) and the help needed by users (motivational support). The constant provision of information to the users was ineffective and the weight lost from the period of app usage was gained back shortly afterwards<sup>18</sup>.

A thorough examination of these mobile applications reveals all their positives and negatives, but a key takeaway remains certain throughout every app: a perfect app could be created with all the convenience features ever wanted of an app, but it will always be down to the individual’s motivation and commitment to their long-term goals that decide whether the app will be a success or not.

### **Use of Machine Learning in Obesity**

Machine learning (ML) is a rising area in the field of obesity and is now a critical part of discovering trends in obese individuals by detecting early signs and other factors. Simmonds et al. used ML to conduct a review to examine measures such as BMI that are used to calculate childhood obesity and could also be a predicting factor for obesity later in life; it was concluded that teenage obesity often continues into adulthood and that early action to reduce teen obesity is one of the most effective methods in reducing adult obesity<sup>22</sup>. Recently, Siqueira et al. researched the relationships between obesity and COVID-19 through hospitalization rates, diagnosis and recovery outcomes, and death rates; it was found that obesity was an adverse condition for COVID-19 and, more specifically, high BMI led to more severe outcomes<sup>23</sup>. Furthermore, Ananthakumar et al. conducted a survey assessing patient responses to talks about additional weight; they concluded that patients were more likely to be open to trusted physicians who showed curiosity in their efforts to lose weight and took the time to discuss with them in a polite manner<sup>24</sup>. Felso et al. offered a review studying the relationship between duration of sleep and childhood obesity; the team concluded that factors such as a sedentary lifestyle, unhealthy diet, and insulin resistance, can increase the risk of

poor sleep, and by extension, weight increase in children<sup>25</sup>.

ML is a broad field, so there are many different techniques that can be used to predict instances of obesity. Generally, ML techniques are separated into 2 categories, with single and hybrid methods.

Results from various studies have shown that artificial neural networks (ANNs) were the most used method<sup>26–28</sup>. ANNs are powerful tools designed to solve many types of multi-variate, nonlinear problems when provided with the correct algorithm and data. ANNs can also be used to predict the risk of disease and other sophisticated problems. ANNs have been a recent source of interest due to their important uses as predictive models and in pattern recognition<sup>4</sup>.

Using ML, it has been found that the cause of obesity is quite complex and is hugely multifaceted. There are numerous influential factors that can predict adult overweightness or obesity. Safaei et al. conducted a review regarding ML in which a table, Table 2, is presented that summarizes several of the key factors that contribute to obesity in individuals<sup>4</sup>.

Table 2. A list of factors that contribute to obesity that were found through ML based on studies from different researchers<sup>4</sup>. Cheng used logistic regression analysis and Pearson correlation, a standard statistical method often used with other ML techniques for initial exploratory data analysis<sup>29</sup>. Choukem et al’s study was a literature review collecting data from studies that used logistic regression, linear regression, neural networks, and decision trees<sup>30</sup>.

Author(s)	Factor(s)
Cheng	• Maternal smoking
	• Neurological functioning
	• Physical exercise
	• Personality and/or intelligence
Choukem et al.	• 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	

Many other studies have been conducted researching the major disorders/diseases associated with obesity. Figure 3 reveals a general overview of the connections that obesity shows to other types of diseases.

Studies have discussed the effects of obesity on several cardiovascular conditions and diseases; for example, overweight or obese patients displayed a greater likelihood of cardiovascu-

lar diseases of nearly every type in comparison with patients with normal BMIs. Multiple studies have indicated the strong relationship between the epidemics of obesity and diabetes as a major global health crisis. These studies show that diabetes was one of the most considered comorbidities of obesity<sup>4</sup>.

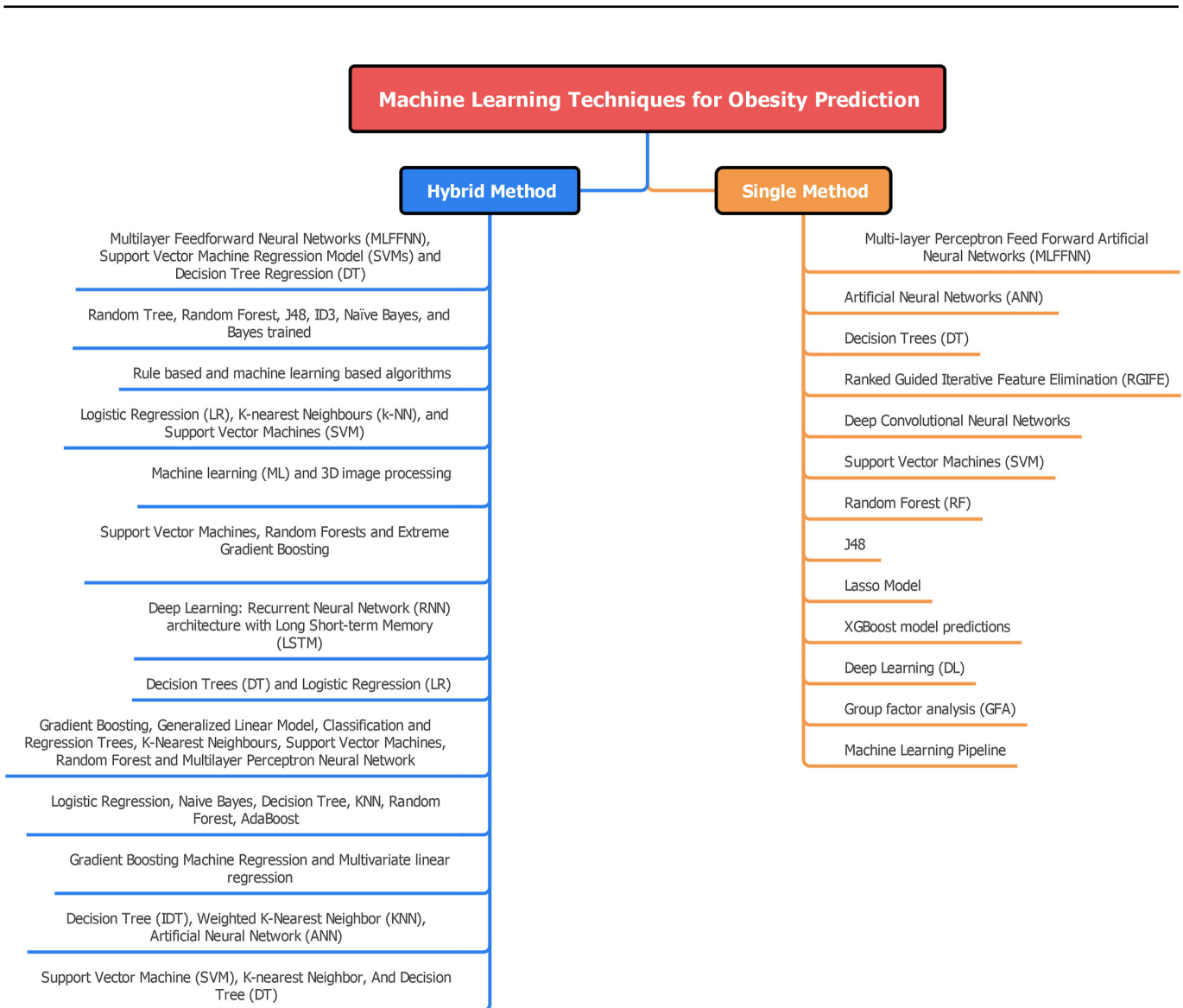
ML is currently continuously used in researching obesity; however, only limited research has reported using ML techniques specifically in detecting obesity. Regardless, this field remains a promising area of research as these methods can provide more comprehensive and in-depth predictions than other simpler methods<sup>4</sup>.

### Use of Virtual Reality in Obesity

Virtual reality (VR) is another rising source of convergence between technology and medicine that has the potential to improve cognitive behavioral protocols, especially with issues such as anxiety and addiction. VR offers controlled experiences to users, without the need for in vivo exposure. It is possible to use VR to improve body image with patients struggling with eating disorders or obesity<sup>31</sup>.

Experiential cognitive therapy is a VR treatment that uses nutritional, cognitive, and behavioral procedures to allow patients to identify and change mechanisms in obesity and eating disorders. In these VR sessions, the therapist uses the “20/20/20 rule.” This rule essentially divides the session into three sections for 20 minutes each. The goal of the first 20 minutes is for the therapist to gain a clear understanding of the patient’s concerns, level of functioning, and experiences regarding food, in which the patient does most of the talking. The next 20 minutes take place in a VR experience when the patient faces a critical situation and is helped with strategies to avoid or cope with the issue. The final 20 minutes is when the therapist dives deeper into the patient’s VR experience such as what reactions were evoked—behavioral and emotional—during the situations they were presented with. The testing of this practice in studies has been shown to produce positive results in the long term with obese and binge-eating patients, also better than other approaches such as nutritional therapy and cognitive behavioral therapy<sup>14</sup>.

Another key aspect in which VR contributes to tackling the issue of obesity in our society is using VR games, a way to give individuals an enjoyable time while doing physical activity. One of the key reasons why obesity and overweight populations in the U.S. are increasing is due to a lack of exercise. A cause of this is that people either don’t find physical activity enjoyable or it simply doesn’t match the thrill received from playing video games. So, the idea of combining entertainment with exercise has become increasingly popular. VR exercise games, specifically, can place a user into the actual game itself. From a series of studies, VR exercise games are thought to be more effective in increasing users’ motivation to exercise and their exercise performance<sup>32</sup>.



**Fig. 2** Machine learning techniques that are used for obesity prediction. It shows the machine learning techniques categorized into hybrid and single methods, techniques that consider multiple parameters versus a single parameter when predicting trends in weight<sup>4</sup>.

The realistic representation of these so-called exergames is likely to increase the exercising experience of users in the long run. Studies have shown that these games can increase users' enjoyment in the exercising experience, potentially allowing them to explore various types of physical activity in the future<sup>32</sup>.

## Discussion/Conclusion

In summary, the use of technology in addressing obesity has shown both positive and negative impacts on individuals' health and well-being. The positives include the use of eHealth and mHealth applications, which offer convenient and effective tools for weight management interventions. These technologies pro-

vide behavior change components, self-monitoring capabilities, and personalized recommendations, enhancing the effectiveness of weight management programs. Additionally, mathematical models have the potential to offer personalized guidance and motivation to individuals seeking to manage their weight. Mobile applications have become increasingly popular for weight management, offering features like self-monitoring, goal-setting, and social engagement. These apps empower users to make healthier choices and connect with others on similar journeys. Virtual reality offers innovative solutions for treating obesity by improving body image and promoting physical activity through immersive experiences and experiential cognitive therapy.

However, there are significant drawbacks associated with the



**Fig. 3** Specific types of diseases related to obesity<sup>4</sup>.

use of technology in combating obesity. Sedentary behaviors induced by technology, such as excessive screen time, contribute to decreased physical activity levels and can lead to weight gain. In addition, inadequate sleep, often linked to technology use, disrupts hormonal regulation and appetite control, increasing the risk of obesity. Unhealthy eating habits are exacerbated by the convenience of food delivery apps, which often promote calorie-dense options, and mindless eating while using electronic devices. Social media and online advertising also play a role in shaping eating habits and body image perceptions. Passive social media consumption can lead to social comparison and dissatisfaction with one's own body image, potentially contributing to eating disorders. Furthermore, advertising, especially for unhealthy food products, influences food choices, especially among children.

The findings presented in this review highlight the multifaceted relationship between technology and obesity. On the one hand, technology offers valuable tools and interventions for weight management, enhancing accessibility and personalization. On the other hand, it poses significant challenges to physical activity, sleep quality, and healthy eating habits. The influence of social media and advertising on body image and food choices underscores the need for greater awareness and regulation in the digital space.

Understanding these dynamics is crucial for healthcare professionals, policymakers, and individuals seeking to combat obesity. It emphasizes the importance of striking a balance between harnessing the benefits of technology and mitigating its

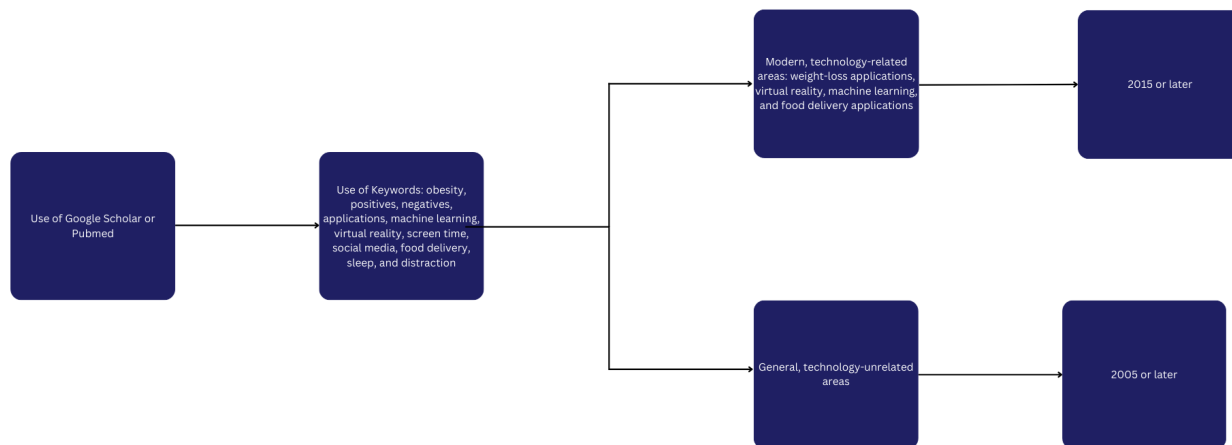
negative effects. Effective interventions should address both the behavioral and environmental factors contributing to obesity in the digital age.

The findings in this review are based on existing research and literature up to around 2022, so there is a possibility of new technological developments already emerging from that time. In addition, this overview may not comprehensively cover every aspect of the relationship between technology and obesity currently in society. Further research is needed in order to explore all the possibilities of technology in impacting obesity prevention and management.

Future research should focus on the long-term effects of technological interventions for weight management. Sustainability in behavioral habits beyond the intervention period is crucial in creating long-term health. Another essential area of research is the policy and regulatory approaches to address the negative influence of online advertising on unhealthy food choices, especially for children and adolescents in developing healthy eating habits. With further advancements in technology, research should continue to explore the use of technologies such as VR, artificial intelligence, and gamification in obesity prevention and treatment. Further studies should further dive into the impact of social media on an individual's body image and self-esteem, along with strategies to avoid these negative influences and instead promote positive interactions. Beyond the research of technological developments and their effects on people, interdisciplinary research is essential between healthcare professionals, technology developers, policymakers, psychologists, and nutritionists in developing holistic approaches to harness the use of technology to combat obesity while addressing its multifaceted causes.

## Methods

The Google Scholar and PubMed databases were searched using combinations of the following keywords: obesity, positives, negatives, applications, machine learning, virtual reality, screen time, social media, food delivery, sleep, and distraction. In order to be included, papers had to be focused on the impact or the specific use of that technology on obesity, whether it has positive or negative effects. All English-language papers from 2005 or later were eligible for inclusion, though for the rapidly changing fields such as weight-loss applications, virtual reality, machine learning, and food delivery applications, papers were required to be from 2015 or later. Peer-reviewed articles, published literature, and original research were eligible along with symposium presented papers. Around 40 studies were extracted. The studies are based on recent technology, so most of them were recent and met the above requirements. Only around 10 of the extracted studies were excluded due to the inability to meet the criteria.



**Fig. 4** A flow diagram of the methodology of the selection process used in this literature review.

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