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REVIEW

Efficacy of Emerging Technologies to Manage Childhood Obesity

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Abstract: Childhood obesity is a widespread medical condition and presents a formidable challenge for public health. Long-term treatment strategies and early prevention strategies are required because obese children are more likely to carry this condition into adulthood, increasing their risk of developing other major health disorders. The present review analyses various technological interventions available for childhood obesity prevention and treatment. It also examines whether machine learning and technological interventions can play vital roles in its management. Twenty-six studies were shortlisted for the review using various technological strategies and analysed regarding their efficacy. While most of the selected studies showed positive outcomes, there was a lack of studies using robots and artificial intelligence to manage obesity in children. The use of machine learning was observed in various studies, and the integration of social robots and other efficacious strategies may be effective for treating childhood obesity in the future.

Keywords: childhood obesity, intervention, exergaming, machine learning, artificial intelligence

Introduction

Childhood obesity is a major concern for healthcare systems and remains a challenge for medical innovation.[1] Cases of overweight or obese children (infant and young) have significantly increased worldwide to 41 million and are continuously increasing.[2] The huge socioeconomic transformations have significantly affected the nutrition and development of children and adolescents, particularly in developing countries. Increasing rates of urbanization has had a global effect on lifestyle, reducing the frequency of physical activity and increasing the calorie intake of nontraditional foods and "fast foods" rather than fruits and vegetables.[3,4] In addition to children showing a greater frequency of being overweight or obese, these food choices lead to nutritional deficits in growing children, which may lead to future health issues.[5]

Without intervention, overweight or obese children are more prone to carrying their condition into adulthood, possibly increasing their chances of developing diseases such as diabetes, cardiovascular diseases, and cancer.[6–8] Approximately 33% of preschool-aged children who are obese or overweight become obese adults, and 50% of obese school-aged children and 80% of adolescents carry obesity into adulthood.[9] Therefore, it is crucial to develop strategies for the early diagnosis, prevention, and management of childhood obesity.

Currently available conventional interventions to manage weight are not always feasible as they are often inaccessible because of high cost, commute inconveniences, and lack of facilities.[10] Extreme cases may require bariatric surgery, which is both expensive and risky.[11] Approximately 80% of children aged 12–17 years are hesitant to engage in any kind of coordinated activities, such as sports; therefore, a need for creative intervention is yet required.[12]

Over the past decade, advances in portable digital technologies that provide personalized access to relevant information have facilitated the evolution of preventive strategies and interactive aids and have become readily available. Smart digital health interventions are designed to cater to a wide number of issues because they help track and monitor health as well as collect information for analysis by a specialist to determine the required treatment strategy. These interventions

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include weight management programs based on websites[13] or social media.[14] They are wearable[15] and are easily accessible via websites and mobile applications. These interventions are easily adaptable to different environments, affordable and time saving. Most importantly, strategies based on these technological tools keep children motivated and engaged while enjoying the comfort of their homes. Technology-based interventions for childhood obesity can be mainly classified into the following categories: (1) active video games or exergaming; (2) website, social media-based activities[16] or mobile application-based activities;[17] (3) machine learning (ML)-based strategies.[18] A combination of those categories does also exists.

Mobile phones are the most readily and commonly available gadgets. They can be conveniently connected to wearables and sensors, providing the user with real-time data and monitoring physiological changes with internet cloud connectivity. Combining sensors and connectivity enables behavior (eg, physical activity and diet) to be monitored and influenced, and health care providers or experimenters can be alerted to changes (eg, weight and glucose). This technology offers a great opportunity to tap into new media channels that are integral to the youth culture because mobile phones are already widely used by children.[19]

The use of exergames, which combine exercise and video games, is another concept that is gaining popularity. These games are designed to encourage children to perform physical exercise or execute certain movements to clear levels and earn rewards in the game. They keep children motivated and engaged over time, making it easier for them to consistently follow a regular fitness program. Many available applications use this concept in combination with a wearable device. Exergames are suitable for every age group. For example, *Let us move* (To move!) is a program designed in the form of a video game to prevent and treat obesity in children.[20] Zamzee is another application for adolescents[21] that records physical activity via a device. The number of points earned is calculated by the computer and can be exchanged for goods from partnering companies.

ML is an emerging strategy[22,23] implemented by many computerized systems used in a clinical context.[24,25] An ML-based approach provides beneficial insight into data to extract relevant information and has been actively used for the prognosis and diagnosis of several chronic conditions, particularly in patients with diabetes and sepsis.[26,27]

Despite being potentially very efficacious in obesity, there are surprisingly few reviews in the literature regarding the application of ML for childhood obesity management and treatment. Available reviews mainly focus on mobile devices, wearables, and interactive electronic media or predictive models based on statistics. One review[28] addressed the potential use of computer decision systems (CDS) showing the main features and results of studies that use ML techniques and CDS.

Social robots are also being developed and tested in various healthcare concepts. Social robots have significant potential to assist healthcare workers and deliver customized care to children because they are more capable than other types of interactive technologies to positively influence the behavior and motivation of the human interactants. This superior potential derives from the fact that social robots, unlike other assistive technologies, are embodied agents with anthropomorphic or zoomorphic features. In some cases, robots also have a limited ability to navigate or manipulate the physical environment, enabling them to engage in embodied interaction with humans and share a concrete focus of attention (object or activity) with them. Furthermore, the ability to express emotions and interest is much more developed in person-like agents, such as robots, compared with impersonal technologies, such as mobile phone or tablet applications.

Robinson et al[29] described the potential of robots and demonstrated that an autonomous social robot can efficaciously motivate adults to reduce the consumption of high-calorie snacks, aiding a low-powered therapy on dietary intake with no human intervention. Building on this and analogous examples of robots acting as coaches and lifestyle advisors, a "virtuous" theoretical approach to robot design has been proposed.[30,31] This "virtuous robotics" approach can be applied to obesity management where robots can be programmed and deployed to cater to specific health and psychological requirements, motivate children to perform physical activities, and encourage healthier eating habits. Robots are suited for this motivational/assistive role because they are perceived as toys by children and can be a source of companionship, provide comfort and relief, and gain the trust of children, which is indispensable to give children explicit instructions and help in reforming their dietary habits.

Several reviews have explored obesity management using different technologies in children and adolescents and compared their efficacy in managing and preventing obesity via various channels.[32,33] No reviews were specifically dedicated to analyzing the efficacy of robots and AI-based strategies compared with other technology-based techniques for obesity management in children and adolescents that have received more attention to date. The present systematic review aims to fill the gap by analyzing and comparing research studies published between the years 2010–2021 to map how ML techniques are used and how they compare with non-AI-based technological strategies in obesity management for children.

Materials and Methods

The present review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines using the following strategic approach. Studies included in this review were identified systematically by searching databases using the following keywords: obesity, obesity management, children, technology, exergaming, robots, machine learning, and overweight. The databases consulted were PubMed, IEEE Xplore, Scopus, and Google Scholar. Moreover, a few references of significant studies[34,35] were scrutinized to extract more relevant articles suited to our review for further investigation and were shortlisted according to our criteria.

Inclusion and Exclusion Criteria

Studies fulfilled the inclusion criteria if they were (1) published in English; (2) published within the years 2010–2021; (3) based on obesity prevention or management (4) included participants aged ≤18 years; (5) were randomized controlled trials (RCTs) or interventions; (6) Used AI, robots or ML techniques.

Studies were excluded if they were (1) not in English; (2) had no reliable outcomes; (3) had participants aged >18 years; (4) did not use any types of technology in their research; and (5) were reviews, book chapters, thesis or conference material.

Quality Assessment Strategy

A modified Delphi list was used to assess the quality of each study.[36] The assessment quality was improved by considering the following elements: age range, sample size, and intervention duration. The latter two were considered with the understanding that a smaller sample size and a shorter intervention duration might negatively impact generalizability and reproducibility.

Additional considerations were given to a study's purpose, whether they were preventive, screening-based, experimental or treatment-based. Also, the methods of the study were taken into consideration if they were activity/video game based, web/mobile based or ML based. The choice of elements included in the quality assessment was guided by a previously published systematic review conducted by Nouchi et al.[34]

Results

A total of 1244 articles obtained from various databases were screened and duplicate articles were rejected. The titles and abstracts of the remaining 250 articles were screened for relevancy, and 75 articles were identified for full-text reading, 26 were finalized for review. A review of each study was performed, and information related to the layout and purpose of the study, as well as details of the participants (age, gender, size, and characteristics) were extracted.

The selection strategy for our review is illustrated (Figure 1). Table 1 shows an overview of the study characteristics, Table 2 outlines the key findings of the included literature, and Table 3 shows the assessment of the quality of studies using a delphi list. The studies were of various types, such as RCTs, experimental studies, or screening studies. The overall sample size analyzed ranged from 17 to 18,818, and the age of the participants ranged from 9 months to 18 years. Most studies were not gender specific and included both males and females, except for one study by Staiano et al that only included females.[42]

All studies focused on technology-based interventions. Most studies[13,37–39,41–45,49–54] involved overweight or obese participants, a few[13,35,36,46–48,52,53] included healthy participants, and others did not specify the characteristics of the participants.[40,55–59] The technology-based interventions were classified into three categories: (1) active video games or exergaming; (2) web, internet-based activities or mobile application-based activities; (3) ML-based strategies;

The duration of the intervention ranged from 1 week[35] to 3 years,[41] and the studies that used ML-based algorithms did not always specify the time period for data collection. Intervention intensity was reported in most studies, but not all,[40,54–59] and

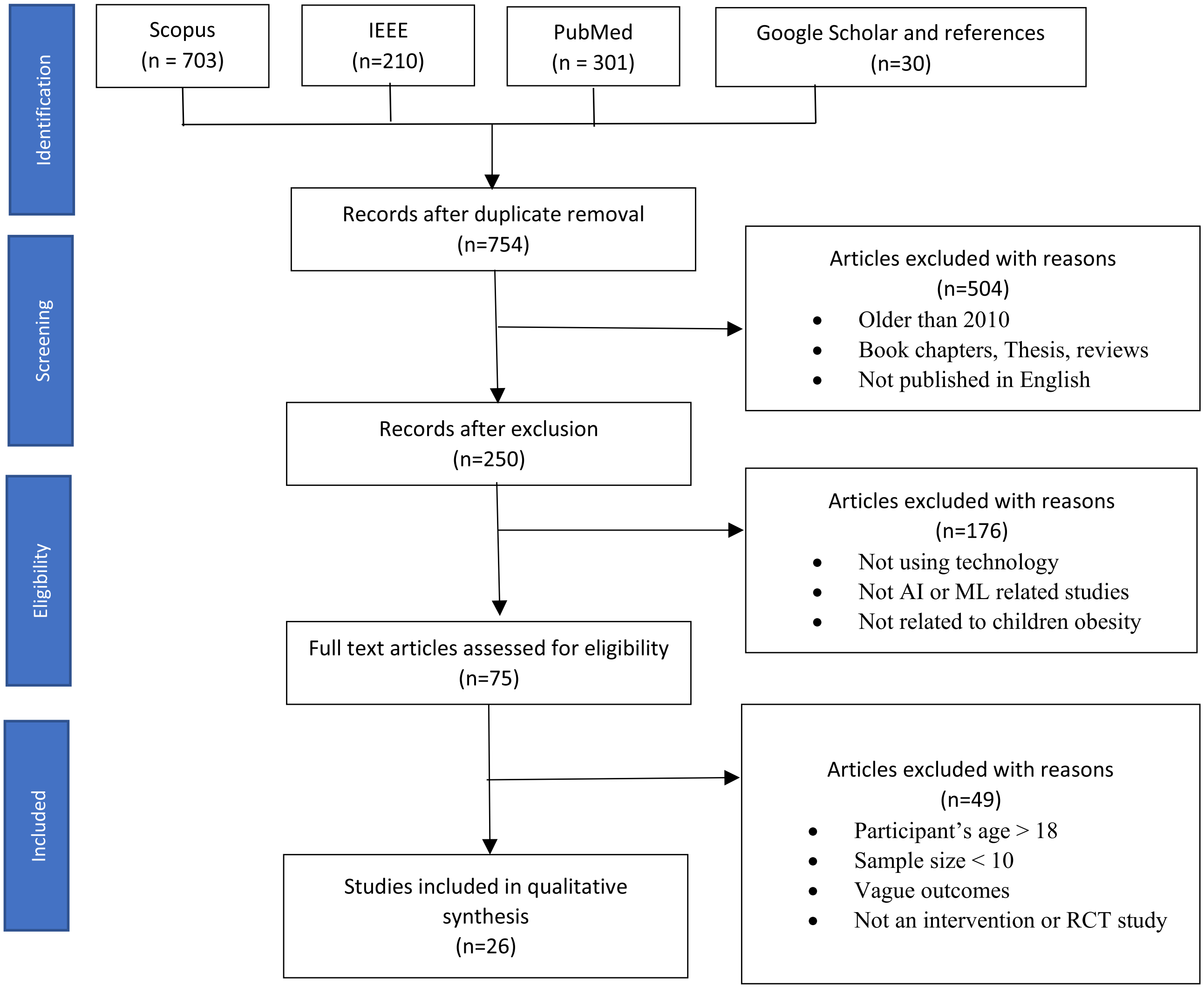

Figure 1 Search strategy used for selection of studies.

was highly heterogeneous. Ten studies[13,35,41,42,46,47,49,51–53] were RCTs that compared technology-driven intervention with a control group and used a non-technology-based intervention[56] in which the control group played video games that were sedentary compared with the intervention group. The outcome of the studies varied according to the aim, but all comprised a body mass outcome, such as body mass index (BMI), BMI z-score, or BMI percentile. Other outcomes commonly observed included other anthropometrical, diet-based, and physical activity measurements.

Active Video Game Interventions

Twelve studies[35,37–47] investigated the efficacy of active video games or exergaming. Lindberg et al[35] incorporated the gaming program Running Othello into the South Korean school physical education (PE) curriculum for the intervention group, while the control group used printed leaflets and the regular curriculum. Positive results were observed in the intervention group as children were more engaged and showed increased heart rates compared with the control group. In another study, Argarini et al[37] investigated the efficacy of moderate intensity exergaming on children with a BMI in the 85th percentile. Exergames were played using Xbox 360, and dance and sports-based games were played for four weeks. The results showed reduced BMI and improved fundamental movement skill, with no significant discrepancy between male and female participants. Adamo et al[38] used the interactive video game, "GameBike" and included stationary cycling for two groups: one group performed stationary cycling with music and the other group used GameBike while

Table 1 Characteristics of the Included Literature

Study Number	Author, Year	Study Design	Study Purpose	Participant Characteristics			
				Number of Participants 1) Intervention 2) Control	**Gender**	**Age in Years**	**Characteristics**
1	Lindberg et al., 2016[35]	RCT	Education and Prevention	1)32 2)29	M + F	10	Healthy 3rd grade elementary children
2	Yang et al., 2017[36]	Non-RCT	Prevention	1) 558 2) 288	M + F	10–12	Healthy school students
3	Argarini et al., 2020[37]	Experimental study	Treatment	17	M + F	6–12	BMI >85th percentile
4	Adamo et al., 2010[38]	Experimental study	Activity	30	M + F	12–17	Overweight children
5	Staiano et al., 2018[39]	RCT	Treatment	1)23 2)23	M + F	10–12	BMI z-score
6	Ruggiero et al., 2020[40]	Comparative study	Experiment	48	M + F	7–13	–
7	Trost et al., 2014[41]	Group RCT	Activity	1)34 41	M + F	8–12	BMI >85th percentile
8	Staiano et al., 2017[42]	RCT	Activity	1)21 2)19	F	14–18	Overweight and obese girls
9	Maddison et al., 2011[43]	RCT	Activity	1)160 162	M + F	10–14	Overweight and obese children
10	Duman et al., 2016[44]	Experimental study	Activity	50	M + F	12–16	Slightly overweight and obese
11	Wagener et al., 2012[45]	Experimental study	Activity	1)21 20	M + F	12–18	BMI >95th percentile
12	Coknaz et al. 2019[46]	RCT	Prevention	106	M+F	9.6 (mean)	Healthy children
13	Gao et al. 2019[47]	RCT	Prevention	32	M+F	4–6 yrs	Healthy children
14	Curiel et al., 2020[48]	Experimental study	Training and Prevention	60	M + F	9 (mean)	Healthy children
15	Nawi et al., 2015[49]	RCT	Education	1)47 2)50	M + F	16	BMI >25 kg/m^2
16	Rio et al., 2019[50]	Quasi-experimental control trial	Activity and Education	1)13 2)10	M + F	6–12	Obese children
17	Chen et al., 2019[51]	RCT	Treatment and Prevention	2)54	M + F	12–15	BMI ≥85thpercentile
18	Rerksuppaphol et al. 2017[52]	RCT	Prevention	3)217	M+F	10.6 (mean)	Healthy children

(*Continued*)

Table 1 (Continued).

Study Number	Author, Year	Study Design	Study Purpose	Participant Characteristics			
				Number of Participants 1) Intervention 2) Control	Gender	Age in Years	Characteristics
19	Nystrom et al. 2017[53]	RCT	Prevention	4)263	M+F	4.5 (mean	Healthy children
20	Hammersley et al. 2019[13]	RCT	Prevention	5)86	M+F	2–5 yrs	Healthy children
21	Fiechtner et al., 2016[54]	Experimental study	Monitoring	498	M = F	6–12	BMI >95th percentile
22	Lingren et al., 2016[55]	ML-based study	Detection	428	M + F	1–6	–
23	Rios-Julian et al., 2017[56]	ML-based study	Screening	221	M + F	6–13	–
24	Fergus et al., 2015[57]	ML-based study	Screening	28	M + F	10–11	–
25	Dugan et al., 2015[58]	ML-based study	Screening	7519	M + F	0–2	–
26	Balbir et al., 2020[59]	ML-based study	Screening	18,818	M + F	9 months–14 years	–

Abbreviations: BMI, body mass index; F, female; M, male; ML, machine learning; RCT, randomized controlled trial.

performing stationary cycling. Regularity of exercise, energy consumption, aerobic fitness, body composition, and the risk of heart disorder in overweight and obese children were monitored. The music group performed considerably better and used more strength than the GameBike group. There were no statistically significant differences between or within groups with respect to BMI.

Staiano et al[39] performed exergaming with Kinect and Xbox 360 gaming consoles using four simultaneous exergames, whereas the control group was required to maintain their regular level of physical activity. Statistically significant differences were observed in the intervention group, which showed improved scores, increased physical activity, and improved cardiometabolic health. Ruggiero et al[40] developed the exergame “MyPlatePick” that combines nutrition education and physical activity to promote movement and encourage healthy behavioral changes. Positive changes in eating behavior and increased physical activity were noticed.

Trost et al[41] evaluated the effect of exergaming on children participating in a group-based program for managing weight. Improvements in physical activity were observed in the gaming group compared with the control group, which only took part in the program and not in the exergaming. The active video game group showed reduced weight and BMI. Another study by Staiano et al[42] examined the effects of dance-based exergaming on females matched to a control group who followed their normal level of physical activity. No statistically significant differences were observed between the groups at follow-up.

Rio et al[50] tested a platform in which weekly group sessions with training were conducted on healthy-eating habits and active video games, and the participants developed their own vocal projects based on healthy activities. This study documented a positive effect on the intervention group in terms of nutritional knowledge and adherence to Mediterranean diet. Wagner et al[45] studied the efficacy of dance-based exergaming on obese adolescents’ observed capability to

Table 2 Key Findings of the Studies

Study Number	Author, Year	Intervention	Intervention Duration and Intensity	Intervention Strategy	Key Findings
1	Lindberg et al., 2016[35]	Exergame RO2 with smartphone and wrist band using South Korean PE curriculum	1 week, 15 min per student	The intervention group studied the curriculum by playing RO2, while the control group learned the curriculum using handouts. Questionnaires were developed to be answered by game groups to rate RO2. A quiz was held at the end of the intervention to calculate learning and retention in both groups.	Positive outcomes were observed; exergames motivated students to play irrespective of their physique. Learning via RO2 was more effective, kept students involved, and increased their heart rates. Learning outcomes showed significant variations between both groups.
2	Yang et al., 2017[36]	HAPPYME platform using quests involving physical activities and healthy dietary habits	12-week test and 6-month follow-up	HAPPYME platform helps teachers and parents to monitor and provide encouragement to participating children. The application asks students to complete quests involving physical activities and healthy eating habits that help prevent obesity. The child acquires points after completing each quest, which adds a motivational aspect. The platform sends feedback to children and parents for monitoring their daily and weekly performance.	Demonstrated the efficacy of a mobile service with a comprehensive intervention program by measuring anthropometric parameters, such as body weight, height, BMI, and percentiles.
3	Argarini et al., 2020[37]	Moderate-intensity exergaming	12 exercises (30–40 min per session) 3 sessions per week for 4 weeks	All measurements were made three days before the first exercise and after exercise, except energy expenditure. Exergaming was played using Microsoft Xbox 360 and Kinect Consoles. Game types: Kinect Dance and Kinect Sports.	Normal distribution with no significant difference between boys and girls. Regular moderate exergaming for 4 weeks in obese and overweight children can reduce BMI and improve fundamental movement skills.
4	Adamo et al., 2010[38]	Interactive video game with stationary cycling	10 weeks	Divided into two groups: (1) interactive video game and stationary cycling (GameBike) and (2) stationary cycling and music.	Similar improvements were observed in the body composition. Cholesterol profiles and fitness in both music and cycling as well as stationary cycling while playing video games in overweight and obese teenagers resulted in improved attendance and a robust concentration of physical activity.

(*Continued*)

Table 2 (Continued).

Study Number	Author, Year	Intervention	Intervention Duration and Intensity	Intervention Strategy	Key Findings
5	Staiano et al., 2018[39]	Exergaming using a gaming console	1 h per session, 3 sessions a week for 24 weeks	Randomized group: • Four exergames using Kinect and Xbox 360 gaming console. • A FitBit Zip was worn during the 24-week period. • Regular meetings with a fitness coach to keep the child motivated. Control group: • Maintained their regular physical activity. • Xbox given at final clinical visit.	BMI z-score, cardiometabolic health, and physical activity levels all improved when performed at home regularly.
6	Ruggiero et al., 2020[40]	Exergaming and educational exercises	Not available	Physical activity and nutrition education combined into technological game created to encourage youth for healthier behavioral change to combat obesity. The educational exergame "MyPlatePicks" promoted movement, delivered knowledge, improved motivation, and changed behavior associated with healthy eating and physical activity.	Initial evaluation showed positive results, changes in physical activity, and healthy eating behavior.
7	Trost et al., 2014[41]	Active gaming and educational program	8–16-week study	A family-based pediatric weight management program (JOIN for ME) was provided to the participants. Gaming console and motion capture device with two activity games were given to the activity group. Console was given to the program group only after program completion.	Adding active video gaming for pediatric weight management curriculum showed promising effects on the activity and weight.
8	Staiano et al., 2017[42]	Dance-based exergaming	1 h per session, 3 sessions per week for 4 weeks	Kinect for Xbox 360 used for dance-based exergaming using Just Dance and Dance Central. Attendance was encouraged, and motivation to exercise was performed by providing incentives. Control group maintained their normal level of activity.	Bone mineral density increased and body fat reduced.

(*Continued*)

Table 2 (Continued).

Study Number	Author, Year	Intervention	Intervention Duration and Intensity	Intervention Strategy	Key Findings
9	Maddison et al., 2011[43]	Active video games	24 weeks	Intervention group used the following hardware: EyeToy camera, Dancemat, and active video games. Control group used their usual video game. Outcome measure was BMI.	A small but considerable impact on BMI and body composition was observed with active video game intervention.
10	Duman et al., 2016[44]	Active video games	3 days per week for 8 weeks	Aerobic exercises with music and active video games were used, and BMI was measured after 8 weeks. Data collected were then analyzed using SPSS 18.0 program.	Exercise program along with active video games showed promising effects as well as a constructive impact on self-respect and psychological wellbeing.
11	Wagener et al., 2012[45]	Dance-based exergaming	3 sessions (40 min per session) per week for 10 weeks	Participants (2–3) stood on dance pads with colorful arrows placed out in a cross shape. Feet were used to hit arrows corresponding to musical and visual cues displayed on the screen.	Increased competence to exercise regularly.
12	Coknaz et al. 2019[46]	A parallel RCT to evaluate the effect of physical fitness, reaction times, self-perception and enjoyment levels by active video games in inactive and technologically preoccupied children	12 weeks	Active games was used as intervention for children from 3 schools and 1 school was a control group. Primary outcomes were weight, body mass and fat ratios.	Active video games led to a reduction in weight gain. They are also beneficial tools in diverting children from inactivity thus preventing obesity.
13	Gao et al. 2019[47]	Home-based educational exergaming intervention effects on preschoolers.	12 weeks	The participants were divided into intervention and control groups. The intervention group did exergaming on Leap TV gaming console control group continued with their regular physical activities,	Home-based educational exergaming may positively impact cognitive flexibility in preschoolers.
14	Curiel et al., 2020[48]	Video game FoodRateMaster to improve knowledge regarding food and encourage healthy eating behavior	12 sessions in 6 weeks	Gaming was used to improve nutritional knowledge and apply techniques to bring about behavioral change, increase awareness of unhealthy and healthy foods, and improve consumption of healthy food. This active game increases physical activity.	Positive outcome was observed as children showed improved food knowledge before and after the game. Parents gave positive feedback and reported that they observed changes in eating habits in their children.

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Table 2 (Continued).

Study Number	Author, Year	Intervention	Intervention Duration and Intensity	Intervention Strategy	Key Findings
15	Nawi et al., 2015[49]	Educational information given via internet and pamphlets	12 weeks	Internet-based intervention ObeseGo! was used in a randomized group (healthy lifestyle and diet information were provided via the internet). Control group was given pamphlets containing health education material.	ObeseGo! showed minimal effect in the reduction of BMI, waist circumference, and percentage body fat.
16	Rio et al., 2019[50]	Physical activity, vocation projects, and training sessions	3 years	Along with training, weekly group sessions on eating healthy as well as health education were conducted using active video games. Vocal projects were created to identify healthy activities using virtual platforms.	Improvements in understanding and obedience to the Mediterranean diet were observed in the experimental group.
17	Chen et al., 2019[51]	Web-based behavior program	8 months	Web-based program to improve self-efficiency for enhancing the understanding and use of problem-solving skills in relation to nutrition and physical activity. An interactive dietary training software program (The Wok) was custom-made according to common Chinese food and was used by participants to check the nutritional information. Internet information included voice overs, graphics, and comics.	Decreased waist-to-hip ratio, reduced blood pressure, increased the intake of vegetables and fruits, increased physical activity, and increased knowledge about nutrition.
18	Rerksuppaphol et al. 2017[52]	Internet based obesity program for obesity prevention in Thai school children	Four months, monthly	Healthy children were randomized to intervention (internet based) program or the control group. Anthropometric characteristics were screened at baseline and for four months in monthly intervals. Changes in the percentage of overweight/obese children and changes in BMI at the end of study were the primary and secondary outcome, respectively	Internet the based obesity prevention program was effective and helped in addressing the rising obesity in children.

(*Continued*)

Table 2 (Continued).

Study Number	Author, Year	Intervention	Intervention Duration and Intensity	Intervention Strategy	Key Findings
19	Nystrom et al. 2017[53]	Mobile health (mHealth) obesity prevention program on body fat, dietary habits, and physical activity in healthy children	6 months	p. 6-month mHealth program. Where the primary outcome was fat mass index (FMI), whereas the secondary outcomes were intakes healthy and unhealthy foods and time spent being non-active and in moderate-to-vigorous physical activity	No difference between the intervention and control group but post intervention the intervention group showed higher composite score than the control group, especially in children with a higher FMI
20	Hammersley et al. 2019[13]	Internet and email based intervention lifestyle program	11 weeks, 6 months follow up	11-week internet-based healthy lifestyle program, by fortnightly emails for 3 months for intervention group. Comparison participants received email communication only. BMI was the primary outcome.	eHealth childhood obesity prevention improved dietary-related practices and self-efficacy but did not reduce BMI.
21	Fiechtner et al., 2016[54]	Monitoring behavior	1 year	CDS system used by clinicians. Family self-guided changes in behavior and coaching for health. Results were recorded as a change in BMI z-score as well as in the intake of sugar-based drinks, fruits, and vegetables.	Distance to a supermarket <1 mile and intervention improved fruit and vegetable consumption by 0.29 portions per day and reduced BMI z-score by 0.04 units compared with controls.
22	Lingren et al., 2016[55]	ML-based algorithms	Not available	ML- and rule-based algorithms from structured and unstructured data from two electronic health record databases were developed to detect severe early childhood obesity and high long-term risk of developing obesity-related comorbidities.	Precision was stressed in the high-fidelity group. The rule-based algorithm achieved the best overall results.
23	Rios-Julian et al., 2017[56]	ML-based algorithms	Not available	The study evaluated the practicability of an automated screening tool for diagnosing obesity using anthropometric variables and an ML approach.	High capacity shown by classifiers for assessing whether or not the participant was overweight.
24	Fergus et al., 2015[57]	ML-based algorithms	Not available	Activities were evaluated using data recorded from wearable accelerometer sensors in free-living environments. Physical activity and assessment was performed using a multilayer perceptron neural network for the classification of physical activities by the type of activity.	Overall accuracy, 96%; sensitivity, 95%; specificity, 99%.

(*Continued*)

Table 2 (Continued).

Study Number	Author, Year	Intervention	Intervention Duration and Intensity	Intervention Strategy	Key Findings
25	Dugan et al., 2015[58]	ML-based algorithms	Data collected over 9 years	An algorithm was used to predict obesity in children aged >2 years with data accumulated before the second birthday using CHICA. Six ML techniques were used: RandomTree, RandomForest, J48, ID3, Naïve Bayes, and Bayes.	Accurate model was created.
26	Balbir et al., 2020[59]	ML-based algorithms	Not available	Overweight or obesity prediction for young people using ML techniques.	Approximately 90% accuracy in prediction for the target class was attained.

Abbreviations: BMI, body mass index; CDS, computer decision system; CHICA, Child Health Improvement through Computer Automation; ML, machine learning; PE, physical education; RO2, Running Othello.

exercise, self-regulation, and BMI compared with a wait-list control group. A statistically significant increase in the perceived ability to exercise was found based on self-reporting by the participants in the intervention group compared with the control group. However, no major variations were found for BMI z-score.

Duman et al[44] used aerobics along with music and video games in their eight-week study and found a positive outcome in the final measurements with the exercise program using video games. Maddison et al[43] investigated the effect of video games on physical activity and fitness compared with standard video games. They found a decrease in BMI and BMI z-score of active group participants compared with the children in the control group.

Web-Based/Mobile-Based Studies

Eight studies[13,36,48–53] used interventions based on internet or smart phone applications. Yang et al[36] developed a mobile-based HAPPYME platform that asks students to complete quests involving physical activity and healthy eating habits. The platform sends feedback to their parents who can then monitor the performance. Curiel et al[48] developed a video game-based mobile application that enabled participants to complete quests based on physical activity and healthy eating. Another study by Nawi et al[49] used the internet-based intervention ObeseGo! that provides information about healthy lifestyle and diet nutrition via the internet. This intervention showed no significant effect on BMI scores. Chen et al[56] developed a web-based program that comprised self-assessment activities to determine problem-solving skills and an interactive software program customized to Chinese food that allowed the user to check nutritional information about the food they ate. Fiechtner et al[54] developed a computerized clinician decision support system that monitored family behavior and found that living within one mile of a supermarket encouraged healthy eating habits.

ML-Based Studies

Five studies[55–59] used ML-based strategies for their interventions. Lingren et al[55] created both rule-based and ML-based algorithms using structured and unstructured data from two large electronic health records to detect severe early childhood obesity and children at a long-term risk of developing complications. The rule-based algorithms performed better overall. Rios-Julian et al[56] used ML to estimate the feasibility of developing an automated screening tool for diagnosing obesity using anthropometric variables. Fergus et al[57] used a wearable accelerometer to collect data that was used to evaluate physical tasks, and a multilayer perceptron neural network was used to classify physical activities according to type of activity. Dugan et al[58] used ML on the collected data to develop an algorithm that could predict childhood obesity in children aged >2 years using data collected before their second birthday. Six different ML

Table 3 Quality Assessment of Included Studies

Sno	Author, Year	Q1	Q2	Q3	Q4	Q5
1	Lindberg et al., 2016[35]	Y	Y	Y	N	N
2	Yang et al., 2017[36]	Y	Y	Y	Y	N
4	Argarini et al., 2020[37]	N	Y	Y	Y	N
5	Adamo et al., 2010[38]	Y	Y	Y	Y	N
6	Staiano et al., 2018[39]	Y	Y	Y	Y	N
7	Ruggiero et al., 2020[40]	Y	Y	Y	?	N
9	Trost et al., 2014[41]	Y	Y	Y	Y	N
10	Staiano et al., 2017[42]	Y	Y	Y	Y	N
19	Maddison et al., 2011[43]	Y	Y	Y	Y	N
20	Duman et al., 2016[44]	Y	Y	Y	Y	N
12	Wagener et al., 2012[45]	Y	Y	Y	Y	N
24	Coknaz et al. 2019[46]	Y	Y	Y	Y	N
26	Gao et al. 2019[47]	Y	Y	Y	Y	N
3	Curiel et al., 2020[48]	Y	Y	Y	Y	N
8	Nawi et al., 2015[49]	Y	Y	Y	Y	N
11	Rio et al., 2019[50]	Y	Y	Y	Y	N
21	Chen et al., 2019[51]	Y	Y	Y	Y	N
22	Rerksuppaphol et al. 2017[52]	Y	Y	Y	Y	N
23	Nystrom et al. 2017[53]	Y	Y	Y	Y	N
25	Hammersley et al. 2019[13]	Y	Y	Y	Y	N
13	Fiechtner et al., 2016[54]	Y	Y	Y	Y	N
14	Lingren et al., 2016[55]	Y	Y	N	Y	Y
15	Rios-Julian et al., 2017[56]	Y	Y	N	?	Y
16	Fergus et al., 2015[57]	Y	Y	N	?	Y
17	Dugan et al., 2015[58]	Y	Y	N	?	Y
18	Balbir et al., 2020[59]	Y	Y	N	?	Y

Notes: Q1, studies with sample size >20; Q2, studies with age details; Q3, studies with the sample characteristic; Q4, studies with intervention duration >3 weeks; Q5, studies with machine learning /artificial intelligence/robots.

techniques, namely, RandomTree, RandomForest, J48, ID3, Naïve Bayes, and Bayes, trained using the Child Health Improvement through Computer Automation system data showed that a precise, sensitive model could be formed. Balbir et al[59] developed ML algorithms to predict the risk of young people becoming obese in the future with a 90% accuracy.

Discussion

The objective of this systematic review was to assess the use of technology-based interventions in the management and prevention of childhood obesity and evaluate the use of ML and other technological strategies. Various technologies have

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been used, including video game-based interventions, mobile-based interventions, web-based interventions, phone communication-based interventions and machine learning-based interventions. It is important to note that along with these, multicomponent mediations, including both dietary intake and physical activity, are required to effectively overcome obesity.

Various parameters, such as BMI, body fat percentage, weight, heart rate, and BMI z-scores, have been used in these interventions to measure the progress and success of the interventions. Among the 26 studies under review, 21 studies showed positive significant outcomes on their respective outcome measures.

The present review classified the selected literature broadly into three categories: active video games or exergaming; internet or mobile-based interventions; and ML-based interventions. The two categories of web- or internet-based and mobile-based strategies were combined as one. The search did not yield any articles based on robot-based techniques to manage obesity in children; therefore, no such studies were included for that category, but one study[60] was found to be using a social robot to manage and spread awareness about obesity in children of Saudi Arabia; however, since it was not an RCT or an intervention with outcomes, it was not included in the review literature.

Because of the complex etiology of childhood and adolescence obesity and the diversity of its possible influencing factors (eg, biological, psychological, dietary, behavioral, and cultural), conventional statistical methods, relying on linear models, have limitations as the analyses they offer typically have a limited predictive power. Most cases use the same prediction values transformed slightly, and it is difficult to find models capable of handling multidimensional data. In contrast, ML-based strategies are valuable tools for multidimensional datasets that involve complex relationships among multidomain variables. ML techniques can search for complicated nonlinear relations between prediction variables and response variables in an automated manner and do not require manual predefinition.[61] Thus, the predictivity, ease of use, and robustness of ML-based models are superior to those of conventional models.[36] Five studies incorporated ML strategies in their interventions. Most of these studies scanned existing electronic health records to prevent or detect obesity. Lingren et al[55] detected severe cases of childhood obesity, and Rios-Julian et al[56] determined the possibility of developing automated screening tools to detect obesity based on anthropometric variables using ML. Dugan et al[58] and Singh et al[59] developed algorithms to predict obesity in children and youngsters.

If a comparison is to be made between ML-based techniques and the other technological methods, it is difficult at this point in the research as ML studies are more focused on screening the databases to identify patterns, which can help in prediction and other strategies involving a different approach by various methods of training, games and information communication. It is not possible to compare two entirely different methods with different objectives, even though the main objective stands in managing and prevention of obesity, the method used is vastly different for them. Since the search did not reveal any AI and robot-based interventions, it can be concluded that this area has a lot of potential for future and needs to be actively researched.

On observing closely most of the studies, it can be broadly recognized as preventive, educational, activity-based, data screening, and treatment-based studies. It was perceived that the preventive and educational interventions were focused more on making the participants aware of the different kinds of food and their impacts on the body. They used various gaming methods to educate children, or internet/telephone-based methods to make children aware of the evil effects of unhealthy foods, high sugar diets, etc. They also highlighted the importance of physical activities and their rewards.

Michie[62] outlines effective techniques in healthy eating and physical activity interventions, stating what makes an intervention effective in successfully changing the lifestyle or behavior of the participants for the better. These were the basic techniques according to S. Michie to bring about change in behavior: formation of an intention, setting up a specific goal, providing performance feedback, behavior self-monitoring and behavior goal reviews. Most of our studies did follow this pattern to some extent, where they had a targeted goal, set up intervention, tracked performance and feedback was taken even after post-intervention to assess self-monitoring efficacy.

Activity-based intervention were focused on exergaming, which kept children engaged and motivated to continue the program. The games came with levels and rewards, which kept the child interested and as a result, continued to play games. These activity-based methods were used for both managing obesity and in prevention strategies.

Even though varied in nature, the studies included mostly had very similar primary outcome measures like BMI score, body fat, BMI-*z* score, physical activity duration, weight measures, etc. Most studies focused on both the genders and did not do any gender-specific study except one study, which was a female-based study.[42]

The studies included in this review were of average quality, as only 5 of the 26 studies used ML or advanced techniques to detect or prevent obesity and did not specify the intervention duration. Furthermore, five studies did not define the characteristics of the participants. None of the studies used simple robots (without AI) or AI-based robots for the management of childhood obesity.

Overall, it can be seen that these different approaches to cater well to the childhood obesity issue have been effectively using technologies to keep children engaged and motivated when carrying out the required activities. Overall, it can be seen that these different approaches to cater well to the childhood obesity issue have been effective using creative methods to keep children engaged and motivated to carry out the required activities, using standard measures as primary outcomes, it gives a standardized way of evaluating the efficacy of each of these studies. Most studies showed positive results in both preventive and management-based approaches.

However, children require a different type of care than elderly people, and robots may be a good platform to fulfill these unique needs.[63,64] Diseases, such as cancer and diabetes, can disrupt a child's normal life, affect their social needs, and pose various challenges during the treatment of illness and change in lifestyle, which in turn also affect the mental health of the child.[65,66] Social robots may prove to be helpful in the management of chronic illnesses because they can provide effective support through encouragement, education to adhere to healthy behaviors, and entertainment useful to mitigate stress thereby providing a sense of comfort and companionship.[67] As such, robots have been shown to be helpful for treating various conditions,[68] and it is reasonable to expect that they can have similar effects on the treatment of obesity, helping children emotionally and motivating them and subsequently leading them to a healthier lifestyle. While ML helps screening datasets to identify children at risk and make predictions about their condition, AI and robotics could be used to develop user-centric strategies based on the real-time customization of the treatment program.

Conclusion

Although almost all the studies analyzed were statistically sound and showed positive outcomes, our review shows that this area still lacks the use of robots and AI-based technologies.

A more efficacious intervention should be developed in the future by combining a more diverse set of techniques. Studies should focus on the positive aspects of each category and develop an integrated system where there is a physical entity, such as a robot with AI and ML capabilities, that can conduct a physical activity program for the participants and educate them regarding good eating habits. These robots can be implemented with adaptive and real-time feedback techniques, making it easier to monitor the progress in real-time from home. Most of the studies included in the present review showed positive statistical outcomes. Exergaming is the most popular strategy among the literature published in the past 10 years. Thus, our review indicates that technology-based interventions have great potential in terms of efficacy in monitoring and managing obesity in children and adolescents, but its potential has not been reached. This area of research still lacks AI and robot-based interventions, which could be combined with exergaming and ML techniques to maximize their effectiveness and establish a strategic synergy to promote children's health. As for the future direction, we are currently at the stage of introducing an adaptable intelligent robot that can personalize the extent of interaction based on the child's personal interest and level of obesity. Such personalization could enhance the benefits of using robots in the management of childhood obesity.

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