# Chapter 5
# Predictive Modeling for Obesity and Overweight in Adolescents, Current Status and Application to the MENA Region

**Kinda Khalaf, Dhanya Menoth Mohan, Nour El Asswad, and Fatme Al Anouti**

## Key Highlights

- Context
  - Adolescent obesity is highly prevalent in the Middle East and North Africa and has been mostly attributed to the rapid urbanization and the sudden transition in nutrition and lifestyle.
  - Predictive models for adolescent obesity are important for prevention and are used to calculate the risk of an adolescent of becoming overweight or obese in the future.
- Objectives
  - To highlight the multifactorial aspects of adolescent and childhood obesity.

K. Khalaf (✉) · D. M. Mohan
Department of Biomedical Engineering, Khalifa University, Abu Dhabi, United Arab Emirates
e-mail: kinda.khalaf@ku.ac.ae; dhanya.mohan@ku.ac.ae

N. El Asswad
Department of Biology, University of Toronto, Toronto, ON, Canada
e-mail: nour.elasswad@mail.utoronto.ca

F. Al Anouti (✉)
College of Natural and Health Sciences, Zayed University, Abu Dhabi, United Arab Emirates
e-mail: Fatme.AlAnouti@zu.ac.ae



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  - To propose a suitable predictive tool for estimating overweight/obesity among adolescents specifically within the MENA.
- Methodology
  - Several databases were used to retrieve literature about adolescent obesity and predictive algorithms/models between the years 2015 and 2020 in MENA adolescent populations.
  - A list of potential predictors and risk factors for suitable future implementation and validation were identified and used to propose a predictive model.
- Key Findings
  - There is a lack of an accurate population-based predictive algorithms for obesity for this target group.
  - Based on literature review, it has been identified that sociodemographic factors, physical activity, diet, screen time, parental obesity, family history of obesity, and duration of sleep are the important risk factors applicable to the MENA population.
- Conclusion and Implications
  - Based on a holistic approach of integrating relevant main risk factors, we proposed an obesity predictive model that could be valuable for informing policy-makers in the region and helping them set up effective national and regional surveillance systems.
  - Future work includes exploring machine learning-based powerful prediction algorithms for adolescent obesity and overweight by acquiring and incorporating a population-specific vast amount of clinical data.
  - The need to examine the various predictive algorithms in the context of different obesity indicators, in addition to BMI, remains an important aspect for establishing a valid predictive model for adolescent obesity.

## 5.1 Introduction

### *5.1.1 Prevalence of Overweight and Obesity*

With more than two billion people (30% of the world's population) overweight or obese and an annual cost of $2.1 trillion, obesity poses severe global health and economic (World Health Organization 2020a). Comprising the fifth leading risk factor for mortality in the world (around 3.4 million annual deaths), obesity significantly increases the risk for developing numerous chronic diseases, including coronary heart disease (by over 50%), ischemic stroke (by 44%), type 2 diabetes (by 23%), as well as many cancers (up to 41%) (World Health Organization 2020a). According to the McKinsey Global Institute (MGI), a devastating $2.1 trillion, or

2.8% of global GDP, is spent on obesity-related health problems annually but less than 1% on prevention (McKinsey Global Report 2015). The problem is expected to worsen, where almost half of the world's adult population is expected to be overweight or obese by 2030 (McKinsey Global Report 2015). The global trend of sustained growth in obesity prevalence indicates that the current measures in the prevention, treatment, and management of the condition are largely ineffective.

The World Health Organization (WHO) 2020 data reveals that the UAE currently ranks fifth in the world in obesity at a prevalence rate of 36% (33% males and 39% females). Three in every ten Emirati males and almost four out of every ten females are obese, with an economic burden amounting to $6 billion/year in associated disease cost (McKinsey Global Report 2015). If we also include the percentage of overweight individuals, based on the most recent Global Burden of Disease report (World Health Organization 2020a), more than 60% of men and 66% of women in the UAE are currently overweight or obese (average of 63% or more than double the global average of 30%). Furthermore, while the UAE slightly fares better than the USA in adult obesity prevalence (US current rate is 38%), Emirati children are 1.8 times more obese than their American counterparts. This reveals a dangerous future trend and prognosis, particularly considering the very young median age of the population (30.3 years), since obesity is an independent risk factor for both T2D and CVD, the major culprits for mortality and morbidity in the UAE (Health Authority Abu Dhabi 2016).

### *5.1.2 Overweight and Obesity Among Adolescents*

In the last couple of decades, the prevalence of obesity has substantially increased during adolescence, a unique stage of human development and a critical time for maintaining good health while experiencing rapid physical, cognitive, and mental growth (World Health Organization 2020a). In 2016, over one in six adolescents aged 10–19 years, worldwide, were overweight (World Health Organization 2018). The WHO defines adolescence as the phase of life between childhood and adulthood, from ages 10 to 19 years old. According to the WHO global data, the prevalence of overweight and obesity among children and adolescents has dramatically risen from 4% in 1975 to approximately 18%, with a total of 340 million obese adolescents in 2016 (World Health Organization 2020a). Importantly, obesity-related diseases are also increasing sharply among adolescents, where three-quarters of all deaths by the year 2020 are expected to be due to non-communicable diseases (World Health Organization 2020a).

In the Middle East region, especially the Gulf Cooperation Council (GCC) countries (UAE, Saudi Arabia, Kuwait, Bahrain, Oman, Qatar), the prevalence of overweight and obesity among adolescents is considered among the highest in the world (Farrag et al. 2017). Musaiger et al. (2012) reported a relatively high percentage of overweight among adolescents (15–18 years) in all studied countries (Algeria, Jordan, Kuwait, Libya, Palestine, Syria, and the United Arab Emirates), ranging from 9.3% in Algeria to 25.6% in Kuwait. Furthermore, several studies indicate that while the prevalence of childhood obesity in the Middle East and GCC is higher among males (Farrag et al. 2017; Musaiger et al. 2013), obesity prevalence among females is quite high when compared to other countries (Al Hammadi and Reilly 2019). The high prevalence of adolescence obesity in the Middle East and GCC has been mostly attributed to the rapid urbanization, which has led to sudden transition in nutrition and lifestyle (Musaiger et al. 2013). A relevant example is the United Arab Emirates (UAE), where the prevalence of obesity and overweight in adolescence has increased by two- to threefold from 1975 to 2017 (Baniissa et al. 2020; AlBlooshi et al. 2016). Al Hammadi and Reilly (2019) used the WHO definition of obesity and identified more than one-third of the sample in the secondary school-age participants as obese or overweight, indicating an increase in prevalence associated with increasing age. According to AlBlooshi et al. (2016), obesity was investigated in the UAE using different methods for BMI interpretation with different outcomes for the same population (6–17 years old), and hence obesity trends in the UAE among adolescents remain unclear.

### *5.1.3 BMI-Based Obesity Assessment: Implications and Its Limitations*

The main tool currently used worldwide for the assessment of obesity is the body mass index or BMI. Defined as the ratio of the weight of an individual (kg) divided by the square of their height ($m^2$), a BMI ratio of >25 indicates overweight, while that of >30 defines obesity (Centers for Disease Control 2020). Developed in the mid-1800s, there are some issues regarding BMI's validity for obesity assessment and associated chronic disease prediction (Centers for Disease Control 2020; National Institute of Health). For example, BMI does not take age, sex, bone structure, fat distribution, or muscle mass into consideration, all potentially important factors in obesity disease prediction. In general, there are three main sources of error when using BMI: (1) BMI is an indirect measure of obesity, (2) errors in self-reported data, and (3) the poor sensitivity and specificity of BMI. Moreover, there is now strong evidence that the cutoffs of BMI, provided by the WHO, do not adequately reflect the overweight or obesity status of all ethnic populations (ACOG committee opinion 2017). For example, a higher body fat percentage is correlated with lower BMIs among Asians, while among Pacific Islanders, higher BMIs are associated with more muscle mass and less body fat (Wang et al. 2006). Most importantly, BMI has been shown as an unreliable predictor of the risk of chronic diseases associated with obesity, such as cardiovascular and type 2 diabetes (T2D) (ACOG committee opinion 2017). Disagreement on the optimal cutoffs linking BMI to disease risk is cited as one of the main reasons behind ineffective early disease prediction and subsequent intervention (Akhabue et al. 2018).

Based on BMI, obesity is divided into three classes: class 1, BMI ranges from 30 to <35; class 2, BMI ranges from 35 to <40; whereas, class 3 is considered as extreme or severe obesity with BMI at 40 or higher (Centers for Disease Control 2020; National Institute of Health). However, adopting one standard universal concept for obesity is not sufficient.

### *5.1.4 Risk Factors of Adolescent Obesity*

A multifactorial condition, obesity is the result of an intricate interplay between genetic, environmental, and inflammation factors with severe functional implications on the neuromusculoskeletal system. Indeed, the literature is rich with many of these factors, including genetics, ethnicity, hormonal and metabolic disorders, adipose tissue distribution imbalances and inflammation, pathogens including viruses and microbiomes, mental stress, sleeping disorders, the effects of high income and urbanization, as well as built environment characteristics including fast food restaurants, available transportation, and lack of walkability (Hruby and Hu 2015). Additional risk factors, which can be detected as early as infancy and early childhood, include high birth weight, rapid weight gain, little or no breastfeeding, early introduction of solid food, maternal and paternal obesity, and maternal smoking during pregnancy (Redsell et al. 2016).

### *5.1.5 Obesity Prediction Models: Relevance and Application*

Despite the work on many aspects of obesity, remarkably few studies have addressed its multifactorial nature, while fewer devised quantitative predictive measures. Predictive measures of obesity are key to prevention, which is a good approach to tackle the burden of obesity since it is difficult to reverse once established. Predictive models for adolescents are used to calculate an adolescent's risk of becoming overweight or obese in the future (Butler et al. 2018). Models that have good sensitivity and specificity should differentiate between high-risk individuals and low-risk individuals. Sensitivity is defined as a model's ability to correctly predict (within an acceptable error) individuals who have or may develop obesity. On the other hand, specificity refers to a model's ability to correctly predict the individuals who do not have or will not develop the condition (Butler et al. 2018). Rautiainen and Äyrämö (2019) analyzed studies which used different types of predictive models of overweight/obesity between the ages of 2 and 33 years, including logistic regression, decision trees, Bayesian, and neural networks and support vector machines. A number of features were used to predict obesity at a certain age, such as gender, height, weight, maternal pre-pregnancy weight status, paternal BMI, maternal smoking during pregnancy, breastfeeding during the first year, number of household members, etc. (Rautiainen and Äyrämö 2019). Several predictive models are available for different populations. However, to the best of the authors' knowledge, there are no published work to date that address overweight/obesity predictive algorithms for the

MENA region, including the GCC in spite of the high prevalence and early onset of obesity and associated non-communicable disease in the region. The main objective of this chapter is to review the available obesity models and algorithms toward proposing a suitable predictive tool for estimating overweight/obesity among adolescents, specifically within the MENA. In particular, this chapter highlights the following:

1. A review of various predictive modeling algorithms applicable for overweight/obesity prediction among adolescents
2. Obesity risk factors relevant to the MENA region
3. A list of potential predictive modeling approaches for future implementation and validation for the MENA region

## 5.2 Methodology

### *5.2.1 Search Strategy*

A literature search was conducted within the databases of Google Scholar, Scopus, Web of Science, and PubMed using the following terms: (1) “obesity” OR “overweight” OR “excess weight” OR “BMI” OR “body mass index,” (2) “childhood” OR “adolescent” OR “child,” (3) “risk factors” OR “lifestyle” OR “socioeconomic” OR “diet” OR “predictors” OR “nutrition” OR “sociodemographic” OR “physical activity” OR “health,” (3) “Region” (“Algeria” OR “Bahrain” OR “Egypt” OR “Iran” OR “Kuwait” OR “Lebanon” OR “Morocco” OR “Oman” OR “Palestine” OR “Qatar” OR “Saudi Arabia” OR “Syria” OR “Tunisia” OR “Turkey” OR “United Arab Emirates” OR “Yemen” OR “Middle East and North Africa” OR “MENA” OR “gulf”), and (4) “prediction model” OR “data mining” OR “predictive” OR “algorithm” OR “machine learning” OR “big data.” The articles were first screened for title, followed by abstract when it was difficult to include/exclude the same based on the title. All articles published in English within the last 20 years (2000–2020) which met the inclusion criteria were selected. The full text of the published articles was retrieved and further studied.

### *5.2.2 Inclusion and Exclusion Criteria*

Papers were included if they addressed (1) the design and implementation of predictive algorithms or prediction tools aimed at predicting adolescent overweight/obesity, (2) the risk factors associated with overweight/obesity among adolescents in the MENA region, and (3) sample population of adolescents aged 10–19 years. Studies involving subjects outside the age limit, as well as those investigating the outcome of subjects receiving special medication, were outside the scope of this review.

### 5.2.3 Data Extraction

The articles were reviewed to understand the different algorithms available for predicting adolescent obesity and/or overweight. Tools that have been implemented for different cohorts, including the MENA were hand-searched. The characteristics of the articles, including author, year, country, study population characteristics in terms of age, BMI, and outcome measures, are tabulated (Table 5.1).

For a particular model, identification of a set of predictors, for example, in this context, the risk factors associated with overweight/obesity, is key to its success. With the aim to propose a suitable prediction model for the MENA, an additional search was conducted to identify articles that estimated various risk factors associated with overweight and obesity among adolescents in the MENA region (see Table 5.2). Sixteen countries/territories which constitute the vast majority of this region were considered in this review. These regional studies have identified a number of independent variables, including anthropometric, sociodemographic, socioeconomic, as well as clinical factors as well as association with the dependent variable, i.e., obesity.

In summary, the purpose of the search was to identify the most relevant predictive algorithms for adolescent overweight/obesity, as well as to propose a list of potential predictors/risk factors particular to the MENA region for proper future implementation and validation.

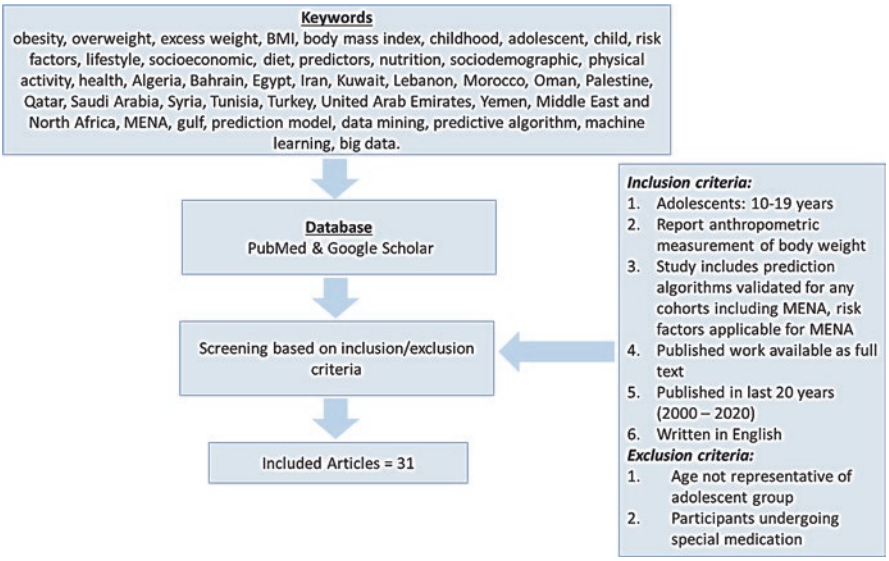


**Fig. 5.1** Flow diagram of the search strategy

**Table 5.1** Literature on overweight/obesity predictive algorithms applicable for adolescents

| Study and dataset/cohort | Input features | Input data recorded at | Prediction model | Prediction outcome | Prediction age | Model performance |
|---|---|---|---|---|---|---|
| Morandi et al. (2012), Finland | Gender, birth weight, gestational weight gain, pre-pregnancy and gestational smoking of mother, BMI and professional category of parents, single parenthood, number of household members | Newborn and parental data | Stepwise logistic regression | Overweight and obesity | Childhood (7 years), adolescents (16 years) for sample development | Adolescent obesity: AUC = 0.75 [0.71–0.79], $p < 0.001$<br>Adolescent overweight/obesity: AUC = 0.71 [0.69–0.73], $p < 0.001$ |
| Pei et al. (2013), German | Birth weight, standardized BMI at the age of 5, education status of parents, gestational smoking of mother, family income | Birth to 5 years and parental data | Logistic regression models | Overweight | 10 years | Mean values of:<br>Sensitivity = 37.1%<br>Specificity = 96.5%<br>PPV = 72.5%<br>NPV = 86.1% |
| Riedel et al. (2014), German | BMI category at 6 years, mother's obesity, and education level | 6 years and parental data | Classification and regression tree | Overweight/obesity | 14 years | BMI ≥ P75 at the age of 6 explained 63.5% [95%CI: 51.1;74.5] and 72.0% [95%CI: 60.4;81.8] of overweight/obesity at the age of 14 in boys and girls, respectively |
| Jator (2014), existing Medical Expenditure Panel Survey (MEPS) data | Age, gender, race, family income | 12–17 years | Modified logistic model, concentration index | Degree of obesity inequality | 12–17 years | n/a |

| Study and dataset/cohort | Input features | Input data recorded at | Prediction model | Prediction outcome | Prediction age | Model performance |
|---|---|---|---|---|---|---|
| Graversen et al. (2015), Finland | Birth weight, maternal BMI, childhood BMI | Birth, 5 years, 8 years | Logistic regression | Overweight including obesity | 13–16 years | Sensitivity:<br>Birth (F/M): 24.0/ 17.4%<br>5 years: 38.9/28.2%<br>8 years: 49.2/38.7%<br>Specificity:<br>Birth: 92.1/91.7%<br>5 years: 94.4/94.2%<br>8 years: 96.0/96.7% |
| Hudda et al. (2019), UK | Weight, height, age, sex, ethnic group | 4–15 years (development dataset), 11–12 years (external validation dataset) | Multivariate linear regression | Fat mass | 4–15 years, 11–12 years (external validation) | Optimism adjusted $R^2$: 94.8%, 95% confidence interval 94.4% to 95.2%<br>External validation: $R^2$:<br>90.0%, 95% confidence interval 87.2–92.8% |
| Kim et al. (2019), Korean | Region, academic_performance, pressure, suicide_thought, sleeping_quality, drinking, smoking, education_father, education_motherwealth, pocket_money, healthy eating, unhealthy_eating, exercise_60 min, exercise_20 min, sitting_time_study(min), smartphone_time(min), smartphone_service, obesity_level | Adolescents (12–18) | General Bayesian network embedded with Markov blanket | Obesity | Adolescents (12–18) | Accuracy: 53.703%, F-measure: 0.535, and AUC: 0.758 |

**Table 5.2** A summary of literature addressing risk factors of adolescent overweight/obesity in MENA

| Country | Study | Criteria | Age | Risk factors |
|---|---|---|---|---|
| Algeria | Allioua et al. (2015) | IOTF | 10–17 | High calories and unbalanced diets, reduced physical activity |
| Bahrain | Musaiger et al. (2014) | Percentiles of National Health and Nutrition ExaminationSurvey-1 (NHANES-1) growth standard | 15–18 | Significant factors include:<br>Mother's education (higher education with obese children) for both male and female<br>Father's education, rank among siblings, burger size and French fries portion, watching TV >3 h/day (males).<br>Protective factors:<br>1. Eating during school breaks, bringing food from home (for female obesity)<br>2. Eating breakfast at home, eating in-between breakfast and lunch, eating between lunch and dinner (for male obesity).<br>Not significant:<br>Intake of vegetables, dairy products, meat, fish, chicken, legumes, canned juices, and chocolates<br>Fast food intake and soft drink size (both male and female)<br>Frequency of consumption of soft drinks and sweets was negatively associated with obesity in males<br>Fruit intake more than thrice a week reduced the risk in males. |
| Egypt | El-Gilany and El-Masry (2011) | CDC | 14–19 | Risk factors include eating starchy food thrice or more per week<br>1. Physical inactivity<br>2. Fast food/snacking/sweets intake ≥3 times/week<br>3. Television viewing ≥ 2 h/day<br>4. Positive family history of obesity<br>Consumption of vegetables/fruits, plant protein, and dairy products ≥3 time/week was protective factor |
| | Talat and El Shahat (2016) | n/a | 12–15 | Low parent education level, skipping breakfast, eating snacks as a substitute, fast food intake, physical activity decline, TV viewing duration >2 h/day, snacking during TV watching |

(continued)

**Table 5.2** (continued)

| Country | Study | Criteria | Age | Risk factors |
|---|---|---|---|---|
| Iran | Abiri et al. (2019) | CDC | 14–17 | Physical activity, computer use, duration of breastfeeding, total sleep time, parental education, economic status |
| Kuwait | Al-Haifi et al. (2013) | IOTF (for 14–17)<br>WHO(for ≥18) | 14–19 | Associated factors are:<br>Physical activity<br>Eating habit: consumption of breakfast (both boys and girls), vegetables (only boys), and fast foods (boys and girls) and potatoes, cakes and doughnuts, and sweets (girls only)<br>No association with:<br>1. Sedentary behaviors, TV viewing, computer usage |
| Lebanon | Nasreddine et al. (2014) | BMI z-score according to the WHO new growth standard. IOTF, CDC | 6–19 (12–19 adolescents) | Positive correlation with male gender, mother's employment status, residence in Beirut, sedentary time, eating fast food, and sugar-sweetened beverages<br>Negative association:<br>1. Borderline significant association between higher physical activity and lower odds of overweight<br>2. Increased intakes of milk/dairy products<br>3. Regular breakfast consumption |
| Morocco (Fez) | El Kabbaoui et al. (2018) | WHO 2007 | 12–18 | Higher education of father or mother, higher family income, motorized transport to school, computer usage >4 h/day, frequent intake of soda and soft drinks<br>No association between overweight/obesity and sleep, TV screen time, physical activity |
| | Nouayti et al. (2020) | IOTF | | Urban residence, father's income (≥ 5000 MAD), and overweight/ obesity, female sex |
| Oman | Waly et al. (2017) | – | 17.2 ± 1.4 | Sedentary lifestyle, unhealthy nutritional habits |
| Palestine | Jildeh et al. (2011) | CDC, IOTF | 11–16 | Less physical activity, lower/ inadequate energy intake |
| | Mikki et al. (2009) | CDC, IOTF | 13–15 | High standard of living among boys, onset of puberty among girls |

(continued)

**Table 5.2** (continued)

| Country | Study | Criteria | Age | Risk factors |
|---|---|---|---|---|
| Qatar | Kerkadi et al. (2019) | IOTF | 14–18 | Significant factors included being male and skipping breakfast.<br>No association between obesity (general and abdominal) and screen time, physical activity<br>Negative association between obesity and intake of unhealthy foods. |
| | Bener et al. (2011) | Qatari growth pattern curves | 6–18 | Watching television for more than 4 h, lack of sleep (5–7 h or less) |
| Saudi Arabia | Al-Hazzaa et al. (2012) | IOTF | 14–19 | Less frequency of vigorous physical activity (in both male and female), skipping breakfast or infrequent consumption of vegetables, frequent consumption of sugar-sweetened beverages |
| | Amin et al. (2008) | According to Cole et al. (2000) | 10–14 males | Urban residence, older age of children, mother's low education status, mother's occupational status, and family size ≤6, consumption of food away from home, infrequent breakfast intake at home, frequent consumption of sweets/candy and carbonated drinks, low servings of vegetables, fruits, and dairy products |
| Syria | Nasreddine et al. (2010) | WHO 2007<br>WHO 1995 and IOTF for comparison | 15–18 | Male gender, positive family history of obesity, increased educational attainment for both parents, lower crowding index than their counterparts, energy consumption from carbohydrate |
| Tunisia | Aounallah-Skhiri et al. (2008) | WHO<br>IOTF for comparison purpose | 15–19 | Males: (Rural area) – working mother, low physical activity<br>(Urban area) – irregular snacking<br>Female: (Rural) – mother's education level<br>(Urban) – not attending school, skipping daily meals |
| | Zarrouk et al. (2009) | Cole et al. (2000) | 8–11 | Physical activity, sedentary time |
| Turkey | Pirinçci et al. (2010) | IOTF | 6–11 | Snacking during television watching, fast food intake |
| | Discigil et al. (2009) | CDC 2000 | 6–16 | High socioeconomic status, preschool care source other than mother<br>No association with gender, adolescence, parental education level, and occupational status of father |

(continued)

**Table 5.2** (continued)

| Country | Study | Criteria | Age | Risk factors |
|---|---|---|---|---|
| United Arab Emirates | Al Junaibi et al. (2013) | CDC | 6–19 | Risk factors include older age, male gender, lack of dairy consumption, higher parental BMI<br>No association with physical activity or family income |
| | Kerkadi et al. (2005) | CDC | 5–14 | Daily intake of breakfast, television watching time more than 2 h/day, parental obesity, physical activity |
| Yemen | Raja'a and Mohanna (2005) | | 10–18 | Private schooling, higher in females, sedentary life style, family history of obesity, education level of father, consumption of unhealthy foods |

## 5.3 Results/Findings

### *5.3.1 Predictive Modeling/Algorithm: An Overview*

With the advent of faster computers, artificial intelligence, and big data tools and methodologies, the concept of predictive modeling has made great strides in healthcare over the past few years. Sophisticated models with accepted levels of accuracy enable healthcare practitioners to devise personalized treatment strategies, as well as early preventive measures in a cost-effective manner. These models use machine learning-based techniques and/or statistical approaches to infer trends in data and predict a future event in real time.

In general, the design and implementation of predictive modeling include four important phases: (i) problem definition and data collection, (ii) model development and internal validation, (iii) model testing in a real-world setting, and (iv) broader dissemination (Cohen et al. 2014). During the initial phase, the problem is defined, and patient data are acquired through electronic health records or other means. A model is then generated using various mathematical relationships, ranging from simple regression methods to complex artificial intelligence-based approaches, such as support vector machines and neural networks. A combination of clinical data is used as input predictors. Further, the model with the highest prediction accuracy is tested and validated on the internal dataset and subsequently on real-world settings. Model validation is considered to be an important phase as it helps the research community to quantify the predictive validity of a model. It explains the applicability of a model derived using one dataset on a completely new dataset (Ivanescu et al. 2016).

### *5.3.2 Predictive Modeling Approaches for Adolescent Overweight or Obesity*

The literature search conducted here identified several prediction tools/algorithms aimed at predicting the occurrence of overweight/obesity in adolescents, considering birth, parental, and/or early childhood data as input features (Table 1). To the best of the authors' knowledge, there are no published works to date that address overweight/obesity predictive algorithms for the MENA region.

Morandi et al. applied stepwise logistic regression analysis on a Northern Finland Birth Cohort and claimed that adolescent obesity could be predicted at birth, with maternal BMI as the strongest predictive candidate and the genetic score as the most modest with regard to the prediction accuracy. This study reported an AUC of 0.75 and 0.71 for adolescent obesity and adolescent overweight/obesity, respectively. In a similar study cohort, Graversen et al. (2015) designed a logistic regression model based on birth weight, maternal BMI, and childhood BMI to predict adolescent overweight and adult overweight/obesity. Internal validation was conducted using the Northern Finland Birth Cohort born in 1966, and external validation was performed on the Northern Finland Birth Cohort born 20 years later, where the prevalence of overweight was high, resulting in satisfactory to good prediction outcomes. Another study developed a similar model using a set of risk factors, including birth weight, standardized BMI at the age of 5 years (60–64 months), parental education, family income, and maternal gestational smoking (Pei et al. 2013). High BMI/overweight at 5 years was found to be a strong predictor of being overweight at 10 years. Although the sensitivity (37.1% for the combined sample) of this model was low, the specificity reached up to 96.5% for the combined data.

Riedel et al. (2014) adopted a classification tree approach to predict overweight/obesity at the age of 14 from BMI calculated at 6 years of age, as well as the education level and obesity of the mother. The BMI value at age 6 was an important predictor in agreement with (Pei et al. 2013).

A modified logistic regression model was used in (Jator 2014) to measure obesity distribution among different races, considering age, gender, race, and family income as input predictors. This study revealed a negative association of family income with adolescent obesity. On the other hand, Hudda et al. developed a multivariate model to predict fat mass levels in children aged 4–15 years (external validation in children aged 11–12 years), where input predictors included simple anthropometric and demographic variables (height, weight, age, gender, and ethnicity) (Hudda et al. 2019). This model showed excellent predictive performance (optimism adjusted $R^2$: 94.8%) on the internal validation promising generalizability. Kim et al. utilized a general Bayesian network embedded with Markov blanket combined with a what-if analysis used for adolescent obesity prediction (Kim et al. 2019). Several parameters as reported in Table 5.1 are considered.

### *5.3.3 Predictive Variables/Predictors Applicable for the MENA Region*

Identifying a set of significant predictive variables or predictors that are strongly correlated to the prediction outcome is crucial during model development. Table 2 highlights research articles that report various risk factors associated with adolescent overweight/obesity in the MENA region.

In general, the risk factors of obesity can broadly be categorized as sociodemographic, dietary, and lifestyle factors. A vast amount of literature is available addressing the association between various risk factors and overweight/obesity.

**Sociodemographic Factors**

The association between overweight/obesity and sociodemographic factors was highlighted by several research studies (Talat and El Shahat 2016; Musaiger et al. 2014; Amin et al. 2008). For example, it has been identified that the mother's higher educational level is linked to obesity in both male and female adolescents in Bahrain, whereas the father's educational level and rank among siblings were significant only among males (Musaiger et al. 2014). These findings contradict the research outcome from Egypt (Talat and El Shahat 2016) and Saudi Arabia (Amin et al. 2008), where low parental education was positively associated with obesity. The effect of parental education was also reported from Iran (Abiri et al. 2019), Tunisia (Aounallah-Skhiri et al. 2008), and Yemen (Raja'a and Mohanna 2005). Besides, no association was found between obesity and parent's education in a study conducted in Turkey (Discigil et al. 2009).

In Morocco, based on logistic regression analysis, a study (El Kabbaoui et al. 2018) found that higher education of parents, higher family income, and motorized transport to school were significant risk factors of excess weight. In line with this study, most recently, Nouayti et al. (2020) reported that father's income higher than 5000 Moroccan Dirhams and urban residence were risk factors among Moroccan adolescents. The higher standard of living index was associated with obesity among adolescent males in Palestine (Mikki et al. 2009). Another study suggested that socioeconomic factors, including the educational attainment of parents as well as lower crowding index (the number of members in a household divided by the total number of rooms, excluding kitchen and bathrooms), were strong predictors (Nasreddine et al. 2010). In Lebanon, urban residence and maternal employment contribute to higher risk of obesity. This corroborates the findings from Saudi that revealed the significance of urban residence and mother's occupational status, in addition to family size (less than 6) (Amin et al. 2008). However, Al Junaibi et al. (2013) found no association between obesity and family income in the UAE population (Al Junaibi et al. 2013).

Nasreddine et al. highlighted that prevalence is higher among male adolescents in Lebanon (Nasreddine et al. 2014) and Syria (Nasreddine et al. 2010). Similar findings were reported by Kerkadi et al. (2019) and Al Junaibi et al. (2013) based on multivariate analyses. However, it was found that female adolescents in Morocco (Nouayti et al. 2020) and Yemen (Raja'a and Mohanna 2005) were at increased risk of developing obesity.

## Dietary Factors

The dietary habits of overweight/obese adolescents in the MENA region, as documented by research studies, reveal incompatible results. For example, in Algeria, Allioua et al. conducted a study among adolescents aged 10–17 years and found that higher consumption of fatty food and the resulting unbalanced diet lead to higher BMI in both genders, as well as increased obesity and abdominal obesity among adolescent girls. This result is in line with another study (El-Gilany and El-Masry 2011) which reported that starchy food, fast food, snacks, and sweets thrice or more per week are among the main factors associated with increased risk. On the other hand, consumptions of vegetables, fruits, plant protein, and dairy products thrice or more per week reduced the risk. A study that examined Egyptian adolescents (12–15 years) showed that skipping breakfast, frequently eating snacks as a substitute, higher intake of fast food, as well as frequently snacking while watching television all lead to increased BMI. In Kuwait, adolescent males and females exhibited mixed dietary behavior, where consumptions of breakfast and fast food (in boys and girls), vegetables (in boys), potatoes, cakes and doughnuts, and sweets (in girls) were found significant predictors of overweight and obesity. Other studies in the MENA region found a significant positive correlation of the frequent consumption of unhealthy food, including fast food, sugar-sweetened beverages, carbonated/soft drinks, and sweets/candy (Amin et al. 2008; Raja'a and Mohanna 2005; Nasreddine et al. 2014; Pirinçci et al. 2010; Al-Hazzaa et al. 2012; El Kabbaoui et al. 2018), lack of dairy intake (Amin et al. 2008; Al Junaibi et al. 2013), infrequent consumption of breakfast and vegetables (Al-Hazzaa et al. 2012; Amin et al. 2008), inadequate energy intake (Jildeh et al. 2011), and energy consumption from carbohydrates (Nasreddine et al. 2010) and irregular snacking (Aounallah-Skhiri et al. 2008; Pirinçci et al. 2010) with excess weight.

Eating during school breaks and bringing food from home were protective factors against overweight/obesity among Bahraini female adolescents, whereas eating breakfast at home, eating in-between breakfast and lunch, as well as lunch and dinner reduced the risk among males (Musaiger et al. 2014). Also, consuming fruits thrice or more per week lessened the risk among males.

In contrast, the same study (Musaiger et al. 2014) reported no association of fast food intake and soft drink size (in both males and females) and consumption of vegetables, meat, seafood, legumes, dairy products, canned juices, and chocolates with overweight/obesity. Furthermore, the study by Nasreddine et al. (2014) found a negative association of obesity with higher dairy intake and regular breakfast consumption in Lebanon. In Qatar, Kerkadi et al. (2019) documented a negative association between obesity and the consumption of unhealthy food.

#### Lifestyle Factor

An association between obesity and reduced physical activity was documented by studies conducted in Algeria (Allioua et al. 2015), Egypt (El-Gilany and El-Masry 2011; Talat and El Shahat 2016), Iran (Abiri et al. 2019), Kuwait (Al-Haifi et al. 2013), Palestine (Jildeh et al. 2011), Saudi Arabia (Al-Hazzaa et al. 2012), and Tunisia (Zarrouk et al. 2009). However, Nasreddine et al. reported higher physical activity as moderately associated with lower odds of overweight on a sample adolescent population in Lebanon (Nasreddine et al. 2014). Also, the logistic regression analysis revealed no statistically significant relationship between overweight/obesity prevalence and physical activity (El Kabbaoui et al. 2018). Similar findings were detected by Kerkadi et al. (2019) and Al Junaibi et al. (2013).

Overweight/obesity prevalence was also found higher among adolescents who spent more time watching television (El-Gilany and El-Masry 2011; Talat and El Shahat 2016; Bener et al. 2011; Kerkadi et al. 2005) and using a computer (Abiri et al. 2019; El Kabbaoui et al. 2018), as compared to those who did not. In contrast, however, other studies have also identified no association between overweight/obesity and screen (Kerkadi et al. 2019; Al-Haifi et al. 2013).

Few studies reported that reduced sleep duration could contribute to weight gain in adolescents (Bener et al. 2011).

#### Other Risk Factors

El-Gilany et al. found that a history of obesity in one or both parents was an independent predictor of obesity among adolescents in Egypt (El-Gilany and El-Masry 2011). Similarly, the study by Nasreddine et al. (2010) and Raja'a and Mohanna (2005) documented that children of obese parents were at a higher risk of developing obesity. Furthermore, the onset of puberty among girls (Mikki et al. 2009) and duration of breastfeeding (Abiri et al. 2019) were also identified as significant obesity risk factors for adolescents in the region.

## 5.4 Discussion and Implications

The CDC designates overweight for children and adolescents as a body mass index (BMI) cutoff point at 85th percentile or above, whereas a cutoff point at 95th percentile or above defines obesity (Centers for Disease Control 2019; Maiti et al. 2013). Extreme obesity is defined at a BMI higher than or equivalent to the 99th percentile for age (ACOG committee opinion 2017). The International Obesity Task Force (IOTF) uses an international BMI cutoff point for specific age and sex to identify overweight and obesity for children and adolescents from age 2 to 18, while the cutoff thresholds for adults are BMI of 25 or above for "overweight" and 30 or above "obesity" (Cole et al. 2000; Maiti et al. 2013). These three most commonly adopted references have several drawbacks. First, these BMI benchmarks or references may not describe optimal growth given the extent of the positive skewness in body weight, which, as a result, may underestimate obesity among adolescents (Butte et al. 2007). Wang et al. (2006) also argue that the current reference data does not accurately reflect populations worldwide. Ethnic variations and the proportion of body fat correlated with adverse health effects have not been considered, as these references were developed on the basis of data collected in one or few developed countries.

There are various contributors to racial or ethnic differences in obesity metabolic comorbidities that might impact fat distribution, resting metabolic rate, insulin secretion and response, and lipids and lipoproteins (Akhabue et al. 2018). For example, adults and children in African American populations have lower visceral and hepatic fat as compared to White and Hispanic populations (Akhabue et al. 2018). Furthermore, White children have higher insulin sensitivity as compared with African American and Hispanic children, while higher rates of basal lipolysis are detected in White cohorts as compared to African American cohorts. These factors play an important role in the development and onset of obesity and its associated comorbidities and should be considered in quantitative assessment and predictive models (Akhabue et al. 2018). In addition, children and adolescent African Americans often have lower rates of adiponectin as compared to white Americans, which may help to better understand their elevated incidence of diabetes and cardiovascular disease despite the lower visceral adiposity (Akhabue et al. 2018).

While the literature indicates that there are several biological differences in the progression of obesity and the development of comorbidities across different races/ethnic groups, the correlations up to date remain far from conclusive. Researchers reviewed the growth data of healthy children in five major geographic regions of Africa, East Asia, South Asia, West Asia, and Europe in comparison with the NCHS/WHO reference. The studied children in most of these regions did not achieve heights similar to the NCHS/WHO reference medians (Butte et al. 2007).

On the other hand, according to Wang et al. (2019), even though obesity could be determined by genetic predisposition and ethnicity, most adolescent obesity results from the lack of physical activity and the consumption of more calories than needed for activity level. Several studies also remarked that the mean height of children differed slightly across ethnic groups relative to the socioeconomic variations within a specific ethnic community for prosperous populations. Furthermore, child development was largely determined by socioeconomic status and not by ethnicity or race in developed countries (Wang et al. 2019).

Although BMI remains the most common assessment tool for obesity, there are various other approaches available for assessing childhood and adolescent obesity, such as skinfold measurement of the visceral skinfold or that of the triceps muscles. Moreover, there are other methods that could be implemented in specific settings and are more accurate than BMI, including bioelectrical impedance, underwater weighing, dual-energy X-ray absorptiometry, and nuclear magnetic resonance (Centers for Disease Control and Prevention; Serra-Majem et al. 2007). Although these techniques can provide more accurate results of body fat and inform better on the likelihood of obesity-related health issues, they are costly, intrusive, not readily accessible, or challenging to standardize through observers or machines (Centers for Disease Control and Prevention).

The main cause for obesity at any age group, including adolescents, is positive energy balance, where the calories consumed are higher than those expended, resulting in fat accumulation and excess body weight (Narciso et al. 2019; Kadouh and Acosta 2017; Hruby and Hu 2015; Palou et al. 2000). As suggested by the (World Health Organization 2020b), a poor diet that is high in "empty" calories, including fast food and sugar-sweetened beverages, along with sedentary behaviors is a significant contributor to adolescent obesity. Multiple studies in fact concur that dietary energy density (Abdul-Rasoul 2012), and low levels of physical activity (Li et al. 2019; Han et al. 2010) are strongly associated with increased body fat in children and adolescents. However, attributing obesity and excess weight to a single or two factors, such as diet and physical activity for adolescent obesity, can be inaccurate and misleading (Ang et al. 2013).

## 5.5 Conclusive Remarks and Future Direction: Toward a Population-Specific Predictive Model

The concept of predictive modeling is well explored by researchers within a healthcare context. For example, Boukenze et al. developed a decision tree (C4.5)-based learning algorithm to predict chronic kidney disease (Boukenze et al. 2016), Kara et al. used artificial neural networks for diagnosing optic nerve disease (Kara et al. 2006), and Maclin et al. adopted a similar approach for cancer diagnosis (Maclin et al. 1991).

The high prevalence of overweight/obesity among adolescents in developed as well as developing countries, including the MENA region, and the resulting growing health and socioeconomic burdens urgently call for early intervention programs and effective prevention strategies. It is thus important to identify children at high risk of developing obesity later in life so that targeted intervention plans can be devised and implemented. Predictive algorithms have seen remarkable advancements in projecting adolescent obesity, utilizing both parental and childhood clinical data. Although obesity is associated with genetic and familial determinants, other elements, including social and environmental factors, contribute predominantly to the current pandemic as illustrated by various studies (Farrag et al. 2017).

Although predictive modeling has been partially implemented in the healthcare sector of some developed countries, specifically for predicting childhood/adolescent/adult overweight/obesity as illustrated in Table 1, there remains a significant scarcity of research that addresses the applicability of such models for the MENA region, where the higher prevalence and earlier onset of obesity are alarming.

The details of the available predictive algorithms for obesity prediction and the respective predictors are provided in Table 1. It can be emphasized that several models have reached good to excellent predictive performance, up to the level of clinical acceptance, when validated with different study cohorts (Pei et al. 2013; Graversen et al. 2015). These models have incorporated both modifiable and non-modifiable risk factors, including birth weight and childhood BMI (preschool BMI and current BMI) as strong predictors, along with other features including maternal data (BMI and smoking habits), sociodemographic factors, dietary, and environmental factors (Table 1). Although these factors yielded better performance, they cannot be directly adopted for the MENA region due to the potential impact of social, cultural, and religious factors. As such, Table 2 summarizes the particular risk factors as documented by the studies specific to the MENA.

Choosing the right set of input predictors or risk factors is critical as it helps to determine the predictive capability of a model. As highlighted in Table 2, sociodemographic factors (age, gender, family income, and parent's educational level and employment), physical activity, diet, screen time, parental obesity, family history of obesity, and duration of sleep are the most important risk factors applicable to the MENA population as revealed by various studies. By combining the findings from Table 1 and Table 2, we propose to consider physical activity, gender, parents' education/occupation, family income, parental obesity, diet, screen time, birth weight, current and childhood BMI, and maternal BMI as the potential predictors in our model.

Machine learning-based prediction techniques have emerged as effective tools to decipher and model big data, in recent years; however, scarcity of clinical data presents a major challenge to its successful implementation. It is thus imperative to initially propose logistic regression-based techniques for the MENA region, for which the performance has already been assessed and proved successful through validation on various cohorts (Rautiainen and Äyrämö 2019). Also, it is to be noted that, prior to any implementation, proper validation of the model considering a set of significant risk factors should be performed.

In conclusion, addressing adolescent obesity is critical toward minimizing its numerous associated chronic health risks. Since childhood and adolescent obesity are predictive of obesity in adults, special attention should be given to predictive models that could be invaluable for early intervention strategies aiming at combating this major public health burden. In this chapter, a predictive model specifically for adolescents in the MENA region had been proposed based on several main risk factors. Future work includes exploring machine learning-based powerful prediction algorithms for adolescent obesity and overweight by acquiring and incorporating a population-specific vast amount of clinical data. Unlike many other countries, adolescents in some countries in the MENA region, including the UAE, come from diverse ethnic backgrounds. It is, therefore, very important to investigate the possible contributions of social risk factor determinants to adolescent obesity. Future research also needs to examine the various predictive algorithms in the context of different obesity indicators, in addition to BMI (e.g., abdominal obesity and percent body fat), to provide more integrative comprehensive and valid predictive models for adolescent obesity.

## Reflection Questions

1. What are the multifactorial aspects and risk factors of obesity/overweight among adolescents within the MENA region?
2. Can previously developed population-based predictive models be suitable for estimating overweight/obesity among adolescents specifically within the MENA region?
3. What are the contributors to racial or ethnic differences in the progression of adolescent obesity and the development of comorbidities?
4. Can obesity predictive models address health and socioeconomic burdens in the future through early intervention programs and effective prevention strategies?
5. Can machine learning improve the applicability of predictive models for adolescent obesity through utilizing vast amount of clinical data and projecting analysis for a larger sample?

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