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Prediction Models for Early Childhood Obesity: Applicability and Existing Issues

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Abstract
Statistical models have been developed for the prediction or diagnosis of a wide range of outcomes. However, to our knowledge, only 7 published studies have reported models to specifically predict overweight and/or obesity in early childhood. These models were developed using known risk factors and vary greatly in terms of their discrimination and predictive capacities. There are currently no established guidelines on what constitutes an acceptable level of risk (i.e., risk threshold) for childhood obesity prediction models, but these should be set following consideration of the consequences of false-positive and false-negative predictions, as well as any relevant clinical guidelines. To date, no studies have examined the impact of using early childhood obesity prediction models as intervention tools. While these are potentially valuable to inform targeted interventions, the heterogeneity of the existing models and the lack of consensus on adequate thresholds limit their usefulness in practice.

Introduction

Clinical prediction models are becoming increasingly prevalent in the medical literature [1]. These models be can either diagnostic or prognostic. Diagnostic models aim to estimate the likelihood of an individual currently having a disease/illness, whereas prognostic models aim to estimate the risk of an individual experiencing a particular outcome at a specified future time. Clinical prediction models are commonly developed using regression modelling, but other approaches such as machine-learning techniques and decision trees have also been utilized [1–4].

Prediction models exist for a wide variety of health outcomes, such as cardiovascular disease [5], lung cancer [6], acute kidney injury [7], and infertility treatment success [8]. There is an overwhelming number of models for the prediction of specific outcomes, with, for example, more than 350 prediction models developed for cardiovascular disease in the general population [5]. Conversely, very few studies have focused on the prediction of overweight or obesity in early childhood (between 2 and 8 years of age) [9–16], which is the focus of this review.

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Childhood Obesity: Prevalence and Associated Health Risks

The prevalence of childhood obesity increased in every region of the world between 1975 and 2016 [17]. It is now estimated that, worldwide, 41 million children under the age of 5 years are overweight or obese [18]. In New Zealand, one third of 4- to 5-year-olds are overweight or obese [19]. Childhood obesity is associated with both long-term and immediate health risks. In the long term, it is predictive of diabetes risk [20, 21], and it is associated with premature mortality [22] and increased cardiovascular risk [21, 22], predominantly as a result of a substantially greater risk of adult obesity [20, 23–26]. In the short term, childhood overweight and obesity are associated with psychosocial distress [22, 27–29], a lower health-related quality of life [30], and a range of physical comorbidities [29, 31]. For example, even among preschool children (aged 3–6 years), an increase in body mass index (BMI) of 1 kg/m^2 has been associated with increased systolic and diastolic blood pressure [32]. Furthermore, conditions that were previously considered restricted to adults (e.g., type 2 diabetes and sleep apnea) are now being diagnosed more and more frequently in obese youth [23, 29, 31].

Treatment versus Prevention

Prevention, rather than treatment, has been argued to be more successful in reducing childhood obesity [23], as obesity is difficult to reverse once established [23, 33]. Interventions to reduce obesity in adults have mostly focused on lifestyle changes alone, and they have struggled to maintain results 36 months after intervention [34]. Weight loss medication and bariatric surgery are associated with side effects and risks [34, 35]. In addition, as childhood obesity is associated with health risks even in very young children [32], it would be preferable to prevent obesity from occurring in the first place.

There are a number of potentially modifiable risk factors that are known to be associated with early childhood obesity, such as excessive gestational weight gain [36, 37], maternal pre-pregnancy BMI [36–38], maternal smoking during pregnancy [36–38], and rapid infant weight gain [36, 38–40]. However, despite the identification of these potentially modifiable risk factors, reviews of interventions to prevent early childhood obesity have reported inconsistent results [41–44].

Early Childhood Obesity Prediction Models

To our knowledge, 7 studies have been published reporting models for predicting overweight/obesity in young children aged ≤8 years [9–15]. Two studies reporting the prediction of childhood obesity and/or overweight beyond 8 years of age were excluded [40, 45]. The study by Morandi et al. [13] reported a number of models with the outcome at various ages, and only those falling within our age range criteria were considered. Additionally, we excluded certain models from 2 studies that predicted obesity and/or overweight within approximately 12 months from the time of prediction [11, 15], but their other models were included in this review.

The details of the derived prediction models included in this review are examined in Table 1, while Table 2 outlines the respective validation models. These models are all prognostic, aiming to calculate the risk of an infant or toddler becoming overweight or obese at a future time point. Six of these studies used regression modelling [9, 10, 12–15], while the remaining study used data-mining methods [11]. The models used a variety of modifiable predictors, including maternal prepregnancy BMI [10, 12–15], paternal BMI [10, 12, 13], and maternal smoking during pregnancy [10, 13] (Table 3; online suppl. Table 1; see www.karger.com/doi/10.1159/000496563 for all online suppl. material). Conversely, non-modifiable risk predictors included infant birth weight [10, 12–14], infant weight gain [10, 11], and sex [10–12, 15] (Table 3; online suppl. Table 1). Table 3 outlines the various predictor variables used in the derivation models, as well as their respective OR where available. Additionally, online supplementary Table 1 describes the predictor variables used in each derivation model. In general, the models focused on predictor variables that can be routinely collected in clinical practice, although 3 models also included paternal BMI [10, 12, 13], and that may not be consistently available. While external validation is strongly recommended following development and internal validation of a prediction model [2, 46], this was only done for 3 of the 7 models [13, 15, 47].

Area under the Receiver Operating Characteristic Curve

The area under the receiver operating characteristic curve (AUROC) is a useful indicator of a model's ability to discriminate between those at high risk and those at lower risk of a given outcome [48]. The following are gen-

Table 1. Summary of published prediction models for early childhood overweight or obesity derived from data collected before 2 years of age

Study	Validation	Participants	Prediction age	Outcome predicted	Risk threshold and/or model	AUROC[1]	Sensitivity, %	Specificity, %	PPV, %	NPV, %
Levine et al. [9]	none	UK: ALSPAC (n = 14,000) and Millennium Cohort Study (n = 18,000)	infancy	overweight/obesity at 5 years	0.02[2]	unreported	92	21	6	98
					0.03[2]	unreported	79	51	8	98
					0.04[2]	unreported	71	61	9	98
					0.05[2]	unreported	63	72	11	97
					0.10[2]	unreported	42	91	20	97
					0.20[2]	unreported	12	98	25	96
Morandi et al. [13]	external (model A only)	Finland: Northern Finland Birth Cohort (n = 4,032)	at birth	obesity at age 7 years (model A)	0.75[3]	0.78 (0.74–0.82)	72	77	9	99
				overweight/obesity at 7 years (model B)	0.75[3]	0.67 (0.65–0.69)	45	79	29	88
Robson et al. [14]	internal	US: Latino mother-child pairs (n = 166)	infancy	obesity at 5 years (reduced model)	0.25[3]	0.82 (0.74–0.89)	96	37	41	95
					0.50[3]	0.82 (0.74–0.89)	80	64	51	88
					0.75[3]	0.82 (0.74–0.89)	46	84	57	77
					0.90[3]	0.82 (0.74–0.89)	24	97	79	73
				obesity at 5 years (full model)	0.25[3]	0.84 (0.77–0.91)	95	35	40	94
					0.50[3]	0.84 (0.77–0.91)	86	66	54	91
					0.75[3]	0.84 (0.77–0.91)	51	85	61	79
					0.90[3]	0.84 (0.77–0.91)	30	99	93	76
Santorelli et al. [15]	internal[4]	UK: Born in Bradford birth cohort (n = 1,868)	6±1.5 months	obesity at 2 years	unreported	0.87 (0.83–0.90)	unreported	unreported	unreported	unreported
Steur et al. [12]	internal	The Netherlands: PIAMA birth cohort study (n = 1,687)	at birth	overweight/obesity at 8 years	≥5%[5]	0.78	97	20	16	97
					≥10%[5]	0.78	82	55	23	95
					≥15%[5]	0.78	67	75	30	93
					≥20%[5]	0.78	50	85	35	91
Weng et al. [10]	internal and external	UK: Millennium Cohort Study (n = 13,513)	6–12 months	overweight/obesity at 3 years	Risk score ≥25[6]	0.72	70	68	38	87
Zhang et al. [11]	none	UK: Wirral child database (n = 16,523)	6 weeks, 8 months	overweight/obesity at 3 years from data by 6 weeks	unreported[7]	0.82	11	96	36	84
					unreported[8]	0.83	2	100	54	83
				overweight/obesity at 3 years from data by 8 months	unreported[7]	0.82	36	92	46	88
					unreported[8]	0.68	46	73	25	87
				overweight/obesity at 3 years from data by 8 months	unreported[9]	0.84	12	98	unreported	unreported
					unreported[10]	0.84	18	97	unreported	unreported
					unreported[11]	0.84	13	98	unreported	unreported
					unreported[12]	0.84	10	98	unreported	unreported
					unreported[13]	0.82	15	96	unreported	unreported
					unreported[14]	0.68	46	73	unreported	unreported
					unreported[15]	0.82	36	92	unreported	unreported
					unreported[16]	0.82	36	92	unreported	unreported

AUROC, area under the receiver operating characteristic curve; NPV, negative predictive value; PPV, positive predictive value. [1] 95% confidence intervals are reported in parentheses (where available). [2] Values represent the predicted probability decision point. [3] Values represent the percentile threshold of obesity risk. [4] Only the results for equation 1 are presented here, as the findings for equation 2 were nearly identical and equation 1 is more clinically useful due to an earlier prediction age. Note that equation 1 was not externally validated due to insufficient numbers. [5] Values represent the estimated risk of overweight at 8 years of age. [6] A risk score algorithm was created with a range of 0–59. [7] Model derived using naïve Bayes. [8] Model derived using support vector machines (SVM). [9] Model derived using decision tree. [10] Model derived using association rules. [11] Model derived using logistic regression. [12] Model derived using neural networks. [13] Model derived using linear SVM. [14]ºModel derived using radial basis function SVM. [15] Model derived using Bayesian network. [16] Model derived using naive Bayesian.

Table 2. Internal and/or external validations of childhood overweight/obesity prediction models based on data recorded before 2 years of age

Study	Validation type	Participants	Prediction age	Outcome predicted	Risk threshold/and or model	AUROC	Sensitivity, %	Specificity, %	PPV, %	NPV, %
Morandi et al. [13]	external	US: Project Viva cohort (n = 1,032)	birth	obesity at 7 years	unreported (model A)[1]	0.73 (0.67–0.80)	unreported	unreported	unreported	unreported
Robson et al. [14]	internal	bootstrap with 1,000 samples	infancy	obesity at 5 years	unreported (full model)	0.78	unreported	unreported	unreported	unreported
					unreported (reduced model)	0.76	unreported	unreported	unreported	unreported
Santorelli et al. [15]	internal	bootstrap with 1,000 samples	6±1.5 months[2]	obesity at 2 years	unreported	0.86 (0.82–0.90)	unreported	unreported	unreported	unreported
	unclear[2]	unclear	phone model A: 6±1.5 months[3]	obesity at 2 years	0.10[4] (model A)	0.85 (0.81–0.90)	51	94	41	96
					0.20[4] (model A)	0.85 (0.81–0.90)	70	84	28	97
					0.30[4] (model A)	0.85 (0.81–0.90)	78	74	21	98
			phone model B: 6±1.5 months[3]	obesity at 2 years	0.10[4] (model B)	0.86 (0.82–0.90)	51	94	41	96
					0.20[4] (model B)	0.86 (0.82–0.90)	71	85	29	97
					0.30[4] (model B)	0.86 (0.82–0.90)	82	75	22	98
Steur et al. [12]	internal	bootstrap with 200 samples	birth	overweight/obesity at 8 years	unreported	0.75	unreported	unreported	unreported	unreported
Weng et al. [10]	internal	UK: Millennium Cohort Study, 20% of the total (n = 13,513)	6–12 months	overweight/obesity at 3 years	risk score ≥25[5]	0.76	77	67	37	89
Redsell et al. [46] (validation of Weng et al. [10])	external	UK: 10% sample from ALSPAC – Children in Focus (CiF) (n = 1,432)	4–12 months	overweight/obesity at 5 years using IOTF criteria [63][6]	unreported[7]	0.67 (0.62–0.72)	unreported	unreported	unreported	unreported
					unreported[8]	0.70 (0.65–0.74)	unreported	unreported	unreported	unreported
					unreported[9]	0.79 (0.72–0.86)	unreported	unreported	unreported	unreported
					2.5%[10]	0.93 (0.88–0.98)	99	5	unreported	unreported
					5%[10]	0.93 (0.88–0.98)	90	24	unreported	unreported
					10%[10]	0.93 (0.88–0.98)	53	71	unreported	unreported
					15%[10]	0.93 (0.88–0.98)	24	92	unreported	unreported
					20%[10]	0.93 (0.88–0.98)	12	98	unreported	unreported
					25%[10]	0.93 (0.88–0.98)	4	99	unreported	unreported
					30%[10]	0.93 (0.88–0.98)	3	100	unreported	unreported

AUROC, area under the receiver operating characteristic curve; NPV, negative predictive value; PPV, positive predictive value. [1] Also externally validated on the Veneto cohort (Italy), but the age range is outside the scope of this review (4–12 years). [2] Only the results for equation 1 are presented here, as the findings for equation 2 were nearly identical and equation 1 is more clinically useful due to an earlier prediction age. [3] These are the models used in the phone application Healthy Infant Weight?; it is unclear whether this is a validation model and what population was used in its development. Phone model A consisted of sex, birthweight z score, and weight z score gain from birth, while phone model B also included maternal BMI. [4] Values represent the percentile threshold of obesity risk. [5] A risk score algorithm was created with a range of 0–59. [6] Results were also reported for UK 1990 (Cole et al. [64])-defined overweight. Only the IOTF (International Obesity Task Force) [63] is reported here as results were similar, and the IOTF was considered more internationally relevant. [7] Clinical model. [8] Recalibrated model. [9] Imputed model. [10] Recalibrated imputed model.

erally accepted interpretations of AUROC values: poor (<0.60), possibly helpful (≥0.60 but <0.70), acceptable (≥0.70 but <0.80), excellent (≥0.80 but <0.90), and outstanding (≥0.90) [48, 49].

None of the models reported here had a poor AUROC, although they did vary considerably (Table 1). The model with the lowest AUROC (i.e., 0.67) predicted overweight/obesity at 7 years, but the authors did not validate it, as they did not deem it clinically useful [13] (Table 1). The highest reported AUROC (i.e., 0.87) was for a model to predict overweight at 2 years based on data gathered at 4.5–6.5 months [15] (Table 1). It is possible that the short time between the prediction age and the outcome age partly explains this high AUROC value. In general, regression models that were supplemented by data on infant weight gain [14, 15] produced higher AUROC values than those that used birth data alone [12, 13], with one exception [10]. These findings suggest that the inclusion

Table 3. Predictors used in derivation models for obesity and/or overweight in early childhood

Level	Predictors	Study	Notes/comment	OR (95% CI)
Maternal	age (years)	Robson et al. [14]		0.90 (0.82–0.99)[1]
				0.92 (0.83–1.26)[2]
	education	Levine et al. [9]	nonuniversity vs. university	unreported
	English proficiency	Robson et al. [14]	no vs. yes	1.73 (0.60–5.00)[1]
	ethnicity	Santorelli et al. [15]	South Asian ethnicity vs. white British	1.80 (1.05–3.11)[3]
	gestational weight gain (%)	Morandi et al. [13]		1.02 (1.01–1.03)[4]
	occupation	Morandi et al. [13]	ranked employment categories 1–4	0.50 (0.31–0.79)[5]
	parity	Robson et al. [14]	first child vs. later children	0.61 (0.23–1.62)[2]
	prepregnancy BMI (kg/m^2)	Morandi et al. [13]		1.13 (1.08–1.17)[5]
				1.13 (1.10–1.16)[4]
		Robson et al. [14]		1.11 (1.02–1.20)[1]
				1.12 (1.02–1.22)[2]
		Steur et al. [12]		unreported
		Santorelli et al. [15]		1.05 (1.00–1.09)[3]
		Weng et al. [10]	18.5 to <25 kg/m^2 (reference: <18.5)	1.76 (1.21–2.56)
			25 to <30 kg/m^2 (reference: <18.5)	2.35 (1.60–3.47)
			≥30 kg/m^2 (reference: <18.5)	2.98 (1.98–4.47)
	smoking during pregnancy	Morandi et al. [13]	yes vs. no	1.84 (1.20–2.81)[5]
			yes vs. no	1.28 (1.05–1.57)[4]
		Weng et al. [10]	yes vs. no	1.33 (1.15–1.55)
Paternal	BMI (kg/m^2)	Morandi et al. [13]		1.19 (1.13–1.27)[5]
				1.11 (1.08–1.15)[4]
		Steur et al. [12]		unreported
		Weng et al. [10]	18.5 to <25 kg/m^2 (reference: <18.5)	1.09 (0.55–2.15)
			25 to <30 kg/m^2 (reference: <18.5)	1.57 (0.79–3.10)
			≥30 kg/m^2 (reference: <18.5)	1.98 (1.00–3.96)
Family	household smoking	Steur et al. [12]	yes vs. no	unreported
	household members (*n*)	Morandi et al. [13]		0.73 (0.63–0.84)[5]
				0.88 (0.84–0.93)[4]
	parental obesity	Levine et al. [9]		unreported
Birth	birth weight (kg)	Morandi et al. [13]		2.12 (1.48–3.04)[5]
				1.45 (1.22–1.73)[4]
		Steur et al. [12]		unreported
		Weng et al. [10]	2.93 to <3.24 kg (reference: <2.93 kg)	1.08 (0.87–1.33)
			3.24 to <3.49 kg (reference: <2.93 kg)	1.24 (1.01–1.51)
			3.49 to <3.81 kg (reference: <2.93 kg)	1.44 (1.18–1.75)
			≥3.81 kg (reference: <2.93 kg)	1.63 (1.33–1.98)
	birth weight >4 kg	Levine et al. [9]		unreported
	birth weight *z* score	Robson et al. [14]		4.02 (2.01–8.03)[1]
				5.47 (2.47–12.1)[2]
		Santorelli et al. [15]		2.09 (1.59–2.75)[3]
		Zhang et al. [11]		unreported[6, 7]
	ethnicity	Levine et al. [9]		unreported
	gestational age <37 weeks	Santorelli et al. [15]		0.26 (0.07–0.96)[3]
	time of gestation	Zhang et al. [11]		unreported[7]
	sex	Robson et al. [14]	male vs. female	1.76 (0.67–4.60)[2]
		Steur et al. [12]	female vs. male	unreported
		Weng et al. [10]	female vs. male	1.15 (1.02–1.29)
		Zhang et al. [11]		unreported[6, 7]

Table 3 (continued)

Level	Predictors	Study	Notes/comment	OR (95% CI)
Infancy	BMI	Zhang et al. [11]		unreported[6, 7]
	height *z* score	Zhang et al. [11]		unreported[6]
	length *z* score	Zhang et al. [11]		unreported[6, 7]
	rapid weight gain	Weng et al. [10]	Δ *z* score ≥0.67 vs. <0.67	4.15 (3.64–4.73)
	weight gain *z* score	Robson et al. [14]		3.15 (1.82–5.46)[1]
				3.85 (2.04–7.28)[2]
		Santorelli et al. [15]		4.45 (3.28–6.04)[3]
		Levine et al. [9]		unreported
		Zhang et al. [11]		unreported[6, 7]
Other	age at introduction of solids	Robson et al. [14]	>6 vs <6 months	0.50 (0.18–1.37)[2]
	breastfeeding	Robson et al. [14]	exclusive vs. not exclusive breastfeeding	0.47 (0.19–1.15)[1]
			exclusive vs. not exclusive breastfeeding	0.48 (0.18–1.26)[2]
			any breastfeeding vs. no breastfeeding	0.72 (0.27–1.94)[2]
		Weng et al. [10]	no breastfeeding vs. any breastfeeding	1.25 (1.09–1.42)
	hospital delivery	Steur et al. [12]	hospital vs. home delivery	unreported

BMI, body mass index; OR, odds ratio. [1] Robson et al.'s reduced model. [2] Robson et al.'s full model. [3] Santorelli et al. developed 3 models, i.e., one for use at 6±1.5 months (equation 1), a second for use at 9±1.5 months (equation 2), and the third for use at 12±1.5 months (equation 3). Only equation 1 is reported here, as results for equation 1 and equation 2 were very similar, and equation 1 was considered clinically more useful because of the earlier prediction age. Equation 3 is not reported because a prediction age of approximately 12 months before the outcome was not considered clinically helpful. [4] Morandi et al.'s model with overweight and/or obesity as the outcome. [5] Morandi et al.'s model with obesity as the outcome. [6] Models developed from data before 6 weeks or 8 months of age, using support vector machines (SVM) or naive Bayes. [7] Models developed from data before 8 months of age, using decision tree, association rules, logistic regression, neural network, linear SVM, radial basis function SVM, naive Bayesian, or Bayesian network.

of infancy weight gain could increase a model's discriminative ability. However, this would occur at the cost of delaying the model prediction and consequently any intervention, which might affect potential success.

Sensitivity, Specificity, and Risk Thresholds

Sensitivity and specificity are key determinants of a model's predictive ability. Sensitivity refers to a model's ability to correctly predict the individuals who either have or will develop the outcome of interest [1]. Specificity refers to a model's ability to correctly rule out the individuals who do not have or will not develop the condition of interest [1]. The ideal model would produce 100% sensitivity and 100% specificity, but this is considered to be unrealistic [48].

The choice of where to set the model's risk threshold (i.e., the level of risk at or above which an individual will be classified as having an outcome) will impact on the sensitivity and specificity levels produced by the model [1]. Some models (e.g., the Framingham risk prediction tool for cardiovascular disease) use thresholds that are supported by clinical guidelines [50], but there are no similar guidelines for the prediction of early childhood obesity [16]. Indeed, some researchers have reported their results at a variety of risk thresholds without any discussion as to the most appropriate one to use [16]. In this context, the model reported by Robson et al. [14] illustrates the impact of varying risk thresholds can have on sensitivity and specificity. At the 25th percentile risk threshold, their model produced 95% sensitivity and 35% specificity, while at the 90th percentile the sensitivity was 30% and the specificity 99% [14]. Decision curve analysis, relative utility curves, and net benefits are methods for determining both risk thresholds and the clinical usefulness of prediction models [51–53]. However, to date, none of these methods have been utilized in the development or evaluation of early childhood obesity prediction models.

Importantly, the characteristics of the proposed intervention and the prevalence of obesity in the target population should also influence the choice of risk threshold. A model that gives a high sensitivity but a low specificity will potentially identify most, if not all, infants likely to develop obesity, but it will also mistak-

enly identify lots of infants as being at risk when they are not (i.e., a high false-positive rate). Such a scenario may be considered acceptable for early childhood obesity interventions that encourage healthy lifestyle behaviors that would not be physically harmful to participants, such as breastfeeding, which is widely accepted as beneficial for the health of infants and mothers alike [16, 54]. On the other hand, such models (i.e., with a high sensitivity and a low specificity) would generally be no different from non-targeted community-wide interventions, yet parents may experience avoidable stigmatization if they are unnecessarily invited to participate in an intervention based on the assumption that their infant will become an obese child. When interviewed about the use of interventions resulting from early childhood obesity risk prediction models, parents were receptive to the concept, but also expressed fears of judgement and concerns about feeling upset, ashamed, and guilty [55]. However, a pilot study of lifestyle counselling to prevent early childhood obesity showed that the intervention was generally acceptable [56], suggesting that any anxiety may be a function of the initial prediction rather than the intervention itself.

Conversely, while a model that produces a low sensitivity and a high specificity will be unlikely to misclassify infants as being at risk of obesity, it will likely fail to identify a large number of infants who will eventually become obese children. This would mean that, although fewer families are at risk of unnecessary stigmatization, more infants would potentially go on to experience known physical and psychosocial obesity comorbidities, including psychological distress due to weight-related stigmatization [20–22, 27–32].

The availability of resources for intervention should also influence the choice of risk threshold. If resources are scarce, a higher risk threshold may be preferable, thereby ensuring that those at a greater risk of developing obesity are prioritized. Alternatively, a low-cost and easily resourced intervention may warrant a lower risk threshold [16]. Lastly, the prevalence of obesity in the target population should also be considered when setting the risk threshold. For populations with a high prevalence of obesity, prediction models would be more useful to identify those at the highest level of obesity risk. On the other hand, in populations where the prevalence of obesity is low, prediction models would likely be more useful, aiming to identify infants across a wider range of the obesity risk spectrum.

Practical Applications and Implications

Prediction models are primarily developed to improve healthcare-related decision making and therefore patient health [57]. In the case of early childhood obesity models, their purpose is to predict an infant's likelihood of being obese by a specified future point that is still early in the individual's life so that preventative measures can be taken to maximize long-term health benefits. As prediction models invariably have a less-than-perfect performance (i.e., sensitivity and specificity levels below 100%), Moons et al. [57] suggested that only impact analysis studies can truly determine their true clinical value. Such studies are generally developed using a comparative intervention approach to assess health outcomes obtained by using the prediction model versus not using it (i.e., standard care) [2]. Although all early childhood obesity prediction models display a less-than-perfect performance, as of yet, none have been subjected to an impact analysis study.

Nonetheless, 2 models have been developed into tools for use by clinicians or parents [16]. Firstly, Santorelli et al. [15] developed their model into a smartphone application called "Healthy Infant Weight?". The application allowed parents to obtain their baby's risk of obesity at 2 years by entering their baby's sex, birthweight, and weight change between birth and 6, 9, or 12 months. Adding maternal BMI was optional but, as can be seen in Table 2, this made little difference to the sensitivity or specificity of the model [15]. Unfortunately, this mobile application was withdrawn due to funding issues [Santorelli, pers. commun.] and no research has been published regarding any outcomes achieved through its use [16].

The second tool is the Proactive Assessment of Obesity Risk during Infancy (ProAsk) [58], which was developed using the prediction model derived by Weng et al. [10] and later externally validated by Redsell et al. [47]. It should be noted that the name of the tool is somewhat misleading given that it does not actually predict the risk of obesity in particular, but instead the risk of overweight. It is also unclear what outcome age was used by ProAsk, although the development and validation models used ages 3 and 5 years, respectively [10, 47, 58]. ProAsk was designed to be used on tablets and adopted the following predictors: birth weight and length, infant's current weight, maternal and paternal weight, maternal smoking during pregnancy, and breastfeeding. The tool also incorporated a therapeutic wheel of suggested behavioral changes to reduce the infant's risk [58]. A feasibility study into the use of ProAsk by UK public health nurses with parents of infants aged 3 months produced disappointing

results: the recruitment target was not achieved and attrition rates were high [58]. There were also methodological issues identified, such as public health nurses not fully adhering to the study protocols. On a positive note, 8 out of 12 parents interviewed at follow-up found ProAsk to be engaging. However, on balance, the researchers concluded that it would require significant additional resources for the delivery of ProAsk to be a feasible part of the public health nurses' role [58].

Both of the above mentioned practical applications of early childhood obesity prediction models utilized digital technology. The relentless increase in worldwide smartphone ownership rates [59] makes them attractive tools for delivering public health interventions. A review of 23 studies on mobile phone applications aimed at changing health behaviors found that 19 reported statistically significant improvements in the behavior of interest [60]. Applications that were more effective utilized behavior change theory, were user friendly, had personalized features or feedback, and had involvement of health professionals [60]. These findings were echoed by Litterbach et al. [61], who found that participant engagement with their infant feeding application was increased by tailored content, user friendliness, and credible information sources. Breastfeeding mothers reported more confidence to continue breastfeeding, while formula-feeding mothers reported more confidence to feed in response to infant hunger cues [61]. These findings suggest that there may be potential for mobile phone applications based on early childhood obesity prediction models (such as Healthy Infant Weight? [15]) to be successfully implemented. However, it should also be noted that sole reliance on smartphone applications for early childhood obesity interventions may further alienate populations that are already traditionally difficult to engage. Worldwide, people with lower incomes and less education report less smartphone ownership and Internet access [59].

The development of tools such as ProAsk [58], which was designed to be used by health professionals on handheld devices, may serve to increase engagement with difficult-to-reach populations as they are easily portable. Indeed, despite the overall disappointing results, 33% of the participants recruited by the ProAsk study were from areas of increased social deprivation. In addition, Salvy et al. [62] identified the US home visitation program for at-risk families as an ideal opportunity for interventions to prevent early childhood obesity, as these programs are already engaging with high-risk families in the home environment where the obesity-promoting behaviors are likely to occur. Thus, it may be that future research could learn from the methodological issues identified in the ProAsk feasibility study [58] and successfully utilize risk prediction models for early childhood obesity prevention in the home setting. However, without any kind of impact analysis study, it is not possible to determine the true clinical value of any early childhood obesity risk prediction model, irrespectively of the use or not of digital technology. This may not be possible until clinically relevant risk thresholds and sensitivity and specificity levels have been agreed upon for early childhood obesity prediction [16].

The rationale for obesity prediction models is to identify young children at risk of obesity for whom targeted interventions can be implemented. In addition, these prediction models could be even more useful if they contained modifiable factors that relate to the preconception and pregnancy phases. This means that early interventions could be put in place to improve the outcome for children born from subsequent pregnancies within a given family. Further, the focus of interventions could also be extended to young women who may become pregnant, to ensure the best possible weight-related outcomes for their offspring. Healthcare professionals communicating the risk of early childhood obesity to families may need specific training regarding the discussion of a potentially distressing topic, and the provision of accurate information about lifestyle changes that can reduce the risk.

Conclusions

To date, 7 studies have been published reporting early childhood obesity prediction models [9–15]. The AUROC, sensitivity, and specificity produced by the models varied greatly, as did the risk thresholds applied to them. Risk thresholds in particular should be defined after careful weighing of the consequences of false-positive versus false-negative predictions in the context of existing (if any) clinically relevant guidelines [16]. Although there are no such guidelines for obesity prediction, methods to assist with the identification of appropriate risk thresholds do exist. However, these have not been utilized in the development of any of the previously published models for the prediction of early childhood obesity. Impact analysis studies of these models are currently absent from the literature, even though 2 models have been developed into tools to be used by parents and healthcare providers [15, 58]. In this context, digital technology may be a promising avenue for the practical application of obesity prediction models. Considering that many of the variables found to be important in published models are

modifiable, they could be useful tools to inform targeted interventions. Nonetheless, it is essential that clinically relevant risk thresholds be determined for early childhood obesity prediction.

Disclosure Statement

The authors have no financial or nonfinancial conflicts of interests to disclose that may be relevant to this work. The funders had no role in the study design, data collection and analysis, the decision to publish, or the preparation of this paper.

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