

The Trend of Body Mass Index (BMI) Changes among Malaysian Children and the Prediction at 48 Months Old

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Abstract

Overweight and underweight are common issues among children in Malaysia and thus, Malaysian government has launched several campaigns to combat these problems. Previous research show that BMI at certain age could be predicted earlier so that early intervention can be initiate. Most of the study are very specific to some locality and certain ethnic, make it hard to generalize to the whole Malaysian. This research aims to investigate significant positive predictors of changes in Body Mass Index (BMI) of young children aged from 12 months to 48 months and to develop a prediction model for their BMI status (normal, overweight, obese, risk of overweight, underweight, and severe underweight). Data consisting of 558 records with 16 attributes involving 18,226 children, who had registered at the National Child Data Centre (NCDC) were analyzed and predicted using the decision tree algorithms of Rapid miner. The BMI of 48 months-old children can be reliably predicted by their BMI statuses at the ages of 21, 24, 27, 36, 42, and 45 months, parents' incomes, and gender while the BMI at the age of 20 months and below are the negative predictors. The prediction model developed in this study may help practitioners to monitor such children's BMI, especially in detecting the signs of severe overweight, obesity, and underweight among such children. Such a BMI prediction model can be used to identify young children who are at risk of being overweight, obese, and underweight such that remedial interventions can be implemented promptly.

Keywords: Body Mass Index, early childhood, prediction model, significant positive predictors.

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Introduction

The Body Mass Index (BMI) is a common measure of body fat based on height and weight of people encompassing adults and children. According to Furlong et al. (2016), growth monitoring continues to be the most valuable clinical and public health tool to monitor the growth and assess the health and nutritional status of children. Their finding shows that BMI-for-age is an appropriate indicator of growth in the first two years of a child's life and has the potential to be used from birth to adulthood.

Monitoring a child's growth status helps to diagnose potential diseases and implement curative and preventive measures (Nazarova & Kuzmichev, 2016). Growth is one of the most important indicators of children's health with measurements of height and weight reflecting long-term and short-term problems (WHO, 2014). In this regard, nutritional disorders can be particularly serious to children, as they can interfere with the growth and development of children and predispose them to many health problems, such as infection and chronic diseases.

Surprisingly, almost half of the Malaysian population are overweight or obese, making it the number one nation in Asia with such a health issue (Lum, 2018). In addition, Wafa and Ghazali (2020) claim that the prevalence of childhood obesity in Malaysia has remained consistently high and within 30 years, Malaysia has undergone a transition from under-nutrition to relative over-nutrition.

Overweight and obesity are major risk factors for contracting diseases, such as cardiovascular diseases, type-2 diabetes, and cancers, which can significantly impair one's life quality (WHO, 2012). To date, several studies have been carried out to predict obesity and propose appropriate measures for early intervention all over the world. Such efforts are hardly surprising given that identifying factors that cause obesity and detecting the likelihood of someone being obese are crucial to tackling health problems related to overweight (Bhattacharya et al., 2014). For example, Ziauddeen et al. (2017) carried out a systematic review on the development and validation of a prediction model for overweight and obesity faced by children whose ages ranged from one to 13 years. Interestingly, Boseley (2019) proposed a predictor tool that parents could use to predict the risk of their children becoming obese and, therefore, recommended appropriate food and activities to reduce such a risk.

Essentially, BMI is a measure of body fat based on a person's height and weight. For

Malaysia, the standard BMI status, which is set by its Ministry of Health, is divided into six categories, namely severe underweight, underweight, normal, overweight, risk of overweight, and obesity. World Health Organization (WHO) (2019) asserts that BMI is easy to measure and calculate and, therefore, has been widely used as a tool to correlate the risk of health problems with weight at the population level.

In fact, there are many more problems that are associated with other categories of BMI in addition to overweight and obesity. Abarca-Gómez et al. (2017) claim that underweight, overweight, and obesity in childhood and adolescence can lead to adverse health problems throughout one's life. Over recent years, efforts to examine the associations between weight issues and severe health risks have been gaining traction among scholars and researchers. For example, Oberle, Samaghabadi, and Hughes (2017) investigated whether orthorexia nervosa could be predicted by demographic variables, such as gender and BMI, and by personality variables, such as self-esteem, narcissism, and perfectionism.

Recently, Dreimüller et al. (2019) carried out a study that focused on the relationships between BMI and major depressive disorder, depressive symptomatology, and antidepressant response. Revealingly, Hartley, Hoch, and Boling (2018) found that BMI was significantly associated with ankle sprain injury among collegiate male athletes. Meanwhile, De Kat et al. (2019) conducted a systematic review of prediction models for preeclampsia, which revealed BMI was the most significant predictor of such ailment. Meanwhile, Te Riele (2018) showed that anemia and BMI were significant predictors of the overall survivability of Laryngeal Squamous Cell Carcinoma (LSCC). Thus, adding anemia and BMI to the existing prognostic model can improve the prediction of such overall survivability.

As highlighted above, the findings of previous studies emphasize the importance of treating BMI as an important predictor of serious health issues. However, studies that focus on the prediction of health problems by BMI at certain ages have been seriously lacking. In this respect, Stuart and Panico (2016) emphasize the need to carry out prediction studies by focusing on a wide range of ages, notably from three to five years of age. Specifically, Furlong et al. (2016) strongly implore the need to determine if BMI-for-age in children less than 2 years is associated with potential health problems.

Although there is some research regarding BMI, overweight, and obesity within the Malaysian context, none of them are focusing on children and various factors contributing to

the BMI of the children. Most of them are focusing on an adolescent with very limited locality and considering very few contributing factors.

Research by Woon et al. (2014) studied the association between behavioural factors and BMI-for-age among early adolescents in Hulu Langat district, Selangor, Malaysia. Besides, Mareh et al.(2020) investigated the associations of sociodemographic factors and body image with body weight status among Yemeni adolescents in Selangor and Putrajaya, Malaysia. Sociodemographic and psychological factors as predictors of body mass index-for-age among adolescents in Sibul, Malaysia was studied by Law et al. (2020). Moreover, the study by Aslan and Sulaiman (2020) investigated the relationship between maternal beliefs and feeding practices with children's body mass index-for-age in Bandar and Jugra Kuala Langat, Selangor.

On the other hand, several research had studied on a specific ethnic such as research by Teh et al. (2020) who study about Orang Asli children in Pahang, and Raymond Leprince et al. (2020) in Negeri Sembilan. However, the studies are only investigated eating habits and feeding practices. Moreover, a cross-sectional study that investigated the association between the school environment and children's body mass index in Terengganu was evaluated by Wafa and Ghazali (2020).

Against such a backdrop, this study was carried out to investigate the changes in BMI of 48 months (four-year-old) children by focusing on their relationships with several important factors or variables based on a three-month interval. The aim is to develop a prediction model for the BMI status. This is a longitudinal study which use technique from data mining that investigates various variables namely gender, BMI statuses at various ages (the ages of 12 months, 15 months, 18 months, 21 months, 24 months, 27 months, 30 months, 33 months, 36 months, 39 months, 42 months, 48 months), mother's salary, father's salary, and locality. The researchers hypothesized that such factors would play a significant role as positive predictors in determining their BMI at the age of 48 months based on the analysis of current data.

Research Methodology

The methodology of this research followed the data mining process, which is a

fundamental component of the Data Science process for developing dynamic data-driven applications (Gibert, 2018). Essentially, the objective of data mining is to extract useful data from a dataset and process them to obtain information that has an understandable structure (Swani & Tyagi, 2017). As highlighted by Wu (2018), the data mining technique has been used with increasing frequency to predict the possibility of contracting diseases using several algorithms and toolkits. However, data preprocessing, including attribute identification and selection, outlier removal, and data normalization, needs to be performed before modeling. Amin et al. (2019) state that it is difficult to use data mining techniques without prior and appropriate preparations. Kavitha and Kannan (2016) assert that data redundancy and inconsistency in a raw dataset can affect the predicted outcome of algorithms. As such, thorough preparations are needed to preprocess datasets to ensure machine learning algorithms can run effectively.

In this research, RapidMiner Studio was used as a tool to conduct the experiment because it supports open source innovation and educational purposes. Moreover, it has various functions that are robust and easy to use, such as easy-to-use visual design environment for building predictive analytic workflows.

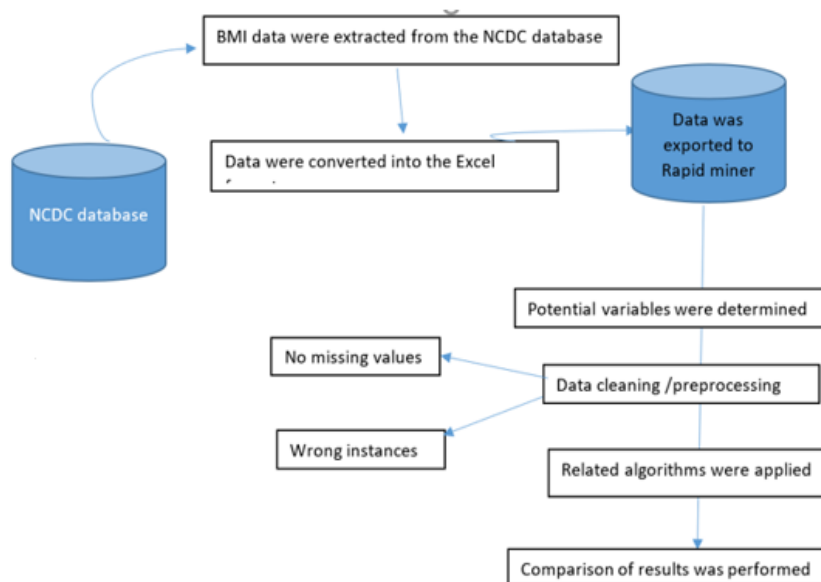


Figure 1. The Experimental Process

Figure 1 shows the workflow of the experiment, in which the BMI dataset was extracted and converted into the Excel format, before it was exported to RapidMiner. Given that there were 16 attributes related to the BMI of a child, it was vital to determine relevant variables to predict BMI over a period of 48 months. This were followed by data cleaning or preprocessing which is an important and critical step. The prediction was then carried out using various algorithms.

Dataset

In this study, 558 electronic records of children aged 1- 48 months were extracted from 18,226 records deposited in the National Child Data Centre (NCDC), a database center that collects and stores data about children's progress in Malaysia. All Malaysian early childcare agencies enter data of all their registered childcare centers into the NCDC system. To the best of our knowledge, this is the largest longitudinal study ever conducted for BMI prediction using machine-learning methods in the Malaysian context.

The NCDC system has several modules, but this study only focused on the BMI. The measurements for each child were collected from the ages of 12 months to 48 months. Data concerning each child had 16 attributes; gender, BMI status at various months (12, 15, 18, 21, 24, 27, 30, 33, 36, 39, 42, 48 months), mother's salary, father's salary, and locality; all of which are treated as nominal data. Table 1 summarizes the 16 attributes of the study data.

Table 1. *Description of the Attributes of Study Data*

Variable name	Description	Domain	Data type
Gender	Gender	Male, Female	Nominal
M12_DESC	BMI status at the age of 12 months	Six (6) categories:	Nominal
M15_DESC	BMI status at the age of 15 months	• Normal weight	Nominal
M18_DESC	BMI status at the age of 18 months	• Severe underweight	Nominal
M21_DESC	BMI status at the age of 21 months	• Underweight	Nominal
M24_DESC	BMI status at the age of 24 months	• Overweight	Nominal
M27_DESC	BMI status at the age of 27 months	• Risk of overweight	Nominal
M30_DESC	BMI status at the age of 30 months	• Obese	Nominal
M33_DESC	BMI status at the age of 33 months		Nominal
M36_DESC	BMI status at the age of 36 months		Nominal
M39_DESC	BMI status at the age of 39 months		Nominal
M42_DESC	BMI status at the age of 42 months		Nominal
M48_DESC	BMI status at 48 months		Nominal

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Salary-F	Father's salary	G0	No information	Nominal
Salary-M	Mother's salary	G1	Less than RM 1,000	
		G2	RM 1,000 - RM 3,999	
		G3	RM 4,000 - RM 6,999	
		G4	RM 7,000 - RM 9,999	
		G5	RM 10,000 and above	
		GX	No income	
Location	Locality of childcare centers	• Urban		Nominal
		• Rural		
Agency	Name of agencies	• Jabatan Kemajuan Masyarakat (KEMAS)		Nominal
		• PERPADUAN		
		• Yayasan Perpaduan Keluarga Terengganu (YPKT)		
		• PERMATA		
		• Jabatan Kebajikan Masyarakat (JKM)		

Missing Data

Based on a systematic review of previous studies by Ziauddeen (2019), various popular methods have been used to handle missing data, one of which is multiple imputations. In this research, only complete records with no missing values for any of the 16 attributes were considered in the first round of handling missing data. Out of 18,226 registered children, only 558 had complete BMI records, with the remaining records having missing values for BMI at certain ages. After screening, some of the selected records were found to have no proper attribute values to indicate the BMI status, such as normal weight, obese, overweight, risk of overweight, underweight, and severe underweight. Thus, such records were treated as records with missing values.

Data Analysis

In the field of machine learning, supervised learning is done with prior knowledge of what the output values for the samples should be. The decision tree is one of the popular supervised learning techniques to support vector machines (SVM), naive Bayes, and logistic regression (Tan, 2015). Yeh et al. (2019) found that the decision tree helped construct the optimum

predictive model for cerebrovascular disease. According to Perveen et al. (2016), the decision tree is one of the most powerful and widely applied techniques for classification and prediction.

Thus, in this study, the researchers used the decision tree algorithm for the prediction of children's BMI. Given that this technique has a recursive structure, it is necessary to select an attribute to be placed at the root node, and then make a branch for each possible value, thus splitting up an example set into several subsets, with each being assigned with an attribute value. Such a process can be repeated recursively for each branch but using only those instances that can reach the branch (Witten et al., 2011). As a tree diagram-based method, the node at the top and nodes at the bottom of its tree structure are the root node and leaf nodes, respectively, with each leaf node being assigned with one target class attribute.

From the root node to every leaf node, there is a path consisting of multiple internal nodes with attributes. This path generates the rule required for classifying unknown data. Moreover, most of decision tree algorithms contain two-stage tasks, namely, tree building and tree pruning. In the tree building stage, a decision tree algorithm can use a unique function to select the best attribute to split a training dataset. At this stage, data contained in the split training subset will belong to only one target class. Recursion and repetition of attribute selecting and set splitting will establish the decision tree's root node and internal nodes. However, some special data in the training dataset may create improper branches of the decision tree structure, the creation of which is called over-fitting. Therefore, tree pruning remove improper branches to enhance the accuracy of the decision tree model in predicting new data (D'heygere, 2003).

Results

Out of 558 children, 268 were females and the remaining 290 were males. A majority of the children's parents (374 fathers and 290 mothers) had incomes between RM1000 and RM3999. Slightly less than two-thirds ($n = 358$) of childcare centers were located in rural areas, while the remaining one-third ($n = 200$) were located in urban areas. The children's BMI over the range of ages from 12 months to 48 months fluctuated slightly.

The findings study showed that BMI changes over a period of 48 months were positive predictors of children's BMI. Specifically, the findings showed the most significant predictor of BMI was children's BMI status at the age of 42 months. Other significant predictors of BMI were children's BMI statuses at the ages of 21, 24, 27, 36 and 45 months, mother's income, fathers' income, and gender. The remaining variables or factors that were not significant predictors were the type of agency and locality (urban or rural), and children's BMI statuses at the ages of 12, 15, 18, 30, 33, and 39 months.

In addition, the findings showed the age range of 20-29 months was a significant predictor. In contrast, the age range of 30-39 months was not a significant predictor, except at the children's age of 36 months (3 years). As such, the significant predictors of children's BMI at the age of four years (48 months) were their BMI statuses at the ages of 24, 36, and 42 months, with the last being the most significant predictor. The BMI of the children at the age of 42 months (3 years and 6 months) was chosen as the root of the decision tree by Rapidminer, signifying that this age factor is the main attribute to predict children's BMI at the age of 48 months (when they turn four-year-old). Despite being close to the age of 48 months, children's BMI status at the age of 45 months did not appear in the decision tree. Figure 2 shows a part of the decision tree which the result is being discussed based on this tree.

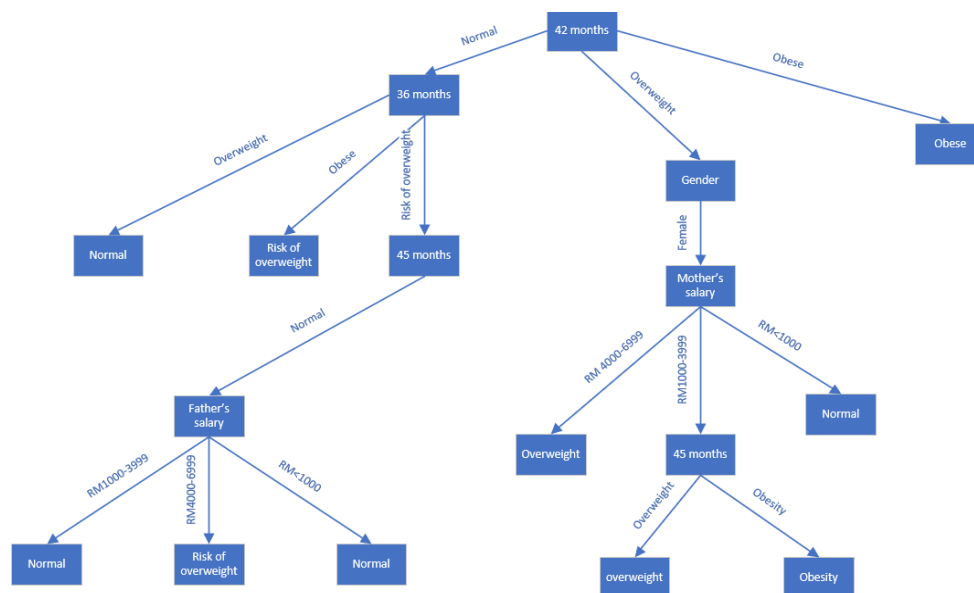


Figure 2. The Root Node of The Decision Tree

As stated earlier, there are six (6) BMI values that indicate the status of children's weights, namely normal weight, overweight, risk of overweight, obese, underweight, and severe underweight. From the decision tree, only the 'obese' status can be predicted directly from the children's BMI at the age of 42 months. This suggests that, without any other contributing factors, obese children whose ages are 42 months will remain obese when they reach the age of 48 months. Moreover, children's BMI statuses or weights at the age of 42 months and 45 months, gender, and mother's salary can predict whether they can be overweight or not when they reach the age of 48 months. For male children, the significant predictors are their BMI status at the ages of 42 months and 45 months. This means that if their BMI indicates that they are overweight at these ages, they are predicted to remain overweight when they reach the age of 48 months. The same argument applies to those predicted to be at risk of being overweight. However, for male children whose BMI indicates they are obese at the age of 45 months but overweight at the age of 42 months, they are predicted to be overweight when they reach the age of 48 months.

Interestingly, a mother's salary can predict whether her daughter will be overweight or not at the age of 42 months. For those whose mothers' incomes are less than RM1000, they are predicted to have a normal weight at the age of 48 months. Children whose mothers' incomes are in the RM1001- RM3999 range who are overweight at the age of 42 months are predicted to be obese or overweight when they reach the age of 45 months. Likewise, those whose mothers' incomes are in the RM4000 - RM6999 range who are overweight at the age of 42 months are predicted to be overweight at the age of 48 months.

In contrast, this does not apply to male children. If they are overweight at the ages of 42 and 45 months, they are predicted to have the same BMI status (being overweight) at the age of 48 months. They are also predicted to be overweight even when their BMI indicates that they are obese at the age of 45 months. However, if their BMI status improved from being overweight at the age of 42 months to be at risk of being overweight at the age of 45 months, they are predicted to be at risk of being overweight at the age of 48 months.

The prediction of being overweight at the age of 48 months also applies for children with normal BMI at the age of 42 months but have a history of being at risk of overweight at the age of 36 months. However, such prediction depends on the children's BMI status at the age of 45 months and their fathers' incomes. Regardless of their gender, children whose fathers'

incomes are in the range of RM4000 - RM6999 are predicted to be at risk of being overweight. In contrast, children whose fathers' incomes are below RM1000 and in the range of RM1000 - RM3999 are predicted to have normal BMI at the age of 48 months. Also, children with a normal BMI at the age of 42 months but have a history of obesity at the age of 36 months are predicted to be at risk of being overweight at the age of 48 months.

The findings of this study indicate that children with normal BMI at the age of 42 months are predicted to have various categories of BMI at the age of 48 months, depending on their BMI statuses at the ages of 24, 36 and 45 months, gender, and fathers' incomes. Specifically, children with normal BMI at the ages of 42 and 36 months but are at risk of being overweight at the age of 45 months are predicted to have a risk of being overweight at the age of 48 months. On the other hand, those having normal BMI at the age of 42 months but are at risk of being overweight at the age of 36 months are predicted to have normal BMI at the age of 48 months. By contrast, children who are obese at the age of 36 months but have a normal weight at the age of 42 months are predicted to be at risk of being overweight when they reach the age of 48 months.

On the other hand, children with a normal weight at the ages 36, 42 and 45 months are predicted to have several weight issues when they reach the age of 48 months, which are significantly influenced by their BMI statuses at the ages of 21, 24 and 27 months together with their gender. For example, children with normal BMI at the ages of 24, 36, 42, and 45 months are predicted to have a normal BMI at the age of 48 months. The same is true for children who are overweight or obese or at risk of being overweight at the age of 24 months but have a normal BMI at other ages. If children's BMI indicates that they are underweight at the age of 24 months, their weight at the age of 27 months will have an impact. Likewise, if their BMI at the age of 27 months shows they are underweight, they are predicted to have a normal weight at the age of 48 months.

Nevertheless, if they have a normal weight at the age of 27 months, their BMI at the age of 21 months will have a profound impact. If children's BMI at the age of 21 months shows a normal weight, they are predicted to have a normal weight at the age of 48 months.

Children with a normal weight at the ages of 27, 36, 42, and 45 months but underweight at the age of 24 months and severely underweight at the age of 21 months are predicted to be at risk of being overweight at the age of 48 months, signifying the dynamic nature of

children's BMI throughout their early childhood lives. In this respect, children's BMI at the age of 24 months is the most significant predictor of their future weights. Children who are either obese or overweight at the age of 24 months but have a normal weight at the ages of 36, 42, and 45 months are predicted to have a normal weight at the age of 48 months.

Children are predicted to be underweight at the age of 48 months if their BMI statuses at the ages of 42 months and 45 months are severely underweight and normal weight, respectively. Underweight was also predicted for children with a normal weight at the age of 36 months but are severely underweight at the age of 45 months. For those who are severely underweight or underweight at the ages of 36 months and 45 months, respectively, they are predicted to be underweight at the age of 48 months. However, they are predicted to have a normal weight at the age of 48 months if their BMI indicates they are severely underweight and underweight at the ages of 42 and 45 months, respectively. Especially, female children whose BMI shows they are underweight at the age of 42 months are predicted to have a normal weight at the age of 48 months. However, male children whose BMI shows they are underweight at the same early age will remain underweight when they reach the age of 48 months. Children who are underweight at the age of 42 months but have a normal weight at the age of 45 months are predicted to have a normal weight at the age of 48 months. On the other hand, children who are underweight or severely underweight at the age of 45 months are predicted to be underweight when they reach the age of 48 months.

Discussion

To our knowledge, this is the first longitudinal study to produce prediction models for childhood BMI within the Malaysian context, which cover all the states in Malaysia. In the present study, various contributing factors were shown to predict BMI at the age of 48 months. Those factors are the mother's salary, father's salary, gender, and BMI changes over time.

The findings indicate that children who have been diagnosed to be overweight will possibly have a normal weight, but such a possibility is low compared to their being obese, overweight, or at the risk of being overweight, depending on their mothers' incomes. In this study, the mother's and father's salary were treated separately. It was found that both factors

contribute to the prediction of the children's BMI at the age of 48 months. These findings also suggest that the prediction of children being overweight and at the risk of being overweight is correlated with their parent's incomes. Such findings concur with Ameer et al.'s (2018) assertion that children from high-income families are more likely to be overweight. Furthermore, their findings suggest that children whose parents are highly educated and whose fathers are employed are more likely to be obese, with boys being more vulnerable than girls in the Saudi Arabian context. However, this study's findings in the Malaysian context suggest that female children are more likely to be obese, depending on their mothers' incomes at certain ages.

Although our study does not compare working mothers in contrast to non-working mothers, it seems aligned with Shuhaimi and Muniandy (2012) finding that obesity among employed mother's children was higher compared to unemployed mother's children. This is also supported by Fitzsimons and Pongiglione (2019), who reported that maternal employment status was associated with increases in children's BMI-for-age. Furthermore, the frequency of overweight and obese children was higher among working mothers compared to non-working mothers was shown in a study by Rosas et al. (2011). They assumed that it might cause working mothers to choose fast foods and ready-to-eat meals for their children. Based on the Consumer Price Index (CPI) figures released by the Department of Statistics Malaysia (DOS) (2020), the Food Away From Home category increased by 1.6% in May 2020 compared to May 2019. Food Away From Home is associated with higher energy and fat intake and lower micronutrient intake, which can lead to increased obesity. As processed foods become more widely available, diets become more loaded with calories and high in sugar. Combined with an inactive lifestyle, the modern diet is an ideal recipe for chronic diseases, especially among the poor. On the other hand, this finding contradicts Aslan and Sulaiman (2020), who found that the number of overweight and obese children was higher among non-working mothers than working mothers.

Interestingly, this study's findings are similar to those of Fitzsimons and Pongiglione's (2019), in which they found that maternal employment had a small but significant effect on children's BMI. In particular, they found that children of working mothers had high BMI levels, which they attributed to poor eating habits among such children. Ameer et al. (2018) also claim that high socioeconomic status is strongly associated with poor dietary behaviours,

a lack of physical activity, and a sedentary lifestyle, eventually resulting in children becoming obese and overweight. Moreover, their findings are in line with this study's findings, showing that children of high-salaried mothers tend to be obese or overweight at the age of 48 months. By contrast, female children of low-salaried mothers will have a normal weight at 48 months, although they may have been overweight previously.

Such findings contradict the findings of this study which found that children of low-income families would manage to get a normal weight at 48 months. Specifically, the latter findings suggest that both children's parents' incomes significantly influence their BMI at different ages. Also, these findings are not consistent with the findings of a study carried out by Noh et al. (2014), who found cases of overweight were prevalent among Korean children from families of low socioeconomic status (SES). Likewise, a study by Apouey (2016) in the United Kingdom found children from high-income families had a low BMI (especially among females), less body fat, and less likelihood of being overweight (for both genders) throughout their early childhood. Other interesting findings can be found in Jabakhanji et al.'s (2018) study, which found parents' SES, the educational level of caregivers, and locality had significant impacts on children's BMI. Based on such findings, they urged all concerned, particularly high-income parents, to foster good eating habits and create an awareness of BMI's impact on their children's health. However, this study's findings are not consistent with those conducted in Britain and South Korea, which showed that children with high-income parents would have a normal weight in their later lives.

Gender of the children is also a significant contributor to the prediction of their BMI at 48 months. However, there is no related study among children. The effect of obesity on Health-Related Quality of Life (HRQOL) in adults differed by gender, as reported by Zhang (2019). Thus, according to them, it is critical to developing effective gender-specific weight control programs.

The finding of this study does not show any contribution of the locality towards the child BMI. However, Jabakhanji et al. (2018) found that children who lived in urban areas had a lower BMI than those who lived in rural areas, which did not change over time. In contrast, this study found that the type of locality in which children lived, being either rural or urban, had no significant influence on children's BMI at 48 months. In addition, a study by Bhattacharya, Ehrenthal, and Shatkay (2014) was carried out to identify children in the

United States who were at risk of being obese by focusing on the growth pattern of such children using a clustering technique. Meanwhile, Furlong et al. (2016) suggest that more efforts are needed to determine if the BMI-for-age of children aged less than two years is associated with future health problems. Such efforts, however, may not be necessary based on the findings of this study, which indicate children's BMI at the age of 48 months has no significant association with those at the ages of less than 24 months.

BMI changes over time is different for male and female children. Generally, it is shown that the BMI at the age of 21 while children's BMI at the age of 21 months was not a significant predictor of their BMI in their later lives. Jabakhanji's (2018) study showed that children's later BMI was closely related to their earlier BMI statuses over five years, one year (12 months) more than this study. These findings suggest that all stakeholders should be concerned with children's BMI only when they are 21 months and above, the ages before entering preschools.

In this study, the category of agencies did not contribute significantly to the prediction of children's BMI at the age of 48 months. Partly, this finding can be attributed to the standard meals provided by such childcare agencies that ensure children consume the same foods, both quantitatively and qualitatively. Likewise, childcare centres' location (being either rural or urban) was not a significant predictor of children's BMI at the age of four years.

Conclusion

In this study, the decision tree algorithm was used in the prediction model of children's BMI at 48 months. The findings showed that eight (8) out of 15 attributes were significant predictors, while the remaining seven (7) were not. In particular, children's BMI statuses at the ages of two years (24 months) and three years (36 months) were found to be significant predictors for determining their BMI at the age of four years (48 months). In addition, their mothers' and fathers' incomes were also significant predictors, suggesting that those with high-income parents are predicted to be overweight or obese or at risk of being overweight in their later lives. This result suggests that programs and policies to address children's health problem and weight-related in Malaysia should include mothers and fathers. Furthermore,

parents should be trained as role model in promoting better weight status among their children as they are the main entities in planning meals for the family. Moreover, the implication of the study suggests that early childhood teachers should attend trainings in order to increase their knowledge of nutrition, eating disorders, obesity and preventive techniques. Teachers should also collaborate with parents in addressing the issue of obesity among children as they are the necessary catalyst for change in the home environment and behaviour development of children. Here, the management of care centre is also important in organising such program for the teachers. Overall, this study's proposed prediction model can help practitioners identify children who are at risk of not having a normal weight (by being underweight or overweight or obese) in their early childhood such that remedial interventions can be planned well in advance. Predictive analytics through the application of data mining has proved the hypothesis that some factors would be positive predictors to the children's BMI at the age of 48 months, within Malaysian context.

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