 doi:10.20944/preprints202201.0408.v1

Article

Obesity Risk Factor Variation Based on Islands Cluster: A Secondary Analysis of Indonesian Basic Health Research 2018

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Abstract: Obesity has become a rising global health problem affecting adults' quality of life. The objective of this study was to describe the prevalence of obesity in Indonesian adults based on the cluster of islands. The study was also aimed to identify the risk factors of obesity in each island cluster. This study analysed secondary data of Indonesian Basic Health Research 2018. Our data for analysis comprised 688,638 adults (>=15 years) randomly selected using proportionate to population size throughout Indonesia. We included 20 variables for sociodemographic and obesity-related risk factors for analysis. Obese status was defined using Body Mass Index (BMI) >= 27.5 kg/m^2. Our current study defined seven major islands cluster as the unit analysis consisting of 34 provinces in Indonesia. Descriptive analysis was conducted to determine the characteristics of the population and to calculate the prevalence of obesity within provinces in each of the island's clusters. Multivariate logistic regression analyses to calculate odds ratios (ORs) was performed using R version 3.6.3. The study results showed that all island clusters had at least one province with an obesity prevalence of more than 20%. Six out of twenty variables, comprising four diet factors (consumption of sweet food, high-salt food, meat food, and carbonated drinks) and two other factors (mental health disorders and smoking behaviour), varied across the island clusters. In conclusion, there was a variation of obesity prevalence of the provinces within and between island clusters. Variation of risk factors raised in each cluster island suggested the government rethink and reframe the intervention to address obesity.

Keywords: Body weight; Indonesia; islands cluster; multiple logistic regression; obesity; risk factor

1. Introduction

Obesity is the major public health causing multiple burdens of co-morbidities and mortalities among adults. The world health organization (WHO) reported that 39% of adults were overweight and 13% was obese, and this number was nearly tripled within the last three decades [1]. In Indonesia, the obesity prevalence was increased significantly from 18.8% in 2007 to 26.6% in 2013 and slightly decreased in 2018 (21.8%) [2–4].

There are many statistical methods for analyzing large-scale study data. The machine learning method is a powerful statistical analysis approach that can be used for predictive model development of health outcomes. A recent systematic review reported various

 doi:10.20944/preprints202201.0408.v1

machine learning techniques that had been performed to predict adult obesity from nation-wide and large cross-sectional data and found that logistic regression analysis had the highest accuracy in predicting obesity [5,6]. In line with our previous study [7], which found that logistic regression has the highest performance in predicting and measuring obesity. Predicting obesity risk factors by considering determinant variations can be advantageous to better design and modify local existing nutrition programs and policies for controlling the obesity problem.

To the best of our knowledge, this is the first study re-analyzing cross-sectional Indonesian Basic Health Research, called RISKESDAS, data based on the main islands in Indonesia (we use the term "island clusters"). The previous study in Indonesia investigating determinants of obesity among adults using the 2007 and 2013 RISKESDAS data concluded that the prevalence of obesity and risk factors was varied among the areas [8]. However, this study only grouped the areas based on Indonesia's three different time regions, which might raise characteristics variation bias within the three groups. Therefore, further analysis for obesity determinants by regions with similar population characteristics is essential to minimise variation bias. We clustered provinces located in the same island into one cluster as the population characteristics within the same island might not be far different.

The main aim of this study is to examine factors contributing to obesity in adults and investigate how it is varied across the island clusters. This study will also describe the prevalence of obesity in seven island clusters in Indonesia and reveal what factors increase or decrease the risk of obesity.

2. Materials and Methods

2.1. Data Source

Secondary data analysis performed in the current study was based on the data from the RISKESDAS study, a nationally representative cross-sectional study in Indonesia conducted by the Ministry of Health in 2018. Detailed information regarding methods, ethical considerations, and other related aspect of RISKESDAS study was published elsewhere [9]. Briefly, the RISKESDAS study sample was selected based on 2010 population census blocks using multi-stage cluster random sampling. Our data for analysis comprised 688,638 adults (>=15 years) from approximately 300,000 households randomly selected using proportionate to population size throughout Indonesia.

The data obtained from the National Institute of Health Research and Development (NIHRD), Ministry of Health, Republic of Indonesia upon request (https://www.litbang.kemkes.go.id/layanan-permintaan-data-riset/).

2.2. Study variables

Socio-demographic, obesity status, and its risk factors and were identified from RISKESDAS 2018 questionnaires prior to data request. We included 20 variables for sociodemographic and obesity related risk factors for analysis. Socio-demographic variables namely sex, education, employment, marital status, and urban-rural status were included.

Obesity status were calculated based on Body Mass Index (BMI) using weight and height, we classify individual as obese with BMI >= 27.5 kg/m2. Mental and emotional disorders (MED) was based on 20 items Self Reporting Questionnaire (SRQ) developed by World Health Organization (WHO) [10], we determined MED with the cut-off point ≥ 6 (positive predictive value = 70%, and negative predictive value = 92%) [11]. Frequency of risky food diet namely sweet foods and beverages, high in salt foods, high in fat foods, meats, carbonated drinks, energy drinks, and instant foods were measured. Eating or drinking of risky food more than 1 times per day were considered as high frequency consumption. Vegetables and fruit consumptions were calculated based on the WHO standard [12], ≥5 portion per day determined as adequate. Smoking was classified as "currently smoking", "quit smoking" and "never smoke" based on participant self-report. Physical

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activity in the current analysis was based on the WHO Global Physical Activity Questionnaire (GPAQ) used in the RISKESDAS study, sufficient physical activity was defined according to the WHO recommendation [13]. Drinking alcohol beverages within 1 months prior to the study was defined as alcohol consumption. Blood pressures was measured using systolic and diastolic blood pressure during data collection, 8th Joint National Committee guideline was used to classify blood pressures [14].

2.3. Islands Cluster

Indonesia is the largest archipelagic country which consist of cluster of islands, these islands are divided into 34 provinces that forming cluster of islands. Our current study defined 7 major islands cluster namely Sumatera (province included: Aceh, North Sumatera, West Sumatera, Riau, Jambi, South Sumatera, Bengkulu, Lampung, Kepulauan Bangka Belitung, and Kepulauan Riau), Java (province included: DKI Jakarta, West Java, Central Java, Yogyakarta, East Java, and Banten), Bali -Nusa Tenggara (province included: Bali, West Nusa Tenggara, and East Nusa Tenggara), Kalimantan (province included: West Kalimantan, Central Kalimantan, South Kalimantan, East Kalimantan and North Kalimantan), Sulawesi (province included: South Sulawesi, Central Sulawesi, Southeast Sulawesi, North Sulawesi, West Sulawesi, and Gorontalo), Maluku (province included: Maluku and North Maluku), and Papua (province included: Papua and West Papua).

2.4. Statistical Analysis

Sample weights for complex survey design was considered in the analysis. Descriptive analysis was conducted to determine the characteristics of the population and to calculate prevalence of obesity within provinces in each of island's cluster.

In order to calculate adjusted odds ratios (ORs), multivariate logistic regression analyses which includes other variables associated with obesity were performed. The selection of multivariate logistic regression to develop prediction model was based on our prior study that showed a high-performance including accuracy, specificity, precision, Kappa, and F_β. Multivariate logistic regression was performed using R version 3.6.3.

3. Results

3.1. Prevalence of obesity across island clusters

The purpose of this study was to describe the prevalence of obese adults by island clusters in Indonesia and assess the risk of obesity caused by determinant factors using the secondary data of RISKESDAS 2018. Figure 1 illustrates obesity prevalence distribution across Indonesia. The result shows that all clusters have at least one province with the prevalence of obesity more than 20% and only three clusters with province more than 25%, namely Java, Kalimantan, and Sulawesi Island.

Figure 1. Distribution of obesity prevalence in Indonesia.

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In Sumatra, Kepulauan Riau had the highest number of obese adults, while South Sumatera and Lampung had the lowest (24.4%, 16.1%, 16.1%, respectively). In the sequence of the regency for the highest and the lowest obesity prevalence in other island clusters were: DKI Jakarta (28.6%) versus Central Java (19%) in Java Island; Bali (22.2%) versus East Nusa Tenggara (9.2%) in Bali and Nusa Tenggara Island; East Kalimantan (27.0%) versus West Kalimantan (15.8%) in Kalimantan Island; North Sulawesi (28.3%) versus West Sulawesi (17.25) in Sulawesi Island; Maluku Utara (22.1%) versus Maluku (18.1%) in Maluku Island; and West Papua (24.1%) versus Papua (18.9%) in Papua Island. DKI Jakarta had the highest proportion of obese population outnumbered the national figure (28.6% vs 21.8%), followed by Sulawesi Utara and East Kalimantan (data was displayed in detail in the Supplementary Table S1).

Table 1 displays the breakdown of the obesity prevalence in all island clusters in Indonesia according to categories of the determinants associated with obesity. It can be highlighted that obesity prevalence was varied according to MED status. The distribution of obesity was higher among those without MED in Sumatra, Java, and Papua Islands. In addition, a few variables show the variation of obesity prevalence by categories, including food high in salt, meat food, carbonated beverages consumption, and smoking status. High education and permanent job (e.g., government/ police/ military officer) have a higher obesity prevalence than their counterparts.

Table 1. Prevalence of obese adults by variables-associated with obesity in all island clusters in Indonesia.

Variables	Categories	Obesity Status						
		Sumatera (N=201,819)	Java (N=224,381)	Bali and Nusa Tenggara (N=56,786)	Kalimantan (N=66,633)	Sulawesi (N=95,465)	Maluku (N=21,151)	Papua (N=22,511)
Obesity status (Y)	Non obese	80.0	79.8	85.1	80.4	80.4	80.3	79.9
	Obese	20.0	21.2	14.9	19.6	19.6	19.7	20.1
Locations (X1)	Rural	17.50	16.90	10.50	15.90	17.20	16.80	16.80
	Urban	23.40	23.60	20.20	23.90	23.20	24.40	27.10
Gender (X2)	Male	13.20	14.00	10.90	13.70	13.20	13.30	15.50
	Female	27.20	28.60	18.80	26.10	25.90	26.40	25.30
Marital Status (X3)	Not married	8.40	10.30	7.10	9.60	8.90	6.80	9.90
	Married	24.30	24.90	17.90	23.50	23.90	24.90	22.90
	Divorce	20.90	20.60	17.10	15.70	18.20	19.60	23.60
	Divorce (death)	22.10	20.40	13.20	16.60	18.50	23.30	19.70
Age group (X4)	<= 47 years	19.10	21.20	14.50	19.40	18.90	18.40	18.90
	48-63 years	25.20	24.70	18.60	22.40	24.20	26.10	26.00
	>=64 years	14.30	12.40	8.70	12.30	13.20	16.20	13.80
Education level (X5)	High	29.70	29.30	22.20	28.50	26.50	31.50	35.50
	Middle	21.40	23.00	17.80	22.30	20.60	19.20	24.00
	Low	18.30	19.70	12.70	17.50	18.10	18.30	16.70
Occupational status (X6)	Unemployed	25.00	26.80	16.00	25.20	24.30	20.70	25.20
	Students	7.40	9.50	5.70	8.10	7.00	5.30	9.80
	Government officer/ military/ police	35.10	34.10	26.60	32.20	31.70	35.20	38.10
	Private company officer	20.60	21.70	20.50	21.20	21.30	22.60	21.90
	Entrepreneur	24.40	26.70	26.60	23.40	25.40	30.50	25.60
	Farmer	14.20	12.40	8.20	11.90	11.70	14.30	13.60
	Fisherman	10.50	14.70	11.80	12.80	11.80	7.60	9.80
	Labor/ driver/ housekeeper	15.10	15.60	12.70	13.40	16.00	19.10	15.40
	Others	25.20	25.10	17.30	24.20	24.00	27.40	28.30
Mental emotional status (X7)	With mental emotional	20.00	21.30	15.30	19.80	19.80	20.30	19.80
	Without mental emotional	21.10	21.70	12.80	18.20	18.20	15.80	22.90
Sweet food (X8)	<3 times/month	22.30	23.70	14.50	21.80	20.60	20.50	18.60
	1-6 times/week	19.90	21.00	15.10	19.70	19.50	19.60	20.10
	> 1 time/day	18.50	20.00	14.50	17.90	19.30	19.90	22.40

 doi:10.20944/preprints202201.0408.v1

Sugar sweetened beverage (X9)	<3 times/month	25.80	28.80	16.70	26.40	24.10	25.40	25.10
	1-6 times/week	20.50	22.00	15.40	20.10	19.70	19.50	18.50
	> 1 time/day	17.00	17.70	12.20	17.20	17.30	18.00	21.30
Food high in salt (X10)	<3 times/month	21.10	22.80	14.90	21.00	21.80	20.40	20.40
	1-6 times/week	19.80	20.70	14.90	19.10	18.00	19.00	19.20
	> 1 time/day	17.90	21.00	15.70	19.30	18.90	21.10	22.50
High-fat food (X11)	<3 times/month	19.50	20.60	12.20	18.20	17.20	19.90	17.30
	1-6 times/week	20.10	21.10	15.80	19.80	19.60	19.60	21.10
	> 1 time/day	20.50	21.80	18.00	20.20	21.80	20.40	23.80
Meat food (X12)	<3 times/month	20.20	21.20	14.70	19.80	19.50	19.60	19.30
	1-6 times/week	19.40	21.40	16.20	18.90	19.90	20.00	21.90
	> 1 time/day	22.60	18.70	18.50	19.20	18.60	20.90	23.20
Carbonated beverages (X13)	<3 rimes/month	20.70	21.80	14.80	20.40	20.10	20.50	20.30
	1-6 times/week	15.40	17.00	15.50	15.20	16.70	16.20	18.70
	> 1 time/day	15.20	16.50	10.20	13.20	20.80	20.60	29.50
Energy drink (X14)	<3 times/month	20.60	21.80	15.30	20.40	20.50	21.10	20.50
	1-6 times/week	13.60	14.40	11.70	13.50	12.90	14.90	18.00
	> 1 time/day	14.50	17.00	6.20	12.00	13.70	16.70	21.80
Instant food (X15)	<3 times/month	22.60	23.10	16.30	21.60	22.70	23.50	21.40
	1-6 times/week	18.40	20.20	13.80	18.90	18.30	18.20	19.20
	> 1 time/day	16.80	20.40	12.90	14.70	14.80	17.00	21.20
FV consumption (X16)	Adequate	24.90	26.80	20.60	26.10	21.90	25.30	28.10
	Not adequate	19.80	21.00	14.60	19.30	19.50	19.30	19.50
Smoking (X17)	Never smoke	24.00	26.10	17.40	23.30	23.70	23.30	22.70
	Quitted	20.60	21.20	17.50	20.80	18.40	26.40	23.60
	Currently smoke	12.50	12.30	9.40	11.60	11.60	12.50	14.00
Physical activity (X18)	Adequate	18.60	19.00	13.10	16.60	17.40	18.20	17.50
	Not adequate	21.10	22.80	16.20	21.60	21.00	20.50	22.50
Alcohol consumption (X19)	No (never)	14.70	16.10	12.80	11.00	12.80	11.90	15.30
	Yes	20.20	21.30	15.20	20.00	20.30	20.70	20.40
Blood pressure (X20)	Normal	10.30	10.10	6.80	8.70	9.70	10.10	11.60
	Prehypertension	19.20	19.20	15.20	16.70	19.70	19.30	19.30
	Hypertension stage 1	29.80	29.20	23.00	27.30	28.30	32.10	31.80
	Hypertension stage 2	38.70	36.90	30.00	34.60	34.90	39.60	43.10

3.2. Cluster variation of obesity risk factors

The results of logistic regression analysis are displayed in Figure 1. Some variables consistently increased the odds of being obese in all island clusters (OR>1) are locations (X01), gender (X02), marital status (X03), occupational status (X06), high-fat food (X11), and blood pressure (X20). Meanwhile, age group (X04), educational level (X05), and sugar-sweetened beverage consumption (X09) factors are positively contributed to the risk of obesity among adult Indonesian.

The study result found that six out of twenty variables show a variation among island clusters. For example, adults working as the government/ military/ police officer are the highest contributor factors of obesity in all clusters but working as the entrepreneur is the highest contributor in Bali and Nusa Tenggara Island (OR=1.775; 95% CI: 1.764-1.786). People with mental-emotional disorders are likely to be the risk factor of obesity only in Sumatra and Papua. Regarding smoking status, those who are still smoke tend to have normal weight status than their counterparts. The ORs number was displayed in more detail in the supplementary Table S2.

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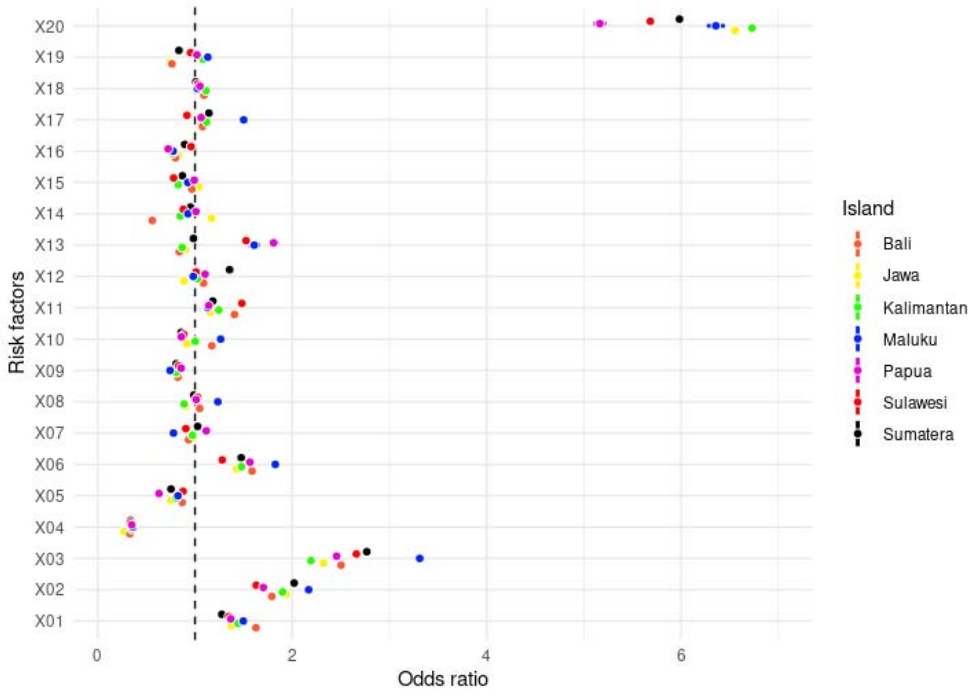

Figure 2. Variation of obesity risk factors by island clusters.

4. Discussion

The present study found that some island clusters share in common obesity risk factors, covering individual and socio-economic factors. Individual factors (e.g., gender, high-fat food consumption and blood pressure) and socio-economic factors (e.g., marital status, occupational status, and locations) contributed to the risk of obesity in seven island clusters, indicating that these variables are probably strong predictors of obesity in Indonesia.

The present study showed that women have greater odds of being obese than men. Women typically have a body fat percentage around 10% higher than men [15,16]. Although other biological factors, such as age and race, also contribute to the adiposity distribution and percentage, women still have more considerable body fat in almost all life spans [15]. This result is supported by a study in a developing country that reported that the prevalence of obesity in adult females was higher than males. The study also revealed that obesity was directly proportional to age but only for females [17].

In this study, only high-fat food consumption (X11) was shown to be significantly contributed to the risk of obesity in Indonesian adults in all clusters. This finding was in line with a previous study which found that consumption of food containing high fat was the risk factor of obesity in all regions in Indonesia and was consistently found in 2007 and 2013 [8]. These results are likely to be related to people's eating habits differing by region. Eastern Indonesia tends to consume high-fat foods. It can be seen that the clusters of Sulawesi and Bali and Nusa Tenggara have a risk factor of 1.4 times of being obese. Fat contributes significantly to the total energy intake, and thus reducing the high-fat food consumption might balance energy expenditures and intakes [18]. Additionally, it should be noted that some fat types have beneficial effects on obesity. For example, replacing protein and short fatty acid (SFA) with polyunsaturated fatty acid (PUFA) was significantly associated with lower obesity risk [19].

Level of education (X5), age group (X4), and sugar-sweetened beverage consumption (X9), on the other hand, are statistically considered lowering obesity risk. Adults with low education levels have a lower risk of being obese than those with high education levels. This result was inconsistent with a larger cross-sectional study that found that the lower years of education, the higher odds of obesity [20]. What is surprising is that more often

 doi:10.20944/preprints202201.0408.v1

of sugar-sweetened beverages consumption had lower odds of being obese. This finding is contrary to many previous studies, which suggested that greater intake of SSBs was associated with overweight and obese in children and adults [21,22]. This inconsistency might be due to the type of sugar contained in the beverages. Studies showed that fructose-sweetened beverages increase adiposity levels greater than other sucrose-sweetened beverages [21,23]. Unfortunately, we did not identify the dominant sugar type contained in the beverages.

Interestingly, mental health disorders (X7), sweet food consumption (X8), high-salt food (X10), meat food (X12), carbonated drinks (X13), and smoking behavior (X17) were varied across the island clusters. Health-related behaviours might be different among areas due to several factors, such as health inequalities, socio-economic status, or household deprivation [24,25]. The most obvious variation was carbonated drink consumption, which becomes the risk factor in Papua Island but protective in Bali and Nusa Tenggara Island (OR= 1.81 vs 0.84). It seems that this variation occurs because the adult diet in Bali and Nusa Tenggara is different from Papua. There is a big difference in ORs values for other diet factors, such as high-salt food, high-fat food, and energy drink consumption. Similar to our findings, a study in children and adolescents found that consumption of SSB (included carbonated drink) was varied by race/ethnicity, sex, and age [26].

Variation among clusters was also found for the mental health disorder factor (X7). This study reported that Papua Island had the highest risk of being obese caused by mental health disorders. Many conditions could trigger mental health issues, including limitation for food choices, poor access to health services, high-risk behaviors, and poor education [27], all of which are challenging in Papua Island. However, there is no information about the source of mental health disturbance of the population. More extensive evidence investigating the roles of mental health in mediating obesity occurrence is required.

Moreover, adults who are already quitted smoking increased the odds of obesity in more than 90% of island clusters. Tobacco's nicotine has an effect on the central nervous system and metabolisms with two possible mechanisms. First, people who quit tobacco tend to replace the hand-to-mouth smoking activity with eating, leading to an increase in calorie intake. Second, taste preference is also changed among those who quit smoking to get pleasure "sensation" replacing tobacco effect [28]. However, this finding must be interpreted with caution because we have no baseline data to describe how much weight gain after smoking cessation. Additionally, the use of tobacco can promote other disease, such as cardiovascular diseases (CVD), hypertension and even mortality, the same risk posed by obese people [29]. Between obesity and tobacco use do not actually show the opposite outcomes. Combining weight management and smoking cessation treatment might be promising in order to improve health quality and prevent the risk of metabolic disease related to obesity and smoking behavior.

Furthermore, we also noted that physical activity was a predictor of obesity in all island clusters. This result was consistent with many studies conducted in Indonesia and elsewhere that reported that physical activity is strongly associated with obesity [30–35]. Performing sufficient physical activity might be beneficial to maintain people's energy expenditure and subsequent energy balance. Therefore, health promotion and education to improve physical activity are required, especially for busy adults in urban areas.

Another important finding of our study indicates that the prevalence of adult obesity was varied across the regencies and cluster of islands. The regency with the highest obesity prevalence was Jakarta (28.6%), while the highest among the island clusters was in Java (21.2%). The breakdown result of the data reveals that the obese adults in urban areas outnumbered the rural areas. Jakarta is the biggest metropolitan city in Indonesia where the population has a higher odd of following sedentary behavior and consuming more "unhealthy foods" than other small cities. A similar finding was reported by a study in Ethiopia that found that men living in metropolitan cities 1.8 times were more likely to become obese than those living in rural areas [32].

The major strength of the present study includes a large sample size. In addition, using weight factors in the analysis might generate analysis results that closely represent the Indonesian population. We also acknowledge some limitations in this study. First, the study data were collected cross-sectionally. Therefore, the causality of risk factors and obesity should be cautiously interpreted. Second, we did not disqualify outlier BMI measurement results in the dataset. However, it was only <1% of the samples, which probably caused a small effect in the analysis.

5. Conclusions

The study implies that there was a variation of obesity prevalence of the provinces within and between island clusters. This study provides evidence that obesity risk factors were varied across the island clusters, which may have implications in rethinking and redesigning policies and interventions to address the obesity problem in Indonesia. Multiple interventions that address specifically greater risk factors considering cluster characteristics are more likely to be effective in preventing obesity and its negative implications.

Supplementary Materials: Table S1: Risk factors of obesity by island clusters in Indonesia from RISKESDAS 2018, Table S2: Odd ratio of obesity based on the risk factors in Indonesia from RISKESDAS 2018.

Author Contributions: Conceptualization and methodology, S.A.T. and D.S.A.; interpretation of data, S.A.T, D.S.A, and A.I.R.; statistical analysis, S.A.T., H.K. and A.L; Visualisation, D.S.A., H.K., and A.L. Drafting of the manuscript, S.A.T., D.S.A., and A.I.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Ministry of Education, Culture, Research and Technology through the PDUPT Grant contract No. 752/UN4.22/PT.01.03/2021.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets generated and analyzed for this study can be found in https://www.litbang.kemkes.go.id/ through request process at the Institute of Health Research and Development of the Indonesian Ministry of Health.

Acknowledgments: The first author and the corresponding author would like to thank the Ministry of Education, Culture, Research and Technology for providing funding to conduct this study. In addition, thanks also to the Ministry of Health through the Research and Community Development Agency for providing access to Indonesia's RISKESDAS data.

Conflicts of Interest: The authors declare no conflict of interest.

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