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Dietary Patterns and Behavioral Factors Among Adults with Obesity and Overweight in Western Romania: A Retrospective Observational Study

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Abstract: (1) Background: Exploring eating habits has revolutionized nutrition studies by elucidating the intricate relationship between food, nutrient interactions, and body composition, highlighting the need for deeper dietary analyses due to the global surge in obesity and its associated health risks, with bioimpedance-based body analysis emerging as a precise tool for body composition assessment. (2) Material and Methods: Using the TANITA BC 418 body composition analyzer, we examined 1015 subjects aged 18-74 years old. The study's objective was to identify risk factors for obesity. Demographic data, clinical characteristics, personal and family history of cardiovascular diseases (CVD), bioimpedance measurements and metabolic disease and 38 parameters/questions regarding dietary habits were recorded. Participants were categorized into four BMI groups: overweight, obese grade I, obese grade II, and obese grade III. (3) Results: Significant gender distribution differences were observed across BMI classes ($p < 0.001$), with more females in overweight and obese categories. Dietary habits such as two-course lunches showed potential associations between BMI groups ($p=0.05$). Psychological and behavioral factors like eating for pleasure ($p=0.008$) and eating alone ($p=0.03$) differed significantly among subgroups, underscoring emotional aspects in obesity management. Environmental factors revealed differences in weekend eating habits ($p=0.02$). Physical activity duration inversely correlated with BMI ($p=0.009$), with home cooking also showing significance ($p=0.03$). While current smoking status had marginal links to obesity ($p=0.05$), smoking cessation did not show significant associations ($p=0.46$). (4) Conclusions: Our study revealed significant differences in eating habits, medical histories, and physical activity among individuals with varying degrees of obesity. These findings underscore the complex interplay of biological, behavioral, and environmental factors contributing to obesity. Personalized approaches are crucial in addressing obesity, considering unique lifestyle factors and medical histories of patients. Our study provides valuable insights for the development of more effective strategies in obesity management and prevention.

Keywords: eating habits; obesity; bioimpedance; dietary patterns.

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Introduction

Weight excess is one of the most important public health issues of the twenty-first century [1]. Over time, the significance of obesity has changed a lot, but the main definition still remains the excess of body fat, characterized among the adults by a BMI over 30 kg/m^2) and being at or over the 95th percentile of BMI among children [2]. Several environmental and genetic factors influence the complexity of this disorder [3,4]. Since the 1980s, when the worldwide obesity pandemic was first recognized, an alarming rate of increase among obesity prevalence has been documented in most countries. According to the Global Burden of Disease Obesity Collaborators, the prevalence of obesity was tripling between 1980 and 2015 in 73 countries and rising steadily in the majority of the rest [6]. A percentage of 39% to 49% of the world's population, approximate 2.8 to 3.5 billion individuals, are thought to be overweight or obese [7]. Between 40-65% of individuals in European nations were overweight or obese in 2019. In that year, Iceland had the highest percentage of obese adults in all of Europe, with over two-thirds of the adult population [8]. Individual risk of weight gain and obesity has also been associated with residential segregation based on race [9,10]. Obesity is more frequently diagnosed among women than men with greatest increases reported in black race [11].

According to previous research, both obesity and overweight have been correlated with dietary patterns in terms of volume, frequency of meals, snacking behaviors composition, diet quality and breakfast skipping, which are the most frequently encountered eating habits nowadays [12,13]. The term "eating patterns" refers to a person's conscious and routine dietary habits, which includes the kind of food consumed as well as their quantities and time of intake in response to social and cultural factors [14,15]. When referring to the diet as a whole, dietary patterns or food patterns refer to the amount, quality, and diversity of meals and drinks consumed, as well as the regularity with which they are typically consumed [16,17]. However, dietary choices are shaped by a complex interaction of genetic, psychological, and environmental variables [3]. In recent years, significant changes have been observed in what consists of both the sizes of the portions, as well as the increase in the frequency of consumption of hypercaloric foods, precursors of energy imbalance and, implicitly, weight gain with the appearance of obesity [17]. An increased risk of obesity was shown to be strongly connected with having breakfast more frequently away from home [18]. Furthermore, there are studies that claim those who skip breakfast consume more calories overall each day. [13]. According to Davy et al., both men and women perceive their own eating patterns very differently [19]. It is essential to consider that people's diets might differ significantly between nations or even within one nation from area to region [20,21,22]. For example, in a Norwegian population, gender variations in the perception of the benefit of a well-balanced diet and its effects on health were examined on 32 women who were more prone than males to modify their opinions about the association between nutrition and health [23]. These health-consciousness variations between the genders are a result of women changing their diets more frequently in response to dietary recommendations and having more health knowledge [23]. Women and men have different models of nutritional behavior in terms of food quality and quantity [24].

Energy-restricted diets can induce significant weight loss in overweight and obese population and reduce a variety of cardiometabolic risk factors [25,26]. It has been more evident that in recent years the dietary pattern evaluation offers a more accurate representation of daily food consumption than does the separation of macronutrient intake measurement [27]. The concept of individualized nutrition, also defined as precision nutrition, has rapidly developed popularity [28]. Over the last years, the impact of dietary consumption, particularly the three primary macronutrients—carbohydrates, fats, and proteins—have been shown to vary considerably throughout the population [29]. Niloufar Arabzadegan et al. have identified an extremely important aspect regarding the role of dietary fibers in weight loss in overweight and obese women, namely the fact that they have beneficial effects on inflammatory biomarkers. More precisely, a weight loss diet rich in dietary fiber from whole grains compared to a diet rich in fiber from fruits and vegetables, respectively the fiber content of both mentioned categories, presents additional benefits on inflammatory biomarkers among women with increased BMI [30].

In order to predict the type of lifestyle a person requires in accordance with their metabolic changes, nutritional interventions will probably develop algorithms based on the type of food ingested, biochemical variables, physical activity, genetic variability, and especially the gut health [28,29]. Precision nutrition aims to generate more dynamic and comprehensive dietary recommendations based on changing, interrelated factors that affect a person's internal and external environment over the course of a lifetime [27]. It was thought that genetic variability may explain how it may influence an individual's metabolic response to a nutrient or meal in comparison to other persons [31]. Although, nutrigenetics will not be the exclusive basis for nutrition [32]. Twin population studies revealed that genetics was not the only factor affecting the response to a particular diet, contrary to what was previously believed [27,31]. According to clinical trials, hyperproteic diets is a safe method for losing weight which reduces CVD risk factors including blood lipids and blood pressure (BP), while maintaining fat free mass [33,34,35]. In comparison to patients assigned to low-fat diets, subjects randomized to Mediterranean diets experienced greater reductions in body weight, body mass index, waist circumference, and also a lower blood lipid level [36].

BMI represents the most common unit of measurement and framing of general distributed adiposity among the population [37]. Although, BMI provides limited information regarding the distribution of adipose tissue mass [38,39]. Also, there are uncertainties regarding the relationship between the values of this item and the risk of mortality [8]. Through clinically accessible technologies like plethysmography techniques (bioelectric impedance, air displacement) or dual energy x-ray absorptiometry (DEXA), determination of adipose fat mass and body composition is important in diagnosing and monitoring the effectiveness of therapy in some patients [40,41]. Bioelectrical Impedance Analysis is a clinical, non-invasive, easy-to-use and increasingly popular method that can be applied to a variety of subjects in terms of body shape and age [42]. In order to assess total body water, fat-free mass, and fat mass, bioelectrical impedance analysis of body composition examines the body's conductivity to a very small alternating electrical current [43,44]. Accurate body composition measurements need costly instruments and labor-intensive procedures such DEXA are frequently beyond the purview of the majority of clinical and health-based services [45,46].

The present study aims to evaluate lifestyle mistakes in overweight and obese patients from the Banat area or the area in western Romania, with the evaluation of their implications on body composition, respectively individual cardiometabolic risk.

Materials and Methods

The observational retrospective study was performed at the Dr. D Medical Center, an endocrinology and metabolic clinic from Timisoara, Romania, starting in February 2008 until December 2018 on 1015 overweight and obese adults, who presented for evaluation the nutritional status and obesity complications and also for a personalized weight loss program, both female and male persons, aged between 18 and 74 years. This study was performed in accordance with the ethical standards of the Helsinki Declaration, and was approved by the University of Medicine and Pharmacy Victor Babes Timisoara's Ethics Committee of Scientific Research (CECS) (No. 69/03.10.2022). All participants in the research have signed an informed consent form.

Patient Inclusion and Exclusion criteria

Inclusion criteria: Patients with excess weight, both overweight and obese, who came to the medical center with the aim of evaluating nutritional status and subsequently initiating a personalized hypocaloric food program for weight loss and reaching the ideal weight. All patients were residents in the same county for at least 5 years ago.

Exclusion criteria: secondary causes of weight gain: hypothyroidism, hypogonadism, Cushing Syndrome, Prader-Willi syndrome and iatrogenic ones (e.g. glucocorticoids, antipsychotics and diabetes medication such as insulin therapy and sulfonylureas) [47,48,49]. Patients with psychiatric pathology were also documented and were not included in the research. Additionally, declining the agreement to answer the questionnaire, an incomplete family or personal medical history, any type of metabolic surgery (e.g. gastric sleeve, gastric band, gastric by-pass, biliopancreatic bypass, or gastric plication) within the previous six months, and the administration of weight-loss medications (Orlistat, Sibutramine, Amfepramone Hydrochloride, or Bupropion/Naltrexone) are also exclusion criteria.

Patient Evaluation

The following items were defined and evaluated in all cases studied:

Body weight measurement: The mechanical scale with metrological certification, which can weigh up to 200 kg, was used to assess body weight. Depending on the medical schedule, mainly in the first part of the day, each participant was instructed to maintain a vertical posture on the instrument while wearing the minimum amount of clothing. A more detailed assessment of the nutritional status was assessed by electrical bioimpedance.

Height measurement: To determine the height of each participant, a calibrated wall-mounted stadiometer was needed. Each participant received instructions to stay in a vertical posture on the platform with no shoes.

Nutritional status: The estimation of the nutritional status of each patient in our study was determined by BMI, a simple, cheap and widely used parameter [50]. The following formula was applied to determine the BMI value: BMI = weight (in kg)/ height^2 (in m^2) [51]. The group of participants was divided into 4 categories as a result of the BMI values: non-obese or overweight (BMI= 25-29.9 kg/m^2) and the 3 grades of obesity (class I obesity: BMI= 30-34.9 kg/m^2, class II obesity: BMI= 35-39.9 kg/m^2 and the last class, respectively class III obesity with a BMI over 40 kg/m^2). [50,51].

Medical History and Conditions: Each participant underwent a structured inquiry concerning the familial medical background encompassing cardiovascular (CV) and metabolic ailments. Particular attention was directed towards ascertaining the presence of first-degree relatives with a history of obesity or overweight, type 1 or type 2 diabetes mellitus, stroke, acute myocardial infarction, and varying degrees of hypertension. Moreover, a meticulous evaluation of personal cardiometabolic risk factors was conducted through targeted questioning pertaining to individual medical histories, including prediabetes, diabetes mellitus, asymptomatic hyperuricemia or gout, dyslipidemia, metabolic syndrome, hypertension, and smoking status. Additional parameters of interest encompassed prior instances of weight loss, weight fluctuations subsequent to metabolic surgery or insulin therapy (excluding changes within the last six months), and weight variations subsequent to smoking cessation. Within the female cohort, specific attention was given to factors such as menopausal onset, preclimax symptoms, the presence of polycystic ovary syndrome, and premenstrual increases in appetite.

Dietary Habits and Preferences: Food consumption, fluid intake, sleep patterns, and physical activity level > basal + active (minimum 30 minutes per day) were the lifestyle factors examined for all patients. The nutritional routine of the patients was detailed through the following three criteria: the presence of the three main daily meals, the serving of breakfast and the consumption of two dishes at lunch. Eating habits were classified in terms of quantity (e.g. big portions, food supplement, postprandial snack, hurry eating), quality (e.g. fast food, home cooked food, restaurant). Components of obsessive-compulsive eating were documented: stress, compulsive eating, reward factor, loneliness factor, nervous factor, big problems eating factor, no attention eating factor, childhood eating patterns). The dining place was analyzed through three items: not on the table, in front of TV and in front of other devices. Social parameters were analyzed by identifying the place where each subject from our group eat a larger amount of food compared to his/her routine, using the following patterns: weekend, vacation and social meetings. The appetite level was appreciated by identifying the following items: eating with pleasure, eating dessert every day, crunching, fatigue and appetite. In this category was included the physical activity component, which were analyzed using as main parameter the time in minutes that the activity lasted (minimum 30 minutes per day). Sleep pattern was identified by an affirmative or negative answer to "Do you sleep less than 8 hours?".

Bioimpedance body analysis: Bioimpedance body analysis was performed on all patients using the TANITA BC-418 Segmental Body Composition Analyzer at the initial nutritional medical examination for the purpose of determining nutritional status. There was a detailed and complete analysis of the complete body composition by means of a constant high frequency current source (50 kHz, 500 μA) using a technology with a tetra-polar eight-point tactile electrode system. The subjects were instructed to keep a straight posture and hold on to the analyzer's handles to make a connection with a total of eight electrodes, two for each foot and hand [52]. During bioelectrical impedance analysis, each participant's body experienced low-level electrical current flow, and impedance (resistance to the current's flow) was measured [53]. The whole procedure took about 3 minutes, and the interpretation was explained and noted for each patient. According to the results, the analyzed parameters were divided into: current weight, BMR (basal metabolic rate), percentage of adipose tissue, percentage of muscle tissue or lean mass, hydration The following personal information were collected and introduced in the operating system of the instrument model used: first name, last name, age, gender and height. Secondary to entering the personal data of each patient, the instrument's operating system automatically generated the BMI and BMR value.

Statistical Analysis

Microsoft Excel and MedCalc Software Version 12.5.0.0 (MedCalc Software Ltd., Ostend, Belgium) were used to gather data. Variables were presented according to the distribution type: mean ± standard deviation for normally distributed data, and median with interquartile range for non-normally distributed data. Categorical variables were reported as frequencies and percentages. Differences among the study groups were assessed using Pearson's chi-squared test for categorical variables. For numerical variables, the Kruskal-Wallis test was utilized for non-normally distributed data, and ANOVA was applied to normally distributed data. Normality of the distributions was evaluated using the Shapiro-Wilk test. Statistical significance was set at a p-value of less than 0.05, with confidence intervals calculated at the 95% level. Data pre-processing and analysis were performed using Python software.

Results

Medical History and Conditions

Table 1 presents a detailed analysis of medical history and conditions across different Body Mass Index (BMI) categories: Class I Obesity, Class II Obesity, Class III Obesity, and Overweight. The data is segmented by the presence or absence of each condition, and p-values indicate the statistical significance of differences across these groups.

Table 1. Medical History and Conditions.

Variable	Class	Class I Obesity	Class II Obesity	Class III Obesity	Overweight	p-value
Gender	**Male**	90	67	55	59	**<0.001**
	Female	228	129	92	272	
FMH Hypertension	**No**	143	76	75	176	**0.008**
	Yes	175	120	72	155	
FMH Stroke	**No**	245	153	109	268	0.37
	Yes	73	43	38	63	
FMH Myocardial Infarction	**No**	290	170	131	298	0.44
	Yes	28	26	16	33	
Premenstrual Syndrome	**No**	274	175	134	287	0.37
	Yes	44	21	13	44	
PCOS	**No**	310	190	142	321	0.95
	Yes	8	6	5	10	
Diabetes Mellitus	**No**	211	120	87	211	0.43
	Yes	107	76	60	120	
Prediabetes	**No**	313	189	135	328	**<0.001**
	Yes	5	7	12	3	
Dyslipidaemia	**No**	287	164	126	317	**<0.001**
	Yes	31	32	21	14	
Arterial Hypertension	**No**	275	167	99	316	**<0.001**
	Yes	43	29	48	15	
Gout	**No**	313	181	144	330	**<0.001**
	Yes	5	15	3	1	
Metabolic Syndrome	**No**	297	170	118	317	**<0.001**
	Yes	21	26	29	14	
Oral Contraceptives	**No**	302	188	143	308	0.21
	Yes	16	8	4	23	
Menopause	**No**	286	170	120	319	**<0.001**
	Yes	32	26	27	12	
Preclimax	**No**	298	182	135	317	0.31
	Yes	20	14	12	14	
Weight gains after Insulin therapy	**No**	316	195	147	331	0.41
	Yes	2	1	0	0	

Postpartum	**No**	296	193	139	316	**0.05**
	Yes	22	3	8	15	
Weight gains post-surgery	**No**	318	196	147	330	0.57
	Yes	0	0	0	1	

Abbreviations: FMH= family medical history.

Significant differences are observed in the distribution of males and females across BMI classes ($p < 0.001$), with more females in the overweight and obesity classes than males. There is a significant association ($p = 0.008$) between BMI classes and family history of hypertension, indicating that this trait varies across different BMI categories. Family Medical History of Stroke and Myocardial Infarction do not show significant differences across BMI classes ($p = 0.37$ and $p = 0.44$, respectively), suggesting that stroke and myocardial infarction history does not vary significantly by BMI category. No significant differences were found across the BMI classes for premenstrual syndrome, PCOS and diabetes mellitus (p-values of 0.37, 0.95, and 0.43 respectively), indicating a uniform distribution across the categories. Both prediabetes and dyslipidaemia show significant differences across BMI classes ($p < 0.001$), highlighting a higher prevalence of these conditions in higher obesity classes. Arterial hypertension, gout and metabolic syndrome also show significant variations across BMI categories ($p < 0.001$), suggesting a strong association with higher levels of obesity. There are significant differences in the prevalence of menopause across BMI classes ($p < 0.001$), but not with the use of oral contraceptives ($p = 0.21$). Preclimax, Weight gains after Insulin Therapy, and Weight Gains Post-Surgery do not show significant variations across BMI categories (p-values of 0.31, 0.41, and 0.57, respectively). A borderline significant result ($p = 0.05$) suggests a potential variation in postpartum weight gains across different BMI categories.

This analysis highlights that certain health conditions and demographic factors are significantly associated with different levels of obesity and overweight status, which could have implications for targeted interventions and further research into the management of obesity (Fig. 1).

Figure 1. Proportion of Individuals with Prediabetes Across BMI Categories. Each bar is segmented to show those with prediabetes (in maroon) and those without (in beige).

Dietary Habits and Preferences

Table 2 provides insights into dietary habits and preferences across four BMI categories: Class I Obesity, Class II Obesity, Class III Obesity, and Overweight. The p-values suggest the statistical significance of differences in these habits and preferences among the different BMI classes.

Table 2. Dietary Habits and Preferences.

Variable	**Class**	**Class I Obesity**	**Class II Obesity**	**Class III Obesity**	**Overweight**	**p-value**
Alimentary Intolerance	**No**	311	192	142	325	0.74
	Yes	7	4	5	6	
Alimentary Craving	**No**	166	103	80	191	0.50
	Yes	152	93	67	140	
Fast Food	**No**	280	162	126	286	0.39
	Yes	38	34	21	45	
Deserts	**No**	243	140	108	253	0.52
	Yes	75	56	39	78	
Whole Grain	**No**	291	175	131	293	0.63
	Yes	27	21	16	38	
Daily Fruit	**No**	288	172	132	298	0.77
	Yes	30	24	15	33	
Alcohol	**No**	231	134	105	248	0.43
	Yes	87	62	42	83	
Smoker	**No**	296	177	141	317	**0.05**
	Yes	22	19	6	14	
More food after Quit Smoking	**No**	308	194	143	324	0.46
	Yes	10	2	4	7	
3 meals/day	**No**	188	118	88	188	0.85
	Yes	130	78	59	143	
Breakfast	**No**	184	112	83	178	0.74
	Yes	134	84	64	153	
2 courses lunch	**No**	128	67	51	148	**0.05**
	Yes	190	129	96	183	

There was no significant variation in alimentary intolerance across the BMI categories ($p = 0.74$), indicating that this dietary issue does not differ significantly by weight status. Similarly, alimentary cravings do not show a significant difference across the BMI classes ($p = 0.50$). There was no significant association between fast food consumption and BMI categories ($p = 0.39$). No significant difference was observed in dessert consumption across different BMI groups ($p = 0.52$). The consumption of whole grains does not vary significantly by BMI category ($p = 0.63$). Daily fruit consumption also shows no significant variation across BMI classes ($p = 0.77$). Alcohol consumption does not significantly differ across the BMI groups ($p = 0.43$). There is a borderline significant association between smoking and BMI categories ($p = 0.05$), suggesting that smoking habits might differ slightly among these groups. No significant difference is observed regarding increased food intake after quitting smoking across BMI categories ($p = 0.46$). The frequency of consuming three meals per day does not significantly vary across BMI categories ($p = 0.85$). There was no significant difference in breakfast consumption habits across BMI groups (p = 0.74). There was a borderline significant difference in the consumption of two courses at lunch across BMI categories (p = 0.05), suggesting that heavier BMI groups might be more likely to have a two-course lunch (Fig.2).

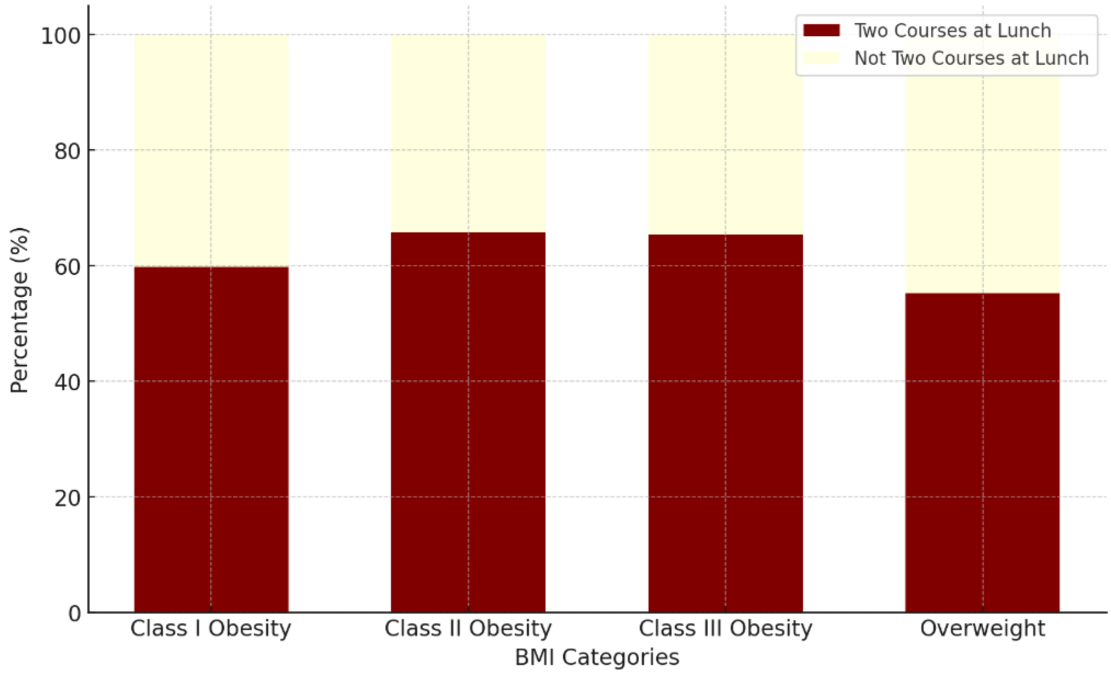

Figure 2. Proportion of Individuals Having Two Courses at Lunch Across BMI Categories. Each bar is divided to show the percentage of individuals who have two courses (maroon) and those who do not (beige).

Psychological and Behavioral Factors

Table 3 focuses on various psychological and behavioural aspects of eating across the same BMI categories: Class I Obesity, Class II Obesity, Class III Obesity, and Overweight. Each variable's p-value indicates whether there are statistically significant differences in these behaviours among the different weight groups.

Table 3. Psychological and Behavioral Factors.

Variable	Class	Class I Obesity	Class II Obesity	Class III Obesity	Overweight	p-value
Stress	**No**	245	145	122	265	0.17
	Yes	73	51	25	66	
Fatigue Habit	**No**	294	184	142	307	0.35
	Yes	24	12	5	24	
Nibbling Habits	**No**	156	89	62	155	0.56
	Yes	162	107	85	176	
Boredom Eating	**No**	251	143	121	272	0.06
	Yes	67	53	26	59	
Compulsive eating	**No**	309	190	138	318	0.34
	Yes	9	6	9	13	
Eating for Pleasure	**No**	294	169	121	295	**0.008**
	Yes	24	27	26	36	

Eating in Solitude	**No**	311	188	135	316	**0.03**
	Yes	7	8	12	15	
Social Eating	**No**	284	178	122	285	0.09
	Yes	34	18	25	46	
Eating quickly/Large portions	**No**	221	124	92	234	0.14
	Yes	97	72	55	97	
Eating without paying attention	**No**	304	186	138	318	0.74
	Yes	14	10	9	13	
Childhood-like eating habits	**No**	312	189	143	318	0.46
	Yes	6	7	4	13	
Anger-related eating habits	**No**	299	189	138	305	0.26
	Yes	19	7	9	26	
Watching TV eating	**No**	297	181	130	313	0.11
	Yes	21	15	17	18	
Using devices eating	**No**	301	187	136	309	0.62
	Yes	17	9	11	22	
Reward	**No**	300	178	135	308	0.47
	Yes	18	18	12	23	
Big portions	**No**	239	132	102	252	0.08
	Yes	79	64	45	79	

No significant differences in eating due to stress across BMI groups (p = 0.17). Similarly, no significant differences are observed in eating habits related to fatigue across the categories (p = 0.35). Nibbling habits do not show significant variation across BMI classes (p = 0.56). There is a borderline significant difference in boredom eating across BMI groups (p = 0.06), suggesting that it may be slightly more prevalent in higher BMI categories. Compulsive Eating does not vary significantly by BMI category (p = 0.34). Significant differences are observed (p = 0.008), indicating that eating for pleasure varies significantly across the BMI categories, possibly more common in higher obesity classes. Regarding eating in solitude, there is a significant difference in this behaviour across the categories (p = 0.03), suggesting varying tendencies to eat alone among different BMI groups. Social Eating shows a trend towards significance (p = 0.09), indicating possible differences in social eating habits across BMI categories. For Eating Quickly/Large Portions, no significant variation is observed (p = 0.14), though the trend suggests it might vary slightly by weight status. The eating without paying attention habit does not show significant variation across BMI groups (p = 0.74). Childhood-like eating habits do not significantly differ across BMI categories (p = 0.46). Regarding anger-related eating habits, no significant differences found (p = 0.26). Watching TV while eating shows a trend towards significance (p = 0.11), suggesting a possible variation in this habit across BMI classes. There is no significant variation in the habit of using devices (like smartphones or tablets) while eating among the different BMI groups (p = 0.62). This suggests that device use during meals is relatively consistent across all categories. Eating as a reward does not show significant differences across BMI classes (p = 0.47). This indicates that using food as a reward is a behaviour that does not vary significantly with obesity or overweight status.

From this analysis, notable findings include significant differences in eating for pleasure and eating in solitude across different BMI categories, with possible trends in boredom eating and social eating (Fig. 3).

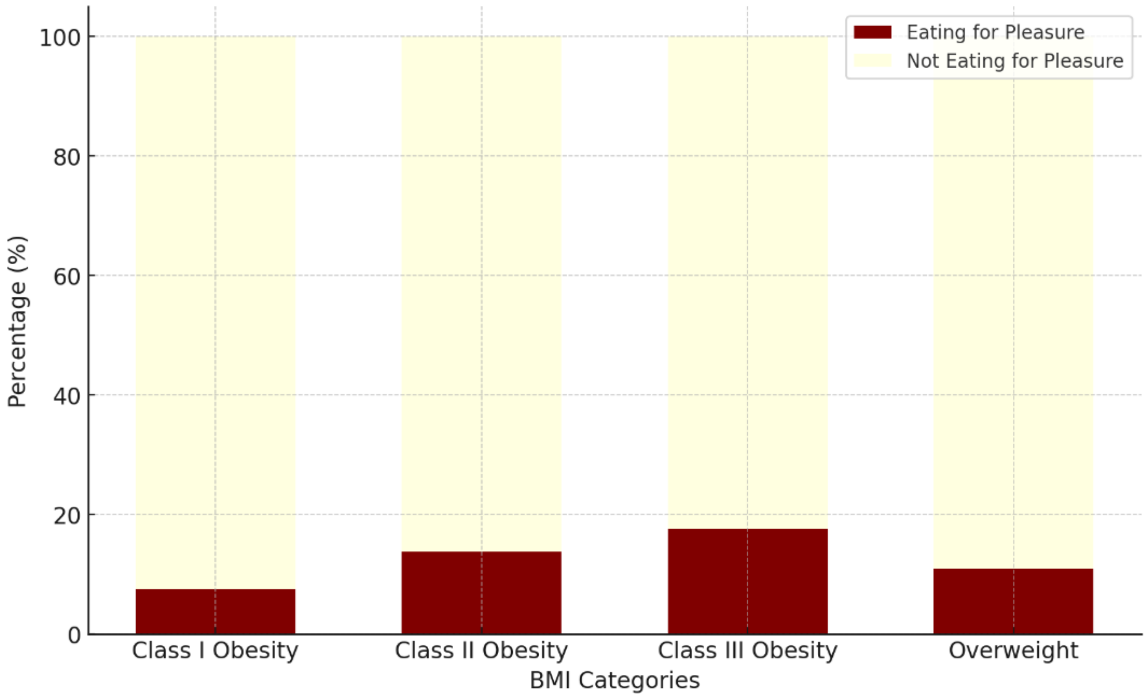

Figure 3. Proportion of Individuals Eating for Pleasure Across BMI Categories. Each bar is segmented to show those who engage in eating for pleasure (maroon) and those who do not (beige).

Environmental and Situational Factors

Table 4 explores the influence of environmental and situational factors on eating habits across different BMI categories: Class I Obesity, Class II Obesity, Class III Obesity, and Overweight. The significance of differences in these behaviours is indicated by p-values.

Table 4. Environmental and Situational Factors.

Variable	Class	Class I Obesity	Class II Obesity	Class III Obesity	Overweight	p-value
Eating at Restaurant	**No**	298	177	135	307	0.54
	Yes	20	19	12	24	
Eating during vacation	**No**	267	172	135	285	0.12
	Yes	51	24	12	46	
Afternoon eating habits	**No**	230	151	117	254	0.31
	Yes	88	45	30	77	
Weekend eating habits	**No**	245	157	131	268	**0.02**
	Yes	73	39	16	63	
Not eating at the table	**No**	257	161	120	272	0.97
	Yes	61	35	27	59	
Big troubles impact eating habits	**No**	308	189	142	318	0.95
	Yes	10	7	5	13	

There is no significant difference in the frequency of eating at restaurants across the different BMI categories (p = 0.54). This suggests that dining out is a common behaviour that does not vary significantly with weight status. No significant variation is observed in the habit of eating more during vacations across

BMI classes (p = 0.12). Although there is a trend indicating that eating behaviours might change during vacations, it's not statistically significant. Afternoon eating habits shows no significant differences across BMI groups (p = 0.31), indicating that those habits are consistent across different weight statuses. There is a significant difference in eating habits on weekends across the BMI categories (p = 0.02). This suggests that changes in eating behaviour on weekends are more pronounced in different BMI classes, potentially with more deviation from typical eating patterns among certain groups. The practice of not eating at the table does not show significant differences across BMI groups (p = 0.97), indicating that this particular habit is uniformly distributed regardless of weight category. There is no significant difference in how major troubles impact eating habits across BMI categories (p = 0.95).

The findings from this table highlight that while most environmental and situational factors do not significantly differ by BMI category, weekend eating habits do show significant variation (Fig.4).

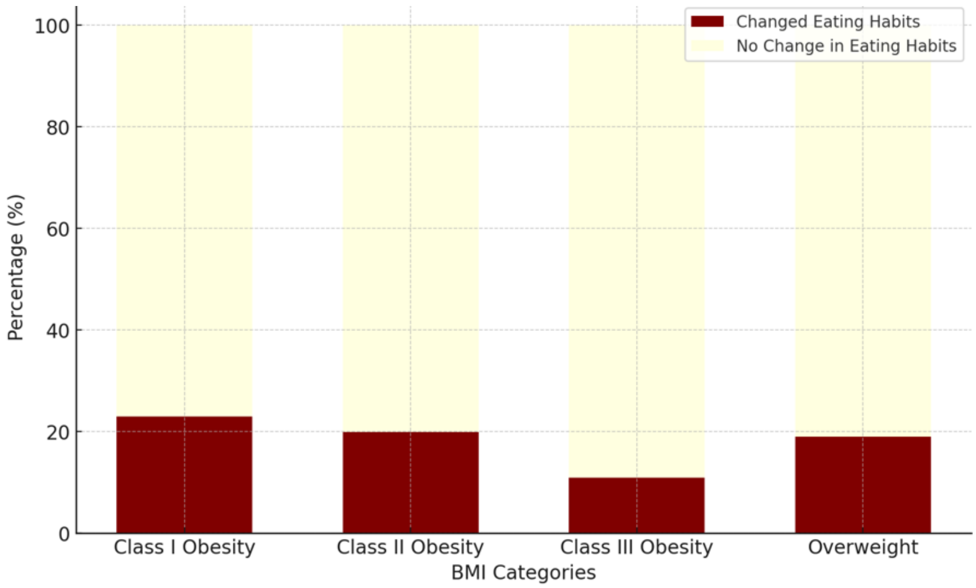

Figure 4. Proportion of Individuals with Changed Eating Habits on Weekends. Each bar is split to show the percentage of individuals who change their eating habits on weekends (maroon) and those who do not (beige).

Physical Activity and Lifestyle

Table 5 provides an analysis of physical activity and lifestyle factors across the same BMI categories: Class I Obesity, Class II Obesity, Class III Obesity, and Overweight. It explores the association of these lifestyle habits with obesity and overweight status, as indicated by p-values.

Table 5. Physical Activity and Lifestyle.

Variable	Class	Class I Obesity	Class II Obesity	Class III Obesity	Overweight	p-value
Min. 30min PA/Day	**No**	278	173	136	271	**0.009**
	Yes	40	23	11	60	
History of Weight Loss	**No**	194	115	90	212	0.65
	Yes	124	81	57	119	

Supplements	**No**	263	158	116	264	0.72
	Yes	55	38	31	67	
Cooked food	**No**	247	158	109	280	**0.03**
	Yes	71	38	38	51	

There is a significant difference in the prevalence of engaging in at least 30 minutes of physical activity per day across the BMI groups (p = 0.009). A higher proportion of the Overweight class meets this criterion compared to the obesity classes, suggesting that lower physical activity levels may be associated with higher obesity classes. There is no significant difference in the history of weight loss attempts across the BMI categories (p = 0.65). This indicates that attempts to lose weight are common across all categories, without a significant variation by weight status. The use of dietary or nutritional supplements does not significantly differ across BMI groups (p = 0.72). There is a significant difference in the consumption of home-cooked food across BMI categories (p = 0.03).

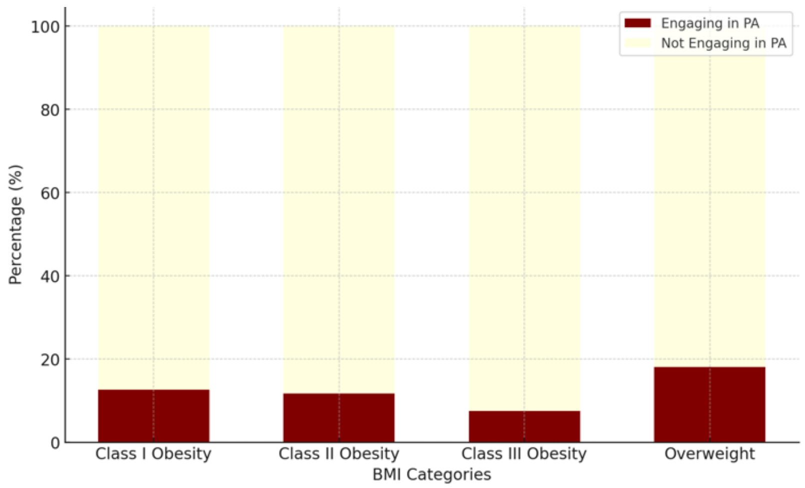

Figure 5. Proportion of Individuals Engaging in at Least 30 Minutes of Physical Activity per Day. Each bar is split into two colours: maroon represents the percentage of individuals engaging in physical activity, and beige shows those not engaging.

Exploring differences among BMI categories with regard of numerical variables

Table 6 presents a comparison of numerical variables across different BMI categories: Class I Obesity, Class II Obesity, Class III Obesity, and Overweight. The values are given as medians and interquartile ranges for non-normally distributed variables, except for muscular tissue percentage, which is presented as mean ± standard deviation (normally distributed). The table includes results from Kruskal-Wallis and ANOVA tests to identify significant differences among these groups, indicated by p-values. The data from this table provides a comprehensive view of how physical characteristics and lifestyle factors such as sleep, and consumption habits vary significantly with obesity class. This information could be crucial for developing targeted health interventions and lifestyle modifications tailored to different obesity classes. It underscores the importance of considering age, body composition, and metabolic differences when addressing obesity-related health issues.

Table 6. Differences among classes with regard of numerical variables.

Variable	Class I Obesity	Class II Obesity	Class III Obesity	Overweight	p-value
Age	37.0 (28.25 - 43.0)	38.0 (28.75 - 46.25)	41.0 (33.0 - 51.0)	31.0 (25.0 - 37.0)	**<0.001**
Unsweetened liquids	2000.0 (1400.0 - 2500.0)	1950.0 (1300.0 - 2325.0)	1800.0 (1000.0 - 2350.0)	1800.0 (1050.0 - 2200.0)	0.43
Coffee	100.0 (0.0 - 200.0)	100.0 (0.0 - 200.0)	0.0 (0.0 - 200.0)	0.0 (0.0 - 200.0)	0.29
Sweetened liquid	0.0 (0.0 - 287.5)	0.0 (0.0 - 300.0)	0.0 (0.0 - 450.0)	0.0 (0.0 - 250.0)	0.11
Sleeping hours	7.0 (7.0 - 8.0)	7.5 (6.5 - 8.0)	7.0 (6.0 - 8.0)	7.5 (7.0 - 8.0)	**0.002**
Fat tissue (%)	39.8 (32.25 - 43.0)	42.9 (34.6 - 46.0)	45.8 (39.2 - 49.85)	35.0 (30.8 - 37.9)	**<0.001**
Muscular tissue (%)	59.12 ± 6.49	56.07 ± 6.35	52.35 ± 6.08	62.69 ± 5.65	**<0.001**
BMR	1642.0 (1512.25 - 1961.5)	1814.0 (1654.5 - 2288.0)	2005.0 (1801.0 - 2546.0)	1482.0 (1380.0 - 1632.5)	**<0.001**

There is a significant difference in age across the categories ($p < 0.001$), with the median age increasing from overweight to Class III obesity. This suggests that higher obesity classes tend to be older. No significant differences in the consumption of unsweetened liquids across BMI categories ($p = 0.43$). This indicates a similar intake across different weight statuses. Coffee consumption also does not significantly differ among the groups ($p = 0.29$), showing a uniform distribution across BMI classes. There is no significant difference in sweetened liquid consumption across the groups ($p = 0.11$), though the trend suggests there may be variations that are not statistically significant. Significant differences in sleeping hours are observed across BMI categories ($p = 0.002$). This could indicate variations in sleep patterns or duration related to obesity status. There is a significant difference in body fat percentage across the categories ($p < 0.001$), with higher fat percentages associated with higher obesity classes. There is a significant variation in muscular tissue percentage across BMI categories ($p < 0.001$). Higher obesity classes have lower percentages of muscular tissue. Significant differences in BMR are observed ($p < 0.001$), with BMR increasing from overweight to Class III obesity. This is consistent with higher body mass requiring more energy for basic functions.

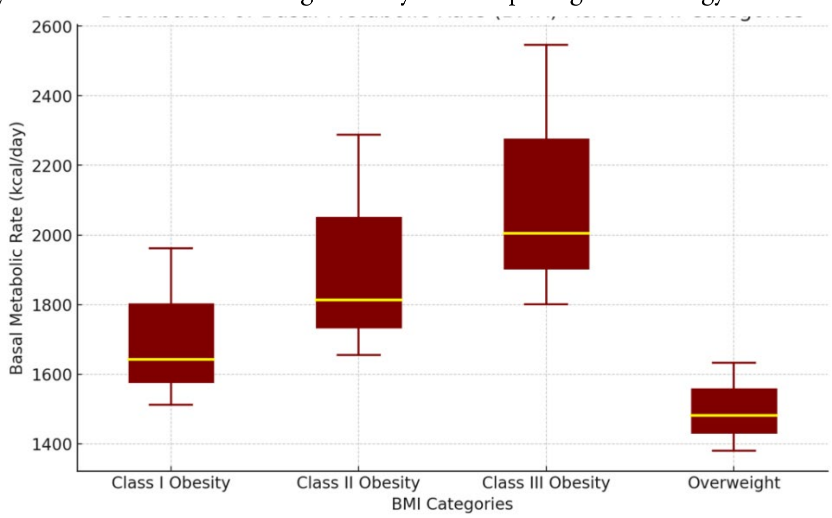

Figure 6. Distribution of Basal Metabolic Rate (BMR) Across BMI Categories.

Discussion

This study examines the dietary patterns of overweight and obese individuals who have opted for weight loss interventions within a specific region of our country. Additionally, it explores potential correlations between these dietary habits and genetic factors, body composition parameters, and other variables identified during medical history and nutritional consultations. The implications of these findings are relevant for nutrition clinicians, offering valuable insights to enhance the assessment of nutrition counseling and develop personalized weight loss strategies. Ultimately, these interventions aim to mitigate the long-term complications associated with obesity. Noteworthy aspects of the study include its focus on assessing dietary habits among individuals with obesity and the substantial size of the participant group from the same region.

Dietary patterns include a variety of factors such as amount, proportion, diversity, nutrients composition and water intake, as well as the frequency of daily consumption [54]. Eating decisions made repeatedly in similar situations are known as eating routines [55]. Similar questions on daily eating habits and how they relate to routine were asked of each patient throughout the assessment in order to provide focused addressability. In accordance with the corporal analysis by bioimpedance were evaluated a total of 25 related questions regarding dietary habits.

Food preferences exhibit a high degree of complexity, subjectivity, and susceptibility to various influencing factors, notably physiological ones [56]. In this study, emphasis was placed on evaluating meal frequency, consumption pace, and dining environment. Psychological factors, including stress, work-related challenges, boredom, and fatigue, were also considered significant contributors. Interestingly, despite societal emphasis on health consciousness, hedonic aspects such as pleasure and taste often took precedence in food selection [56]. Furthermore, the inclination towards consuming high-calorie foods between meals to boost energy levels was examined within the same context.

Diet absolutely plays an essential role in maintaining human health and preventing disease. Personal dietary decisions, however, also take into account the causes, techniques, and circumstances in which food and nutrients are consumed [57]. Emotional eating is a problematic dietary pattern that frequently results in making poor food decisions. Female aged more than 18 years old who are overweight or different grades of obesity are frequently involved with emotional eating [58,59]. In our research, within the category of psychological and behavioral factors, only a select few parameters exhibited statistically significant variances among the subgroups of examined patients. Specifically, eating for pleasure and solitary eating emerged as the notable representatives within this variable subgroup. Overall, the results shows that most dietary habits and preferences do not significantly differ across BMI categories, except for smoking and possibly the structure of lunch. This suggests that while some eating behaviours are consistent across different weight statuses, certain patterns like smoking and more elaborate lunches might be more prevalent in specific groups. On the other hand, in present study, the effect of significant personal troubles on eating behaviour is similar across all groups.

Breakfast skipping is related to BMI values, however the exact relationship depends on how skipping is classified, according to Dialektakou et al. [60]. In a systematic review, Marielly Rodrigues Souza et al. noted that studies that took into account skipping breakfast five or more times per week, or every day generally revealed a higher frequency of positive associations between this aspect and cardiometabolic diseases, including modified lipid panel, markers of body adiposity, and BP [61]. According to research by Bui et al., engaging in other behaviors including binge drinking, smoking, and sedentary status were linked to choosing unhealthy food decision [57,62]. Garcidueñas-Fimbres stated that a faster rate of food intake is associated with an additional risk of weight gain, metabolic syndrome, type 2 diabetes mellitus and other metabolic complications, while a higher frequency of meals would be consistent with an improvement in diet and a lower risk of metabolic syndrome and obesity [63]. Furthermore, within the environmental and situational factors category, our findings underscore significant variations in weekend eating habits. This observation suggests a potential focal point for interventions targeting weight management, particularly in addressing the fluctuations in dietary patterns during less regimented periods such as weekends.

With a high sugar content, a high glycemic index, and a greater calorie density compared with the daily energy need, fast food is a poor provider of fiber and micronutrients [67,68,69]. Shah T et al demonstrated the existence of a direct association between the frequent consumption of fast food and the nutritional status of overweight and obesity represented by BMI [67]. Other studies in the same direction have established the similar association between fast food and BMI [61,70,71,72]. Moreover, A. Mohammadbeigi et al. showed that fast food consumption could be linked to abdominal obesity represented by an increased abdominal circumference, but this was not related to general obesity based on BMI values [73].

Numerous factors, some less well-researched than others, can contribute to weight gain. Insufficient physical activity, which is defined as less than 30 minutes per day, smoking cessation, long-term weight gain after bariatric surgery and long-term weight gain after insulin therapy, both which have not occurred in the last 6 months, were some of the factors our study identified and analyzed as potential causes of weight gain in the adult population with overweight and obesity. New research on 222,497 Australian adults found that prolonged sitting increases the probability of mortality from any cause, even for those who get the recommended 150 minutes per week of exercise [74]. Tucker JM et al. have shown that both average weekly physical activity and high-intensity physical activity measured by accelerometry over a 20-month period decreased significantly among middle-aged obese women compared to normal-weight women [75]. It was found that any type of physical activity contributes to the reduction of cardiometabolic risk, and an adequate 420 physical condition significantly reduces the relative risk [76,77]. The present study identified statistically significant differences in the level of physical activity, particularly those engaging in at least 30 minutes per day, among the evaluated groups. These findings underscore the importance of adhering to recommended daily time intervals for physical activity. Age serves as a crucial yet unalterable risk factor for overweight, largely due to the decline in basal metabolic rate that accompanies aging. Our research revealed statistically significant associations between age and varying degrees of obesity and overweight.

Like obesity, smoking is a strong CV risk factor for cardiometabolic risk and associated diseases [78]. Although quitting smoking reduces this risk, it has been shown to be associated with weight gain due to increased appetite and reduced energy consumption [76]. Moreover, a recent Korean study found a greater reduction in CV risk among people who gained more than 4 kg after quitting smoking compared to the group whose weight remained the same [79]. In their study on the impact of weight increase after ceasing to smoke on CVD, Clair et al. have proven that compared to smokers, weight gain after quitting smoking had no influence on the relationship between smoking cessation and the risk of developing incident CVD [80]. Our research revealed a notable association between smoking status and obesity groups, including overweight individuals. Specifically, we observed a limited association between current smoking status and these groups, with the number of smokers showing an inverse relationship with BMI. Surprisingly, we found no significant association between smoking cessation and BMI.

In our study, statistically significant differences were recorded between obese menopausal adult women compared to the non-obese group ($p<0.001$). According to D. J. Clegg, the absence of estrogen hormones among menopausal women, which increases metabolic dysfunction, is an important risk factor for weight gain, obesity, metabolic syndrome, and CVD [81,82,83]. Some researchers argued that the decrease in the level of circulating estrogens was associated with a redistribution of adipose tissue, causing a decrease in peripheral subcutaneous adiposity and an increase at the abdominal level [84]. Pre-climax women are three times less likely to develop obesity and obesity-related disorders compared to menopausal women [85]. The use of COCs among obese patients increases the risk of developing venous thromboembolism by up to 12-24 times compared to non-obese women who do not use COCs [86,87]. In our study, no significant differences were identified between obese women with polycystic ovary syndrome compared to the non-obese group. Polycystic ovary syndrome, the most common endocrine disorder in women of fertile age, is frequently associated with obesity, insulin resistance, lipid profile changes, cardiometabolic risk factors [88,89,90].

Satiety after a meal as well as food choices throughout a day can be influenced by the possible opportunities to have snacks. Although this term does not have a static definition, some data from the literature associated it with the type and amount of food consumed, the location and even the time interval [93,94]. Most of the time, snacks are associated with the consumption of healthy foods when there is a real feeling of hunger, but in the absence, more often, the snacks are processed foods, high in calories and rich in saturated fats [95]. Chapelot et al. supported the idea that junk snacks are one of the causes of weight gain [96]. Myhre JB et al. demonstrated in a cross-sectional study of 1,787 Norwegian subjects over 18 years of age that workplace snacks are a source of protein with a lower sugar content, thus separating a favorable nutritional profile compared to eaten snacks holidays, restaurants. or even at home [97]. Depending on the location of snack consumption, a cross-sectional study on a group of 958 Irish adults identified their nutritional role in the daily diet (98). Eating in other locations such as restaurants than at home has been associated with larger portions and a high fat and fiber content [98]. In current study, we found that individuals from the overweight category may be more likely to consume home-cooked meals compared to those in higher obesity classes, which could be associated with better dietary control or preferences that influence weight.

There is a borderline significant difference in the tendency to eat big portions across the BMI groups ($p = 0.08$). This suggests that eating larger portions may be more prevalent among individuals with higher BMIs, although the relationship is not strong enough to be considered statistically significant at traditional levels (e.g., $p < 0.05$). In this case, certain behaviours like eating big portions may trend with higher BMI. These insights suggest that psychological factors and eating context may play roles in the eating behaviours of individuals with different BMI statuses.

Even though there is evidence attesting to the negative 463 impact of prolonged television viewing and reduced physical activity in the development of obesity and increased cardiometabolic risk in the long term, but other devices have not been associated in this sense [99], there is insufficient data in the literature to specialty to confirm with certainty the frequent consumption of snacks during the time spent in front of the television or other devices [100]. On the other hand, according to Chapman CD et al., there was evidence that some television programs can promote the lifestyle in a positive way, thus there is an increase in fruit consumption among people who watched boring shows [101].

These insights suggest that certain lifestyle factors, particularly physical activity, and the consumption of home-cooked food, are significantly associated with BMI categories. The findings particularly emphasize the importance of physical activity in maintaining a healthier weight status and suggest potential areas for intervention, such as promoting more home-cooked meals, which could have beneficial effects on weight management and overall health.

Measures were done in comparable levels of hydration to prevent misinterpretation since BIA is particularly sensitive to total body water. This method was used to calculate estimates for total body water, and percentage of fat mass, fat free mass as well as intracellular and extracellular water [102,103]. With regard to its use throughout sports and medicine, the raw BIA variable of phase angle (eg, the percentage of resistance to reactance) given with certain BIA devices has acquired prominence [103]. Several more studies have shown the reliability among both single-frequency and multi-frequency instruments, coming to the conclusion that BIA may substitute DXA for the analysis of whole-body and segmental body composition in large populations [104,105].

A variety of nutrition-related disorders that have an influence on both individual and public health may be evaluated, managed, and treated with great benefit from the measurement of fat, muscle, bone, and water [102]. Although baseline measurements enable the development of a nutritional program initially, periodic modifications and the monitoring of changes are required during its lifetime in order to measure success and set reasonable short-term targets [102,103]. Single-frequency devices and segmental assessments show considerable discrepancies compared to DXA in patients with very high BMI values, despite the validity and accuracy of body bioimpedance analysis having been established [104,105].

The significance of our research lies in its unique focus on a specific regional demographic over a ten year period. While previous studies have explored the relationship between dietary patterns and cardiometabolic risk, our study distinguishes itself by homing in on the population of obese and overweight patients in Western Romania. This focused approach allows to uncover nuanced patterns and trends that may be specific to this particular group, providing essential insights into a region where such investigations are limited. By examining data collected over a decade, this study captures long term trends and fluctuations in dietary habits and their impact on cardiometabolic health within this specific population. Thus, the novel aspect of our research lies in its localized perspective and the comprehensive analysis of data spanning a significant timeframe, offering a valuable contribution to the understanding of dietary influences on cardiometabolic risk in this specific demographic context.

This article represents the initial study conducted on a substantial cohort of patients, aiming to highlight dietary habits through a meticulous survey in accordance with anthropometric parameters and the results of body composition analysis using bioimpedance. Considering the significant group of patients with obesity, the strength of this study is that it managed to approve the links between the food factors prevalent in the western part of Romania and the cardiometabolic risk. Until now, no other study has addressed this topic in such a precise manner, but nevertheless, there are certain limitations. The empirical findings presented in this study should be interpreted within the context of certain limitations. The study may not account for cultural or regional variations in dietary patterns, which could impact the generalizability of the findings to populations with different cultural or regional dietary habits regardless of origin. At the same time, in the assessment of food routine, a validated questionnaire was not used, but the questions were precise, and the food survey was established in a complex way for all participants. The primary objective was not to calculate and correlate a validated food questionnaire with other medical parameters; rather, the aim was to elucidate a potential association between dietary habits prevalent in the western region of Romania and the occurrence of metabolic and CVD. The cross-sectional design of the study cannot establish a possible relationship between cause and effect in terms of eating habits, body analysis parameters through bioimpedance and cardiometabolic risk. Additionally, longitudinal studies are needed in order to determine a time sequence of these connections and even include and interpret the results using validated questionnaires. Additionally, the retrospective nature of our study might have limitations in capturing real-time dietary changes and their immediate impact on cardiometabolic health. Moreover, the study's scope was confined to a specific region and timeframe, which might limit the generalizability of our findings to broader populations or different time periods. We also recognize that self-reported dietary data, inherent to studies of this nature, may carry a risk of recall bias, influencing the accuracy of our results. In light of these limitations, we are committed to addressing these concerns in future research endeavors.

Conclusions

In conclusion, our study has brought to light significant disparities in eating patterns, personal and familial medical histories of cardiometabolic conditions, and body composition parameters among individuals with varying degrees of obesity and overweight in the western region of our country. These findings underscore the intricate interplay of biological, behavioral, and environmental factors contributing to obesity, a pressing public health issue.

Key dietary habits, including pleasure-driven eating, weekend eating habits, consumption of cooked foods, two courses lunch and emotional eating, exhibited notable differences among participants based on their BMI values. Additionally, age emerged as a significant variable, highlighting its association with different obesity categories. Furthermore, inadequate physical activity, defined as less than 30 minutes per day according to established guidelines, was identified as a risk factor across the evaluated groups. While the current smoking status of participants showed borderline associations with obesity and overweight categories, smoking cessation did not demonstrate significant links. These findings emphasize the need for personalized approaches in addressing obesity, considering each patient's unique lifestyle, dietary behaviors, and medical history.

Our study underscores the importance of multifaceted strategies in obesity research and interventions. By shedding light on the complex factors contributing to obesity, our findings contribute valuable insights to the development of more effective, tailored approaches to obesity management and prevention. Ultimately, this study represents a significant step towards mitigating the global obesity epidemic.

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