

# Cluster-based analysis to determine nutritional profiles among cancer patients receiving chemotherapy

Riani Witaningrum<sup>1</sup>, Satria Perdana<sup>1\*</sup>

<sup>1</sup> Department of Health and Nutrition, Faculty of Medicine, Public Health, and Nursing, Universitas Gadjah Mada, Sleman, Special Region of Yogyakarta, Indonesia

## ABSTRACT

**Background:** Chemotherapy remains the major strategy in cancer treatment, although it increases the risk of malnutrition. Evidence identifying hierarchical clusters of malnutrition risk factors beyond chemotherapy remains limited despite their importance for improving nutritional risk stratification. **Objectives:** This study aims to identify the proximity of malnutrition-related factors among cancer patients, thereby generating phenotypic clusters of cancer patients at risk of malnutrition. **Methods:** A cross-sectional study was conducted among 148 cancer patients undergoing chemotherapy in Dr. Sardjito Hospital, Yogyakarta. Malnutrition status, body composition, and anthropometric indicators were assessed using Patient Generated-Subjective Global Assessment (PG-SGA), Bioimpedance Analysis (BIA), and standardize measurements, while dietary intake was collected using semi-quantitative food frequency questionnaire (SQ-FFQ). Data were standardized using z-score and analyzed using k-means clustering. Associations between clusters and clinical characteristics were examined using chi-square tests ( $p < 0.05$ ), and multinomial logistic regression was applied to identify predictors of malnutrition risks. **Results:** Three clusters (High-fat-high-intake (HFHI), Lean muscular (LM), and Low intake-low body composition (LILB)) were positively associated with gender, smoking status, and cancer type ( $p < 0.05$ ). Compared to cluster LILB, cancer type significantly increased the likelihood of a person being included in both cluster HFHI (OR=7.34;  $p < 0.001$ ) and LM (OR=4.35;  $p = 0.001$ ). Furthermore, gender had a significant effect on being included in cluster HFHI (OR=6.34;  $p = 0.031$ ), but not in cluster LM. Smoking status was not significantly linked with any cluster ( $p > 0.05$ ). **Conclusions:** Clustering approach can reveal varied nutritional status patterns among cancer patients, necessitating more tailored and multimodal nutritional therapy management.

**KEYWORDS:** cancer; chemotherapy; k-means clustering; malnutrition; nutrition profiles

## INTRODUCTION

Cancer is a group of diseases characterized by the uncontrolled growth and spread of abnormal cells throughout the body [1]. Cancer is the leading cause of death worldwide, with global statistics indicating nearly 20 million cancer incidents and nearly 10 million cancer-related deaths in 2022. Demographic-based predictions indicate that the number of new cancer cases will reach 35 million by 2050, a 77% increase from 2022 [2]. Globally, cancer types vary widely including carcinoma, sarcoma, leukemia, and lymphoma with the

largest number of cases being breast cancer (66,271), lung cancer (38,904), and cervical cancer (36,964) [2]. The increasing global burden of cancer has substantial clinical implications, extending beyond mortality to treatment-related complications, including nutritional deterioration and metabolic disturbances.

Commonly used treatment strategies for cancer include chemotherapy, hormone therapy, immunotherapy, radiotherapy, and surgery [3]. Despite the promising development of new treatments targeting oncogenes and immunotherapy, chemotherapy remains the mainstay of cancer patient management [4] which nearly always

**Corresponding author:** Satria Perdana, Department of Health and Nutrition, Faculty of Medicine, Public Health, and Nursing, Universitas Gadjah Mada, Sleman, Special Region of Yogyakarta, Indonesia, email: [satriaprnd13@mail.ugm.ac.id](mailto:satriaprnd13@mail.ugm.ac.id)

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causes significant systemic side effects [5]. Physical symptoms include fatigue, hair loss, changes in appetite, mouth ulcers, weight changes, nausea, vomiting, and increased systemic inflammation, which simultaneously increase the risk of malnutrition and cause a major challenge in nutrition care [6,7].

The European Society for Clinical Nutrition and Metabolism (ESPEN) defines malnutrition as reduced intake or absorption of nutrients that can impact body composition, considering body mass index (BMI) criteria, weight loss, and fat-free mass index (FFMI) [8–10]. Thirty-five percent of hospitalized cancer patients are at risk of malnutrition even if the BMI is within the normal or excessive [7,10,11]. Currently, a high-energy (generally between 25-30 kcal/kg/day) and high-protein (between 1-1.5 g/kg/day) diet [8] is well-known nutritional management to combat malnutrition for cancer patients that provided concurrently with medical therapy [12]. However, the nutritional quality is considered scarce, inadequate and less effective in reducing premature morbidity and mortality due to cancer [8,13].

As widely recognize, malnutrition is a multifactorial condition; however, nutritional interventions in clinical practice are often focused on a single therapeutic modality. In this context, closer investigation of nutritional profiles among cancer patients receiving chemotherapy, and potentially at risk of malnutrition, would offer valuable insights into this issue so that more accurate nutritional interventions can be determined. Our main aim was therefore to describe the factors causing malnutrition, resulting in hierarchical profiles of cancer patients at risk of malnutrition based on guideline-defined malnutrition indicators. Identifying hierarchical groupings of malnutrition risk factors beyond chemotherapy remains limited, despite their importance for improving nutritional risk stratification.

## METHODS

### Study design and participants

This study used a cross-sectional design to examine 148 cancer patients undergoing chemotherapy at Tulip ward, Dr. Sardjito General Hospital, Yogyakarta, Indonesia, between January-August

2025. Subjects were recruited using a consecutive sampling technique. All eligible patients who attended the Tulip ward for physician consultation or cancer treatment were approached and invited to participate on a voluntary basis. All participants were recruited by trained enumerators including two nutrition students and one dietitian. The inclusion criteria for this study were: 1) male or female aged >18 years; 2) patients diagnosed with cancer by oncologist; 3) patients who were in nonsurgical treatment phase (receiving chemotherapy) at Tulip ward, Dr. Sardjito General Hospital, Yogyakarta, Indonesia; 4) patients who were willing to participate in the study and receive compensation (mug or water bottle). The exclusion criteria were: 1) patients with terminal-stage cancer; 2) patients with a history of mental illness, mental disorders, or current psychological problems; 3) patients who were required to fast; 4) patients who were pregnant or breastfeeding. Data were collected using interview techniques, direct measurements using several tools, and secondary data collection through medical records.

The interview technique was carried out using: 1) a patient identity and characteristics questionnaire; 2) a Semi-quantitative Food Frequency Questionnaire (SQ-FFQ) for food intake data; 3) Patient-generated Subjective Global Assessment form (PG-SGA) v3.22.15 for weight loss data; and 4) self-reported and medical records data of height measurement. Direct measurements were performed using: 1) Body Impedance Analysis (BIA) Omron brand HBF-375 series for measuring body weight and body composition; and 2) measuring tape for examining upper arm circumference and calf circumference. The authors declare that the ethical guidelines of this research have been complied with based on ethical clearance (Ref: KE/FK/1319/EC/2024 and Continuing Review Approval of Approval Ref: KE/FK/1535/EC/2025) issued by the Ethics Commission of Faculty of Medicine, Public Health and Nursing, Gadjah Mada University.

### Measures

The collected data was pre-processed by equating all variables in the form of z-scores. The variables

entered were body mass index (BMI), mid-upper arm circumference (MUAC), fat-free mass index (FFMI), percent fat, percent energy intake, and protein intake. Food intake data using SQ-FFQ interviews inputted into the Nutrisurvey application. The patient's energy needs calculated according to the recommended energy needs for cancer patients from ESPEN (25 kcal/kgBW for women and 30 kcal/kgBW for men) [8]. The energy (kcal) data obtained from the Nutrisurvey was compared with the calculated energy requirements according to the patient's gender to generate a percentage of energy intake. Hierarchical clustering was performed using Ward's method to determine the optimal number of clusters. The number of clusters obtained by merging two smallest increases in total within-cluster variance before the largest cluster is formed. This was the method to minimize the variance within cluster by calculating the average (mean point) for each of their clusters, and then for each person. So, the Euclidean distance was computed between all observations, and the clustering results were visualized using a dendrogram. The optimal number of clusters was determined by cutting the dendrogram at the stage prior to substantial increase in the merging distance, indicating a marked rise in within-cluster variance. The data were then analyzed using the k-means clustering technique. The results of the analysis were shown by the interpretation of each cluster based on the z-score results and the distribution of the number of patients in each cluster.

### Data analysis

Statistical analysis was performed by handling missing data through the multiple imputation method. Imputation was a process of replacing missing data or missing values with logical replacement values, using statistical procedure to ensure the dataset remains intact without eliminating large numbers. The multiple imputation method carried out to produce 20 complete datasets, and the intermediate results are pooled together to yield final cluster assignment of each individual in the dataset. Descriptive statistics for each cluster were calculated based on the first imputation results, as the cluster structure was formed from this dataset. The dataset was then selected using

the first dataset condition to ensure consistency of the results. The relationship between the formed clusters and clinical variables was tested using the Chi-square test with a significance level of  $p < 0.05$ . Clinical variables that showed a significant relationship were further analyzed using multinomial logistic regression to assess the influence of clinical variables on cluster membership. All statistical analyses were performed using IBM SPSS Statistics software version 26 with a significance level set at  $\alpha = 0.05$ .

## RESULTS

The study population consisted of 65 men and 83 women with an average age of  $54.53 \pm 11.576$ . The distribution of demographic characteristics, lifestyle factors, and comorbidities is presented in **Table 1**. The dendrogram results in **Figure 1** show that the cuts were made at a scaled distance of 15–20, resulting in three

**Table 1. Baseline characteristic populations**

Characteristic (n, %)	Overall (n = 148)
Age, mean±SD	54.53±11.576
Gender	
Male	65 (43.9)
Female	83 (56.1)
Smoking status	
Yes	42 (28.4)
No	106 (71.6)
Nutrition counselling	
Yes	41 (27.7)
No	107 (72.3)
Comorbid	
Yes	55 (37.2)
No	93 (62.8)
Cancer type	
Gastrointestinal	58 (39.2)
Non-gastrointestinal	90 (60.8)
Cancer stage	
I-II	32 (21.6)
III-IV	116 (78.4)
Metastasis, n, %	
Yes	20 (13.5)
No	128 (86.5)
Chemotherapy cycle	
1 - 4	78 (52.7)
>4	70 (47.3)

main clusters. Cluster 1 describes cancer patients with adequate energy and protein intake status, but with a high percentage of body fat and a lower free fat mass. Cluster 1 can be called the “high-fat-high-intake” or “HFHI” cluster. Cluster 2 shows cancer patients with a body composition that is predominantly high muscle mass and fat-free mass, a normal percentage of body fat, and a high BMI and MUAC. Cluster 2 can be called the “lean muscular” or “LM” cluster. Meanwhile, the

characteristics of cancer patients in Cluster 3 are patients with poor nutritional status, inadequate energy and protein intake, and a body composition that is low in fat and muscle. This can be called the “low intake-low body composition” or “LILB” cluster.

After determining the number of clusters, using six variables: BMI, MUAC, FFMI, % fat, % energy intake, and protein intake. The results in **Table 2** show the characteristics of each cluster with Z-score interpretation. The three clusters, shown in **Table 3**, were associated with patient characteristics, such as gender, smoking status, and cancer type, with a p-value <0.05. Negatively, three clusters were not associated with age, nutrition counselling, comorbid conditions, cancer stage, metastasis, chemotherapy cycle, weight loss, or gastrointestinal-related side effects. Multinomial logistic regression was then performed to see the influence of each significant variable on cluster division.

The results of the multinomial logistic regression analysis in **Table 4** showed that, compared to cluster LILB, the type of cancer variable significantly influenced the likelihood of an individual being included in both cluster HFHI (OR=7.34; p<0.001) and cluster LM (OR=4.35; p=0.001). Furthermore, gender also significantly influenced the likelihood of being included in cluster HFHI (OR=6.34; p<0.001), but not in cluster LM (p=0.952). Conversely, smoking status was not significantly associated with any cluster classification (p>0.05). Thus, cancer type was the primary predictor of cluster formation in respondents’ nutritional status, while gender only influenced clusters with specific characteristics.

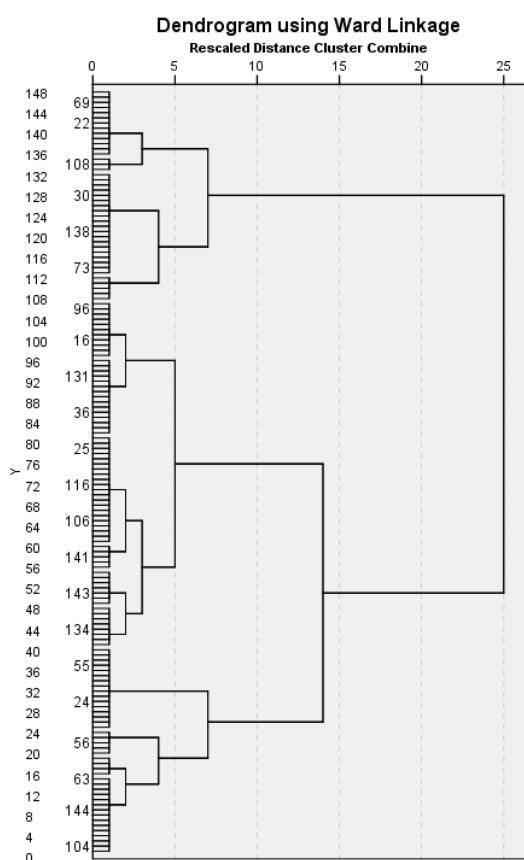


Figure 1. Ward’s linkage method dendrogram

Table 2. Cluster interpretations using Z-score standardized

Variables	Cluster 1 (Z-score)	Cluster 2 (Z-score)	Cluster 3 (Z-score)
BMI	-0.8995 (↓)	1.02305 (↑)	-0.62218 (↓)
MUAC	-0.00173 (↓)	0.97566 (↑)	-0.63978 (↓)
FFMI	-0.66049 (↓)	0.95863 (↑)	-0.26480 (↓)
% Fat	0.81591 (↑)	0.31316 (↑)	-0.65623 (↓)
% Energy intake	1.15519 (↑)	-0.26238 (↓)	-0.46563 (↓)
Protein intake	0.9189 (↑)	-0.00741 (↓)	-0.50247 (↓)
Interpretation	High-fat-high-intake (HFHI)	Lean muscular (LM)	Low-intake-low body composition (LILB)

Mean = (+) score above mean population, (-) score under mean population; Arrows = (↑) increase, (↓) decrease  
 BMI = body mass index; MUAC = mid-upper arm circumference; FFMI = fat-free mass index

**Table 3. Association between clusters and study characteristics**

Variables	Clusters (n, %)			p-value
	HFHI (n = 37)	LM (n = 44)	LILB (n = 67)	
Age				
21 - 30	1 (2.7)	0 (0.00)	3 (4.5)	0.417
31 - 40	3 (8.1)	4 (9.1)	9 (13.4)	
41 - 50	6 (16.2)	12 (27.3)	9 (13.4)	
51 - 60	16 (43.2)	19 (43.2)	23 (34.3)	
>60	11 (29.7)	9 (20.5)	23 (34.3)	
Gender				
Male	6 (16.2)	20 (45.5)	39 (58.2)	<0.001**
Female	31 (83.8)	24 (54.5)	28 (41.8)	
Smoking status				
Yes	5 (13.5)	12 (27.3)	25 (37.3)	0.035*
No	32 (86.5)	32 (72.7)	42 (62.7)	
Nutrition counselling				
Yes	10 (27)	11 (25)	20 (29.9)	0.851
No	27 (73)	33 (75)	47 (70.1)	
Comorbid				
Yes	14 (37.8)	16 (36.4)	25 (37.3)	0.990
No	23 (62.2)	28 (63.6)	42 (62.7)	
Cancer type				
GI	6 (16.2)	12 (27.3)	40 (59.7)	<0.001**
Non-GI	31 (83.8)	32 (72.7)	27 (40.3)	
Cancer stage				
I-II	6 (16.2)	15 (34.1)	11 (16.4)	0.057
III-IV	31 (83.8)	29 (65.9)	56 (83.6)	
Metastasis				
Yes	7 (18.9)	5 (11.4)	8 (11.9)	0.538
No	30 (81.1)	39 (88.6)	59 (88.1)	
Chemotherapy cycle				
1 - 4	22 (59.5)	19 (43.2)	37 (55.2)	0.294
>4	15 (40.5)	25 (56.8)	30 (44.8)	
Weight loss				
<5%	30 (81.1)	33 (75)	51 (76.1)	0.945
5 - 10%	3 (8.1)	4 (9.1)	5 (7.5)	
>10%	4 (10.8)	7 (15.9)	11 (16.4)	
GI-related side effects				
Yes	13 (35.1)	7 (15.9)	12 (21.6)	0.068
No	24 (64.9)	37 (84.1)	55 (82.1)	

\*p-value <0.05, significant; HFHI = high-fat-high-intake; LM = lean muscular; LILB = low-intake-low-body composition

## DISCUSSION

This study identified three distinct nutritional risk profiles among chemotherapy patients and demonstrated that gender and cancer type were significant predictors

**Table 4. Multinomial logistic regression analysis of the association between clusters and cancer type, gender, and smoking status**

Cluster*	Variables	B	p-value	OR (CI)
HFHI	Cancer type	1.993	<0.001	7.337 (2.539-21.204)
	Gender	1.847	<0.001	6.342 (1.188-33.869)
	Smoking status	0.102	0.31	1.107 (0.176-6.971)
LM	Cancer type	1.470	0.001	4.350 (1.831-10.334)
	Gender	0.033	0.952	1.034 (0.351-3.034)
	Smoking status	0.672	0.266	1.958 (0.599-6.396)

\*The reference is LILB cluster

of cluster membership. We identify three hierarchical profiles (HFHI, LILB, and LM clusters) of cancer patients undergoing chemotherapy who were at risk of malnutrition, with cancer type and gender emerging as significant predictors.

Cancer patients in the HFHI cluster are characterized by being female, suffering from non-gastrointestinal cancer, and having no problems consuming high-energy and high-protein foods, but having low muscle mass and high fat mass. Cancer patients in the LM cluster are characterized by being female or male, suffering from non-gastrointestinal cancer, having good body composition (sufficient fat and muscle reserves), but have seen a decrease in food intake. Patients in the LILB cluster are characterized by being male, suffering from gastrointestinal cancer, still smoking during chemotherapy, having poor body composition (decreased fat and muscle mass), and a higher decrease in food intake compared to other clusters.

Findings in the LM cluster (n=44) specifically indicated a good energy and protein reserve capacity. This was demonstrated by higher muscle mass and MUAC percentages compared to other clusters (Z-score = 0.95863; Z-score = 0.97566, respectively) and relatively high body fat percentage (Z-score = 0.31316) despite an overall inadequate dietary intake. This group is considered a robust but physically unmuscular patient population and is at risk of malnutrition. According to the ESPEN guidelines for cancer patients, muscle protein synthesis is not known to be reduced in cancer patients. The necessary amino acids obtained from protein sources will still provide a muscle synthesis response, especially in higher amounts than in healthy individuals (recommended >1-1.5 g/kg/day) [8] by stimulating

mammalian Target of Rapamycin (mTOR) pathway as the marker in driving protein synthesis [14].

The characteristics of the LILB cluster (n=67) resemble a classic group of malnourished cancer patients with reduced muscle density. Inadequate dietary intake and disease-related malnutrition reduce fat and protein reserves, resulting in loss of fat and muscle mass. Muscle depletion involuntarily is one of the indications of cancer cachexia [8,15]. Data suggested that cancer cachexia cannot be managed solely by providing a high-energy diet due to a persistent catabolic metabolic shift, yet the muscle protein synthesis is not blunt [8,15]. We did not examine cancer cachexia in our study, thus, cancer patients in cluster LILB may require somewhat higher quantity amino acids such as additional oral nutritional supplements (ONS) to shift their metabolic balance to an anabolic one. Multiprofessional support is also needed to improve physiological, fitness, social, and spiritual well-being to maintain quality of life [15].

In contrast to the LILB Cluster, the HFHI Cluster (n=37) represents a group of cancer patients often referred to as “skinny fat” or anabolic resistance. Skinny fat is a condition in which a person has a high percentage of body fat but low muscle mass. Skinny fat can be an independent factor that worsens the prognosis of cancer patients receiving surgery and chemotherapy and can even worsen the prognosis of radiotherapy [10]. Furthermore, the combination of decreased anthropometric indices and decreased FFMI is known to be associated with increased morbidity and mortality in cancer patients [10], as seen in the HFHI and LILB Clusters. This study demonstrates that the high-energy, high-protein diet principle adopted by cluster LILB does not guarantee increased body protein reserves, given that increased whole-body protein turnover does not automatically result in skeletal muscle protein anabolism [16,17]. One contributing factor is the frequent presence of anabolic resistance in muscle [8,16]. During this period, the utilization and incorporation of dietary protein into body tissues are compromised [8]. Long term insulin treatment and amino acid supplementations were ineffective in inducing anabolic response [8,16,18]. However, a study showed anabolic potential in advanced cancer patients after provided by formulated nutrition consisted

of casein and whey protein, enriched with 10% free leucine, specific oligosaccharides and fish oil [18]. The inconsistent findings regarding anabolic resistance across cancer studies may be reflect to multiple factors, including differences in the study population characteristics (e.g., nutritional status depending on tumour type and tumour stage, life expectancy, inflammation which induces muscle proteolysis), dietary protein intake (the quality and quantity), and treatment agents that contribute to muscle and fat wasting by altering lipid metabolism [17]. Therefore, the intervention approach in this cluster should focus on increasing muscle mass through resistance exercise while not altering the protein intake at least 65% from low-fat, high protein sources to support muscle anabolism [16]. Future trials are needed to clarify the existence of protein anabolic resistance in cancer using muscle protein turnover, distinctly in Indonesian population.

This study found significant differences ( $p < 0.001$ ) between clusters with gender as the variable. This proves that gender differences influence nutritional status based on anthropometry, body composition, and intake patterns. Women were predominantly represented in the HFHI cluster, whereas men were more prevalent in the LILB cluster. In contrast, no significant gender difference was observed in the LM cluster. Women tended to be in clusters with good energy and protein intake compared to men. Meanwhile, men were significantly more prevalent in clusters with a high risk of malnutrition. These findings align with other studies that suggest higher cancer prevalence and mortality in men than in women [19,20]. Furthermore, male cancer patients are at a fourfold higher risk of malnutrition, with a reported risk of severe malnutrition of 25.35% ( $p = 0.033$ ), especially in patients undergoing chemotherapy [21,22]. Differences in diet, smoking habits, alcohol consumption, psychosocial factors and cancer type contribute to these results beyond biological factors such as male-specific gene expression that plays an active role in oncogene activity [20,23,24].

Further results of this study observed that smoking habits is not the independent predictor of malnutrition between clusters ( $p > 0.05$ ). The LILB cluster, which represents characteristics of poorer nutritional status and lower intake, had the highest proportion of smokers

(37.3%) compared to HFHI cluster and LM cluster. Indonesia is known to have the highest male smoking population in the world (70%) [25]. Other studies have also shown that up to 18% of patients continue smoking after being diagnosed with cancer and receiving chemotherapy [26]. The observed value in this study was higher than in previous studies. Furthermore, research by Kaduka proved that the incidence of malnutrition will increase 3.95-fold in cancer patients who smoke, so it can be said that smoking is an independent predictor of cachexia [22]. Individuals exposed to nicotine in cigarettes show impaired taste perception in the central nervous system, so they tend to consume less food and high alcohol consumption [27]. This condition can ultimately worsen the side effects of cancer treatment, metastasis, complications, morbidity, and mortality [26].

Cancer type is known to be one of the malnutrition factors [17]. Fifty-nine percent of cancer patients in the LILB cluster suffered from gastrointestinal cancer ( $p < 0.001$ ). In this study, gastrointestinal cancers included colorectal cancer, gastric cancer, pancreatic cancer, ileal cancer, gallbladder cancer, and liver cancer, with or without metastasis. A 2017 study by Kaduka found a similar finding, with the highest incidence of malnutrition occurring in 24% of oesophageal cancer patients [22]. Another study by Karami in 2021 also found that the highest risk of malnutrition was in patients with gastrointestinal cancer [21]. Studies in Italy and Iran have also found the same thing, namely that patients with pancreatic and gastroesophageal tumours were observed to have a higher frequency of malnutrition compared to breast cancer [28]. Specifically, up to 80% of patients induces weight loss in upper gastrointestinal cancer (head and neck area) patients who receive radiotherapy [15]. This condition is based on the fact that patients with gastrointestinal cancer have a 23-fold higher risk of experiencing severe malnutrition caused primarily by impaired intake, such as anorexia, mucositis, food transport and absorption, and damage to the intestinal barrier [9,15].

The results of the multinomial logistic regression analysis conducted in this study proved that there was a relationship between cluster formation and significant predictors or risk factors for malnutrition. Gender (OR

= 6.342; 95% CI = 1.188-33.869) and cancer type (OR = 7.337; 95% CI = 2.539-21.204) were significant predictors in the HFHI Cluster when compared to the LILB Cluster. The analysis comparing the LM Cluster with the LILB Cluster found that cancer type (OR = 4.350; 95% CI = 1.831-10.334) was the single significant predictor in the LM Cluster when compared to the LILB Cluster. Women were 6.3 times more likely to be in the HFHI Cluster than men. A meta-analysis found that obesity is significantly associated with cancer in female patients [29]. These findings support previous findings showing that female cancer patients receiving chemotherapy and radiotherapy have a 10.6% lower FFMI than male patients [10]. A low FFMI combined with weight loss is associated with poor survival, even in patients with a normal BMI [10]. This low FFMI is associated with a worsening prognosis and performance status in cancer patients, particularly in late stages (III and IV) [10,30]. The low muscle mass reflected in the FFMI values in the HFHI Cluster may indicate decreased muscle mass due to decreased protein intake, metabolic changes, and increased inflammation. Although this study did not specifically analyse [31] inflammatory factors, we assume that the majority of cancer patients experience chronic inflammation due to the disease and side effects of its treatment.

In addition to gender, cancer type was found to be a predictor in the HFHI and LM Clusters. Patients with non-gastrointestinal cancers were 7.3 times more likely to be in the HFHI Cluster and 4.3 times more likely to be in the LM Cluster compared to the LILB Cluster. This information aligns with the characteristics of cancer patients in the HFHI Cluster, which show increased energy and protein intake and increased body fat percentage. As many as 70-80% of cancer patients experience anorexia syndrome, especially in the late stages. The prevalence of anorexia depends, among other things, on the type of cancer. Anorexia syndrome occurs in 80% of patients with primary tumours in the pancreas and gastrointestinal tract, followed by 54-60% of lung and prostate cancer patients, and 32-48% in breast cancer, sarcoma, and leukaemia patients. All of these figures can result in poor clinical outcomes and contribute to decreased treatment tolerance, decreased quality of life, and increased morbidity [32]. However, previous research specifically stated that

food intake in hospitalized breast cancer patients was considered fluctuating due to incompatibility of food tastes and preferences, not only due to impaired food intake, transport, and absorption [33]. Anorexia syndrome in cancer patients is characterized by the breakdown of muscle mass without loss of fat mass, which causes progressive weight loss [32]. As many as 75% of patients are in the pre-cachexia group in the LM cluster, namely systemic inflammation with unintentional weight loss of <5%. Therefore, appropriate nutritional intervention to stabilize nutritional status at this point is essential to prevent patients from developing cachexia and improve their quality of life.

Several limitations were found in this study. First, the researchers did not use cut-offs for FFMI and fat percentage in cluster formation, so it is unknown whether the characteristics of FFMI and fat percentage are considered higher or lower than the reference values in cancer patients. However, data standardization with Z-scores is the most robust method in applying K-Means cluster analysis. Second, the researchers did not use the gold standard tool for measuring body composition, namely computed tomography (CT), because it was not available in the study and the cost was not sufficient to perform CT measurements. However, BIA measurements have been used in extensive cancer research and provide high specificity and sensitivity. Third, the researchers did not include inflammatory biomarkers that can exacerbate malnutrition due to the lack of complete laboratory data, especially for NLR and PLR values. However, we can assume that the majority of cancer patients experience chronic inflammation due to their disease and the side effects of their treatment, as mentioned in the references.

## CONCLUSIONS

The findings of this study indicate that the clustering approach can identify heterogeneous nutritional status patterns among cancer patients, necessitating more personalized and multidisciplinary nutritional management to support precision oncology treatments. By simultaneously integrating multiple nutritional and clinical variables, clustering provides a data-driven approach to identify distinct phenotypic subclusters that

may susceptibility to malnutrition. To go further, it will be interesting based on our results, to target specific malnutrition preventions strategy for those most at risk (LILB cluster), by helping them to stimulate anabolic response and eliminate nutritional issues including impaired food intake.

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### *Declaration of conflicting interests*

The authors declare no conflict of interest.

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