Association of Nutritional Status with Survival in Patients with Solid Tumors: A Stage Based Analysis

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REVIEW

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ABSTRACT

In this paper, we investigate the correlation between nutritional status and survival outcomes in patients with solid tumors, specifically focusing on Pancreas, Liver, Large intestine, Stomach, and Breast cancers. The recognition of malnutrition's profound impact on cancer outcomes, including compromised immunity and treatment-related complications, underscores the significance of early intervention. Existing tools like the Malnutrition Universal Screening Tool (MUST) and risk estimation tools have limitations, necessitating more comprehensive evaluations beyond BMI.

Conducted at the Community Cancer Institute in Clovis, California, our study adopts a retrospective approach, analyzing patient data from 2009-2019. Initial findings from a pilot study reveal intriguing correlations, such as between BMI and survival rates in liver cancer patients and a positive link between BMI and breast cancer metastasis. Subsequent analysis with an expanded sample size identifies additional correlations, underscoring the potential of blood-related nutritional parameters as valuable prognostic indicators.

Acknowledging study limitations, including incomplete nutrition intake and biomarker data, the findings highlight the promise of nutritional evaluations in predicting survival outcomes. Over 77% of cancer patients in our dataset exhibit overweight or obesity, supporting existing research on the BMI-cancer prevalence association. Future research directions involve exploring changes in body composition post-treatment and evaluating the impact of pre-conditioning with nutritional supplementation. This ongoing research aims to enhance strategies for optimizing cancer treatment outcomes and improving patient well-being.

Keywords: Body mass index, mid-arm muscle circumference, past medical history, alanine aminotransferase, aspartate aminotransferase.

ABBREVIATIONS

MUST - Malnutrition Universal Screening Tool

ASPEN - American Society of Parenteral and Enteral Nutrition

BMI - Body Mass Index

ACS NSQIP - American College of Surgeons National Surgical Quality Improvement Program

MAMC - mid-arm muscle circumference

CCI - Community Cancer Institute

PMH - past medical history

ALT - Alanine aminotransferase

AST - Aspartate aminotransferase

INTRODUCTION

According to the American Society of Parenteral and Enteral Nutrition (ASPEN) guidelines, malnutrition is defined as 'an acute, subacute or chronic state of nutrition, in which varying degrees of over-nutrition or undernutrition with or without inflammatory activity have led to a change in body composition and diminished function [1].

In the context of cancer, the impact of malnutrition on outcomes was first recognized in the mid-20th century [2, 3] when studies showed that malnourished cancer patients had poorer treatment outcomes and higher mortality rates than well-nourished patients [4, 5].

Malnutrition is a pervasive concern in cancer care, affecting up to 85% of patients and stemming from altered metabolism, treatment side effects, and cancer-related symptoms. To assess and address malnutrition, healthcare professionals rely on parameters such as Body Mass Index (BMI), serum albumin and prealbumin levels, nutritional screening tools, and dietary intake assessments. Malnutrition significantly impacts cancer treatment outcomes, contributing to delayed wound healing, heightened susceptibility to infections, increased treatment-related toxicity, reduced tolerance to therapies, impaired quality of life, and diminished survival rates. Early identification and management of malnutrition through nutritional support and interventions are crucial to improving patient prognosis and well-being in the context of cancer care [1-4].

In recent years, there has been growing recognition of the importance of addressing malnutrition in cancer patients early on, as studies have shown that malnutrition can occur even in patients who are overweight or obese [4, 5]. Malnutrition poses significant risks to cancer patients, stemming from factors such as the metabolic effects of cancer, treatment side effects, and psychological distress. Its consequences are diverse and impactful. Malnutrition can weaken the immune system, leaving cancer patients more susceptible to infections and complications. Wound healing may be delayed, affecting surgical and radiation therapy outcomes. Impaired response to treatment, including reduced tolerance and the need for dose adjustments or discontinuation, is also observed [6, 7]. Treatment-related toxicities, such as nausea, vomiting, diarrhea, and mucositis, are heightened in malnourished patients, further exacerbating the condition [8]. Moreover, malnutrition can contribute to fatigue, weakness, and a decreased quality of life for cancer patients. Recognizing and addressing malnutrition in cancer care is crucial to optimize treatment outcomes and enhance patient well-being and survival [4, 9, 10].

The Malnutrition Universal Screening Tool (MUST) is a validated and widely used tool for screening malnutrition in various healthcare settings. It comprises three components: body mass index (BMI), unintentional weight loss, and acute disease effect. Despite its effectiveness in identifying patients at risk of malnutrition, the MUST has limitations. Its focus on weight loss and BMI may overlook other aspects of malnutrition, such as micronutrient deficiencies. BMI may not be accurate for certain populations, and reliance on self-reporting can introduce inaccuracies. The tool may not be applicable to pediatric populations or certain clinical settings. Additionally, it may lack sensitivity in detecting early stages of malnutrition while potentially over-diagnosing patients who do not require intervention. Therefore, the MUST should be used alongside clinical judgment and other measures to ensure comprehensive nutritional assessment and appropriate intervention [7]. Likewise, there are several risk estimations tools available to help guide cancer treatment decisions. Some examples include:

Oncotype DX-This tool is used to predict the likelihood of breast cancer recurrence and the potential benefit of chemotherapy in treating early-stage breast cancer [11].

Adjuvant! Online - This tool estimates the risk of cancer recurrence and death in patients with early-stage breast cancer, and can help guide decisions about the use of adjuvant therapy (such as chemotherapy or radiation) [12].

TNM staging system- This system is used to stage many types of cancer based on the size and extent of the primary tumor, the involvement of nearby lymph nodes, and the presence of metastases. The stage of the cancer can help guide treatment decisions [13, 14].

Memorial Sloan Kettering Cancer Center (MSKCC) nomograms- These are a set of tools used to estimate the likelihood of cancer recurrence and the potential benefit of adjuvant therapy for various types of cancer, including breast, prostate, and lung cancer [15, 16].

Lung Cancer Screening Decision Tool- This tool is used to estimate the risk of developing lung cancer and can help guide decisions about lung cancer screening in current or former smokers [17, 18].

ACS NSQIP risk calculator - Despite being built on an extensive dataset of over 4.3 million operations from 780 hospitals and later expanded to include data from over 5.0 million operations across 855 participating hospitals from 2015 to 2019, the ACS NSQIP risk calculator, which serves as a valuable resource for risk estimation, cannot be relied upon for assessing the nutritional status of targeted patients. Even though the notable efforts made by the American College of Surgeons National Surgical Quality Improvement Program (ACS NSQIP) in developing a universal and comprehensive risk estimation tool, [19-22] limitations persist in adequately addressing nutrition assessment. While this calculator emphasizes the importance of inputting complete and accurate patient information to enhance risk precision, it primarily relies on BMI as the sole nutritional marker. Yet, BMI has inherent limitations as a marker for malnutrition, as it solely considers weight and height without accounting for body composition [23, 24].

While these tools may encompass various aspects related to treatment risk, such as tumor characteristics, comorbidities, and treatment modalities, they often lack a specific focus on nutrition assessment. The absence of a dedicated component for evaluating nutritional status within these risk estimation tools highlights a significant gap in the comprehensive evaluation of cancer patients. Addressing this gap by incorporating a nutrition assessment component could provide valuable insights into the impact of nutrition on treatment outcomes and guide tailored interventions to optimize patients' nutritional well-being during cancer treatment. As seen above, none of them adequately address the comprehensive assessment of nutrition. Therefore, no existing screening tool effectively addresses both nutrition assessment and predicting poor nutrition-related outcomes [7, 19, 20].

Therefore, there is a need to further enhance the nutritional assessment component within risk estimation tools to encompass more robust markers of malnutrition beyond BMI, thus enabling more accurate risk predictions and tailored interventions for optimal patient outcomes.

Nutritional scoring systems that take into account laboratory values and anthropometric measurements, as a whole and complementary factor, can be useful in assessing the nutritional status of cancer patients. These systems typically use a combination of blood markers, such as serum albumin levels, prealbumin levels, and anthropometric measurements like BMI, and/or body composition to identify patients who may be at risk of malnutrition.

ASPEN disapproves of using visceral proteins as indicators for malnutrition. Their primary rationale is that while serum albumin and prealbumin, long regarded as reliable visceral proteins for nutritional evaluations, have been traditionally valued, recent literature casts doubt on their usefulness in this context. The emerging perspective suggests that these proteins mainly indicate inflammation rather than the nutritional status or protein-energy malnutrition of individuals. Both critical and chronic illnesses can trigger inflammation, leading to the hepatic reordering of protein synthesis, which, in turn, causes reduced serum levels of these proteins [25]. However, laboratory values, such as serum albumin and prealbumin levels, can provide important information about a patient's protein status. Low serum albumin levels have been associated with poor outcomes in cancer patients, including

increased morbidity and mortality. Prealbumin levels, which have a shorter half-life than albumin, can provide more real-time information about a patient's protein status [26, 27].

Furthermore, anthropometric measurements, such as BMI and mid-arm muscle circumference (MAMC), can provide information about a patient's overall body composition. Low BMI and MAMC values have been associated with increased risk of complications and poor outcomes in cancer patients [28, 29].

All of these findings emphasize that both malnutrition and obesity have considerable impacts on the survival rates and clinical outcomes of cancer patients.

Consequently, in this paper we investigate the complex relationship between nutritional variables, Blood markers, BMI, and clinical outcomes in cancer patients at Community Cancer Institute, Clovis, California, by examining the evidence, data and clinical implications.

The study involves two phases: an initial pilot study and an expanded sample size analysis.

Our goal is to study the crucial relationship between nutritional status and clinical outcomes in cancer patients, with a focus on solid tumor categories like Pancreas, Liver, Large intestine, Stomach, and Breast. This study addresses a critical knowledge gap in the field of cancer care, highlighting the importance of incorporating comprehensive nutritional assessments into clinical practice.

METHOD

After obtaining IRB approval, this retrospective study was conducted on patient admissions between 2009-2019 at the Community Cancer Institute (CCI). As a sentinel pillar for cancer care in Community Health System, Community Cancer Institute is a healthcare facility located in Clovis, California which is dedicated to providing comprehensive cancer care services to patients in the Central Valley of California. The patient data were collected through the Community Cancer Institute's Electronic medical records. Electronic medical records of the patients who have been admitted at CCI for treatment and diagnosed with solid tumors including liver, pancreas, small intestine, large intestine, stomach, and breast were reviewed to determine the effect of nutrition-related factors on the treatment outcomes and survival of these patients. Please see Table -1 for more details. This table summarizes the CCI's cancer volumes and further stratifies it based on cancer stage and demographics. The highlighted cancer sites were chosen for this study, based on the availability of the data and their outcome correlation with nutrition, and available literature.

Patients' gender, age, past medical history (PMH), weight change, height, ethnicity, comorbidities, food history, family history, BMI, Length of hospital stay, readmission, and biochemical data were gathered retrospectively. Patients' five-year survival rate also was extracted and analyzed.

Again, in this study, we sought to determine the association of nutrition and its related measured parameters such as BMI with cancer treatment outcomes in five different solid tumors including: Pancreas, Liver, Large intestine, Stomach, Breast. Data collection on this study started in Spring 2020, and corresponding patients' charts were reviewed for all of the 5 index cancer groups mentioned above. This study included two distinct phases.
Initial phase included designation of a pilot study. This pilot study was comprised of data-gathering from 250 patient charts for mentioned cancer types, during which a comprehensive analysis of 50 randomized patient records per cancer type, averaging approximately 5 patients per year of study was performed. The main goal of this pilot study was to identify a meaningful degree of correlation between certain mentioned nutrition related variables and patient outcomes such as patient survival.

As the second phase, thereafter, we intended to expand our sample size based on the pilot study findings.

In order to test our hypothesis, patient BMI and survival rates were analyzed against following metrics: Age, Albumin, Glucose, Creatinine, and BUN levels. Patient's laboratory values represent their latest biochemical profile after the diagnosis. The blood draws were performed during the last medical visit along the cancer care continuum. Multi regression and t-tests were used to determine any

significant associations between these variables. Please see table-2 for all of the variables collected for this study. Exclusion Criteria for this study include Pediatric patients (Age Less than 18), Pregnant patients and Prisoners.

RESULTS

1) Initial phase, Pilot Study results:

In this phase using statistical analysis, various correlations between the nutritional variables such as visceral proteins and anthropometric data like BMI were analyzed against patient outcomes such as 5-year survival rate. The statistically significant findings for each of the mentioned index solid tumors is detailed below from our pilot study:

Liver Cancer- Only 46 patients out of 50 met our selection criteria. As shown in table-3, the mentioned analysis only showed a meaningful correlation between BMI and pertinent measured outcomes. Our findings indicate that among the variables examined, Albumin demonstrated a statistically significant correlation with BMI. However, due to its relatively long half-life (14-18 days), Albumin is not as sensitive in indicating visceral protein status compared to certain other plasma proteins with shorter half-lives (e.g., Prealbumin with a half-life of 2 days). Nevertheless, Albumin still exhibits an intriguing negative correlation with BMI in patients with liver cancer, suggesting that higher BMI values are associated with lower Albumin levels. In other words, liver cancer patients who have higher weight may be prone to malnutrition, if we concede low albumin level as a marker for malnutrition.

Breast Cancer- Additionally, our study revealed a positive association between BMI and the occurrence of breast cancer metastasis. These results lead us to propose a hypothesis that higher BMI values may be linked to an increased likelihood of cancer spreading in breast cancer patients. However, it is crucial to highlight that our pilot sample size comprised only 43 patients due to missing information in some cases. Indeed, expanding the sample size could potentially yield more robust and statistically significant outcomes. Please see table-4 for more details.

Pancreas, Colon and Stomach cancer - Out of the 50 patient charts reviewed in each of these categories, it was determined that only 43 of them fulfilled the specified criteria set forth for this study. Regrettably, our analysis revealed no statistically significant correlation between BMI and survival rates with various other variables/markers examined in this investigation.

2) Second Phase, expanded sample size results

Through a comprehensive analysis of primary data from our pilot study, we successfully identified a certain degree of correlation between nutritional variables such as BMI and clinical outcomes in some of the five various types of solid tumors. Therefore, to reinforce the current findings pertaining to the relationship between the nutritional status of cancer patients and their body mass index (BMI), it becomes imperative to expand the sample size. As a result, we have made the decision to focus our attention on two particularly promising cohorts, namely liver and breast cancer, with the intention of obtaining a larger and more representative sample size to further analyze our initial findings. Therefore, a total of 227 new patients, including 102 new patients with breast cancer and additional 125 new patients with liver cancer were incorporated and thoroughly analyzed in the second phase.

Heatmap analysis

To better understand the correlation between these variables, we employed a heatmap test to examine the interrelationships among various variables. Heatmaps, recognized for their efficacy in visual representation, serve as valuable tools for illustrating variance across multiple variables and unveiling patterns within correlations. Furthermore, heatmaps offer a graphical depiction of data, utilizing color-coded cells to signify the magnitude or density of a given variable across distinct categories or dimensions. In a heatmap, each category or dimension is represented by a row or column, and the color intensity of each cell within the grid signifies the value of the variable pertaining to that specific category or dimension. The numbers shown in this heatmap are the Pearson Correlation

Coefficient which measures the degree of correlation between the two parameters (row and column). Positive and negative Pearson r means that the two parameters have Positive and Negative Correlations respectively while higher values for person's correlation coefficient regardless of being positive or negative (such as 0.8 or -0.8) means higher degree of correlation. Of course, the p-value of every single pair of parameters are later measured to check if the data is not randomly distributed and if the Pearson's r are valid. Typically, warmer hues such as red or orange indicate higher values, while darker shades indicate lower values. Please see Figure 1 for more details.

In summary, heat maps provide a valuable and intuitive means of analyzing and presenting extensive datasets, empowering researchers to gain comprehensive insights through visual exploration.

Liver Cancer- The heatmap analysis was performed for all of the measured variables for liver cancer patients, represented in figure 2. The significant pertinent findings are summarized in table 5.

As seen in figure 3, the analysis presented in the table 5 demonstrates a positive association between abnormal albumin levels (ranging from 3.4 to 5.4 g/dL) and the presence of distant metastasis in patients.

The association between albumin levels and the occurrence of distance metastasis in liver cancer patients is likely influenced by multitude of factors, including the stage of liver cancer, coexisting comorbidities, and the overall health status of the patient and the liver. Low levels of albumin may serve as indicators of malnutrition, inflammation, and compromised liver function, all of which have the potential to contribute to the advancement of the disease and inferior treatment outcomes [30, 31, 32].

Interestingly enough, it is important to note that while albumin alone did not exhibit any correlation with survival rate, the ratio of albumin to pre-albumin (Alb/Pre-Alb) emerged as a statistically significant indicator of the survival. This superiority is attributed to the relatively longer half-life (14-18 days) of albumin compared to pre-albumin, which has a half-life of 2 days. As corroborated in our paper, several studies identified low Alb/Pre-Alb ratio as a prognostic indicator associated with unfavorable outcomes and decreased survival among patients with hepatocellular carcinoma, the most prevalent form of liver cancer [31-34] The Alb/Pre-Alb ratio holds promise as a useful prognostic marker in patients with liver disease, as it reflects both liver function and nutritional status. Again, a low Alb/Pre-Alb ratio may signify malnutrition, inflammation, and impaired liver function, all of which contribute to disease progression and poorer outcomes. Consequently, monitoring and evaluating the Alb/Pre-Alb ratio can provide valuable insights into the prognosis of liver disease patients [35, 36].

We have found no meaningful relationship between BMI and patient outcomes such as survival or distant metastasis in liver cancer patients. For example, a high BMI may be protective against liver cancer in patients with non-alcoholic fatty liver disease, but may be a risk factor for liver cancer in patients with chronic hepatitis B or C [37, 38].

There is a significant positive correlation between normal alanine aminotransferase (ALT) and aspartate aminotransferase (AST) levels with the survival rate in patients diagnosed with liver cancer. Extensive research investigations have been conducted to explore the association between AST, ALT, and survival outcomes in individuals affected by liver cancer.

Our results showed that 84% of alive patients had a normal range of ALT vs 46% abnormal. 79% of alive patients had a normal range of AST and 64% abnormal range for AST.

Recent research has shown a negative connection between higher AST and ALT levels and the survival rates of individuals diagnosed with cancer. Consequently, the AST/ALT ratio could serve as a promising biomarker for evaluating overall health and long-term mortality [39, 40].

It is essential to emphasis that correlation does not necessarily indicate causation. While increased levels of AST and ALT may be linked to poorer outcomes in liver cancer patients, it is crucial to acknowledge the potential presence of additional contributing factors influencing disease progression and survival. Furthermore, the application of AST and ALT as prognostic markers may be limited by their

lack of specificity and sensitivity in capturing the full complexity of the disease and its multifaceted nature.

Breast Cancer- The heatmap analysis was performed for all of the measured variables for breast cancer patients. The most relevant results from heat map test for the breast cancer patients' chart are summarized in table 6.

When conducting a comprehensive assessment by comparing the distinct categories of body mass index (BMI) with the prevalence of breast cancer, our analysis confirming that individuals characterized by a higher BMI exhibit an obvious propensity towards an increased prevalence of breast cancer. Our dataset demonstrates that a significant majority of cancer patients (77%) exhibit overweight and/or obesity, as illustrated in the accompanying graph. See Figure -3 for more details. These findings align with previous research highlighting the association between body mass index (BMI) and the prevalence of breast cancer [41, 42, 43].

Our comprehensive analysis reveals a statistically significant positive association between normal alanine aminotransferase (ALT), aspartate aminotransferase (AST), and albumin levels within the survival rate. As shown in figure 4, among the patients who remain alive, a substantial majority (96%) exhibit normal albumin levels, compared to 62% who display abnormal albumin levels. Similarly, 91% of alive patients demonstrate normal ALT levels, and 92% exhibit normal AST levels, while in contrast to 50% of patients who present with abnormal ALT and AST levels. These findings highlight the potential of these markers—ALT, AST, and albumin—as potential predictive factors for the survival rate of these patients. Their significant association with survival outcomes underscores their hypothetical utility in patient prognosis.

The other interesting funding was a correlation between receiving nutrition supplement with normal range of albumin as shown in Table - 6. The observed correlation between receiving nutrition supplements and maintaining normal albumin levels in breast cancer patients suggests a potential positive impact of these supplements on nutritional status. However, further research is required to establish a cause-and-effect relationship, investigate underlying mechanisms, and assess the effectiveness of specific nutrition supplement interventions. Controlled clinical trials with larger sample sizes and rigorous methodologies are needed to provide more robust evidence on the relationship between nutrition supplements and albumin levels, as well as their overall impact on patient outcomes.

DISCUSSION

The present study investigates the association of nutrition and its related variables such as BMI with cancer treatment outcomes like five-year survival rate in five different solid tumor categories including: Pancreas, Liver, Large intestine, Stomach, and Breast. In this research, we show that cancer patients who suffer from malnutrition and/or display obesity exhibit reduced survival rates and less favorable clinical results. Conversely, well-nourished patients diagnosed with solid tumors demonstrate significant enhancements in their clinical outcomes. Our study has revealed significant insights into the complex relationship between nutritional variables, BMI, and clinical outcomes in liver and breast cancer patients. To further balance our argument and provide a more complete interpretation of the findings, we should consider several key points.

Firstly, while our initial pilot study showed meaningful correlations between BMI and certain markers in liver cancer patients, it is essential to acknowledge the limitations and complexities inherent in assessing nutritional status solely based on BMI. BMI alone may not capture the nuances of nutritional status in cancer patients, as it does not distinguish between muscle mass and fat mass or account for changes over time. Therefore, a more comprehensive evaluation of nutritional status, including measures of muscle mass and other relevant markers, should be considered in future research.

Additionally, the significance of the observed correlations between BMI and albumin levels in liver cancer patients should be interpreted cautiously. Although Albumin demonstrated a negative correlation with BMI, it

has a relatively long half-life, making it less sensitive in indicating visceral protein status compared to other plasma proteins with shorter half-lives [33, 34]. While this correlation is intriguing; it should be understood within the context of other nutritional markers and patient-specific factors.

In the second phase of our study, the expanded sample size allowed us to explore the relationships more thoroughly. The use of heatmap analysis provided a comprehensive visual representation of the data and identified correlations among various variables. However, future research should explore the potential confounding factors that may influence the observed correlations, such as the stage of cancer, comorbidities, and overall health status of the patients.

Regarding the Alb/Pre-Alb ratio as a prognostic marker [33, 34], while our study supports its potential utility, further research is needed to validate its effectiveness in predicting outcomes in liver cancer patients. Controlled clinical trials with larger sample sizes and rigorous methodologies are essential to provide more robust evidence in this regard.

It is worth mentioning that the retrospective nature of this study had posed limitations particularly concerning the lack of available or missing intake, laboratory and/or anthropometric measurement values for some of our studied patients. For example, there were significant deficiencies in recorded 24-hour nutrition recalls, which could have provided valuable insights into the dietary intake of these patients. Additionally, the documented levels of pre-albumin and C-reactive protein and some other blood markers were limited, reducing our ability to comprehensively assess the patients' nutritional and inflammatory status.

The findings of this study suggest that nutritional evaluations hold promise as valuable tools for predicting the survival outcomes. Our dataset demonstrates that a significant majority of some type of cancer patients (Breast - 77%) exhibit overweight and/or obesity. These findings align with previous research highlighting the association between BMI and the prevalence of breast cancer [41-43]. Furthermore, blood related nutritional parameters such as Albumin, Alb/pre-Alb ratio, AST and ALT were found useful in survival prognostication in our study.

It is important to mention that the ASPEN does not endorse some of the factors included in our nutritional markers such as Albumin due to the complex relationships and associations between malnutrition, inflammation, and infection markers, and plasma proteins [25]. However, these markers have found valuable in assessing the malnutrition status of patients and their subsequent clinical outcomes in various hospital settings and clinical studies [27, 28, 31, 36, 44-46].

Based on our research findings, several areas within the hospital setting could be modified to provide accurate understanding regarding nutritional scoring and cancer patients outcomes.

First of all, as BMI relies solely on overall weight without distinguishing its composition [19], analyzing the body composition, specifically the contrast between Lean Body Mass and Fat Mass, before and after treatment, and examining its association with blood markers, could offer valuable insights into the impact of nutritional interventions on cancer patients. By assessing parameters such as muscle mass, fat mass, and overall body composition, researchers can better understand how alterations in these factors may impact treatment response, prognosis, and overall survival. Correlating these changes with blood markers, such as Albumin, pre-Albumin, [32-34] and inflammatory markers, could further elucidate the relationship between nutritional status, treatment outcomes, and disease progression.

Secondly, the recorded data on specific nutrition supplement and/or other intake was limited to fewer than 20 patients in our study population. This lack of data hindered our ability to evaluate the potential impact of any supplementation including different type of vitamins, proteins, multivitamin/ minerals or a combination of all, on the nutritional status and survival outcomes of the patients.

In conclusion, these limitations highlight the need for improved data collection procedures and adherence to comprehensive documentation practices in patient care. The availability of complete and robust data sets would

enable researchers to more accurately assess the nutritional status of cancer patients and establish stronger associations with survival outcomes. Investigation in these areas will contribute to the development of effective nutritional strategies to optimize cancer treatment outcomes, enhance patient well-being, and ultimately improve survival rates for cancer patients. Our study serves as a steppingstone in this direction, emphasizing the need for a holistic approach to cancer care that includes robust nutritional assessments and tailored interventions.

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This project was conducted without external funding.

DATA AVAILABILITY STATEMENT (DAS)

Data are available from the corresponding author (Shabnam Pooya, PhD) on request.

CONFLICT OF INTEREST

The authors declare no conflicts of interest related to the research presented in this article. There are no financial, personal, or professional relationships that could potentially bias or influence the content and findings of this work. This manuscript is an honest and transparent representation of the research conducted.

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PEER REVIEW

Not commissioned. Externally peer reviewed.

FIGURES

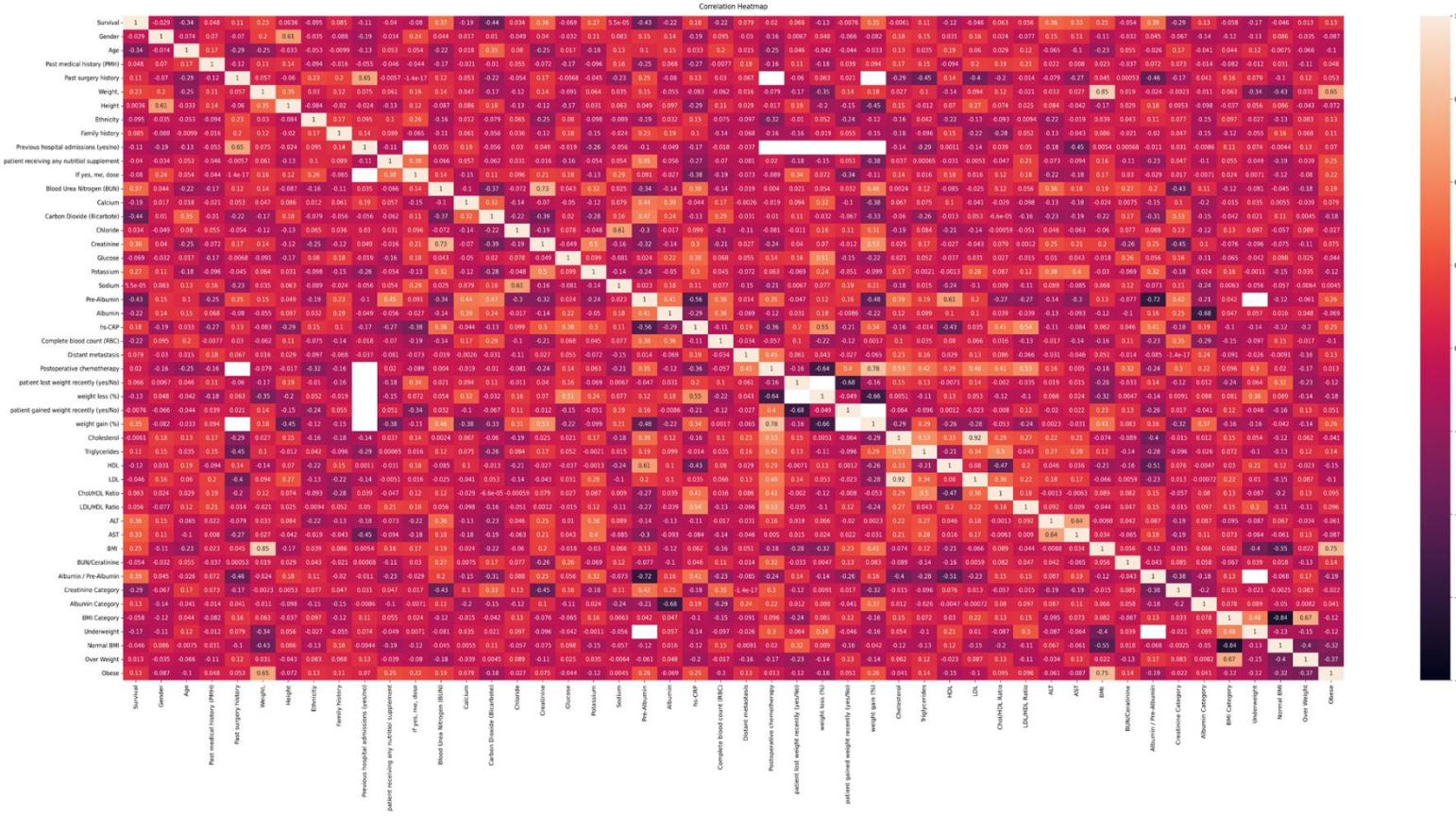
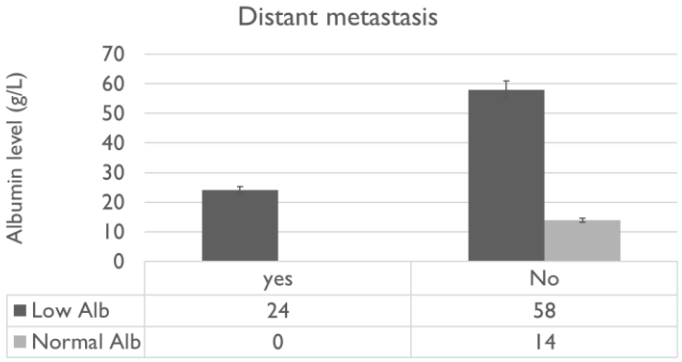


Figure 1: Comprehensive heat map test analysis for liver cancer patients.



Normal range: 3.6 to 5.1 g/dL (36 to 51 g/L)

Figure 2: Correlation between distant metastasis with Albumin in patients with Liver cancer.

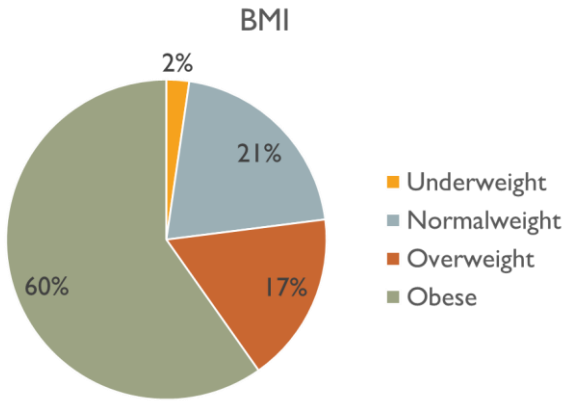


Figure 3: BMI distribution of breast cancer patients.

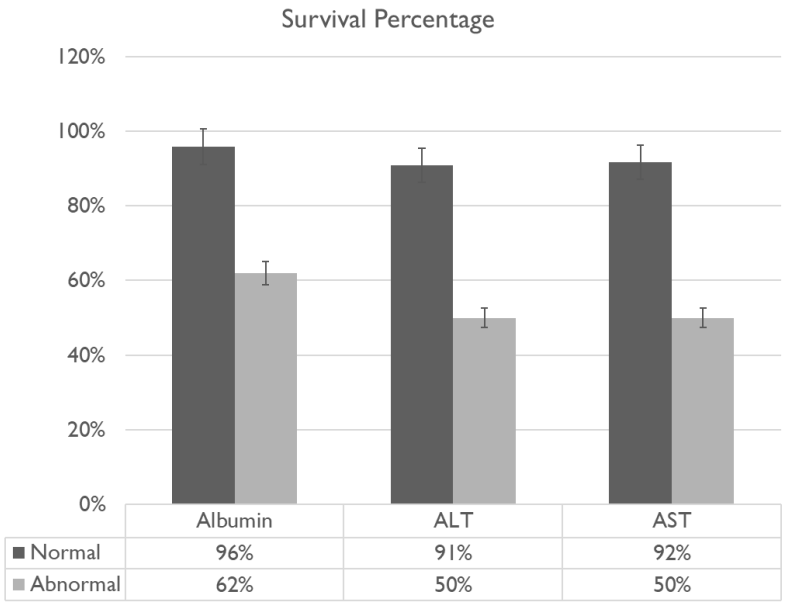


Figure 4: Correlation between Survival rate with Albumin, ALTand AST in Breast cancer patients.

TABLES

Table 1: Community Cancer Institute, cancer site table for 2022.

Site	Total	Sex			Stage				
Group	Cases	M	F	Other	Stage 0	Stage I	Stage II	Stage III	Stage IV
ALL SITES	3157	1375	1780	2	96	752	364	325	586
BREAST	608	1	606	1	71	287	74	33	26
PROSTATE	298	297	0	1	0	50	76	34	47
LUNG/BRONCHUS-NON SM CELL	242	130	112	0	2	50	13	30	97
NON-HODGKIN'S LYMPHOMA	215	130	85	0	0	27	24	23	70
COLON	183	87	96	0	5	26	35	45	44
KIDNEY AND RENAL PELVIS	146	79	67	0	0	73	8	10	23
CORPUS UTERI	111	0	111	0	0	64	10	22	8
PANCREAS	97	43	54	0	1	16	8	9	42
RECTUM & RECTOSIGMOID	95	62	33	0	0	11	13	26	22
LIVER	93	62	31	0	0	17	17	9	27
HEMERETIC	88	50	38	0	0	0	0	0	0
OTHER NERVOUS SYSTEM	84	16	68	0	0	0	0	0	0
THYROID	64	11	53	0	0	44	11	0	1
BRAIN	63	30	33	0	0	0	0	0	0
BLADDER	61	47	14	0	14	7	9	2	11
STOMACH	57	29	28	0	0	7	8	6	21

Table-2: Collected variables.

I- General information	II. Blood test	III. Tumor location	*IV. Distant metastasis*	V. Postoperative chemotherapy
1. Gender 2. Age 3. Past medical history (PMH) 4. Weight, 5. Weight trends (weight changes in past 12 months) 6. Height 7. Ethnicity 8. 24h recall 9. Family history 10. Previous hospital admissions	1. Blood Urea Nitrogen (BUN) 2. Calcium 3. Carbon Dioxide (Bicarbonate) 4. Chloride 5. Creatinine 6. Glucose 7. Potassium 8. Sodium 9. Pre-Albumin 10. Albumin 11. hs-CRP 12. Complete blood count 13. Lipid profile	1. Stomach 2. Breast 3. Large intestine 4. Liver **5.** Pancreas	1. Negative 2. Positive	1. Negative 2. Positive

Table 3: Most relevant data correlation with BMI in Liver cancer patients, sample size 46.

Variables	P-Value	Pearson R
Albumin	0.01***	-0.672
Blood Urea Nitrogen (BUN)	0.278	-0.512
Creatinine	0.671	0.198
Glucose	0.177	0.413
Gender	0.985	-0.004
Age	0.284	0.264
Five years Survival rate	0.095	0.344

Distance metastasis	0.429	0.177

* P-value < 0.05, *** P-value <0.01

Table-4: Most relevant data correlation with BMI in Breast cancer patients, sample size 43.

Variables	P-Value	Pearson R
Albumin	0.99	0.00
Blood Urea Nitrogen (BUN)	0.96	0.01
Creatinine	0.47	0.17
Glucose	0.69	0.07
Age	0.36	0.00
Five years Survival rate	0.35	-0.92
Distance metastasis	0.05*	1.97

* P-value < 0.05, *** P-value <0.01

Table 5: Liver cancer- the most significant heat map results.

Variables	Survival	Distant metastasis	Postoperative

					chemotherapy
	P-Value	**Pearson R**	**P-Value**	**Pearson R**	**P-Value**
Patient receiving any nutrition supplement	0.6629		0.4316		0.9299
Blood Urea Nitrogen (BUN)	_		0.8538		0.9859
Creatinine	_		0.793		0.2844
Glucose	0.45		0.5918		0.5261
hs-CRP	0.4051		0.3851		0.644
Cholesterol	0.9563		0.0539		0.0638
Triglycerides	0.338		0.1952		0.1365
Chol/HDL Ratio	0.5754		0.481		0.1642
LDL/HDL Ratio	0.62		0.592		0.0599
ALT	0.000004***	0.38	0.7655		0.466
AST	0.0003***	0.32	0.6563		0.9823
BUN/Creatinine	0.5583		0.8938		0.1476
Albumin / Pre-Albumin	0.02798*	0.394	0.6612		0.574
Albumin	0.1525		0.0192*	0.23	0.3343
Underweight	0.0665		0.8033		0.1791
Normal BMI	0.6124		0.9292		0.9299

Overweight	0.883		0.1184		0.4456
Obese	0.15		0.2054		0.9545

(_) not enough data to run the test. * P-value < 0.05, *** P-value <0.01

Table 6: Breast cancer- the most significant heat map results.

	Survival	Pearson R	patient receiving any nutrition supplement	Pearson R	Distant metastasis	Postoperative chemotherapy
Glucose	0.0021***	0.31	0.7043		0.8521	0.7974
Cholesterol	0.341		0.2591		0.8553	0.4519
Triglycerides	0.2088		0.2517		0.6119	0.7654
HDL	0.2028		0.0138		0.4384	0.7548
LDL	0.8099		0.8414		0.5508	0.4654
Chol/HDL Ratio	0.8253		0.6315		0.4567	0.7061
LDL/HDL Ratio	0.8038		0.6498		0.9177	0.5465
ALT (SGPT)	0.0000001***	0.48	0.2719		0.8893	0.8068
AST (SGOT)	0.0000001***	0.44	0.5141		0.879	0.741
BMI	0.2916		0.2206		0.6056	0.7703
Albumin / Pre-Albumin	_		_		0.4975	_
BUN/Creatinine	0.119		0.3708		0.81	0.7144
Creatinine	0.0972		0.6258		0.9572	0.5567

Albumin	0.0000001***	0.44	0.0000001***	0.40	0.5093	0.5019
Under weight (Low BMI)	0.5937		0.3097		0.6923	0.8602
Normal weight	0.0767		0.1505		0.7564	0.4804
Overweight	0.9165		0.1983		0.9203	0.5718
Obese	0.3581		0.1562		0.1614	0.2476

(_) not enough data to run the test. * P-value < 0.05, *** P-value <0.01