**Introduction**

Food insecurity (FI) involves the inability to procure sufficient quantities of safe and nutritious foods that promote the physical, emotional, and psychosocial domains of health and well-being [1]. It is a leading public health issue that affected approximately 13.8 million (10.5 %) U.S. households in 2020 and disproportionately affects low-income households, single parent households, communities of color, and those with a recent diagnosis of cancer [1,2]. For many households, experiencing a sudden cancer diagnosis and its side effects may worsen FI status. Increasing treatment costs and side effects attributable to those treatments may prompt lower quality of life (QOL) and physical disability in cancer survivors, which magnify the risks of unemployment and financial sequelae [3,4]. The culmination of these factors, alongside other known risk factors of FI, including younger age, being less educated, belonging to a marginalized community, and having lower income, may ultimately lead to cancer survivors experiencing FI [5] . Moreover, estimates from non-nationally representative data suggest that the prevalence of FI in the cancer survivor (defined as any person with a history of cancer, from the time of diagnosis to the end of life) population may be higher than the national average [6–8].

National guidelines from the WCRF/AICR Third Expert Report describe modifications to lifestyle that cancer survivors may implement following a diagnosis. These recommendations include dietary modifications that emphasize consumption of whole grains, vegetables, and fruit, while curtailing the consumption of sugar sweetened beverages and processed meats, as these foods may bolster cancer risk and progression [9]. Though following these evidence-based guidelines may improve QOL and disease outcomes, it is unclear how FI impacts cancer survivors’ capacity to adhere to those recommendations [10]. Ultimately, the combination of treatment-associated sequelae and FI may aggravate nutritional inadequacy in food insecure cancer survivors.

Ascertaining population-specific dietary patterns may reveal critical needs and play a role in developing clinical best-practices or food policy targeted at specific at-risk populations. Consequently, the goal of this study was to delineate major dietary intake patterns among food-insecure cancer survivors using nationally representative data from the National Health and Nutrition Examination Survey (NHANES). With the advent of numerous statistical approaches to characterize empirical dietary patterns, we implement penalized logistic regression and principal components analysis for characterizing the dietary patterns of our target population and later validate those patterns by examining their relationship to the risk of being food insecure. To our knowledge, this is the first study to employ NHANES data to analyze empirical dietary intake patterns in cancer survivors with self-reported FI.

**Materials and Methods**

Data from ten consecutive cross sections of the NHANES study, between the years 1999-2018, were employed for the analysis. The analytical outline and strategy is displayed in Figure 1. NHANES is a biennial national cross-sectional study, conducted by the Center for Disease Control and Prevention (CDC) and National Center for Health Statistics (NCHS), that surveys health, nutrition, and other lifestyle factors across the noninstitutionalized civilian population of the United States [11]. The study employs a multistage probability selection design to generate a nationally representative sample of the American population and to ascertain prevalence of major diseases and associated environmental and behavioral risk factors [12]. Participants are subjected to a household screener as well as a home interview. The latter consists of a series of questionnaires administered in their homes that cover a range of areas including demographic, occupational, health, and dietary related matters. Individuals may be selected for a medical examination, which includes a variety of physical measurements, a dental examination, and biological specimens for laboratory testing. Examination data were collected in the Mobile Examination Center. In addition, dietary data were collected via 24-hour recalls to ascertain frequency of consumption and estimate nutrient intake. Cancer, diabetes, cardiovascular disease, and renal disease statuses are assessed as self-reported items in the medical conditions questionnaire. Clinical measurements delineating tumor stage are not part of the survey. All study procedures and protocols were approved by the NCHS Ethics Review Board and all participants provided informed consent.

*Study Sample*

Figure 1 details a flow diagram of the sample selection process. We used data from nine survey cycles, spanning the years of 1999-2018 that included a subsample of 5,166 participants, aged at least 20 years, with a self-reported history of cancer and reliable dietary data, as defined by the NCHS. To ascertain cancer history, survey respondents were asked in the Medical Conditions Questionnaire (MCQ) “Have you ever been told by a doctor or health professional that you had cancer or a malignancy of any kind?”. Individuals reporting a history of non-melanoma skin cancer (*n* = 576) and no other cancer type were recoded as not having a significant cancer history. Dietary patterns extraction procedures using penalized logistic regression models were performed on individuals reporting a history of a cancer diagnosis and who demonstrated complete records for food security status, data on receipt of Supplemental Nutrition Assistance Program (SNAP) benefits, household size, and age (subsample A, *n* = 3,317). To extract dietary patterns that characterized intake in the population of food insecure cancer survivors using principal components analysis (PCA), we further excluded individuals reporting full or marginal food security (*n* = 2,884) (i.e., only food-insecure cancer survivors—subsample B, *n* = 433). Validation analyses examining the relationship between computed diet pattern indices and the risk of FI were performed on the pooled subsample of food secure and food insecure cancer survivors (subsample A, *n =* 3,317)

*Demographic and Physical Health Covariates*

Demographic characteristics were self-reported and captured in the home interview. Age was modeled continuously, and sex was coded dichotomously (Male and Female). Race and ethnicity were categorized as Mexican American, Other Hispanic, Non-Hispanic White, Non-Hispanic Black, and Other/Multiracial (although we note that our final analytical models implemented a binary-coded version given the small sample size—non-Hispanic White and non-White) . We considered income status using the family income-to-poverty ratio (FIPR) classified into two categories: < 1.3 or ≥ 1.3. This value was chosen deliberately as it is a threshold commonly employed by various federal safety net programs to evaluate low socioeconomic status for program eligibility [13]. We modeled household size numerically.

Health-related and behavioral characteristics included body mass index (BMI) (modeled continuously in units of kg/m2), smoking status, which was categorized as current smoker (currently smoking every day or some days), former smoker (not currently smoking but with a lifetime history of ≥ 100 cigarettes), or never smoker (a lifetime history of smoking < 100 cigarettes), and drinking status, which classified participants as heavy drinkers (≥ 14 g/d for women and ≥ 28 g/d for men), moderate drinkers (0.1-13.9 g/d for women and 0.1-27.9 g/d for men), and abstainers (< 0.1 g/d) [14,15]. Finally, we computed a modified version (given limitations with the data provided through NHANES and those required for full computation of the metric) of the Charlson Comorbidity Index and weekly metabolic equivalents (MET), as previously described, to evaluate comorbidity burden and physical activity, respectively, and modeled those measures as continuous variables [16,17].

*Dietary Assessment Data*

Dietary data are collected using the 24-hour recall method from NHANES participants during an in-person interview (performed in the MEC) [18]. A subsequent, unannounced 24-hour recall is collected via telephone within 3-10 days following the interview. Dietary interview protocols and the administered 24-hr recall were designed to provide detailed dietary data by capturing the foods and beverages consumed by participants within the preceding 24 hours. The methodology for the dietary interview component was developed by the USDA’s Food Surveys Research Group and incorporates the USDA’s automated multiple-pass method [18,19]. Dietary data collected between 1999 and 2002 included only one day of intake from participants whereas data collected between 2003 and 2018 included two days of recalls from each participant. To make full use of the available data, we averaged intake values across both days of data collection. For subjects missing a second day of recall data, we imputed their intake values from their first 24-hour recall.

Daily total energy and nutrient intake data were obtained for each participant. Total energy and nutrient intake values were estimated from foods noted in the dietary interview while cross-referencing the Food and Nutrient Database for Dietary Studies [20].

Intake according to food groups data were obtained from the publicly available USDA Food Patterns Equivalents Database (FPED) and MyPyramid Equivalents Database (MPED) [21,22]. The FPED and MPED use a database of 8,356 commonly consumed food items to compute intake equivalents across 37 food pattern components. Considering this classification scheme, a modified, yet similar, food-grouping scheme involving 26 food groups was adopted for this analysis. These 26 groups and the way they were collapsed are detailed in Table S1. Prior to any dietary patterns extraction procedures, food group intake equivalents were divided by a subject’s total caloric intake so that a multivariate density model could be implemented to adjust for total energy intake and minimize the likelihood of confounding by total energy intake in any of the subsequent models fit [23].

*Cancer and Food Security Data*

The MCQ provides survey participants with an avenue for self-reporting data on medical conditions. A comprehensive subsection of the survey captures history of up to four cancer diagnoses per participant and age at the time of diagnoses for each. Data on cancer types were coalesced into a single variable for each participant by recording cancer type reported for their first diagnosis and new variables for time since each cancer diagnosis were computed as the difference between the age of the participant at the time of survey collection and their reported age at each diagnosis. A final variable was computed as the maximum from the set of these time variables and represented the time (in years) since their first cancer diagnosis. Time since diagnosis was subsequently categorized ( 2 years, 2 and 6 years, and 6 years). Using these data, participants with a history of a cancer diagnosis were grouped into their primary cancer type. That is, the cancer type with the longest associated time since diagnosis. Lastly, the 32 cancer types listed in the NHANES MCQ were collapsed into a set of 8 primary cancer groups using a slightly modified approach, given the small sample size, proposed by colleagues (Breast, Gastrointestinal, Genitourinary, Gynecological, Male Reproductive, Melanoma, Skin-Unknown, and Other) [24].

Food security status was assessed using the U.S. Food Security Survey Module (U.S. FSSM), an 18-item screener employed by NHANES since the 1999 cycle to assess food security experienced by subjects over the preceding year [25]. The questionnaire was administered in the home interview setting with one adult in the household responding on behalf of all individuals in that household, regardless of whether they were included in the survey. The survey is comprised of 10 items dedicated to households without children and 8 items for households with children. Counts and affirmative responses on the questionnaire are used to bin subjects into overall food security categorizations. Those responding in the affirmative to 2 items were categorized as food secure while those responding in the affirmative to 3 items were categorized as food insecure and these followed validated cutoffs [25]. Additionally, receipt of food assistance and specifically participation in the Supplemental Nutrition Assistance Program (SNAP) is reported in the U.S. FSSM. These data were captured by prompting participants on whether any household member was authorized to receive SNAP benefits in the 12 months preceding the interview.

*Dietary Patterns Extraction: Principal Components Analysis (PCA)*

PCA, a dimension-reduction procedure commonly employed in data-driven methods for ascertaining dietary patterns in epidemiologic studies, was selected as one method for deriving dietary patterns from the 26 centered and standardized food group variables (Table 2) [26,27]. In PCA, eigen decomposition of the covariance matrix containing the predictor variables of interest yields a set of eigenvectors (containing the parameters or weights that multiply each of the *n* variables as a linear combination) and their corresponding eigenvalues [28]. In this sense, the first eigenvector represents a projection that maps the original data onto a new vector space (i.e., reducing it onto a single dimension) with the additional quality that it retains as much of the variance in the original data and whose eigenvalue represents its variance [28]. Geometrically, the goal of PCA can be explained as creating a set of orthogonal projections on the data that explain as much of variance in the set of predictors. Eigenvalues, a scree plot, and general interpretability of the components were used to guide decisions on the number of components to retain (Supplementary Figure 1. We accounted for the complex sampling design by implementing dietary patterns extraction via PCA using the *svyprcomp* function from the *survey* package in R [29]. Dietary patterns extraction using PCA was implemented on subsample B. A loadings matrix from this procedure is found appended to Supplementary Table 2.

*Dietary Patterns Extraction: Penalized Logistic Regression*

Regularized regression models introduce a penalty term to the likelihood function for estimating model parameters in a variety of regression frameworks [30]. Addition of a penalty effectively shrinks parameter coefficients as well as their associated variances, which is particularly useful in high-dimensional settings or in the presence of collinearity. This yields a set of more interpretable and well-behaved parameter estimates [31]. In the context of dietary patterns analysis, whereby there may be substantial collinearity amongst food groups, this becomes notably advantageous. The penalty term is added to the likelihood function, when solving the logistic regression problem, in the following form:

where and are the penalty tuning parameters; controls the elastic net penalty and controls the overall magnitude of the penalty term [32]. When = 1, the solution amounts to the LASSO regression problem and the coefficients are penalized by the norm of the coefficients vector whereas when = 0 it yields the solution to the ridge regression problem involving only penalization. Otherwise, the elastic net assumes giving it flexibility over the former counterparts in that it allows for variable selection potentially leading to a parsimonious model (unlike ridge regression) and will not arbitrarily remove all variables except one in a group of correlated explanatory variables (unlike the LASSO model). In this application, we used known risk factors of FI (dichotomized as: age ≥ 60 years, household receipt of SNAP benefits in the last 12 months, and household size ≥ 5) in addition to the outcome of FI itself to implement the penalized regression models for deriving dietary patterns associated with those outcomes [33,34]. These patterns would subsequently be named accordingly (FI, Age, SNAP, and Household Size) for the remainder of the analysis. The models were fit using the *glmnet* package in R on data from cancer survivors in subsample A. Optimal combinations of and for each of the outcome models were ascertained via 10-fold cross-validation and iterating over a grid of values ranging from 0 to 1 (inclusive of LASSO and ridge regression). The set of coefficients linked to the combination of and that minimized the deviance was retained as the ultimate set of parameters for a given outcome. Food group explanatory variables were centered and standardized prior to fitting the semodels in the same manner as the PCA procedure. Given that the *glmnet* software uses a model-based approach rather than a design-based approach for ascertaining model estimates and variances, we weighted the analysis using normalized weights [35].

*Statistical Analysis*

Descriptive statistics were tabulated on demographic variables across levels of food security/cancer status using subsample A (Figure 1). A Pearson correlation matrix was generated to evaluate relationships amongst the dietary patterns and food groups in subsample A (*n* = 3,117). To validate the extracted dietary patterns, we used the loadings and coefficients (from the PCA and elastic net procedures, respectively) to compute dietary patterns scores for subjects identifying with a history of cancer (subsample A, *n* = 3,317). The validation phase of the analysis comprised the analytical goal of determining the relationship between the extracted pattern scores and the risk of FI in the cancer survivor population (Figure 1). To this end, we implemented logistic regression models that modeled the log odds of being food insecure as a function of the dietary patterns scores and relevant covariates. This step included all subjects with a reported history of cancer (subsample A, *n* = 3,317). In order to minimize the likelihood of collinearity, alcohol consumption was not included as a covariate in these models given that the extracted patterns already considered alcohol consumption in their computation. We modeled the diet scores using a number of approaches to evaluate the robustness of the results. First, we modeled the scores categorically after binning participants into quintiles. A test for linear trend across the quintiles was performed by generating a new variable that assigned each subject the median value of their respective quintile and modeling that new variable continuously. Second, we standardized the diet scores by dividing each them by their respective standard deviation and then modeling them as continuous variables. Third, we added a quadratic term to the previous model to assess for divergence from a linear relationship. Lastly, we modeled the diet scores using restricted cubic splines with five knots to flexibly model the relationship and again evaluate for linearity. All models were adjusted for relevant confounders including age, sex, race/ethnicity, family income-to-poverty ratio, highest level of education attained, household size, SNAP participation status, BMI, estimated caloric intake, weekly MET minutes, primary cancer site, smoking status, and the Charlson Comorbidity Index score. To assess for effect modification, we fit additional stratified models according to sex, time since primary cancer diagnosis, and attained level of education. We accounted for the complex and multi-stage probability design of the study by following NCHS analytical guidelines and weighting our analyses accordingly [36]. All analyses were conducted at = 0.05 and were performed in R version 4.2.1. All accompanying R code and data files necessary to reproduce these analyses can be found at: https://github.com/cmainov/NHANES-Diet-Penalized-Regression.

**Results**

Sociodemographic, clinical, and behavioral characteristics are summarized in Table 1. On average, those with a reported history of cancer and with self-identified low food security were younger than food secure cancer survivors, were more likely to identify as female, live in a home with ≥ 5 individuals, and belong to a minority group compared to those identifying as food secure with a history of cancer who were older, had a more balanced ratio of the sexes, and were disproportionally white. Food insecure survivors also had lower attained educational status compared to food secure individuals, tended to have a lower FIPR, reported being more physically active throughout the week, and were more likely to be receiving food assistance through SNAP in addition to, on average, consuming over 200 fewer daily calories compared to their food secure counterparts. Regarding cancer site, food insecure survivors disproportionally reported gynecological cancers as their primary form of cancer compared to a lower rate in the food secure survivors. Concomitantly, there was a larger proportion of male reproductive cancers represented in the food secure sample relative to the food insecure sample. There were no gross difference observed in time-since-diagnosis across the two groups, though food insecure individuals had a slightly larger mean Charlson Comorbidity Index score than food secure participants. Finally, those identifying as food insecure were more likely to report being current smokers than food secure individuals with cancer.

*Discovery Phase: Dietary Patterns Extraction*

There were six dietary patterns extracted from both procedures. The patterns derived using penalized logistic regression were named according to the outcome variable used in each of those models (we named these the Food Insecurity (FI), Age, SNAP, and Household Size patterns, respectively). Supplementary Figure 1 illustrates the optimal combinations of and that were ultimately selected for each model. For the model with FI as the response variable, the LASSO regression ( solution was optimal while the ridge regression solution ( was the optimal model for the model with household size as the response. The models with age and SNAP benefits as the outcomes yielded optimized solutions with in the elastic net range, (0,1). The coefficients for each of these models are found in Supplementary Table 2. We note that the coefficients for several food groups shrunk to zero, effectively eliminating them from subsequent score computations.

In Table 2, we detail the Pearson correlation coefficients amongst pattern scores and food groups. The FI pattern was positively and moderately correlated with intakes of processed meat, solid fats, eggs, potatoes, and strongly with added sugars while moderately and negatively correlated with seafood, oils, milk, yogurt, alcohol, fruits (all categories), vegetables (all categories other than potatoes), tomatoes, soy products, refined grains, whole grains, and nuts. The Age pattern was modestly and positively correlated with intakes of seafood, solid fats, oils, milk, yogurt, fruits, potatoes, other vegetables, dark-yellow vegetables, starchy vegetables, nuts, and whole grains while negatively correlated with poultry, cheese, alcohol, dark-green vegetables, legumes, soy, refined grains, and added sugars. Overall, this pattern was negatively correlated with the FI pattern (*r* = -0.28). The SNAP dietary pattern was strongly and positively correlated with the FI pattern (*r* = 0.80) as well as with solid fats, legumes, refined grains, and added sugars while being negatively correlated with poultry, seafood, oils, yogurt, alcohol, all fruit categories, all categories of vegetables, soy, whole grains and nuts. The final Household Size pattern was also strongly and positively correlated with the FI pattern (*r* = 0.63) and negatively correlated with intakes of seafood, solid fats, milk, yogurt, cheese, alcohol, fruits and vegetables (all categories other than potatoes), refined and whole grains while being positively correlated with intakes of poultry, oils, legumes, soy, refined grains, and strongly with added sugars.

For the patterns extracted with PCA, we evaluated a scree plot initially and found that an “elbow” appeared after the fourth principal component. However, upon evaluation of the factor loading matrix (Supplementary Table 2) and the table of correlations (Table 2) only the first and second principal components had interpretable loadings that were deemed meaningful. Thus, a decision was made to retain only the first two components. The eigenvalues suggested that these first two components accounted for 14.1% of the variation present in the 24-hour recall data. Both patterns shared similarities in that both were positively correlated with vegetable consumption and negatively correlated with added sugar and alcohol. However, while the first principal component emphasized modest meat, processed meat, solid fat, oil, eggs, milk, cheese, potato, soy, nuts, and refined grains consumption, the second principal component emphasized fruit, poultry, eggs, milk, yogurt, high n-3 seafood, soy, and whole grains. The second principal component was also negatively correlated with meat and processed meat consumption, cheese, solid fat, cheese, legumes, and refined grains intakes and, overall, had stronger positive correlations to whole grains, fruit, soy, nuts, and vegetable intake compared to the first component. Given the both healthful and unhealthful aspects of the first principal component, we termed this pattern the Modified Western pattern [37,38]. In contrast, the second principal component was termed the Prudent pattern, given its greater and more consistent emphasis on the pillars of healthful eating cited previously in the literature [39].

Differences across sociodemographic covariates between high and low median splits of each of the six dietary patterns in the subsample of cancer survivors (subsample A, *n* = 3,317) are presented in Table 3. On average, those with higher scores on the Age pattern tended to be older. Subjects with greater scores on the FI, SNAP, and Household Size patterns also tended to be younger and have a lower FIPR than those with lower pattern scores. Subjects with high scores on the household size pattern were also more likely to report living in a home with ≥ 5 persons compared to low scorers while high scorers on the FI and SNAP patterns were more likely to identify as food insecure and receive SNAP benefits compared to low scorers. Finally, high scorers on the Prudent pattern were, on average, more likely to report as never smokers and less likely to report as current smokers compared to low scorers.

*Validation Phase: Logistic Regression*

Using binary logistic regression models, we found, after multivariable adjustment, significant associations between the extracted pattern scores and the odds of being food insecure (Table 4). The FI, SNAP, and Household Size patterns were all strongly and positively associated with the risk of being food insecure. Among those, the FI pattern had the largest magnitude of association with the odds of FI being 2.42-fold greater in the fifth quintile compared to the first quintile. Similarly, all three of those patterns had similar magnitudes of association when the diet score was modeled linearly. For the FI pattern, a one standard deviation increase in the score was associated with 50% increase in the odds of being food insecure. Concerning associations in the opposite direction, only the Prudent pattern was inversely associated with FI, with the highest quintile observing a 60% reduction in the odds of being food insecure compared to the first quintile. A one standard deviation increase in this pattern scores was also significantly associated with a 24% decrease in the odds of being food insecure. For all the noted dietary patterns, tests for linear trend revealed linear behavior, in their respective directions, across the quintiles and these findings were generally supported by the results from fitting models with restricted cubic splines (Figure 2), although the strongest relationship, again, appeared to belong to the FI pattern.

Results from stratified models are presented in Supplementary Table 3. Despite that the main analytical models adjusted for sex, we found that relationships between each of the diet pattern scores and risk of FI were significantly stronger in females as compared to males. The highest quintile of the FI pattern demonstrated a 3.48-fold greater risk of being food insecure compared to the lowest quintile while the signal in the male population was blunted with only a non-significant 1.46-fold greater risk of FI in the fifth relative to the lowest quintile. Likewise, comparisons between the SNAP, Household Size, and Prudent patterns displayed similar phenomena (Supplementary Table 3), When comparing time since primary cancer diagnosis, we found that the FI pattern was associated with 4.72 -fold greater risk of FI in those subjects intermediately removed from a cancer diagnosis at greater than two and less than six years removed from their diagnosis. Within this group, the strongest association belonged to the SNAP pattern where the fifth quintile demonstrated a 7.90-fold greater risk of FI than the lowest quintile and a one standard deviation increase in pattern score was associated with a significant 1.65-fold increased risk of FI. In those to 6 years removed from their primary diagnosis, there were no significant associations between the patterns derived via penalized logistic regression though the highest quintile of the prudent pattern was associated with a 67% reduction in the risk of being food insecure compared to the first quintile and there was evidence of a significant linear trend. Notably, in those to two years removed from their diagnosis, the magnitudes of association were the smallest when comparing all three groups. Finally, when examining education status, it was revealed that strong and significant associations were present in the FI, SNAP, Household Size, and prudent patterns for those reporting some level of college or greater but not those with only a high school education or less.

**Discussion**

The results we present highlight major dietary patterns associated with FI in the cancer survivor population, a population plagued by high nutritional requirements and, often because of treatment-related or other side effects, limited nutritional intake. FI, a critical social determinant of health, may aggravate prognoses and health outcomes in cancer survivors [40]. Underserved populations, such as the food insecure cancer survivor population, are not only medically underserved but also nutritionally underserved in the sense that a robust understanding of the dietary intake patterns of this population are lacking in the literature. Using a combination of empirical methods, we extracted six dietary patterns to characterize the dietary intake patterns of this population. We used supervised learning in the form of penalized logistic regression to model FI and other risk factors of FI by regressing them on the 26 food groups considered in the analysis. Some of the resulting patterns were similar and consistent in that three of them emphasized comparable food groups all to a similar extent, although they contained notable differences. Namely, high consumption of added sugars and low consumption of various classes of whole fruits and vegetables were themes seen consistently in those patterns (FI, SNAP, and Household Size patterns). With respect to the differences across those patterns, we found that the patterns complemented one another and, when evaluated together, gave us a more thorough understanding of the dietary patterns extant in the study population. Decreased consumption of whole grains, nuts, and legumes also highlighted these patterns, which taken together, may suggest that food insecure survivors were, on average, more likely to be following a diet comprised, principally, of processed foods. Regarding their relationship to FI in the cancer survivor population, we found that the FI, SNAP, and Household Size patterns, in particular, were strongly and positively associated with the risk of FI.

Within the broader context of studies addressing FI and diet quality, we found that those patterns extracted from the data using penalized logistic regression shared many similarities with similar studies done in other populations. In particular, the strong relationship between the extracted patterns and intake of added sugars is consistent with reports stressing the pervasiveness of sugar-sweetened beverage and added sugar consumption in other food insecure populations [41–45]. Furthermore, though several classical studies employing unsupervised learning methods such as PCA to extract dietary patterns empirically have consistently yielded “Western” patterns that highlight high consumption of meat and processed meat, this was not a consistent finding in our study. Meat intake was emphasized to modest degrees in the patterns we extracted with penalized logistic regression. Nonetheless, this finding, supported by evidence elsewhere in the literature, may highlight restraint on the part of food insecure individuals from purchasing more cost-prohibitive food items, such as meat, and resorting to other low-cost and high calorie alternatives instead [46]. All in all, we find that the clinically meaningful evidence we describe lends further support and validation of the penalized logistic regression approach as a viable alternative for extracting dietary patterns that are outcome-specific.

Unlike the patterns derived via PCA, the penalized regression models are a form of supervised learning and resulted in sparse solutions. That is, certain food categories, not relevant to the outcome, had coefficients shrunk to zero (Supplementary Table 2), effectively removing them from consideration when computing index scores. This yielded a smaller set of relevant food group coefficients that were more interpretable [47]. LASSO regression was previously demonstrated as an alternative to traditional *a posteriori* methods of dietary patterns analysis although validating studies, such as ours, were lacking [48,49]. Moreover, a novel aspect of our study is that we operationalized the derived patterns by computing scores for each subject using the coefficients from the elastic net models (which we modeled with standardized explanatory variables) to create summary composite scores, which is akin to how scores along principal components are computed in PCA as well as in reduced rank regression [50,51]. This allowed us to test these dietary patterns directly in validation models that evaluated their relationships to pertinent health outcomes. Unlike conventional regression methods, regularizing model coefficients is especially appropriate in the context of our study and for other epidemiological studies evaluating dietary intake, given that dietary intake variables tend to have a large degree of correlation while one of the primary intents of penalized regression is to address collinearity [52].

As a comparative analysis, we implemented unsupervised learning in the form of PCA to derive dietary patterns. An established method of deriving dietary patterns, PCA is a powerful tool but also suffers from limitations. For instance, interpretability of the principal components may be equivocal [47]. Moreover, PCA may not always be suitable approach for extracting patterns that are associated with a condition or disease outcome and this notion was substantiated by the results of our study as well. Given that the procedure only aims to constrain as much of the variation in the dietary intake data onto a single dimension, predictive potential is not an inherent characteristic of this approach [47]. We found that the patterns extracted using penalized regression were more consistent with previous reports in the literature detailing diet quality in other food insecure subpopulations. Moreover, in light of the supporting studies we describe above, we stress that in our study PCA did not yield dietary patterns that were consistent with diet quality patterns described in other food insecure populations.

In the validation phase of our analysis we found that the FI, SNAP, and Household Size patterns were positively and strongly associated with FI while the Prudent pattern was strongly and inversely associated with being food insecure in the cancer survivor population after controlling for several relevant confounders. Stratified analyses yielded interesting findings. Notably, we found that stratifying the validation models by sex revealed strong effect sizes, for the aforementioned associations, in females but not males. This finding was particularly interesting when evaluated in the context of preceding studies reporting sex-specific disparities within FI research. FI itself has been demonstrated to be a highly gendered and sex-specific outcome that disproportionately affects females and, specifically, females that head households as opposed to male-headed households [53]. Even within our sample of food insecure cancer survivors we demonstrated that females were disproportionately affected by FI. Downstream of FI itself, it is also understood that FI impacts males and females disparately with regard to clinical outcomes, with food insecure females being significantly more likely to experience obesity compared to their food insecure male counterparts [54–58]. A biological basis for explaining these disparate associations is not readily accessible, with some in the field suggesting, rather, that these relationships may be explained by the gendered societal norms concerning childcare traditionally imposed on women [54]. We posit that our results may provide an additional layer of evidence for understanding the dynamic between FI and sex-specific disparities though we are limited in our conclusions given the potential for reverse causality as a result of the cross-sectional design. Nevertheless, within the context of the food insecure cancer population this conjecture would only help to understand those relationships in younger cancer survivors of child-bearing age and not necessarily in post-menopausal survivors. Albeit, the question of why sex-specific differences exist and many of its aspects remains largely elusive and will necessitate further surveillance and study.

In addition to strong effect sizes in females there were disparities across time since primary diagnosis that emerged. The association between the penalized logistic regression patterns and FI was strongest in those 2-6 years removed from a cancer diagnosis. These findings suggest that dietary intake may be more relevant for predicting FI status among cancer survivors who are within this group and not, necessarily, those proximal or distal to a diagnosis. However, previous findings in the literature have not found a significant moderating effect of time since diagnosis on FI [8,59]. Therefore, it is difficult to pinpoint how time since diagnosis may be moderating the results in our validation models. Nonetheless, our results may be consistent with the hypothesis that any FI resulting from financial hardship encountered throughout the cancer care continuum may not impact survivors immediately and may persist for several years before later abating.

The results we present have public health ramifications. Clinically, FI continues to be an underappreciated social determinant of health, particularly afflicting low-income populations. A consequence of FI manifests in the trade-offs exacted on food insecure survivors when faced with competing demands of nutrition and medical care [60]. Furthermore, there are currently no known recommendations or guidelines from any influential medical association or organization stressing the need for food security screenings in this population, again underscoring the urgency and relevance of this research [60]. It was previously shown that the rates of FI in the cancer population may be substantial in the low-income cancer population when compared to the general population [61]. Social and economic factors are especially important in prognosis and survival following diagnosis and nutrition may be a mediating factor in survivorship. Moreover, it is imperative to underscore that compared to food secure cancer patients, food insecure cancer patients comprised a substantially larger proportion of individuals from minority racial and ethnic groups, which is also consistent with what has previously been reported [62].

In considering the study’s findings within the framework of guidelines established in the WCRF/AICR third expert report, we conclude the cancer food insecure population within the United States may be hindered from meeting the report’s benchmarks. The report stresses a vital role for fruits, vegetables, legumes, and whole grains for prevention of incident cancer, cancer control, and bolstered survivorship [9]. We found that dietary patterns derived in both manners, although more robustly with penalized logistic regression, suggested that FI in the cancer survivor population was associated with poor dietary quality that was not aligned with those guidelines. Future studies, specifically those with longitudinal cohort designs, should more closely examine relationships of FI and dietary intake with prognostic outcomes in this population.

Cancer presents as a caustic burden, increasing nutritional requirements and the likelihood of cachexia, particularly in more aggressive forms and later-staged manifestations [63]. It is crucial not to lose sight of the interaction between social determinants of health and tumor evolution. For instance, it is well understood that individuals from minority or economically disadvantaged backgrounds are more likely to succumb to poorer outcomes following a cancer diagnosis [64]. Specifically, cancer survivors with membership in marginalized groups are at higher risk for experiencing financial hardship or being uninsured, which may contribute to poorer outcomes following a cancer diagnosis [65]. We also consider our results within the context of the COVID-19 pandemic, although our analysis did not utilize data collected during this era. FI has been projected to increase across the United States in response to food supply chain shocks throughout the pandemic [66]. With continued and looming uncertainty around supply chain stability, we hypothesize that observed cost hikes passed onto consumers are likely to intensify FI woes in the cancer survivor population by diminishing healthy food affordability, a phenomenon already reported at the global level [67]. Future studies should provide analysis on the effects of COVID-19 pandemic on food insecure cancer survivors.

This analysis has several strengths including the large, combined sample size, nationally representative sampling, control for other confounding variables, and the use of a validated module for measuring food security status. There are weaknesses in our study worth noting. As is characteristic in observational studies, residual confounding and the presence of reverse causality cannot be ruled out, particularly given the cross-sectional study design. Whether FI caused the observed dietary patterns or vice versa is not a conjecture we can explicitly arrive at with these data. Furthermore, the use of a household FI metric is essential to consider given that FI at the household level may impart unequal burdens on its residents. With regards to dietary intake measurements, we cannot rule out any systematic biases introduced by the dietary measurement protocol. We note that the use of 24-hour recalls for dietary assessment introduces its own set of limitations, such as its role in providing a snapshot of subject intake and its weakness in capturing long-term, habitual intake of foods [68]. With regards to the specific methodologies employed in the analysis for empirically ascertaining dietary patterns of a target population, we recognize that supervised learning methods demand that the investigator have *a priori* knowledge of risk-factors and other variables related to the principal outcome of the analysis unlike PCA, which does not require a specified outcome variable as a form of unsupervised learning. Moreover, we must again stress that there are, to our knowledge, no current published design-based modeling software allowing users to perform penalized regression (e.g., Ridge or LASSO regression) on complex survey data. Nonetheless, weighting those procedures with normalized weights, as we did in our analysis, was deliberate as a strategy for curtailing any parameter or standard error bias introduced by not using all components of the complex survey design. Finally, we highlight some considerations related to the specific study population, which include that patients farther removed from their initial diagnosis may be more likely to engage or relapse into unhealthful behavioral patterns such as the use of tobacco products or decreased fruit and vegetable intake than counterparts temporally closer to their diagnosis [69]. Additionally, we must also consider that it is possible that selection bias arises when we include a greater proportion of individuals further removed from their diagnosis that may have less aggressive or more treatable forms of cancer that do not preclude them from engaging in impaired eating, experiencing debilitating cachexia, or otherwise worse prognoses.

In summary, we conclude that dietary intake in the food insecure cancer population may be nutritionally inadequate, as measured by guidelines from numerous national institutions and organizations, and is characterized by consumption of processed and unhealthful foods with a concomitant dearth of fruits and vegetables [9,15]. These deficiencies are important to highlight in a nutritionally vulnerable population already suspectable to malnutrition as they may lend themselves to poorer clinical outcomes, though further evidence in this regard is warranted. In addition to evaluating the effects of these dietary patterns on clinical outcomes, future studies, particularly prospective longitudinal cohort studies, are needed to highlight the impact that nutritional consequences of FI have on cancer-related outcomes. Ultimately, the results of this analysis reinforce the notion of food security as a critical social determinant of health with consequences to nutritional intake that may require persistent screenings. These findings are especially important given that there are currently no best-practice guidelines or consensus criteria in place, within the cancer survivor population, to ultimately abrogate the prevalence of FI and bolster patient prognoses [60].

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