**Introduction**

Food insecurity 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 food insecurity 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 food insecurity, including younger age, being less educated, belonging to a marginalized community, and having lower income, may ultimately lead to cancer survivors experiencing food insecurity [5] . Moreover, estimates from non-nationally representative data suggest that the prevalence of food insecurity 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 food insecurity may aggravate nutritional inadequacy in food insecure cancer survivors.

Delineating population-specific dietary patterns may illuminate critical needs and may play a role in developing clinical best-practices or food policy targeted at specific at-risk populations. Consequently, the goal of this study is 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 probability 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 food insecurity.

**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 {CITE}. the I76Dietary 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 food insecurity 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 very 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 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]. Details relating to this schema may be reviewed in Supplementary Table 2.

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 calculate a series of overall food security categorizations. However, we examined FI at the household level. 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 constructed centered and standardized food group variables (Table 2) [30,31]. 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 [32]. 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 [32]. Geometrically, the goal of PCA is to create a set of orthogonal projections on the data that explain as much of variance in the set of predictors. Eigenvalues, a scree plot, and 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 [33]. Dietary patterns extraction using PCA was implemented on subsample B. A loading matrix from this procedure is found in Supplementary Table 1.

*Dietary Patterns Extraction: Penalized Logistic Regression*

Regularized regression models introduce a penalty term to the likelihood function for estimating model parameters in various regression models [34]. 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 [35]. 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 [36]. 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 the ridge regression counterpart) and will not arbitrarily remove all variables expect 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 elastic net model for deriving dietary patterns associated with those outcomes [37,38]. 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 subjects 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 model 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 [39].

*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 B (*n* = 433). 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 two analytical goals: i) to assess the relationship in the cancer population between the extracted pattern scores and the risk of food insecurity and ii) to assess the utility of these scores to predict meaningful clinical outcomes (i.e., survival after a cancer diagnosis) for food insecure cancer survivors (Figure 1). To ascertain the first goal of the validation phase, we proceeded with 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. To assess for effect modification, we fit additional stratified Cox proportional hazards models according to sex, age, and physical activity (weekly MET minutes = 0 vs weekly MET minutes > 0) categories. We accounted for the complex and multi-stage probability design of the study by following NCHS analytical guidelines and weighting our analyses accordingly [40]. All analyses were conducted at = 0.05 and were performed in RStudio version 1.4. Accompanying code and data files to reproduce the analyses described can be found at:

**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 genitourinary cancers as their primary form of cancer compared to a lower rate in the food secure sample. There was no gross difference observed in time-since-diagnosis across the two groups, though food insecure individuals had a 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 the elastic net and PCA procedures. The patterns derived using elastic nets 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 2 illustrates the optimal combinations of and that were ultimately selected for each model. For the model with food insecurity 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 had solutions 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 later score computations.

In Table 2, we detail the Pearson correlation coefficients amongst pattern scores and food groups. The FI pattern was positively correlated with intakes of processed meat, eggs, potatoes, and added sugars while negatively correlated with seafood, solid fats, oils, milk, alcohol, fruits (all categories), vegetables (all categories other than potatoes), refined grains, whole grains, and nuts. The Age pattern was positively correlated with intakes of seafood, eggs, solid fats, oils, milk, yogurt, fruits, potatoes, other vegetables, starchy vegetables, and whole grains while negatively correlated with meat, processed meats, poultry, cheese, alcohol, dark-green vegetables, legumes, soy, refined grains, and added sugars. Overall, this pattern was negatively correlated with the FI pattern (*r* = 0.40). The SNAP dietary pattern was strongly and positively correlated with the FI pattern (*r* = 0.80) as well as with intakes of legumes and added sugars while being negatively correlated with poultry, eggs, oil, milk, alcohol, all fruit categories, all categories of vegetables, refined grains, whole grains and nuts. The final Household Size pattern was also strongly and positively correlated with the FI pattern (*r* = 0.68) and negatively correlated with intakes of seafood, solid fats, oils, milk, yogurt, cheese, fruits and vegetables (all categories other than potatoes), refined and whole grains while being positively correlated with intakes of legumes, soy, added sugars, and to a more limited extent meat products.

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, solid fat, oil, milk, cheese, potato, 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 processed meat and processed meat consumption, cheese, solid fat, cheese, legumes, and refined grains intakes and, overall, had stronger positive correlations to fruit 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[41,42]. In contrast, the second principal component was termed the Prudent pattern, given its greater emphasis on pillars of healthful eating cited previously in the literature [43].

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 Food Insecurity, SNAP, and Household Size patterns were all strongly and positively associated with the risk of being food insecure. The Food Insecurity pattern had the largest magnitude of association with the odds of food insecurity being 2.43-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 food insecurity pattern, a one standard deviation increase in the score was associated with 51% increase in the odds of being food insecure. Concerning associations in the opposite direction, only the Prudent pattern was inversely associated with food insecurity, with the highest quintile observing a 59% reduction in the odds of being food insecure compared to the first quintile. A one standard deviation increase in this pattern scores was also 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 across the quintiles and these findings were generally supported by the results from fitting models with restricted cubic splines (Figure 3).

*Validation Phase: Survival Analysis*

There were 4,130 person-years of contributions used in the survival analysis of 242 food insecure cancer survivors (subsample C), 57 documented deaths from all causes, and 21 cancer-related deaths. Using multivariable Cox Proportional Hazards models, we found several associations between the extracted patterns and risk of all-cause mortality in this subsample (Table 5). Three of the patterns derived using the elastic net models were significantly and positively associated with the risk of all-cause mortality after multivariable adjustment. The highest quintile for the FI pattern observed a 397% increased risk of all-cause mortality compared to the lowest quintile and a test for linear trend across the quintiles suggested the presence of one. Moreover, a one standard deviation increase in the pattern score was significantly associated with a 62% increase in the risk of all-cause mortality. The SNAP and Household Size patterns were similarly positively associated with all-cause mortality. For the SNAP pattern, the highest quintile observed a 532% increased risk of all-cause mortality compared to the lowest quintile while a standard deviation increase in the score was associated with a 63% increase in the risk of mortality. The highest quintile of the Household Size pattern observed a 446% increase in the risk of all-cause mortality compared to the first quintile and a standard deviation increase in this score predicted a 43% increased risk of mortality although this last figure was not statistically significant. The highest quintile of the Prudent pattern was associated with a 70% reduction in the risk of all-cause mortality although this figure did not attain the threshold for statistical significance (*p* = 0.06).

When considering cancer-specific mortality, a one standard deviation increase in the Modified Western pattern was associated with a 42% decrease in the risk of cancer-related mortality although there was no further significant nor strong evidence in any of the other operationalizations of this pattern score. Evidence for linear or nonlinear dose response behaviors were also generally lacking (Figure 4).

In stratified models of all-cause mortality (Table S1), there were no gross suggestions of effect modification by age, sex, or level of weekly physical activity. Concerning all-cause mortality, the SNAP and Household Size dietary patterns were significantly and positively associated with mortality in males but not females. With regard to cancer-specific mortality, there were no significant robust results to suggest effect modification.

**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 [44]. 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 elastic net 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 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. also Regarding their relationship to food insecurity in the cancer survivor population, we found that each of these patterns were strongly and positively associated with the risk of food insecurity.

Unlike the patterns derived via PCA, the elastic net models resulted in sparse solutions. That is, certain food categories, not relevant to the outcome, had coefficients shrunk to zero, effectively removing them from the model. This yielded a smaller set of food group coefficients that were more interpretable [45]. 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 [46,47]. 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 [48,49]. 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 appropriate in the context of our study, given that dietary intake variables tend to have a large degree of correlation while one of the primary intents of this approach is to address multicollinearity and overfitting [50].

As a comparative analysis, we implemented 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 [45]. Moreover, PCA may not always be suitable approach for extracting patterns that are associated with a condition or disease outcome. Given that the procedure only aims to reduce as much of the variation in the dietary intake data into a single dimension, predictive potential is not an inherent characteristic of this approach (CITE).

In the validation phase of our analysis we found that the FI, SNAP, and Household Size patterns were positively and strongly associated while the Prudent pattern was strongly but inversely associated with being food insecure in the cancer survivor population after control for confounding variables. Concerning clinical outcomes, the FI, SNAP, and Household Size patterns were also significantly and positively associated with the outcome of all-cause mortality after adjustment for several confounders. There was a suggestion that the Prudent pattern was inversely associated with all-cause mortality although those parameter estimates were not statistically significant. We believe it is also imperative to underscore that the method of using elastic net models to extract dietary patterns associated with a particular outcome yielded more clinically meaningful and significant results in both steps of the validation phase.

Considering these results in light of others in our analysis, they support the conjecture that food insecure subjects may be at risk of nutritional inadequacy, by being more likely to consume unhealthful patterns when compared to food secure survivors. Adherence to these patterns, in turn, may pose deeper ramifications for survivors that may culminate in a worse prognosis. In stratified analyses, we found disparities across levels of sex where the SNAP and Household Size patterns were significantly associated with cancer mortality in males but not females. There were also some sex-specific differences, to a lesser extent, when considering all-cause mortality and generally reflected more pronounced associations in males rather than females. Sex disparities in epidemiologic studies of exposures with cancer outcomes have been reported elsewhere in the literature [51,52]. The nuances of these disparate relationships are hypothesized to involve hormonal differences between the two sexes in addition to sex-specific differences in nutrient metabolism [53]. We consider, for instance, that alcohol was a component of these diet scores and it is understood that females and males have differential metabolic capacities for dealing with ingested ethanol and that this phenomenon may, in part, be contributing to the sex-specific disparities [54]. Albeit, the question of why sex-specific differences exist remains largely elusive and will necessitate further surveillance and study.

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 that must be exacted by food insecure survivors when faced with competing demands of nutrition and medical care [55]. 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 [55]. 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 [56]. 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 [57]. We also note that in our analysis we found that genitourinary cancer survivors were disproportionately represented in the food insecure cancer population, which is a finding consistent with other studies suggesting greater a financial toxicity burden for individuals experiencing those forms of cancer (CITE,33820747,33252300,34752150).

The analysis of dietary patterns has evolved to paramount significance in nutritional epidemiology. However, a comprehensive understanding of major dietary patterns in the food insecure cancer survivor population are lacking, especially at the national level. The impetus for studying dietary patterns rather than nutrients is motivated by the complexity of dietary intake, which is surmised from the facts that nutrients and foods may be correlated, hampering the ability to model them as single variables, and that there are food-food as well as host-food interactions that are not well accounted for by the reductionistic lens of the single-nutrient approach [58]. *A posteriori*, or empirical, techniques for delineating dietary patterns from a set of observed data include the applications unsupervised learning methods such as principal components analysis (PCA), exploratory factor analysis, *k*-means and hierarchical clustering, or supervised learning methods such as reduced-rank regression. The application of novel statistical methodologies for ascertaining dietary patterns from empirical data continues to be of ongoing interest in nutritional epidemiology. As of late, colleagues in the field have reported on the use of penalized, or regularized, regression (LASSO regression) as a novel means of characterizing dietary patterns in observational studies [47]. Nonetheless, validating studies employing this new approach are lacking and none have, to our knowledge, been performed in a population of cancer survivors. Furthermore, less is understood about how dietary patterns, in turn, affect prognostic outcomes, such as survival in this target population.

Cancer presents as a caustic burden, increasing nutritional requirements and the likelihood of cachexia, particularly in more aggressive forms and later-staged manifestations. 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 [59]. Specifically, cancer survivors with membership in marginalized groups are at higher risk for experiencing financial hardship, being uninsured with could contribute to poorer outcomes after cancer diagnosis (CITE, 34752150) Our results are supported by others in the literature showing that food insecure individuals have a greater risk of all-cause mortality [60]. Though our target population was the cancer population, we can fathom, as the results of our study suggest, that diet quality may play a role in the prognosis of individuals in this population. We also consider our results in 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 [61]. 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 [62]. Future studies should provide analysis on the effects of COVID-19 pandemic on food insecure cancer survivors.

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 is severely 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 explored in this analysis suggested that FI in the cancer survivor population was associated with poor dietary quality that was not aligned with those guidelines and our results are further corroborating evidence that those patterns may be deleterious to prognosis as well. Together, these findings bolster the hypothesis that the study population may be at increased risk of adverse outcomes related to their diagnosis due to inadequate access to the foods understood to benefit their condition. Future studies, specifically those with longitudinal cohort designs, should more closely examine relationships of FI and dietary intake with prognostic outcomes in this population.

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 worth noting, including, as with many observational studies, residual confounding, and the presence of reverse causality, especially within a cross-sectional study design, cannot be ruled out. 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 systemic biases introduced by the dietary measurement protocol, though the use of only the first day of dietary measurements from the NHANES dataset was strategic for this very purpose. 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 inability to capture long-term, habitual intake of foods [63]. With regards to the specific methodology employed in the analysis for empirically ascertaining dietary patterns of a target population, we recognize that this methodology demands 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. 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 [64]. 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 and characterized by consumption of processed and unhealthful foods or lack of fruits and vegetables, and that these deficiencies are important to highlight in a nutritionally vulnerable population already suspectable to malnutrition as they may procure poor survival based on our findings. Future studies, particularly prospective longitudinal cohort studies, are needed to highlight the impact of the nutritional consequences of FI on cancer-related outcomes. Ultimately, the results of this analysis are meant to reinforce the notion of food security as a critical social determinant of health with consequences to nutritional status that require persistent screenings, given that there are currently no best-practice guidelines or consensus criteria in place, in the cancer survivor population to ultimately abrogate its prevalence and bolster patient prognoses.

**References**

1. Coleman-Jensen, A.; Rabbitt, M.P.; Gregory, C. a; Singh, A. Household Food Security in the United States in 2019 Available online: http://www.ers.usda.gov/publications/pub-details/?pubid=99281 (accessed on 12 August 2021).

2. Charkhchi, P.; Fazeli Dehkordy, S.; Carlos, R.C. Housing and Food Insecurity, Care Access, and Health Status Among the Chronically Ill: An Analysis of the Behavioral Risk Factor Surveillance System. *J. Gen. Intern. Med.* **2018**, *33*, 644–650, doi:10.1007/s11606-017-4255-z.

3. Kudre, D.; Chen, Z.; Richard, A.; Cabaset, S.; Dehler, A.; Schmid, M.; Rohrmann, S. Multidisciplinary Outpatient Cancer Rehabilitation Can Improve Cancer Patients’ Physical and Psychosocial Status—a Systematic Review. *Curr. Oncol. Rep.* **2020**, *22*, 122, doi:10.1007/s11912-020-00979-8.

4. Mariotto, A.B.; Enewold, L.; Zhao, J.; Zeruto, C.A.; Yabroff, K.R. Medical Care Costs Associated with Cancer Survivorship in the United States. *Cancer Epidemiol. Biomarkers Prev.* **2020**, *29*, 1304–1312, doi:10.1158/1055-9965.EPI-19-1534.

5. Han, X.; Zhao, J.; Zheng, Z.; de Moor, J.S.; Virgo, K.S.; Yabroff, K.R. Medical Financial Hardship Intensity and Financial Sacrifice Associated with Cancer in the United States. *Cancer Epidemiol. Biomark. Prev. Publ. Am. Assoc. Cancer Res. Cosponsored Am. Soc. Prev. Oncol.* **2020**, *29*, 308–317, doi:10.1158/1055-9965.EPI-19-0460.

6. Simmons, L.A.; Modesitt, S.C.; Brody, A.C.; Leggin, A.B. Food Insecurity Among Cancer Patients in Kentucky: A Pilot Study. *J. Oncol. Pract.* **2006**, *2*, 7.

7. NCI’s Dictionary of Cancer Terms.

8. Gany, F.; Leng, J.; Ramirez, J.; Phillips, S.; Aragones, A.; Roberts, N.; Mujawar, M.I.; Costas-Muñiz, R. Health-Related Quality of Life of Food-Insecure Ethnic Minority Patients With Cancer. *J. Oncol. Pract.* **2015**, *11*, 396–402, doi:10.1200/JOP.2015.003962.

9. The American Institute for Cancer Research/World Cancer Research Fund *Diet, Nutrition, Physical Activity and Cancer: A Global Perspective*; 3rd ed.;

10. Thompson, K.L.; Elliott, L.; Fuchs-Tarlovsky, V.; Levin, R.M.; Voss, A.C.; Piemonte, T. Oncology Evidence-Based Nutrition Practice Guideline for Adults. *J. Acad. Nutr. Diet.* **2017**, *117*, 297-310.e47, doi:10.1016/j.jand.2016.05.010.

11. Curtin, L.R.; Mohadjer, L.K.; Dohrmann, S.M.; Kruszon-Moran, D.; Mirel, L.B.; Carroll, M.D.; Hirsch, R.; Burt, V.L.; Johnson, C.L. National Health and Nutrition Examination Survey: Sample Design, 2007-2010. *Vital Health Stat. 2.* **2013**, 1–23.

12. About the National Health and Nutrition Examination Survey.

13. Wolfe, A.M.; Lee, J.A.; Laurson, K.R. Socioeconomic Status and Physical Fitness in Youth: Findings from the NHANES National Youth Fitness Survey. *J. Sports Sci.* **2020**, *38*, 534–541, doi:10.1080/02640414.2020.1713688.

14. Agarwal, S. The Association of Active and Passive Smoking with Peripheral Arterial Disease: Results from NHANES 1999–2004. *Angiology* **2009**, *60*, 335–345, doi:10.1177/0003319708330526.

15. Dietary Guidelines Advisory Committee; OverDrive, I. *Dietary Guidelines for Americans 2015-2020*; 2016; ISBN 978-0-16-093465-0.

16. Zhao, H.; Pan, Y.; Wang, C.; Guo, Y.; Yao, N.; Wang, H.; Li, B. The Effects of Metal Exposures on Charlson Comorbidity Index Using Zero-Inflated Negative Binomial Regression Model: NHANES 2011–2016. *Biol. Trace Elem. Res.* **2021**, *199*, 2104–2111, doi:10.1007/s12011-020-02331-4.

17. Tucker, L.A. Physical Activity and Telomere Length in U.S. Men and Women: An NHANES Investigation. *Prev. Med.* **2017**, *100*, 145–151, doi:10.1016/j.ypmed.2017.04.027.

18. Blanton, C.A.; Moshfegh, A.J.; Baer, D.J.; Kretsch, M.J. The USDA Automated Multiple-Pass Method Accurately Estimates Group Total Energy and Nutrient Intake. *J. Nutr.* **2006**, *136*, 2594–2599, doi:10.1093/jn/136.10.2594.

19. Moshfegh, A.J.; Rhodes, D.G.; Baer, D.J.; Murayi, T.; Clemens, J.C.; Rumpler, W.V.; Paul, D.R.; Sebastian, R.S.; Kuczynski, K.J.; Ingwersen, L.A.; et al. The US Department of Agriculture Automated Multiple-Pass Method Reduces Bias in the Collection of Energy Intakes. *Am. J. Clin. Nutr.* **2008**, *88*, 324–332, doi:10.1093/ajcn/88.2.324.

20. Montville, J.B.; Ahuja, J.K.C.; Martin, C.L.; Heendeniya, K.Y.; Omolewa-Tomobi, G.; Steinfeldt, L.C.; Anand, J.; Adler, M.E.; LaComb, R.P.; Moshfegh, A. USDA Food and Nutrient Database for Dietary Studies (FNDDS), 5.0. *Procedia Food Sci.* **2013**, *2*, 99–112, doi:10.1016/j.profoo.2013.04.016.

21. Bowman SA, Clemens JC, Friday JE, and Moshfegh AJ. 2020. Food Patterns Equivalents Database 2017-2018: Methodology and User Guide [Online]. Food Surveys Research Group, Beltsville Human Nutrition Research Center, Agricultural Research Service, U.S. Department of Agriculture, Beltsville, Maryland. October 2020. Available at: Http://Www.Ars.Usda.Gov/Nea/Bhnrc/Fsrg.

22. Bowman SA, Friday JE, Moshfegh A. (2008). MyPyramid Equivalents Database, 2.0 for USDA Survey Foods, 2003-2004 [Online] Food Surveys Research Group. Beltsville Human Nutrition Research Center, Agricultural Research Service, U.S. Department of Agriculture, Beltsville, MD. Available at: Http://Www.Ars.Usda.Gov/Ba/Bhnrc/Fsrg.

23. Willett, W.C.; Howe, G.R.; Kushi, L.H. Adjustment for Total Energy Intake in Epidemiologic Studies. *Am. J. Clin. Nutr.* **1997**, *65*, 1220S-1228S, doi:10.1093/ajcn/65.4.1220S.

24. Petrova, D.; Catena, A.; Rodríguez-Barranco, M.; Redondo-Sánchez, D.; Bayo-Lozano, E.; Garcia-Retamero, R.; Jiménez-Moleón, J.-J.; Sánchez, M.-J. Physical Comorbidities and Depression in Recent and Long-Term Adult Cancer Survivors: NHANES 2007–2018. *Cancers* **2021**, *13*, 3368, doi:10.3390/cancers13133368.

25. Bickel, G.; Nord, M.; Price, C.; Hamilton, W.; Cook, J. Guide to Measuring Household Food Security 2000.

26. Linkage Methods and Analytical Support for NCHS Linked Mortality Data.

27. Cain, K.C.; Harlow, S.D.; Little, R.J.; Nan, B.; Yosef, M.; Taffe, J.R.; Elliott, M.R. Bias Due to Left Truncation and Left Censoring in Longitudinal Studies of Developmental and Disease Processes. *Am. J. Epidemiol.* **2011**, *173*, 1078–1084, doi:10.1093/aje/kwq481.

28. Foreman, A.; Lai, G.; Miller, D. Surviving Left Truncation Using PROC PHREG.

29. Song, M.; Wu, K.; Meyerhardt, J.A.; Yilmaz, O.; Wang, M.; Ogino, S.; Fuchs, C.S.; Giovannucci, E.L.; Chan, A.T. Low-Carbohydrate Diet Score and Macronutrient Intake in Relation to Survival After Colorectal Cancer Diagnosis. *JNCI Cancer Spectr.* **2018**, *2*, pky077, doi:10.1093/jncics/pky077.

30. Fransen, H.P.; May, A.M.; Stricker, M.D.; Boer, J.M.A.; Hennig, C.; Rosseel, Y.; Ocké, M.C.; Peeters, P.H.M.; Beulens, J.W.J. A Posteriori Dietary Patterns: How Many Patterns to Retain? *J. Nutr.* **2014**, *144*, 1274–1282, doi:10.3945/jn.113.188680.

31. Kant, A.K. Dietary Patterns and Health Outcomes. *J. Am. Diet. Assoc.* **2004**, *104*, 615–635, doi:10.1016/j.jada.2004.01.010.

32. Abdi, H.; Williams, L.J. Principal Component Analysis: Principal Component Analysis. *Wiley Interdiscip. Rev. Comput. Stat.* **2010**, *2*, 433–459, doi:10.1002/wics.101.

33. Lumley, T. Analysis of Complex Survey Samples. *J. Stat. Softw.* **2004**, *9*, doi:10.18637/jss.v009.i08.

34. Friedman, J.; Hastie, T.; Tibshirani, R. Regularization Paths for Generalized Linear Models via Coordinate Descent. *J. Stat. Softw.* **2010**, *33*, 1–22.

35. Tibshirani, R. Regression Shrinkage and Selection Via the Lasso. *J. R. Stat. Soc. Ser. B Methodol.* **1996**, *58*, 267–288, doi:10.1111/j.2517-6161.1996.tb02080.x.

36. Hastie, T.; Qian, J.; Tay, K. An Introduction to `glmnet` 2021.

37. Lee, J.S.; Frongillo, E.A. Nutritional and Health Consequences Are Associated with Food Insecurity among U.S. Elderly Persons. *J. Nutr.* **2001**, *131*, 1503–1509, doi:10.1093/jn/131.5.1503.

38. Kohn, M.J.; Bell, J.F.; Grow, H.M.G.; Chan, G. Food Insecurity, Food Assistance and Weight Status in US Youth: New Evidence from NHANES 2007-08: Food Insecurity, Assistance and Weight. *Pediatr. Obes.* **2014**, *9*, 155–166, doi:10.1111/j.2047-6310.2012.00143.x.

39. McConville, K. Improved Estimation for Complex Surveys Using Modern Regression Techniques. *Colo. State Univ. Fort Collins CO USA*.

40. Clifford Johnson; Paulose-Ram, R.; Ogden, C.L.; Carroll, M.; Kruszan-Moran, D.; Dohrmann, S.; Curtin, L. National Health and Nutrition Examination Survey. Analytics Guidelines, 1999-2010. *Vital Health Stat. Ser. 2* **2013**, 1–16.

41. Kopp, W. How Western Diet And Lifestyle Drive The Pandemic Of Obesity And Civilization Diseases. *Diabetes Metab. Syndr. Obes. Targets Ther.* **2019**, *12*, 2221–2236, doi:10.2147/DMSO.S216791.

42. Azzam, A. Is the World Converging to a ‘Western Diet’? *Public Health Nutr.* **2021**, *24*, 309–317, doi:10.1017/S136898002000350X.

43. Arthur, A.E.; Peterson, K.E.; Rozek, L.S.; Taylor, J.M.G.; Light, E.; Chepeha, D.B.; Hébert, J.R.; Terrell, J.E.; Wolf, G.T.; Duffy, S.A.; et al. Pretreatment Dietary Patterns, Weight Status, and Head and Neck Squamous Cell Carcinoma Prognosis. *Am. J. Clin. Nutr.* **2013**, *97*, 360–368, doi:10.3945/ajcn.112.044859.

44. Gundersen, C.; Ziliak, J.P. Food Insecurity And Health Outcomes. *Health Aff. (Millwood)* **2015**, *34*, 1830–1839, doi:10.1377/hlthaff.2015.0645.

45. Zhao, J.; Li, Z.; Gao, Q.; Zhao, H.; Chen, S.; Huang, L.; Wang, W.; Wang, T. A Review of Statistical Methods for Dietary Pattern Analysis. *Nutr. J.* **2021**, *20*, 37, doi:10.1186/s12937-021-00692-7.

46. McEligot, A.J.; Poynor, V.; Sharma, R.; Panangadan, A. Logistic LASSO Regression for Dietary Intakes and Breast Cancer. *Nutrients* **2020**, *12*, 2652, doi:10.3390/nu12092652.

47. Zhang, F.; Tapera, T.M.; Gou, J. Application of a New Dietary Pattern Analysis Method in Nutritional Epidemiology. *BMC Med. Res. Methodol.* **2018**, *18*, 119, doi:10.1186/s12874-018-0585-8.

48. Hoffmann, K. Application of a New Statistical Method to Derive Dietary Patterns in Nutritional Epidemiology. *Am. J. Epidemiol.* **2004**, *159*, 935–944, doi:10.1093/aje/kwh134.

49. Newby, P.K.; Tucker, K.L. Empirically Derived Eating Patterns Using Factor or Cluster Analysis: A Review. *Nutr. Rev.* **2004**, *62*, 177–203, doi:10.1111/j.1753-4887.2004.tb00040.x.

50. Zou, H.; Hastie, T. Regularization and Variable Selection via the Elastic Net. *J. R. Stat. Soc. Ser. B Stat. Methodol.* **2005**, *67*, 301–320, doi:10.1111/j.1467-9868.2005.00503.x.

51. Boyle, T.; Fritschi, L.; Platell, C.; Heyworth, J. Lifestyle Factors Associated with Survival after Colorectal Cancer Diagnosis. *Br. J. Cancer* **2013**, *109*, 814–822, doi:10.1038/bjc.2013.310.

52. Lam, T.K.; Cross, A.J.; Freedman, N.; Park, Y.; Hollenbeck, A.R.; Schatzkin, A.; Abnet, C. Dietary Fiber and Grain Consumption in Relation to Head and Neck Cancer in the NIH-AARP Diet and Health Study. *Cancer Causes Control CCC* **2011**, *22*, 1405–1414, doi:10.1007/s10552-011-9813-9.

53. Kim, S.-E.; Paik, H.Y.; Yoon, H.; Lee, J.E.; Kim, N.; Sung, M.-K. Sex- and Gender-Specific Disparities in Colorectal Cancer Risk. *World J. Gastroenterol.* **2015**, *21*, 5167–5175, doi:10.3748/wjg.v21.i17.5167.

54. Seitz, H.K.; Egerer, G.; Simanowski, U.A.; Waldherr, R.; Eckey, R.; Agarwal, D.P.; Goedde, H.W.; von Wartburg, J.P. Human Gastric Alcohol Dehydrogenase Activity: Effect of Age, Sex, and Alcoholism. *Gut* **1993**, *34*, 1433–1437, doi:10.1136/gut.34.10.1433.

55. Patel, K.G.; Borno, H.T.; Seligman, H.K. Food Insecurity Screening: A Missing Piece in Cancer Management. *Cancer* **2019**, *125*, 3494–3501, doi:10.1002/cncr.32291.

56. Gany, F.; Lee, T.; Ramirez, J.; Massie, D.; Moran, A.; Crist, M.; McNish, T.; Winkel, G.; Leng, J.C.F. Do Our Patients Have Enough to Eat?: Food Insecurity among Urban Low-Income Cancer Patients. *J. Health Care Poor Underserved* **2014**, *25*, 1153–1168, doi:10.1353/hpu.2014.0145.

57. Gany, F.; Bari, S.; Crist, M.; Moran, A.; Rastogi, N.; Leng, J. Food Insecurity: Limitations of Emergency Food Resources for Our Patients. *J. Urban Health Bull. N. Y. Acad. Med.* **2013**, *90*, 552–558, doi:10.1007/s11524-012-9750-2.

58. Hu, F.B. Dietary Pattern Analysis: A New Direction in Nutritional Epidemiology. *Curr. Opin. Lipidol.* **2002**, *13*, 3–9, doi:10.1097/00041433-200202000-00002.

59. Ward, E.; Jemal, A.; Cokkinides, V.; Singh, G.K.; Cardinez, C.; Ghafoor, A.; Thun, M. Cancer Disparities by Race/Ethnicity and Socioeconomic Status. *CA. Cancer J. Clin.* **2004**, *54*, 78–93, doi:10.3322/canjclin.54.2.78.

60. Sun, Y.; Liu, B.; Rong, S.; Du, Y.; Xu, G.; Snetselaar, L.G.; Wallace, R.B.; Bao, W. Food Insecurity Is Associated With Cardiovascular and All‐Cause Mortality Among Adults in the United States. *J. Am. Heart Assoc.* **2020**, *9*, doi:10.1161/JAHA.119.014629.

61. Gundersen, C.; Hake, M.; Dewey, A.; Engelhard, E. Food Insecurity during COVID-19. *Appl. Econ. Perspect. Policy* **2020**, doi:10.1002/aepp.13100.

62. FAO; IFAD; UNICEF; WFP; WHO The State of Food Security and Nutrition in the World 2021.

63. Willett, W. *Nutritional Epidemiology*; 3rd ed.; Oxford University Press, 2013;

64. Bluethmann, S.M.; Basen-Engquist, K.; Vernon, S.W.; Cox, M.; Gabriel, K.P.; Stansberry, S.A.; Carmack, C.L.; Blalock, J.A.; Demark-Wahnefried, W. Grasping the “Teachable Moment”: Time since Diagnosis, Symptom Burden and Health Behaviors in Breast, Colorectal and Prostate Cancer Survivors. *Psychooncology.* **2015**, *24*, 1250–1257, doi:10.1002/pon.3857.