COMPARISON OF NEURAL NETWORK AND LINEAR REGRESSION MODELS IN STATISTICALLY PREDICTING MENTAL AND PHYSICAL HEALTH STATUS OF BREAST CANCER SURVIVORS

by

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DEDICATION

For Jake. Thanks for your wisdom, your patience, and for never giving up.

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ABSTRACT

Comparison of Neural Network and Linear Regression Models in Statistically Predicting Mental and Physical Health Status of Breast Cancer Survivors:

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In the U.S., there are currently 13.7 million cancer survivors (38). Many cancer survivors experience problems with post-treatment mental and physical functioning. Although research has identified important contributing factors regarding these problems, traditional predictive statistical modeling accounts for less than half the variance in mental and physical function (16; 17; 113). The relationship among these factors may be better accounted for by a non-linear modeling approach. The goal of this doctoral study was to determine whether a non-linear, adaptive predictive model demonstrated better model fit, showed greater predictive accuracy, and accounted for a greater contribution of independent variables over a traditional statistical model with regard to mental and physical functioning in post-treatment breast cancer survivors.

Using demographic, medical, and clinical variables, linear regression was compared to neural network modeling in predicting mental functioning and physical functioning in a sample of post-treatment breast cancer survivors.

Contrary to the *a priori* hypotheses, the neural network model did not outperform the linear regression model in predicting mental and physical functioning of post-treatment breast cancer survivors. However, both linear regression and neural network modeling identified modifiable variables (clinical domains of the Cancer Survivor Profile) as important predictors of post-treatment mental and physical functioning, with the neural network confirming the findings of the linear regression models. The neural network model also added to the results of the linear regression by identifying additional important variables (age, time since diagnosis) that may have a non-linear relationship with mental and physical functioning. These findings may promote a better understanding of post-treatment health status and promote targeted clinical interventions.

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CHAPTER 1: Background

INTRODUCTION

The goal of the present study was to evaluate the self-reported mental and physical function of post-treatment breast cancer survivors using a traditional statistical approach (linear regression) and a neural network approach. Although linear regression models are a commonly used statistical approach in cancer survivor research, these models may not account for the full variability of symptoms in the post-treatment experience (16; 17) which may be related to limitations in modeling complex, nonlinear relationships. Neural network models are nonlinear, adaptive predictive model. These models are iterative and learn from the characteristics of the variables used in the model to reduce overall error in the model, potentially allowing for more accuracy and complexity in model prediction. As a result, neural network models may provide a better model fit, more predictive accuracy, and better sensitivity to the relationships among predictor variables and measures of mental and physical function. More accurate predictive models may assist researchers in identifying optimal areas for interventions that improve mental and physical functioning in breast cancer survivors.

The two statistical approaches (linear regression and neural network analysis) were compared to determine which method provided the best model fit, showed the greatest predictive accuracy, and accounted for the greatest contribution of the independent variables in statistically predicting the mental and physical function of cancer survivors. Model fit was determined by comparing the mean square error (MSE) of each predictive model and mean absolute percentage error (MAPE) was used to compare the predictive accuracy of each model. A global sensitivity analysis was

originally planned to determine the contribution of each independent variable to each predictive statistical model; however, this analysis could not be conducted because of limitations in the neural network software that did not provide a method to hold the contributions of the independent variables in the full neural network model constant for the required comparative analyses. Instead, an alternative sensitivity analysis was conducted comparing squared semipartial correlation coefficients among the models to determine which independent variables were most important in model prediction.

With regard to the population studied, breast cancer survivors comprise the largest population of female cancer survivors and these individuals can experience difficulties with post-treatment mental and physical function (6; 19; 22; 38; 53; 111). Extensive research has been conducted with this cancer survivor population using traditional linear statistical methods to identify what variables predict post-treatment mental and physical functioning (8; 16; 17; 33; 103); however, these models account for less than half the variance in mental and physical functioning in breast cancer survivors (16; 17). These findings suggest that contributing factors for over half of the variance in these outcomes is still unknown. Neural network analyses use an adaptive, iterative modeling process that reduces predictive error in the model and has the ability to identify nonlinear, complex relationships which may better account for this additional variance and identify important modifiable factors that may respond to interventions. To date, no research has evaluated the use of neural network models in predicting mental and physical functioning in breast cancer survivors.

This doctoral dissertation project consists of a review of breast cancer epidemiology, survivorship, stages, treatment, and health status. Then, predictive

statistical modeling is also discussed. These sections provide a framework to support the need for this study. This project also includes an outline of the study's methodology, analytic plan, results, clinical implications, and recommendations for future research.

EPIDEMIOLOGY

U.S. epidemiological data estimate that more than 1.6 million individuals (855,220 men; 810,320 women) received a diagnosis of cancer in 2014 (5). Among U.S. women, the three most commonly diagnosed cancer types in 2014 were projected to be breast, lung/bronchus, and colorectal cancer (5). Incident female breast cancer cases were projected in 232,670 women which accounts for 29% of all new female cancers (5; 56; 102). The median age of women diagnosed with breast cancer is 61 (56).

Although diagnoses of lung, breast, prostate, and colorectal cancer comprise the largest group of incident cancer types in the U.S., deaths of individuals with lung cancer far exceed deaths of individuals with breast cancer (102). As a result, female breast cancer survivors account for 22% of all cancer survivors in the U.S. and comprise the largest cancer survivor group (with prostate cancer survivors accounting for 20% of all survivors) (38). Breast cancer survivors can also report difficulties with post-treatment health status such as mental and physical functioning. Identifying which factors are significant predictors of post-treatment health status is an important step in being able to develop effective interventions to improve mental and physical functioning, especially with regard to factors that are modifiable. Research evaluating health status in breast cancer survivors revealed that significant predictors of mental function included age, being partnered, income, race, cognitive/mood status, social/emotional status, fatigue, fear of recurrence, sleep difficulties, and number of chronic conditions (8; 16; 17; 24; 33;

103). Significant predictors of physical function included age, income, race, employment status, anticancer treatment received, menopausal status, social/emotional status, diet and exercise, fear of recurrence, fatigue, dizziness, urinary incontinence, lymphedema, children in the home, and number of chronic conditions (8; 16; 17; 24; 33). However, research studies examining post-treatment health status in breast cancer survivors often use traditional statistical approaches such as linear regression which account for less than half the variance in mental and physical functioning in this population (8; 16; 17; 33; 103). Neural network modeling of these same factors may produce a more accurate predictive model. Therefore, breast cancer survivors represent an important population to understand post-treatment mental and physical functioning.

CANCER SURVIVORSHIP

There are currently 13.7 million cancer survivors in the U.S. (38) and this population is growing, largely due to advances in cancer detection and treatment (101; 102). Cancer survivorship can be defined in many ways. Many advocacy groups use an expansive definition of survivorship that starts from the time of diagnosis until the end of life and extends not only to the cancer patient, but also to his or her family, friends, and caregivers (55). However, because the experiences of diagnosis and active treatment can differ from experiences in post-treatment (66), the most common definition of cancer survivorship used in research refers to an individual who has completed primary treatment (79). For the purposes of this study, cancer survivors were defined as those individuals who are living with a history of cancer and have completed primary anticancer treatment.

There are 28.8 million cancer survivors worldwide (15.2 million women and 13.5 million men) (18). Of these cancer survivors, breast cancer accounts for 34% (5.2 million) of all female cancers (18). In the U.S., the female breast cancer survivor population is 2.9 million, accounting for 22% of all cancer survivors and 41% of all female cancer survivors (38; 101).

Cancer survivorship can be characterized by various long-term and late effects of the cancer and/or anticancer treatment that may not manifest until months or years following the end of primary treatment (55). Late and long-term effects of cancer survivorship can be affected by stage at diagnosis, time since diagnosis, treatment received, time since treatment, age, race, education, socioeconomic status, social support, and health status (15; 54). The above cancer survivorship research, as well as experience with previous studies of breast cancer survivorship (19; 22; 53; 112), informed the decision to include the following as independent variables in the current doctoral dissertation project: age, race, education, partner status, employment, income, stage at diagnosis, time since diagnosis, treatment received, adjuvant treatment, time since treatment, menopausal status, symptom burden, function, health behavior, and health service needs (see Table 1).

STAGES

Cancer stage at diagnosis can impact the late and long-term effects experienced by breast cancer survivors. Staging is a classification method used to describe the extent of cancer in the body (2). The standardized guidelines for specific cancer staging referred to as the TNM (*tumor, node, metastasis*) staging system are outlined in the American Joint Committee on Cancer (AJCC) (7). T indicates the size of the primary

tumor by numbers 0 to 4 with higher numbers indicating a larger mass. N describes the spread of the tumor to regional lymph nodes using numbers 0 to 3 as categorical representations of the number of nodes affected (higher numbers indicate a greater number of affected nodes). M denotes whether the cancer has metastasized, or spread, to distant organs or lymph nodes with 0 representing no distant spread and 1 representing distant spread. Specific cancer stages are established based on the type of cancer and the TNM grades assigned. Although there are standardized staging guidelines, staging systems vary depending upon the specific cancer type.

Stages of breast cancer range from 0 to IV and are assigned based on the AJCC guidelines (7). Stage 0 breast cancer indicates the earliest form of breast cancer known as *carcinoma in situ* (CIS) which describes a cancerous tumor that is localized to the cells of the breast ducts or lobules (4). Stage I breast cancer describes a primary tumor that is 2 centimeters or less in size with or without micrometastases (i.e., metastases to localized tissue nodes) to axillary lymph nodes. Stage II breast cancer is diagnosed for primary tumors that are less than 2 centimeters but with a greater level of axillary node micrometastases than Stage I, primary tumors between 2-5 centimeters with or without axillary node micrometastases, or tumors that are larger than 5 centimeters without any indication of axillary node micrometastases. Stage III breast cancer consists of a primary tumor less than 5 centimeters around with a higher level of axillary node micrometastases than that of Stage II, a primary tumor greater than 5 centimeters with micrometastases to axillary or mammary lymph nodes, a primary tumor that has invaded the wall of the chest or skin with or without micrometastases to axillary or mammary lymph nodes, or a primary tumor of any size with micrometastases to the clavicle and/or a higher level of

micrometastases to axillary or mammary lymph nodes. Stage IV breast cancer (also referred to as metastatic breast cancer) describes cancer of any size that has metastasized, or spread, to distant organs or lymph nodes.

Stage at diagnosis is an important factor to include in this study of post-treatment breast cancer survivors because it is associated with intensity and type of anticancer treatment received which can have an effect on mental and physical functioning. Specifically, early-stage breast cancer survivors (i.e., stage 0 to II) often receive lower levels of chemotherapy and radiation than those who are later-stage at diagnosis (i.e., stage III to IV) (6). Similarly, women with later stage breast cancer are more likely to receive adjuvant therapies than women with early stage breast cancer (6). Although traditional regression models have been used to evaluate these factors in previous research (16; 24; 33), the adaptive, iterative nature of a neural network analysis may provide a more accurate model of the relationship among stage at diagnosis, anticancer treatment, adjuvant treatment, and mental and physical functioning in this population.

TREATMENT

Treatment for cancer varies based on prognostic factors such as familial history of cancer and stage at diagnosis, as well as patient preference (81-84). General primary treatment options include no intervention, surgery, radiation, and/or chemotherapy (101). Adjuvant therapy refers to treatment which is given in addition to primary treatment and designed to lessen the probability of disease recurrence or metastases. Adjuvant treatment can include hormonal therapies, chemotherapy, radiation, or other treatments.

Treatment for breast cancer includes surgical treatment such as breast conserving surgery (lumpectomy) or mastectomy, radiation therapy, or chemotherapy (81). Because

Stage 0 breast cancer (CIS) is non-invasive, the nature of treatment for this stage is generally conservative compared to treatment of other stages of breast cancer. Typical treatments for CIS consist of various surgical approaches such as excision of the affected duct(s), breast conserving surgery or lumpectomy which describes a wider local excision area, or mastectomy (11). Although generally considered non-lethal with a low mortality rate, treatment of CIS is important because CIS is the precursor to potentially invasive, lethal forms of breast cancer (4; 64). Adjuvant hormonal therapies are also recommended in the treatment of breast cancer (81). Tamoxifen is the gold standard adjuvant therapy for premenopausal women with hormone-receptor (HR) positive, early stage breast cancer; whereas aromatase inhibitors are indicated for post-menopausal women with HR-positive, early stage breast cancer (80; 94). Of women diagnosed with early stage breast cancer (stage I and II), 57% are treated with breast conserving surgery, 36% undergo mastectomy, and 1% receive no intervention (101). Most women with an early stage diagnosis who undergo breast conserving surgery also receive adjuvant therapy with almost 50% treated with adjuvant radiation and 33% receiving radiation plus chemotherapy (101). Among women with late stage breast cancer (stage III and IV), 13% undergo breast conserving surgery, 60% are treated with mastectomy, 18% have no surgery, and 7% receive no intervention (101). The majority of women with a late stage breast cancer diagnosis who have received surgery are also treated with chemotherapy in addition to other, unspecified therapies (101).

Anticancer treatment and adjuvant therapy have shown an association with factors that are significant predictors of mental and physical functioning in breast cancer survivors such as memory and thinking problems, cancer-related distress, fatigue,

changes in appetite/diet, lymphedema, pain, and sexual problems (6). Linear regression models have also demonstrated a statistically significant correlation between anticancer treatment received and physical functioning (16; 24; 33). However, a linear regression model which revealed treatment to be a significant predictor accounted for only 46% of the variance in the physical function measure (16). The adaptive, iterative nature of a neural network model designed to identify complex, nonlinear relationships may provide a better understanding of how treatment received impacts breast cancer survivors' mental and physical health status.

HEALTH STATUS

Health status may generally be defined by two categories, mental and physical function. A recent population-based study of breast, prostate, and colorectal cancer survivors > 1 year post-diagnosis demonstrated that cancer survivors endorsed worse general health ($p < 0.001$) and greater activity limitations ($p < 0.004$) than matched controls (68). A systematic review of post-treatment breast, prostate, colorectal, and gynecological cancer survivors by Harrington and colleagues (54) reported that the most common physical and psychological symptoms endorsed were depressive symptoms, anxiety, pain, and fatigue; however, sleep problems, sexual difficulties, and cognitive limitations were also reported.

Linear regression studies examining mental and physical post-treatment functioning in breast cancer survivors accounted for 36-41% of the variance in mental function and 38-46% of the variance in physical function (16; 17). These findings suggest that a significant proportion of the variance in these factors remains unknown and may be related to limitations in linear regression modeling. Specifically, linear

regression approaches are bounded (i.e., not iterative or adaptive) and less able to model complex, nonlinear relationships. Neural network models offer a statistical approach that is adaptive to the inputs in the model and able to evaluate complex, nonlinear relationships (48) such as those that may exist among the demographic, medical, and clinical variables in this study and mental and physical functioning in breast cancer survivors.

Mental Function

Although many cancer survivor populations endorse problems with mental functioning, breast cancer survivors report worse general mental functioning than prostate and colorectal cancer survivors (42; 122). Breast cancer survivors report difficulties with psychological problems such as depressive symptoms, anxiety, and cognitive problems (54). Depressive symptoms have been endorsed by 30% of breast cancer survivors immediately following treatment (40) and at rates of 21 - 48% up to 6 months post-treatment (20; 35; 37; 40). Breast cancer survivors up to 6 months post-treatment reported anxiety at rates of 45 - 48% (20; 35) and cognitive problems at rates of 31 - 61% (31; 100; 106; 119). A prospective study of health outcomes in post-treatment breast cancer survivors using multiple linear regression reported the following factors were statistically significant predictors ($p < .05$) of mental function immediately following treatment: age at baseline short temper, tendency to take naps, difficulty concentrating, early awakening, and forgetfulness (47).

Physical Function

Physical problems reported by breast cancer survivors at post-treatment include pain and/or functional limitations (e.g., lymphedema), fatigue, sleep disturbance, and

sexual dysfunction (54). Pain and functional limitations have been reported by 12-79% of breast cancer survivors studied within the first 6 months post-treatment and these symptoms are associated with type of treatment received (3; 34; 36; 65). Symptoms of fatigue were endorsed at the end of treatment (67) through 6-months post-treatment for 17-28% of breast cancer survivors (9; 62). Difficulties with sleep were endorsed immediately following treatment to 8 weeks post-treatment by 35-54% of breast cancer survivors (34) and by 14% of breast cancer survivors at 3-6 months following adjuvant treatment (76). Sexual dysfunction (e.g., vaginal dryness, pain, or decreased desire) also has been reported by 21-63% of breast cancer survivors studied within the first 6 months following primary and/or adjuvant treatment (34; 76). One prospective study of physical functioning in post-treatment breast cancer survivors reported that adjuvant chemotherapy had a greater association with poor physical outcomes (e.g., musculoskeletal pain, vaginal problems, difficulties with weight, and nausea) than did primary treatment modalities (46). Another prospective study using multiple linear regression to evaluate health outcomes in breast cancer survivors immediately post-treatment reported that the following symptoms were statistically significant predictors ($p < .05$) of physical functioning: lumpectomy only, lumpectomy plus chemotherapy, age at baseline, breast sensitivity, aches and pains, muscle stiffness, numbness and tingling, and unhappiness with appearance (47).

Studies evaluating post-treatment breast cancer survivors have used linear regression models to predict post-treatment health status (8; 16; 17; 33; 103). These studies have revealed important demographic, medical, and clinical predictors of mental and physical function, but account for less than half the variance in these measures (16;

17) suggesting that there may be more complex relationships among these variables that are not captured by traditional linear statistical modeling. Neural network statistical approaches are adaptive to the variables included in the model and better able to identify nonlinear relationships (48). As a result, neural network analysis may provide a more accurate model in predicting post-treatment mental and physical functioning as compared to linear regression models. The information that follows provides an overview of these two statistical approaches.

PREDICTIVE STATISTICAL MODELS

The current study aimed to evaluate whether one statistical model demonstrated a better model fit, showed greater predictive accuracy, and accounted for a greater contribution of the independent variables over the other statistical model with regard to predicting mental function and physical function in post-treatment breast cancer survivors. Although linear regression is considered a traditional statistical approach, it was hypothesized that the neural network model would outperform the regression model on these three outcomes. A brief overview of these two statistical methods is provided in the following sections.

Linear Regression

Linear regression is a traditional statistical model that is widely used to predict an outcome based on a set of predictor (independent) variables (41). Unlike logistic regression which statistically predicts the probability of a case falling within a certain category (dichotomous dependent variable), linear regression techniques calculate the statistically predicted value of a continuous outcome variable (41). Regression models belong to the family of correlational techniques; however, regression uses a more

sophisticated statistical approach to determine the interrelationships among independent and dependent variables than do correlational techniques (90). Once the data points of the independent and dependent variables are known, the data points can be graphed. The independent variable data points can be plotted on a horizontal *X*-axis and the dependent variable data points can be plotted on a vertical *Y*-axis. A regression line can then be drawn through the plotted data points to represent the line of best fit from which to make predictions about the values of the dependent variable given the values of the independent variable (41). In this regard, the dependent variable is expressed as a linear function of the independent variable (41). The deviation of a specific data point from the regression line is referred to as the error or residual value in the model (114). Smaller deviations of these data points from the predictive regression line produce an overall model with smaller variability and greater predictive accuracy (114). Rather than graphing these data points, a basic formula can also be calculated to determine the regression line. The basic regression formula is expressed as follows:

$$\hat{Y} = a + bx$$

where $\hat{Y}$ is the predicted level of the dependent variable, a represents the regression constant (or intercept or the value of $\hat{Y}$ when $x = 0$), b is the slope of the regression line (amount of difference in $\hat{Y}$ for a one-unit change in x), and x represents the value of the independent variable (41).

Multiple linear regression is an extension of the basic formula above applied to multiple independent variables in predicting a continuous dependent variable. The formula for multiple regression is expressed as follows:

$$\hat{Y} = a + b_i(x_i) + \varepsilon_i,\ i = 1, 2, 3, 4, \ldots, m$$

where $\hat{Y}$ is the predicted level of the dependent variable, a represents the regression constant (or intercept or the value of $\hat{Y}$ when $x = 0$), b_i is the regression coefficient representing the unique contributions of each independent variable to the dependent variable, x_i represents the value of the independent variable, ε_i is the error (or residual) in the model, and m represents the number of independent variables (114). As with basic linear regression, the dependent variable in a multiple linear regression is expressed as a linear function of the independent variables and smaller deviations from the predictive regression line in a multiple linear regression model represent less variability and greater predictive accuracy of the model. See Figure 1 for a conceptual diagram of a multiple linear regression model.

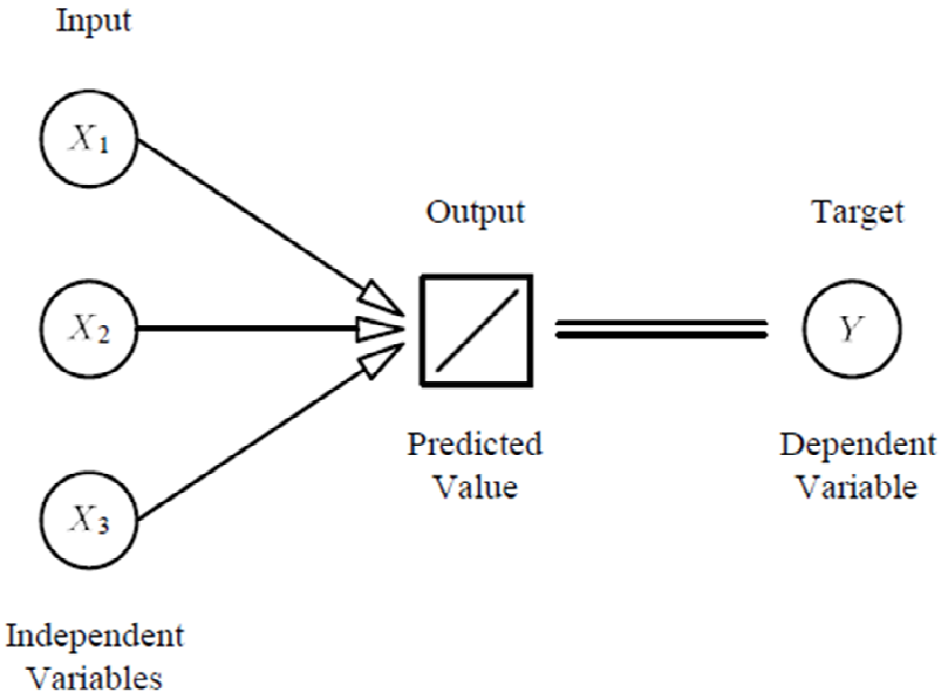

Figure 1. Model of Multiple Linear Regression.
From Sarle (1994).

Neural Network Analysis

Neural network analysis was developed and modeled based on the connectivity and functions of neurons in the brain (48). This statistical analysis uses an adaptive, iterative approach that learns the characteristics of the variables in the model to reduce overall error and increase the predictive accuracy of the model. Specifically, this analysis uses a model comprised of highly interconnected nodes which process information to determine predictions (10). A set of nodes (or neurons) is referred to as a layer and a basic neural network model consists of three layers: input, hidden, and output (48). See Figure 2 for a conceptual diagram of a neural network model. The input layer nodes are comprised of the predictor variables (or independent variables) and are responsible for sending information about the predictor variables (e.g., weights of the connections) to the hidden layer. Nodes (or neurons) in the hidden layer have a dual purpose. Hidden layer nodes first sum the weights of the inputs from the input layer (predictor variables). Next, a specific function algorithm, referred to as the *activation function* or *activation rule*, is applied to these summed values (48). Applying this activation function is also known as *squashing* the inputs. There are many types of activation functions which may be used in a neural network model, but the most common algorithm used is the sigmoid function (a bounded function that ranges from 0 to 1) (48). Once the input values have been squashed, these weights are summed again and sent to the output layer. The output layer nodes represent the predicted values of the outcome of interest (e.g., physical functioning, mental functioning) (97) given the weighted inputs provided from the hidden layer. The model then compares these predicted values to the target values (also referred to as the dependent variables), which are known values, to determine the accuracy of the

predictions (97). The difference between the predicted values and the known values represents the *error* in the neural network model (48).

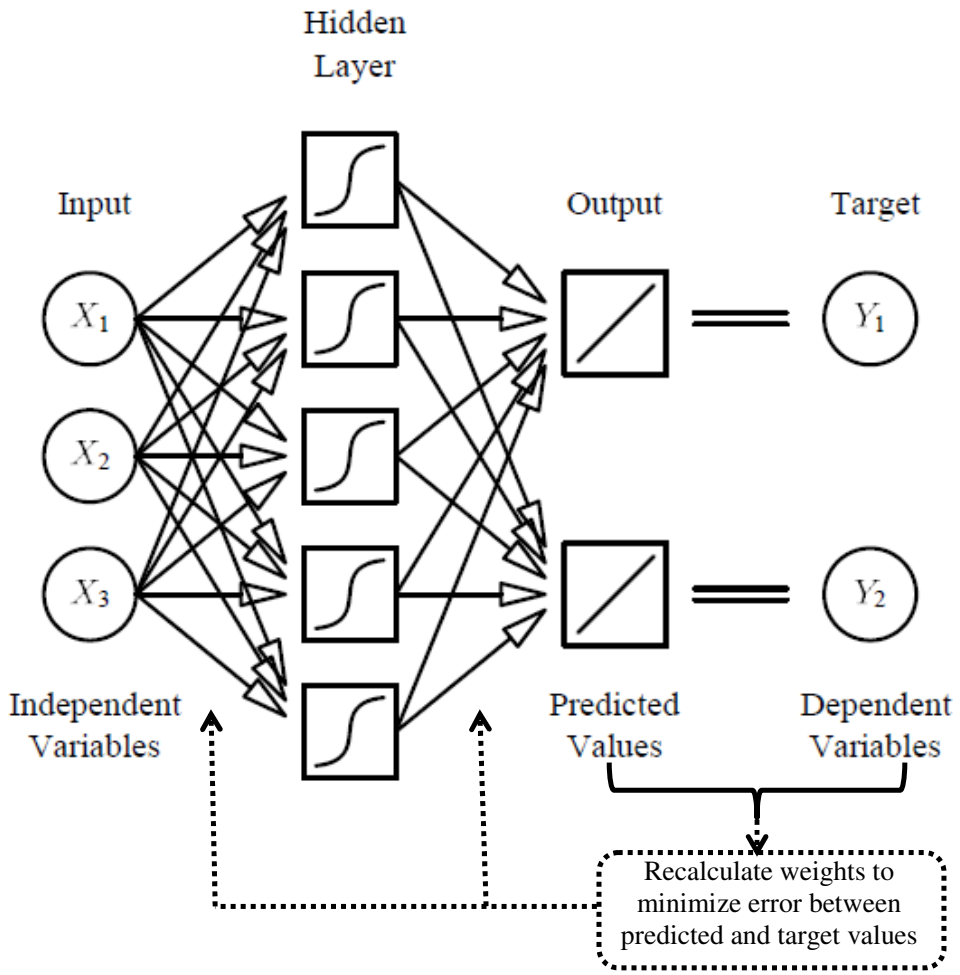

Figure 2. Model of Neural Network.
Adapted from Sarle (1994).

There are many types of neural network models, but the most commonly used model is *backpropagation* (115). Initially, the backpropagation procedure randomly assigns small weights to the nodes in the input layer (i.e., the layer containing the independent variables). A feedforward network is then applied to these random weights such that they are sent forward (or provided) to the hidden layer to be summed and squashed, and then these values are fed in (or provided) to the output layer to where the output predictions can be compared to the target (dependent) variables to determine the error in the model (48). Ultimately, the difference between the predicted output layer and the actual target values (i.e., dependent variables) are then computed as errors that are back propagated through the model to adjust the initial weights of the connections between the layers with the aim of reducing the overall error in the model (48). These errors are determined by the sum-of-squares errors calculation. Multiple iterations of this back propagation method occur until the error between the predicted output values and the actual target values (i.e., dependent variables) is minimized to achieve the smallest amount of error in the model. As a result, a back propagation neural network model uses an iterative learning process to evaluate the data, minimize error, and make predictions.

In a comparative review, Tu (115) outlined several advantages of neural network analysis over logistic regression. Although logistic regression uses a sigmoid curve (rather than a straight line) to represent the strength of the relationship between independent and dichotomous dependent variables (41), many of the arguments articulated by Tu are still applicable to a comparison of neural network models and linear regression models. Because neural networks require less formal statistical knowledge than linear regression, they may be easier to understand from a conceptual standpoint.

Neural networks also are capable of implicit detection of complex non-linear relationships among variables in the model and able to determine interactions automatically. Additionally, neural networks are adaptable to various and multiple training algorithms (i.e., activation functions), whereas linear regression models are limited to one linear regression equation. Perhaps the most pronounced benefit of neural network analysis, specifically the backpropagation method, is that it is adaptive. Neural networks have the ability to minimize the error variance in the model by using an iterative training process. This method increases the accuracy of the final model and cannot be duplicated in linear regression. However, one drawback to this approach is that multiple iterations may be prone to overfitting the model to the specific dataset which can reduce the generalizability of the results (115). Stopping rules may be applied (either manually or automatically) to minimize the potential for overfitting (60). Early stopping is a technique in which the researcher stops the network early using an *ad hoc* determination point; however, research suggests that early stopping may result in a less accurate final model (91). As a result, other stopping rules may be used such as setting a maximum training time for the model or setting the model to train toward a specified convergence so that training iterations stop once there is little added accuracy from the training (60). The stopping rule used can be determined in advance by the researcher, or may be determined by the software package used. In the case of the SPSS Neural Network program, if the stopping rule is automatically determined by the software, then data must go through one complete round of analysis by the model before stopping rules are applied in a hierarchical fashion: maximum steps without a decrease in model error,

maximum training time, maximum training epochs (data passes), minimum relative change in training error, and minimum relative change in training error ratio (60).

The many benefits of neural network models suggest they may be able to improve on the predictive performance of linear regression models. Specifically, the study rationale that follows underscores why the neural network analysis is likely to outperform linear regression modeling in predicting breast cancer survivors' post-treatment mental and physical function.

STUDY RATIONALE

Studies of cancer survivors which have used measures of mental and physical functioning as outcome measures (such as the Mental Component Summary (MCS) and the Physical Component Summary (PCS) derived from the SF-36) have examined the contribution of a wide variety of factors in statistically predicting mental and physical functioning (Appendix 1). With regard to mental functioning, factors in these studies that demonstrated a statistically significant association included: age, race, partner status, income, occupation, comorbidity/number of chronic conditions, cognitive status, social/emotional status, fear of recurrence, fatigue, insomnia, and changes in emotional support. In these studies, physical functioning showed a statistically significant relationship with factors such as: age, race, employment, income, occupation, children younger than 18 living in the home, stage at diagnosis, time since diagnosis, treatment received, menopausal status, comorbidity/number of chronic conditions, dizziness, urinary incontinence, social/emotional status, caregiving/financial status, exercise and diet, fear of recurrence, fatigue, and current lymphedema. These studies typically used linear statistical approaches. However, there is little consistency across studies regarding

the contribution of these factors or which factors are most important to predict the mental and physical functioning of cancer survivors. Studies using linear regression report that the variance accounted for in the SF-36 component summary scores by linear statistical models ranges from 36 - 41% of the variance in mental functioning and 38 - 46% of the variance in physical functioning (16; 17). These ranges suggest that contributing factors for about half of the variance in mental and physical function remain unknown. These findings may be explained in part by the linear nature of the models. Specifically, the diverse findings represented in Appendix 1 suggest that the relationships among these factors may be more complex than those relationships that can be obtained through traditional linear approaches. This complexity suggests that these variables may in fact be non-linearly associated and, therefore, unable to be fully accounted for a by a linear statistical model. **A non-linear model may allow for a more complete description of the complex associations among the independent variables and the outcomes of interest.** Moreover, a non-linear model that learns and adapts to the factors used to construct the model has the capacity to be more sensitive by reducing overall error in the model and increasing predictive accuracy.

Although linear approaches allow the specification of interaction terms to detect interrelationships among independent variables, such interaction terms become difficult to interpret when they include more than two variables. When linear approaches are used with factors that truly have non-linear relationships, the linear model will underestimate the true relationships between the predictor and outcome variables, increasing the potential for Type II error (87). Additionally, when a large number of predictor variables are included in a linear model, a common practice when studying more complex health

outcomes and typically seen with multivariate regression, this approach can increase the likelihood of a Type I error (87).

Linear regression is a commonly used approach in statistical prediction models. Linear regression models are useful and easy to interpret; however, they demonstrate several disadvantages when compared to neural network analysis. Linearity between the predictor and outcome variables is assumed with this approach because a linear function is used to determine each independent variable's unique contribution to the outcome measure. However, the inflexibility of a linear approach diminishes a linear model's ability to accurately predict complex interrelationships among variables, making this approach unsuitable if the relationship between the predictor and outcome variables is not truly linear. **Additionally, unlike neural network models, linear regression is not adaptive.** Error is defined as the difference between the value predicted by the model and the true outcome value. However, linear regression does not adjust the original input variable weights after identifying the amount of error in the model. As such, there may be a more useful statistical approach (other than a linear regression model) to determine the associations among demographic, clinical, and medical variables and mental and physical functioning. A predictive model that learns, or adapts, to the characteristics of the variables used to build the model might be more adept at reducing the overall error in the model and increasing the predictive accuracy. Such a model may be more sensitive, providing a more accurate picture of the relationship among predictive factors and the outcome of interest, and possibly improving the ability to identify specific areas for intervention. Neural network analysis is one type of an adaptive, learning model.

Neural network models are non-linear, adaptive statistical approaches to understanding complex relationships among variables. Such models may be especially useful in this application given that less than half of the variance in mental and physical functioning is explained by linear regression models (16; 17). The predictive plane for a neural network can range on a continuum of non-linearity from slightly to highly non-linear. The hidden layer of the neural network includes hidden nodes, each with an estimation algorithm (typically, sigmoid curves). Multiple hidden nodes in the hidden layer of the model indicate multiple estimation algorithms (e.g., sigmoid curves). The use of multiple sigmoid curves in a neural network produces a non-linear function which, unlike linear regression, creates a non-linear predictive line that can assume varying lengths and degrees of rotation. This non-linear prediction line can account for non-linear relationships and multiple combinations of variables, thus reducing error and producing a more accurate predictive model. More hidden nodes in the network equate to more non-linear estimation algorithms (e.g., sigmoid curves), which in turn increases the non-linearity of the predictive estimation line. A conceptual comparison of the linear predictive line of linear regression and the non-linear predictive line of a neural network is presented in Figure 3. This conceptual comparison demonstrates the potential of a non-linear model to reduce overall predictive error by providing flexibility in the predictive line.

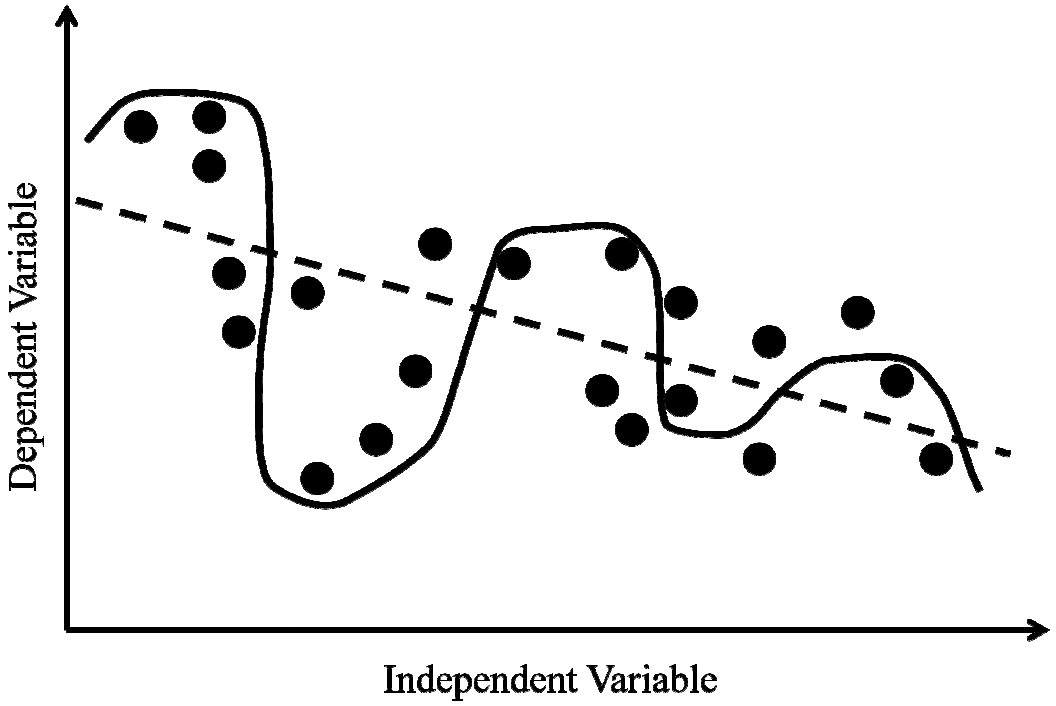

Figure 3. Comparison of Linear and Non-linear Predictive Lines.
The dashed line indicates the linear predictive line of a multiple linear regression. The solid line represents the non-linear predictive line of a neural network model for the same data points.

Neural networks are also adaptive to the inputs from the model. For example, back propagation neural networks are able to self-analyze their performance with regard to the amount of error in the model's prediction and then adjust that prediction to minimize model error. If error between the predicted classification and the actual classification is identified, then the neural network feeds this information back through the model to adjust the original input weights of the predictor variables. Once the weights are adjusted, the neural network runs the model again and assesses for error. This process repeats until the error in the model is satisfactorily minimized (i.e., as long as decreases in error are evident). In this manner, the neural network adapts to the information it is provided, suggesting a more accurate statistical approach than standard linear regression can offer.

Despite the benefits of neural network analysis, few researchers examining cancer survivorship have used a neural network approach, with the exception of those researchers studying diagnostic tests for cancer or mortality from cancer. In fact, a literature search revealed only one study of cancer survivors which used a neural network model to evaluate post-surgical function and quality of life in breast cancer survivors (114). In this study, the authors compared the performance of two neural network models to that of a multiple linear regression model in predicting mental and physical functioning following breast cancer surgery. The neural network models generally demonstrated smaller mean square errors and greater predictive accuracy than the regression model.

The current study aimed to examine the differential predictive utility of each of these models (linear regression and neural network analysis) with regard to health status in a post-treatment sample of breast cancer survivors using demographic, medical, and

clinical predictor variables. Because the relationships among these predictor variables and health status outcomes appear to be highly complex and likely non-linear, a non-linear, adaptive statistical approach is warranted. A highly accurate non-linear statistical model, such as neural network analysis, has the potential to clarify these relationships and broaden knowledge of post-treatment mental and physical functioning by reducing predictive error or identifying different relationships among variables.

CHAPTER 2: Specific Aims and Hypotheses

This section presents the specific aims and hypotheses associated with the present study.

SPECIFIC AIM 1

To determine which statistical model would produce the **best model fit** (as defined by the model with the smallest mean square error [MSE]) in statistically predicting mental and physical functioning in breast cancer survivors.

Hypothesis 1.1: It was hypothesized that a neural network model would demonstrate a lower MSE than linear regression in statistically predicting **mental functioning** in breast cancer survivors.

Hypothesis 1.2: It was hypothesized that a neural network model would demonstrate a lower MSE than linear regression in statistically predicting **physical functioning** in breast cancer survivors.

Rationale for Hypotheses 1.1 and 1.2: Unlike the linear predictive line of a linear regression, the non-linear predictive line produced by a neural network allows the statistical model to more closely predict the values of the target (dependent) variables (see Figure 3). This non-linear predictive line becomes especially useful when dealing with complex interrelationships among variables (115). Furthermore, a neural network is adaptive because it undergoes a repetitive, iterative learning process designed to teach the model about patterns in the data and decrease the overall error in the model (48; 115). Decreased error in the neural network predictions improves the overall fit of the model. Linear regression is limited in this regard because it does not use an iterative process to improve model performance.

SPECIFIC AIM 2

To determine which statistical model would demonstrate greater statistically **predictive accuracy** (as defined by the model with the smallest mean absolute percentage error [MAPE]) in statistically predicting mental and physical functioning in breast cancer survivors.

Hypothesis 2.1: It was hypothesized that a neural network model would demonstrate a lower MAPE than linear regression in statistically predicting **mental functioning** in breast cancer survivors.

Hypothesis 2.2: It was hypothesized that a neural network model would demonstrate a lower MAPE than linear regression in statistically predicting **physical functioning** in breast cancer survivors.

Rationale for Hypotheses 2.1 and 2.2: Unlike the linear predictive line of a linear regression, the non-linear predictive line produced by a neural network allows the statistical model to more closely predict the values of the target (dependent) variables (see Figure 3). This non-linear predictive line becomes especially useful when dealing with complex interrelationships among variables (115). Furthermore, a neural network is adaptive because it undergoes a repetitive, iterative learning process designed to teach the model about patterns in the data and decrease the overall error in the model (48; 115). Decreased error in the neural network predictions improves the overall fit of the model. Linear regression is limited in this regard because it does not use an iterative process to improve model performance.

SPECIFIC AIM 3

To determine which statistical model would account for the greatest **independent variable sensitivity** (as determined by global sensitivity analysis) in statistically predicting mental and physical functioning in breast cancer survivors.

Hypothesis 3.1: It was hypothesized that the full set of independent variables (Table 1) in the neural network model would account for a greater global sensitivity ratio than the same set of independent variables (Table 1) in the linear regression model with regard to **mental functioning** in breast cancer survivors.

Hypothesis 3.2: It was hypothesized that the full set of independent variables (Table 1) in the neural network model would account for a greater global sensitivity ratio than the same set of independent variables (Table 1) in the linear regression model with regard to **physical functioning** in breast cancer survivors.

Rationale for Hypotheses 3.1 and 3.2: Studies using linear statistical models to predict mental and physical function cancer survivors report that these linear models account for less than half the variance in each of these measures (16; 17; 113). These ranges suggest contributing factors for over half of the variance in these measures remains unknown. However, these findings may be explained in part by the linear nature of the models which may not be able to account for the complex relationships among the variables studied. Additionally, when linear approaches are used with factors that truly have non-linear relationships, the linear model will underestimate the true relationships between the predictor and outcome variables (87). A non-linear model, such as a neural network, may allow for a more complete description of the associations among the independent variables and the outcomes of interest.

Table 1. List of Independent Variables

Demographic	**Medical**	**Clinical (CSPro Domains)**
Age	Stage at Diagnosis	Symptom Burden
Race	Time since Diagnosis	Function
Education	Treatment Received	Health Behavior
Partner Status	Adjuvant Treatment	Health Service Needs
Employment	Time since Treatment	
Income	Menopausal Status	

CHAPTER 3: Method

PARTICIPANTS

The present study was conducted using data from a validation study of the CSPro which consisted of 400 female breast cancer survivors (112). The study conducted by Todd and colleagues (112) was designed to establish the reliability and validity of the retained items in the final CSPro measure. Inclusion criteria for all participants in the original study included breast cancer survivors who self-reported female gender, were diagnosed with breast cancer stages I-III, had completed primary anticancer treatment no more than five years prior to the study, had no history of previous cancer or current second cancer, were aged 21 or older, and had access to the Internet.

Cancer survivors with a history of a previous or current second cancer were excluded from the study because survivors with a history of multiple cancers report poorer general health and psychosocial outcomes than cancer survivors with a history of a single primary cancer (110). Cancer survivors with a stage 0 diagnosis were excluded from the proposed study because these individuals tend to undergo less invasive treatments and therefore may have a different symptom burden than those survivors diagnosed with stage I-III cancers. Similarly, survivors with a stage IV diagnosis or metastatic cancer diagnosis were excluded from the study because their treatment regimen is typically more invasive and intense than that of cancer survivors with a stage I-III diagnosis (101) and such intense treatment may be associated with different survivorship outcomes.

RECRUITMENT

The original study (112) recruited participants through advertisements and leaflets disseminated to comprehensive cancer care centers, primary care clinics, support groups, hospital

bulletin boards, newspapers, and websites across the United States. Online surveys were used to collect data from participants. After answering web-based screening materials, eligible participants were then directed to a main website to provide informed consent and the study measures using an Internet-based platform.

MEASURES

Findings from cancer survivor research (15; 54) as well as experience with previous cancer survivorship studies (19; 22; 53; 112) informed the selection of the following measures from the original CSPro validation study for analysis in the current study (112).

Demographic and Medical Measures

Participants completed questions regarding demographic and medical information using questions that our research group has used in three independent Internet surveys (19; 21; 53). Questions are listed in Appendix 2. Demographics consisted of age, race, education, partner status, occupational status, and socioeconomic status. Medical questions included stage of tumor at diagnosis, time since diagnosis, treatment received (i.e., surgery, radiation, chemotherapy), adjuvant therapies received, time since completion of primary treatment, and menopausal status.

Cancer Survivor Profile (CSPro)

Participants also completed the Cancer Survivor Profile (CSPro) (Appendix 3). The CSPro is a screening measure of problems experienced by cancer survivors (112) which provides a profile of patient-reported problems. The CSPro was originally developed using a female breast cancer survivor population diagnosed with stages I-III, who had completed primary anticancer treatment no more than five years prior to the study, had no history of previous cancer or current second cancer, and were aged 21 or older. The profile is a 107-item questionnaire

designed to be administered in a clinical setting with the goal of measuring problems in four specific domains: symptom burden (anxiety, fear of recurrence, body image, pain, fatigue, depression), function (social support, work, sleep, cognitive function, sexual function), health behaviors (physical activity/exercise, diet), and health service needs (health competence, patient-provider communication, economic barriers, health information). CSPro scores are provided as standardized t-scores which have a mean of 50 and a standard deviation of 10. Confidence intervals (95%) for each score also are provided.

The psychometric properties of the CSPro have been evaluated by a principal component analysis (a type of factor analysis) to provide factor loadings for the items within the four CSPro domains. Factor loadings indicate how well a particular item in a measure correlates with the construct on which the item loads (90). Factor loadings are generally considered weak if less than .4, moderate if .4 to .6, and strong if above .6 (49). Preliminary psychometric data for the CSPro items show good factor validity. Six constructs of the symptom burden domain have item factor loadings ranging from .51 to .92. The function domain consists of five constructs with item factor loadings in the range of .62 to .94. The two constructs on the health behaviors domain had item factor loadings ranging from .58 to .82. The health service needs domain is comprised of four constructs with item factor loadings ranging from .70 to .92. Three of the original constructs (alcohol consumption, cigarette smoking, and fertility distress) could not be included in the preliminary factor analysis because these constructs were not applicable to all respondents.

Outcome Measures

The following outcome measures were administered to all participants to yield two separate indices of mental functioning and physical functioning.

Center for Epidemiological Studies - Depression Scale (CES-D)

The Center for Epidemiological Studies - Depression Scale (CES-D) (Appendix 4) was selected as the dependent variable measuring mental functioning in this study. The CES-D is a 20-item self-report measure of affective depressive symptoms (93). The CES-D was selected as an outcome measure in this study because it is considered a gold-standard measure of depression in research, has been validated in cancer populations, and demonstrates acceptable psychometric properties (117). The CES-D has also been used extensively with cancer survivor populations (40; 57; 113). Similar to studies accounting for less than half the variance in mental functioning as measured by the Short Form-36 (SF-36) (16; 17), linear statistical modeling in a study of health and well-being in female cancer survivors accounted for 48% of the variance in the Center for Epidemiological Studies - Depression Scale (CES-D) when using various health and demographic variables as predictors (113).

Behavioral Risk Factor Surveillance System (BRFSS) - Physical Activity

The Behavioral Risk Factor Surveillance System (BRFSS) - Physical Activity scale (Appendix 5) was chosen as the dependent variable measuring physical functioning in this study. The BRFSS consists of seven items inquiring about participant physical activity over the last month (27). This scale yields a metric of physical activity that can be converted into a metabolic equivalent of task (MET) which is a standardized measure of energy expenditure (26). The BRFSS was chosen as an outcome measure in this study because it has been used with cancer survivor populations (69; 85) and demonstrates acceptable reliability and validity (86; 123).

Regarding physical function as measured by the Behavioral Risk Factor Surveillance System (BRFSS) - Physical Activity, the percentage accounted for by linear regression models is not clear; however, logistic regression models demonstrate an association between certain predictor variables and physical activity (as measured by the BRFSS) in cancer survivors (69). Furthermore, the paucity of research examining the variance in the BRFSS under various predictive statistical models suggests an additional need for the present study.

ANALYTIC PLAN

Descriptive analyses were conducted to evaluate the characteristics of the data gathered. Categorical variables were analyzed for response frequencies and any missing data. Continuous variables were evaluated for summary statistics (i.e., mean, median, and standard deviation), data distribution, and missing data.

All measures were evaluated for response frequencies and patterns of missing data. To determine the pattern of missing data, independent *t*-tests were computed for all continuous variables and chi-square analyses were conducted on all categorical variables to compare any statistically significant differences between *complete records* and *incomplete records* (45).

Developing the Predictive Models

Following an approach used by Comrie (32), the analysis in the present study called for keeping both the linear regression and neural network models as simple as possible to facilitate comparison of the results. While both models can be adapted to develop quite sophisticated predictive architectures, more complexity in the models increases the model differences thereby reducing the interpretability of the comparison. Constructing the models in their most basic, straightforward architecture allows for a more direct comparison and suggests that any

differences observed likely resulted from the basic predictive model, rather than specific adjustments to each architecture.

Using SPSS 20, two statistical models (linear regression and neural network) were constructed for comparison to predict depression ratings, as measured by the CES-D, and physical activity ratings, as measured by the BRFSS. The independent variables in both models were identical. Demographic independent variables were age, race, education, relationship status (partnered), employment, and income. Medical independent variables included tumor stage at diagnosis, number of years post-diagnosis, primary anticancer treatment type, adjuvant treatment, number of years post treatment, and menopausal status. The following domains of the CSPro represented clinical independent variables: symptom burden, function, health behavior, and health service.

Linear Regression Models

Standard linear regression was conducted for each outcome variable (depression and physical activity) to determine the contribution of the independent variables in predicting each outcome variable in the study. Because linear regression treats each predictor variable as a covariate (i.e., the results show the unique contribution of each independent variable when the other independent variables are controlled), there is no need to identify separate covariate terms for this analysis.

To evaluate depressive symptoms, all independent variables were entered into the regression model simultaneously to determine each variable's unique contribution in predicting the CES-D scores. Higher CES-D scores indicate more depressive symptoms. Physical activity was also analyzed through a linear regression with each independent variable simultaneously entered into the model to determine the unique contribution in predicting the physical activity

scores of the BRFSS. In this case, higher scores on the BRFSS represent higher levels of physical activity.

Neural Network Models

A neural network model was also constructed using the same independent variables and dependent variables as those used in the linear regression model. The neural network model used was a multilayer perceptron architecture which is a back propagation model. The term *perceptron* was coined in the 1960s by Frank Rosenblatt and colleagues to describe a specific neural network architecture that used an iterative approach to learning and reducing predictive error by *feeding information forward* to the next layer in the model (77). This term is adapted from the word *perception* because the researchers who developed this approach believed it closely resembled how the brain processes sensory information (77). In a practical sense, *perceptron* describes the learning algorithm used to calculate and correct synaptic weights with the goal of reducing model error (48; 77). This specific architecture uses a feed forward network such that the effects of the input layer are sent forward (or fed) to the hidden layer, which are then sent forward (or fed) into the output layer (48). The hidden layer uses an algorithm to sum the weights of the inputs from the input layer (predictor variables) before sending this information to the output layer (48). As discussed above, the input layer consists of the independent (or predictor) variables and the output layer consists of the dependent (or outcome) variables. The differences between the predicted values of the dependent variables and the actual (or target) values of the dependent variables are then computed as errors that are back propagated through the model to adjust the weights of the connections between the layers in order to minimize overall model error (48).

The neural network model was constructed to include one hidden layer and set to automatically select the optimal number of nodes for the hidden layer using an estimation algorithm (60). See Table 2 for the specific settings used in the neural network model for this project. An activation function is the learning rule that sums the values of the inputs from the previous layer and applies an algorithm to these values before sending them to the next layer (48). In this model, the activation function for all nodes in the hidden layer was set to a sigmoid function (60). Use of a sigmoid function allows non-linearity to be introduced into the neural network model (48). For nodes in the output layer (prediction nodes), the identity activation function was applied. The identity function is appropriate for use with continuous dependent variables because it retains the scale of the variable for the prediction so that it is comparable to the actual values of the target variable (which is also continuous).

A batch training approach was used so that adjustment of the connection weights would be calculated after all cases were simultaneously entered into the model (60). Batch training updates the synaptic weights and calculates error in the model only after all the information in the dataset has been reviewed (gone through one complete pass) (60). Although a train-test approach was attempted with the model, this approach could not be successfully implemented because one or more cases in the testing sample contained variable values that did not occur in the training sample which would have excluded those cases from the final analysis (60). In order to implement supervised learning, a scaled conjugate gradient (SCG) was applied to determine the weights of the connections in the model. SCG uses a step-size, or scaled approach to estimate the initial weights of the connections between the layers (74). In this regard, SCG reduces the training time required because the initial weights assigned to the model by the SCG are designed to produce smaller gradients between the predicted values (output layer) and the

actual (or target) values of the dependent variable at the outset of training (74). To avoid overfitting the data, the program was set to automatically detect convergence of the model so that training iterations stopped once the model experienced no added accuracy from additional trainings (60). The relative change in training error criterion (0.0001) was achieved for each neural network models predicting the outcomes of interest.

Following the approach used to construct the linear regression models, the neural network analysis evaluated each outcome or dependent variable (depressive symptoms from the CES-D and physical activity ratings on the BRFSS) using the same independent variables applied in the linear regression analysis. These variables were entered into the input layer simultaneously (rather than using a stepwise approach). Therefore, depressive symptoms were predicted from the neural network model with all independent variables concurrently entered into the input layer of the model. A separate model was built to predict physical activity from the neural network model with all independent variables simultaneously entered into the model.

A specific number seed was set and recorded prior to running the neural network model so that results could be replicated. Additionally, the order of the cases and the order of the independent variables were kept constant (and identical to the order used in the linear regression model). These procedures are not required in linear regression models. However, the adaptive, iterative nature of a neural network model is highly sensitive to the initial weights assigned to the inputs and the ordering of cases and variables; therefore, to replicate study results exactly, it is essential to identify these elements at the outset.

Table 2. Settings used in the Neural Network Models

Rescaling Method for Covariates	None
Number of Hidden Layers	One
Number of Nodes in Hidden Layer	Automatically compute
Activation Function	Sigmoid
Output Layer Activation Function	Identity
Rescaling Method for Scale Dependents	None
Type of Training Method	Batch
Optimization Algorithm	Scaled Conjugate Gradient
Stopping Rules	Max steps without a decrease in error = 1
Minimum Relative Change in Training Error	0.0001
Minimum Relative Change in Training Error Ratio	0.001

Data Analysis for Specific Aims

Specific Aim 1: To determine which statistical model would produce the **best model fit** (as defined by the model with the smallest mean square error [MSE]) in statistically predicting mental and physical functioning in breast cancer survivors.

The goodness of fit for each statistical model (linear regression and neural network) in predicting each of the two outcome variables (mental functioning as measured by the CES-D and physical activity as measured by the BRFSS) were compared by calculating each model's MSE. MSE has been used in previous research as a goodness of fit measure in comparing models of linear regression and neural network analysis (99; 114). MSE is calculated by computing the difference of the predicted values from the model and the actual values of the dependent variable, and then averaging these differences across the all data (99; 114). The lower the model's MSE, the less error in the overall model, and the better the model fit. The formula for MSE is as follows (99):

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

where n represents the number of cases, Y_i indicates the actual (or target) value of the i^{th} observation, and $\widehat{Y}\imath$ represents the predicted value of the i^{th} observation provided by the model.

Specific Aim 2: To determine which statistical model would demonstrate greater statistically **predictive accuracy** (as defined by the model with the smallest mean absolute percentage error [MAPE]) in statistically predicting mental and physical functioning in breast cancer survivors.

The predictive accuracy for each statistical model (linear regression and neural network) in predicting each of the two outcome variables (mental functioning as measured by the CES-D and physical activity as measured by the BRFSS) were compared by calculating the MAPE for each model. MAPE has been used in previous research comparing linear regression and neural network modeling to compare the predictive accuracy of the models (99; 114). The MAPE provides an indication of the model's mean deviation from the actual (target) value of the dependent variable and is typically expressed as a percentage (99; 114). MAPE values of 10% or less indicate excellent predictive accuracy (99; 114). A MAPE of 10 - 20% indicates high predictive accuracy, 20 - 50% represents average accuracy, and higher than 50% indicates low predictive accuracy (99; 114). The formula for MAPE is as follows (99):

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|Y_i - \hat{Y}_i|}{Y_i} \times 100\%$$

where n represents the number of cases, Y_i indicates the actual (or target) value of the i^{th} observation, and $\widehat{Y}i$ represents the predicted value of the i^{th} observation provided by the model.

Specific Aim 3: To determine which statistical model accounts for the greatest **independent variable sensitivity** (as determined by global sensitivity analysis) in statistically predicting mental and physical functioning in breast cancer survivors.

In general, sensitivity analysis demonstrates the change in performance of a statistical model when a specific independent variable is omitted from the model (107). As such, sensitivity analysis highlights the relative importance of each independent variable to the performance of the overall model (14). Global sensitivity analysis was proposed for each model (linear regression and neural network) in the present study to determine the contribution of each independent variable to the accuracy of the model in statistically predicting each outcome variable (mental functioning as measured by the CES-D and physical activity as measured by the BRFSS). However, limitations of the neural network software program did not allow the contributions of the independent variables to be held constant with the values of these variables in the full neural network model. As a result, an accurate comparison could not be made among the MSE of the full neural network model and the MSE of the neural network model with a variable omitted and global sensitivity analysis could not be conducted as planned on the neural network model. Therefore, an alternative sensitivity analysis was conducted to compare the models and determine which independent variables were most important in model prediction (see Results section). Despite this alternative sensitivity analysis, the global sensitivity analysis was conducted on the linear regression model to identify any independent variables that should be removed from the final model (i.e., variables that degraded overall model performance); therefore, an overview of global sensitivity analysis follows.

The global sensitivity of an independent variable may be expressed as a ratio of the full model's error when a given independent variable is omitted to the model to the full model's error with all independent variables included (99; 114). For example, consider a full statistical model (with all independent variables included) that has a sum-of-squares error ($SSE_{\text{full model}}$) of .90. If one of the independent variables (X_1) is omitted from the model and the new SSE (i.e. $SSE_{X1\ \text{omitted}}$) is .50, then the accuracy of the full model is degraded by -.40 when the X_1 variable is omitted (suggesting that X_1 degrade the performance of the full model). Furthermore, the contribution of X_1 to the full model may be expressed as the ratio of the error in the model without X_1 (i.e., $SSE_{X1\ \text{omitted}}$, .50) to the error in the full model (i.e., $SSE_{\text{full model}}$, .90). A ratio of ≤ 1 indicates that the independent variable significantly degrades the performance of the model and should be removed from the model (99; 114). This ratio can be expressed as follows:

$$\frac{SSE_{Xi\ \text{omitted}}}{SSE_{\text{full model}}}$$

Although there is no statistical procedure to evaluate the impact of independent variable sensitivity in two different statistical models, the sensitivity ratios of each independent variable in the separate models can be compared with appropriate software. This comparison can be accomplished by the following analysis. First, the SSE of each full model ($SSE_{\text{full model}}$) is calculated. Next, each independent variable in the models are omitted one at a time (with replacement) and an SSE is calculated for each of the models without that specific independent variable (e.g., $SSE_{X1\ \text{omitted}}$, $SSE_{X2\ \text{omitted}}$, $SSE_{X3\ \text{omitted}, \ldots}$, $SSE_{Xn\ \text{omitted}}$). A sensitivity ratio can then be calculated for $SSE_{Xn\ \text{omitted}}$ and $SSE_{\text{full model}}$. For example, an SSE for each statistical model can be calculated with the first independent variable (e.g., age) omitted (referred to as $SSE_{\text{age omitted}}$). The sensitivity ratio of age can then be calculated for both the linear regression model and the neural network model in statistically predicting the outcome variables. The sensitivity

ratio of age for the linear regression model can be compared with the sensitivity ratio of age for the neural network model to determine whether the sensitivity ratios for age differ between the two statistical models in predicting mental and physical function. The age independent variable can then be replaced and the next independent variable (e.g., gender) can be omitted from both statistical models and evaluated for its effects on model sensitivity. Again, the sensitivity ratios for gender can be compared between the linear regression model and the neural network model. This process can be conducted for all independent variables in the models. As a follow-up analysis, independent variables with a global sensitivity ratio of ≤ 1 represent a variable that significantly degrades model performance and should be removed from the model from which this ratio was calculated (i.e., linear regression or neural network). Each of the models (i.e., linear regression and neural network) should then be conducted and compared again, excluding those independent variables identified by a low sensitivity ratio. Again, in the present study, global sensitivity analysis was only possible for the linear regression model because the neural network software used did not allow for the original weights of the independent variables to be held constant for comparison. An alternative sensitivity analysis was employed to allow for the comparison of the two models (see Results section).

Although linear regression approaches are commonly used predictive statistical models in cancer survivor research, comparing a linear regression model to a neural network model may reveal a more sensitive approach or different pattern of relationships for understanding which factors are related to mental and physical functioning in cancer survivors. The non-linear, adaptive nature of neural networks allow these models to learn the characteristics of the data and use an iterative approach to reduce the overall error in the model's predictions suggesting that

neural network analysis may be a more sensitive, accurate predictive model than linear regression.

CHAPTER 4: Results

DESCRIPTIVE ANALYSES

The original dataset consisted of 400 breast cancer survivors. Only those participants who had complete data on all variables evaluated in the current study were retained in this analysis. This approach resulted in 194 breast cancer survivor participants in the models predicting depression scores on the Center for Epidemiological Studies - Depression Scale (CES-D), and 192 breast cancer survivors in the models predicting physical activity scores on the Behavioral Risk Factor Surveillance System (BRFSS). Chi-square and independent sample t-test analyses demonstrated no significant differences for those participants retained in the present study as compared to those who were removed on any of the independent variables in the models (see Table 3). With regard to the dependent variables in the models, no significant differences were observed for retained versus removed participants on CES-D scores (t (362) = -.54, p = .59); however, the BRFSS scores were significantly different (χ^2 =15.80, df = 3, p = .00) for those participants who were retained as compared to those removed. Participant demographic, medical, and clinical characteristics for each dependent variable are presented in Table 4.

Bivariate correlations assessing direction and strength of relationships for each of the independent variables and dependent variables are presented in Table 5 for CES-D and Table 6 for BRFSS. Collinearity diagnostics were also conducted to evaluate any multicollinearity among the independent variables. Although some level of multicollinearity is to be expected between certain predictors, high levels of multicollinearity can artificially reduce the statistical significance of the affected predictor variables and increase the likelihood of a Type II error (89). In this preliminary analysis, variables were considered collinear if they demonstrated a variable inflation factor (VIF) greater than or equal to 10, or a tolerance value less than .10 (90). No

multicollinearity was identified for the independent variable relationships; therefore, all variables were retained in the initial analyses.

Following this preliminary analysis, the two predictive models (linear regression and neural network) were constructed for each dependent variable: CES-D and BRFSS. Models predicting the same dependent variable were compared on model fit, predictive accuracy, and independent variable sensitivity analysis.

Table 3. Significant Differences for Retained versus Removed Participants for each Dependent Variable

Characteristic	CES-D (N = 194)			BRFSS (N = 192)		
Demographic Characteristic						
Age	t = 1.84	df = 277	p = .07	t = 1.74	df = 277	p = .08
Race	χ^2 = .87	df = 4	p = .93	χ^2 = .41	df = 4	p = .98
Education	χ^2 = 10.16	df = 6	p = .12	χ^2 = 8.06	df = 6	p = .23
Partnered	χ^2 = .00	df = 1	p = 1.00	χ^2 = .30	df = 1	p = .59
Employment	χ^2 = 1.31	df = 3	p = .73	χ^2 = 1.14	df = 3	p = .77
Income	χ^2 = 2.73	df = 6	p = .84	χ^2 = 5.75	df = 6	p = .45
Medical Characteristic						
Tumor stage at diagnosis	χ^2 = 1.83	df = 2	p = .40	χ^2 = 1.54	df = 2	p = .46
Years since diagnosis	t = .08	df = 393	p = .93	t = .05	df = 393	p = .96
Primary anticancer treatment type	χ^2 = 1.95	df = 4	p = .74	χ^2 = 3.10	df = 4	p = .54
Adjuvant treatment received	χ^2 = .05	df = 1	p = .83	χ^2 = .00	df = 1	p = .96
Years since treatment	t = .97	df = 389	p = .34	t = .94	df = 389	p = .35
Menopausal status	χ^2 = 1.71	df = 2	p = .43	χ^2 = 2.69	df = 2	p = .26
Clinical Characteristic /CSPro Domain						
Symptom Burden	t = -1.08	df = 359	p = .28	t = -.89	df = 359	p = .38
Function	t = -.35	df = 358	p = .73	t = .13	df = 358	p = .90
Health Behavior	t = -1.0	df = 383	p = .31	t = -.36	df = 394	p = .72
Health Service	t = -.72	df = 365	p = .47	t = -.45	df = 365	p = .65

CES-D = Center for Epidemiological Studies – Depression Scale, BRFSS = Behavioral Risk Factor Surveillance System – Physical Activity, CSPro = Cancer Survivor Profile

Table 4. Participant Demographic, Medical, and CSPro Characteristics for each Dependent Variable

Characteristic	CES-D		BRFSS	
	N	%	N	%
Cancer History Breast cancer survivor	194	100%	192	100%
Demographic Characteristic				
Age	M = 50.62 (SD = 10.81)		M = 50.65 (SD = 10.69)	
Race				
Asian	4	2.1%	4	2.1%
Black or African American	12	6.2%	11	5.7%
Caucasian	172	88.7%	171	89.1%
Native American/Alaska Native	2	1.0%	2	1.0%
Other	4	2.1%	4	2.1%
Education				
High school	14	7.2%	14	7.3%
Some college	41	21.1%	40	20.8%
Associates degree	26	13.4%	25	13.0%
Bachelors degree	44	22.7%	42	21.9%
Some graduate school	16	8.2%	17	8.9%
Graduate degree	53	27.3%	54	28.1%
Partnered				
No	62	32.0%	64	33.3%
Yes	132	68.0%	128	66.7%
Employment				
Unemployed by choice	40	20.6%	38	19.8%
Unemployed not by choice	19	9.8%	21	10.9%
Working full-time	104	53.6%	105	54.7%
Working part-time	31	16.0%	28	14.6%
Income				
Less than $10,000	7	3.6%	8	4.2%
$10,000 - $19,000	6	3.1%	7	3.6%
$20,000 - $39,000	27	13.9%	24	12.5%
$40,000 - $59,000	37	19.1%	38	19.8%
$60,000 - $79,000	38	19.6%	36	18.8%
$80,000 - $99,000	26	13.4%	27	14.1%
$100,000 or more	53	27.3%	52	27.1%
Medical Characteristic				
Tumor stage at diagnosis				
Stage I	74	38.1%	73	38.0%
Stage II	73	37.6%	73	38.0%
Stage III	47	24.2%	46	24.0%
Years since diagnosis	M = 2.86 (SD = 1.96)		M = 2.86 (SD = 1.95)	

Primary anticancer treatment type				
Surgery only	19	9.8%	20	10.4%
Surgery + Chemotherapy	35	18.0%	36	18.8%
Surgery + Radiation	30	15.5%	27	14.1%
Chemotherapy + Radiation	1	0.5%	1	0.5%
Surgery, Chemotherapy, and Radiation	109	56.2%	108	56.3%
Adjuvant treatment received				
Yes	116	59.8%	114	59.4%
No	78	40.2%	78	40.6%
Years since treatment	M = 2.09 (SD = 1.49)		M = 2.09 (SD = 1.49)	
Menopausal status				
Premenopausal	46	23.7%	44	22.9%
Premenopausal before cancer /postmenopausal after treatment	78	40.2%	79	41.1%
Postmenopausal	70	36.1%	69	35.9%
Clinical Characteristic /CSPro Domain				
Symptom Burden	M = 79.96 (SD = 20.63)		M = 79.78 (SD = 20.71)	
Function	M = 49.84 (SD = 13.63)		M = 49.53 (SD = 13.60)	
Health Behavior	M = 9.11 (SD = 2.12)		M = 9.04 (SD = 2.10)	
Health Service	M = 48.53 (SD = 14.33)		M = 48.35 (SD = 14.34)	

CES-D = Center for Epidemiological Studies – Depression Scale, BRFSS = Behavioral Risk Factor Surveillance System – Physical Activity, M = mean, SD = standard deviation, CSPro = Cancer Survivor Profile

Table 5. Pearson correlations for variables in CES-D analysis

Pearson Correlation	CES-D†	Age	Race	Education	Partnered	Employment	Income	Stage	Years post-diagnosis	Treatment	Adjuvant	Years post-treatment	Menopausal status	CSPro-S‡	CSPro-F‡	CSPro-HB‡	CSPro-HS‡
CES-D†																	
Age	-.24																
Race	-.03	.06															
Education	-.18	.04	.01														
Partnered	-.18	-.07	.02	.03													
Employment	-.10	-.21	.18	.11	-.14												
Income	-.25	-.01	.18	.36	.34	.11											
Stage	.08	-.13	.04	-.04	-.02	.04	-.06										
Yrs post-dx	-.09	.19	.05	.01	-.06	.12	-.04	.12									
Treatment	.00	.02	-.06	.04	.07	-.08	-.01	.36	.04								
Adjuvant	.06	-.10	.00	-.07	-.11	-.01	-.18	-.03	-.11	-.07							
Yrs post-tx	-.10	.25	.05	-.03	-.06	.09	-.07	.00	.75	-.05	-.07						
Menopausal	-.14	.54	.10	-.11	-.06	-.17	-.06	-.09	-.08	.02	-.05	.02					
CSPro-S‡	.78	-.20	-.04	-.15	-.13	-.14	-.24	.10	-.04	.03	.08	-.10	-.10				
CSPro-F‡	.70	-.05	.02	-.24	-.09	-.10	-.23	.06	-.06	.00	.00	-.07	-.03	.79			
CSPro-HB‡	.26	-.13	.00	-.09	.04	-.08	-.05	.11	-.05	.05	-.01	-.05	-.06	.30	.27		
CSPro-HS‡	.50	-.18	-.07	-.16	-.10	.02	-.26	.21	-.07	.05	.01	-.15	-.07	.62	.61	.40	

†Higher scores on CES-D indicate more depressive symptoms. ‡Higher scores on the CSPro domains indicate more difficulties in this area (e.g., more symptoms, more difficulties functioning, poorer diet and exercise, and more difficulties getting health services needs met). CES-D = Center for Epidemiological Studies – Depression Scale, Yrs post-dx = years since diagnosis, Yrs post-tx = years since treatment, CSPro-S = Symptom Burden Domain, CSPro-F = Function Domain, CSPro-HB = Health Behavior Domain, CSPro-HS = Health Service Domain

Table 6. Pearson correlations for variables in BRFSS analysis

Pearson Correlation	BRFSS†	Age	Race	Education	Partnered	Employment	Income	Stage	Years post-diagnosis	Treatment	Adjuvant	Years post-treatment	Menopausal status	CSPro-S‡	CSPro-F‡	CSPro-HB‡	CSPro-HS‡
BRFSS†																	
Age	-.03																
Race	-.05	.06															
Education	.11	.04	.00														
Partnered	.03	-.08	.02	.03													
Employment	.06	-.20	.18	.12	-.10												
Income	.15	.00	.17	.36	.37	.15											
Stage	.02	-.12	.04	-.02	-.06	.03	-.10										
Yrs post-dx	.00	.18	.05	.03	-.08	.15	-.04	.14									
Treatment	.08	-.01	-.05	.05	.05	-.06	.00	.39	.06								
Adjuvant	-.04	-.12	.00	-.11	-.11	.02	-.20	-.03	-.08	-.07							
Yrs post-tx	-.03	.25	.06	-.01	-.08	.13	-.07	.02	.74	-.04	-.03						
Menopausal	-.03	.54	.09	-.08	-.04	-.16	-.04	-.13	-.10	-.02	-.06	.01					
CSPro-S‡	-.22	-.18	-.04	-.19	-.16	-.16	-.30	.09	-.03	.04	.05	-.08	-.09				
CSPro-F‡	-.19	-.04	.02	-.26	-.09	-.13	-.25	.06	-.05	.01	-.03	-.07	-.03	.79			
CSPro-HB‡	-.40	-.15	-.01	-.12	.01	-.05	-.08	.13	-.03	.01	-.04	-.02	-.06	.31	.27		
CSPro-HS‡	-.24	-.18	-.07	-.19	-.11	.02	-.30	.23	-.05	.05	-.03	-.13	-.08	.63	.62	.39	

†Higher scores on BRFSS indicate more physical activity. ‡Higher scores on the CSPro domains indicate more difficulties in this area (e.g., more symptoms, more difficulties functioning, poorer diet and exercise, and more difficulties getting health services needs met). BRFSS = Behavioral Risk Factor Surveillance System – Physical Activity, Yrs post-dx = years since diagnosis, Yrs post-tx = years since treatment, CSPro-S = Symptom Burden Domain, CSPro-F = Function Domain, CSPro-HB = Health Behavior Domain, CSPro-HS = Health Service Domain

PRELIMINARY MODEL PERFORMANCE

The overall performance of the standard linear regression in predicting scores of depression (CES-D) from 16 independent variables (age, race, education, partner status, employment, income, stage at diagnosis, time since diagnosis, treatment received, adjuvant treatment, time since treatment, menopausal status, symptom burden, function, health behavior, and health service needs) yielded a statistically significant model which explained 65.4% of the variance in depression scores, F (16, 177) = 20.951, $p < .001$. In predicting physical activity scores (BRFSS), the standard linear regression used the same 16 independent variables which also resulted in a statistically significant model that accounted for 21.3% of the overall variance, F (16, 175) = 2.952, $p < .001$. With regard to neural network analysis, there is no absolute criterion for determining statistical significance of a model; however, as described above, the neural network models developed in the present study used the same 16 independent (predictor) variables to predict the same dependent (output) variables in order to compare the different statistical models. The original neural network model predicting depression scores (CES-D) resulted in 4 nodes (plus the bias node) in the hidden layer (see Figure 4). In predicting physical activity (BRFSS), the constructed neural network model also resulted in 4 nodes (plus the bias node) in the hidden layer (see Figure 5). As a reminder, nodes in the hidden layer serve the dual purpose of summing the error weights from the inputs and applying an activation function to these summed weights, which allows non-linearity to be introduced into the predictive model. Findings from these analyses are explored in further detail below.

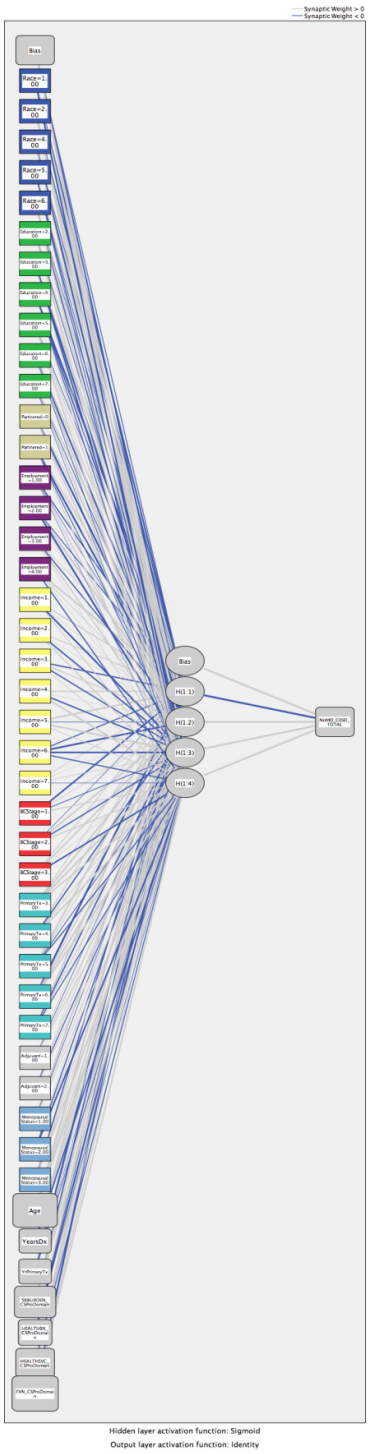

Figure 4. Full Neural Network Model of Depression Scores

Note: The size of each rectangle provides a pictorial representation of the contribution of that independent variable to the prediction of depression scores (Table 8 illustrates the numerical importance of each independent variable in the predictive model)

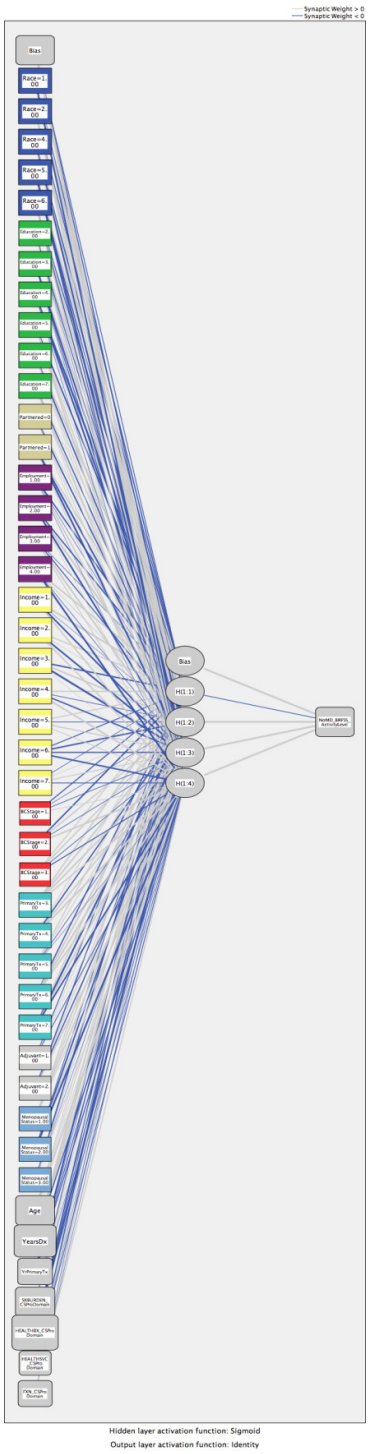

Figure 5. Full Neural Network Model of Physical Activity Scores
Note: The size of each rectangle provides a pictorial representation of the contribution of that independent variable to the prediction of physical activity scores (Table 8 illustrates the numerical importance of each independent variable in the predictive model)

To provide a thorough basis from which to compare the two models, a variety of recommended statistical indices (120) are provided in Table 7. The observed mean (O) and standard deviation (s_o) of the actual (or observed) scores on the dependent variables are provided in the top of the table. The predicted mean (P) and standard deviation (s_p) scores are also provided. In this analysis, the standard deviation of all predicted values is lower than the observed standard deviation of the dependent variable, indicating that both models failed to fully account for the variability in the dataset. Perhaps most notable is the marked disparity between the standard deviation of the neural network model predicting CES-D scores and the observed standard deviation. This disparity is not as pronounced in the linear regression model, and suggests that the neural network model was less able to capture the true variance represented in the original data. Model performance is further highlighted when comparing the observed ranges ($Range_o$) to the model predicted ranges ($Range_p$). In both cases, the neural network model demonstrated a markedly restrictive predictive range as compared to the observed values of the dependent variable, suggesting the neural network model may have been less sensitive to more extreme scores.

Mean bias error (MBE) is a general indicator of whether a model over- or under-predicts scores on the dependent variable, with under-prediction indicated by a negative MBE value (28). MBE is calculated by subtracting observed values of the dependent variable from predicted values from the model (P – O). As shown in the table, the neural network model tended toward slight under-prediction for both dependent variables.

Table 7. Full Predictive Models Performance Statistics

Models predicting CES-D (N = 194)			**Models predicting BRFSS** (N = 192)		
O = 35.42 s_o = 12.59 $Range_o$ = 20.00 to 74.00			O = 2.78 s_o = 1.12 $Range_o$ = 1.00 to 4.00		
	Linear Regression	**Neural Network**		**Linear Regression**	**Neural Network**
P	35.42	35.51	P	2.78	2.80
s_p	10.18	3.85	s_p	0.52	0.25
$Range_p$	13.44 to 62.16	32.54 to 40.88	$Range_p$	1.18 to 4.07	2.45 to 3.30
MBE	0.00	-0.09	MBE	0.00	-0.02
SSE	10567.46	10686.20	SSE	190.07	108.70
MSE	59.70	60.37	MSE	1.09	0.62
RMSE	7.73	7.77	RMSE	1.04	0.79
MAE	5.84	8.45	MAE	0.83	0.92
MAPE	583.52%	844.52%	MAPE	83.12%	92.31%

CES-D = Center for Epidemiological Studies – Depression Scale; BRFSS = Behavioral Risk Factor Surveillance System – Physical Activity; O = average of the observed values of the dependent variable; s_o = standard deviation of the observed values of the dependent variables; $Range_o$ = range of the observed values of the dependent variable; P = average of the predicted values of the dependent variable; s_p = standard deviation of the predicted values of the dependent variable; $Range_p$ = range of the predicted values of the dependent variable MBE = mean bias error (difference between the average observed and average predicted values); SSE = sum of squares error; MSE = mean square error; RMSE = root of mean square error; MAE = mean absolute error; MAPE = mean absolute percent error

One measure of error used in both the linear regression and the neural network models is the sum-of-squares error (SSE; also commonly referred to as the sum-of-squares residual) (58; 60). The SSE is calculated by squaring and summing the differences between the actual and predicted values of the dependent variable; yielding an overall sum of the squared errors in model prediction. The SSE alone may not provide sufficient information to compare predictive models; however, the SSE can be divided by the residual degrees of freedom to produce the Mean Square Error (MSE). MSE provides a general indicator of overall model fit, with a lower MSE suggesting a better fitting model (99; 114).

COMPARISON OF MODEL FIT

In this study, best model fit was defined as the model yielding the smallest MSE. The first specific aim of the present study was to determine which statistical model, linear regression or neural network, produced the best model fit in statistically predicting depressive symptoms and physical functioning in breast cancer survivors. The *a priori* hypotheses for this specific aim were that the neural network models would yield a lower MSE, indicating better model fit, than the linear regression models in predicting both depressive symptoms and physical activity. For the models predicting depression scores (CES-D), this hypothesis was not confirmed (see Table 7). In this case, the linear regression demonstrated a lower MSE (59.70) as compared to the neural network MSE (60.37), suggesting the regression analysis provided a better overall model fit of depression scores than the neural network model; however, the differences in MSE scores between the two models is less than one, indicating no difference between the two models. For the models predicting physical activity scores (BRFSS), this hypothesis was

confirmed with a lower neural network MSE (0.62) than the regression model MSE (1.09) indicating a better model fit for the neural network analysis. Here again, though, there was no appreciable difference between the models.

The Root Mean Square Error (RMSE) is also provided in Table 7. RMSE is referred to in regression analysis as the standard error of the estimate, indicating the standard deviation of the error (or residual) term. RMSE is calculated by taking the root of the MSE term. RMSE is a useful statistic in that it provides a more intuitive understanding of the size of the model's typical prediction error because the squared term has been removed yielding a measurement that is in the same units as the original data. Here, the linear regression demonstrated an RMSE of 7.73 compared to the neural network RMSE of 7.77 in predicting depression (CES-D). Again the difference between the RMSE of each model was negligible. Similarly, the neural network RMSE (0.79) was not markedly different than the linear regression RMSE (1.04) in predicting physical activity (BRFSS).

COMPARISON OF MODEL PREDICTIVE ACCURACY

High predictive accuracy was defined in the present study by the lowest mean absolute percentage error (MAPE). The MAPE indicates the model's mean deviation from the observed value of the dependent variable and is typically represented as a percentage (99; 114). To calculate the MAPE, mean absolute error (MAE) is first calculated by taking the average of the absolute values of the model's prediction errors. Like the RMSE, the MAE statistic uses the same units as the original data and, as a result, may be a more intuitive indicator of the overall accuracy of the model. However, multiplying the MAE by 100% converts this statistic into the MAPE, which is a

percentage measurement that can be compared to a criterion of performance to assess predictive accuracy. Specifically, MAPE values of $\leq$ 10% suggest excellent predictive accuracy; 10 – 20% suggests high predictive accuracy; 20 – 50% indicates average accuracy; and, $\geq$ 50% suggests low predictive accuracy (99; 114).

The second specific aim of this study was to determine which predictive model, linear regression or neural network, produced the highest predictive accuracy in statistically predicting depressive symptoms and physical functioning in breast cancer survivors. The *a priori* hypotheses for this specific aim were that the neural network models would have a lower MAPE, indicating better accuracy, than the linear regression models in predicting both depressive symptoms and physical activity. These hypotheses were not confirmed for both dependent variables (see Table 7). In both cases, the linear regression model produced a lower MAPE (CES-D MAPE = 583.52%; BRFSS MAPE = 83.12%) than the neural network model (CES-D MAPE = 844.52%; BRFSS MAPE = 92.31%), suggesting higher predictive accuracy for the regression analyses. However, neither of the models performed particularly well in accurately predicting the dependent variables. Both models produced an extremely high MAPE when predicting depression scores (CES-D); and, although the models fared somewhat better in predicting physical activity scores (BRFSS), the MAPE values were still much higher than the threshold criterion of 50%, suggesting markedly low predictive accuracy for both models. This poor performance may be explained in part by the characteristic of the MAPE statistic. Specifically, the MAPE is highly sensitive to large percentage errors in small predictive zones (59). For example, if the actual data yields a score of 5 yet the model predicts a score of 10, this equates to a 50% error; however, if the actual score is 100 and the model

predicts a score of 70, this is only a 30% error but a much larger difference in the actual error than that produced by the smaller zone. Indeed, this bias of the MAPE may be most evident in the models predicting depressive scores because the actual values of the CES-D indicated a non-normal distribution (Kolmogorov-Smirnov statistic = .14, $p < .001$) and a positive skew of 1.02, suggesting a distribution with more scores in the lower range. Similarly, BRFSS scores also showed a non-normal distribution (Kolmogorov-Smirnov statistic = .22, $p < .001$). However, actual values of the BRFSS consisted of a much smaller range of scores (i.e., 1 to 4) and demonstrated a slightly negative skew of -.33. This negative skew indicates more scores in the higher range which would suggest less opportunity for the MAPE to be biased by predictive errors. However, the MAPE may also be lower in the models predicting BRFSS simply because of the smaller range of scores.

COMPARISON OF MODEL SENSITIVITY ANALYSIS

Sensitivity analysis demonstrates the change in performance of a statistical model when a specific independent variable is omitted from the model (107). As such, sensitivity analysis highlights the relative importance of each independent variable to the performance of the overall model (14). The third specific aim of this study was to determine which statistical model accounted for the greatest independent variable sensitivity in predicting depressive scores (CES-D) and physical activity (BRFSS) in post-treatment breast cancer survivors. The comparison measure for this particular aim was a global sensitivity analysis. The global sensitivity of an independent variable may be expressed as a ratio of the full model's error, when a given independent variable is omitted, to the full model's error with all independent variables included (99; 114). In

this case, error refers to the sum-of-squares error (SSE). Given this information, an error ratio can be calculated for each independent variable. Ratios ≤ 1 indicate that the independent variable significantly degrades the performance of the model and should be removed from the model (99; 114). The *a priori* hypotheses for this specific aim were that the neural network models would account for the greater independent variable sensitivity than the linear regression models in predicting both depressive symptoms and physical activity. Originally, the analytic plan called for conducting global sensitivity ratios in the manner outlined above and comparing the ratios of the two predictive models for each independent variable for specific aim 3; however, this particular analysis could not be conducted because of the iterative nature of the neural network model which caused the model to behave erratically when variables were removed and did not provide sufficient data to determine accurate global sensitivity ratios as described here. Specifically, the model did not allow for the original connection weights of the remaining variables to be maintained which did not allow for an accurate comparison to determine the neural network's global sensitivity ratio. This unexpected effect may be the result of the neural network software used in the present study (SPSS Neural Network Add-on) which did not allow the contributions of the independent variables to be held constant with the values of these variables in the full neural network model. As a result, an accurate comparison could not be made among the MSE of the full neural network model and the MSE of the neural network model with a variable omitted. Therefore global sensitivity analysis could not be conducted as planned on the neural network model. This analysis was conducted for the linear regression model, and revealed that no variables

should be removed from the model (i.e., none with a ratio ≤ 1 that would suggest significantly degraded model performance).

Although the original specific aim could not be evaluated as proposed, an alternative sensitivity analysis was conducted to evaluate which independent variables were most important in model prediction. Independent variable importance is a sensitivity analysis that demonstrates how much the model's overall variance would decrease if the specific variable was removed from the model (60; 78; 90). Using independent variable importance sensitivity analysis, independent variables can be ranked and ordered by level of importance in model prediction (60; 78; 90). In linear regression, this information is provided by the semipartial correlation coefficients (or part correlations) represented by the statistic *sr*. The semipartial correlation coefficient can be squared (sr^2) and then multiplied by 100% to provide the percentage of variance in the dependent variable (i.e., CES-D or BRFSS) uniquely explained by the particular independent variable (90). For example, in the linear regression model of CES-D, the CSPro-Symptom Burden variable had an sr^2 of .0864, which suggests that the CSPro-Symptom Burden uniquely explains 8.64% of the variance in the CES-D. Additionally, if the CSPro-Symptom Burden variable were removed from the model, the variance in the overall model of CES-D would decrease by 8.64%. In the neural network analysis, these coefficients are provided in an independent variable importance output (60), and can be converted in the same manner (squared and multiplied by 100%) to yield the same information.

Table 8 provides the comparisons and totals of the independent variable importance analysis, with each model's predictor variables presented in rank order of

importance. The *a priori* hypotheses were that the neural network models would demonstrate a higher aggregate sr^2 than the linear regression models in predicting both depressive symptoms and physical activity. In the models predicting depressive scores (CES-D), the hypothesis was confirmed in that the neural network model produced a total sr^2 of .1993 as compared to the linear regression's aggregate sr^2 of .1321. Although these findings suggest that the neural network model uniquely accounted for more of the variance in the CES-D, these findings must be examined in context and include the results from the first two specific aims which suggested that the neural network model did not outperform the linear regression model with regard to goodness of fit or predictive accuracy in predicting CES-D. With regard to the models predicting BRFSS, the hypothesis was not confirmed. In this case, the linear regression model produced a higher aggregate sr^2 of .1474 as compared to the neural network's total sr^2 of .1322. Despite these findings, the difference between the total sr^2 of the models appears to be non-significant.

Perhaps a more interesting comparison is provided when examining which variables were considered most important in the overall predictions of each model. Traditional linear regression analysis provides a threshold criterion for statistical significance of independent variables in predicting the dependent variable of interest. This statistic is presented as the p-value, where a value $\leq .05$ indicates that the specific independent variable made a unique, statistically significant contribution to the model's overall prediction of the dependent variable (90). Although no specific statistical criterion exists for retaining variables in a neural network model (50; 73; 118), variables that uniquely accounted for $\geq 1\%$ of the variance in the dependent variable were

examined for comparison to those independent variables identified as statistically significant in the linear regression analysis. In the linear regression model predicting depressive scores (CES-D), the two statistically significant variables were CSPro-Symptom Burden (*beta* = .54, $p < .001$) and CSPro-Function (*beta* = .27, $p = .001$). There were four variables in the neural network model with a correlation with the independent variable of importance of $\geq$ 1%. These variables were CSPro-Function, age, CSPro-Symptom Burden, and CSPro-Health Service Needs. In the linear regression model predicting physical activity (BRFSS), the only statistically significant variable was CSPro-Health Behavior (*beta* = -.37, $p < .001$). By comparison, the neural network model identified four independent variables with importance values $\geq$ 1%. These variables were CSPro-Health Behavior, years since diagnosis, CSPro-Symptom Burden, and age. Again, the results of this sensitivity analysis should be examined in the context of all the statistical analyses which suggested no appreciable differences in the performance of the linear regression and the neural network model in the areas of goodness of model fit and predictive accuracy for both dependent variables.

However, comparison of the two approaches may have clinical relevance. Specifically, the neural network model showed that four variables (CSPro-Function, age, CSPro-Symptom Burden, and CSPro-Health Service) were related to depressive scores in this breast cancer survivor sample whereas the linear regression demonstrated statistical significance for only CSPro-Symptom Burden and CSPro-Function. Similarly, the neural network model predicting physical activity scores revealed four correlates (CSPro-Health Behavior, years post-diagnosis, CSPro-Symptom Burden, and age) compared to the linear regression which only identified one statistically significant variable (CSPro-Health

Behavior). These findings suggest that the neural network models concluded that more variables are related to outcomes of interest than the linear regression models in predicting both depressive and physical activity scores. These results support the notion that neural networks may account for more complexity in variable relationships and that different patterns of variables may be important clinically with regard to depression and physical activity.

Table 8. Independent Variable Importance Analysis

Models predicting CES-D (N = 194)				**Models predicting BRFSS** (N = 192)			
Linear Regression		**Neural Network**		**Linear Regression**		**Neural Network**	
CSPro-S**	.086436	CSPro-F	.077841	CSPro-HB**	.110224	CSPro-HB	.056644
CSPro-F*	.023104	Age	.060025	Age	.007056	Years post-dx	.030276
Partnered	.007225	CSPro-S	.036481	Income	.005476	CSPro-S	.017161
Age	.006400	CSPro-HS	.020449	Race	.005476	Age	.015876
Years post-dx	.002916	CSPro-HB	.002916	CSPro-HS	.005041	Years post-tx	.003721
CSPro-HS	.001369	Yrs post-tx	.000961	Stage	.004624	CSPro-F	.002500
Years post-tx	.001089	Years post-dx	.000441	CSPro-S	.002704	Employment	.001225
Menopausal	.001024	Treatment	.000049	Treatment	.002209	Race	.001156
CSPro-HB	.000676	Education	.000036	Adjuvant	.001681	Income	.001024
Income	.000529	Menopausal	.000025	CSPro-F	.001296	Education	.000784
Employment	.000484	Income	.000025	Partnered	.000900	Partnered	.000676
Education	.000400	Employment	.000016	Years post-tx	.000361	Treatment	.000484
Adjuvant	.000400	Race	.000016	Menopausal	.000121	CSPro-HS	.000256
Stage	.000036	Stage	.000009	Employment	.000081	Menopausal	.000256
Treatment	.000001	Partnered	.000001	Years post-dx	.000064	Adjuvant	.000144
Race	.000001	Adjuvant	.000000	Education	.000049	Stage	.000001
TOTAL sr^2	.132090	TOTAL sr^2	.199291	TOTAL sr^2	.147363	TOTAL sr^2	.132184

Values represent squared semipartial correlation coefficients (sr^2); *p = .001; **p < .001

CES-D = Center for Epidemiological Studies – Depression Scale, BRFSS = Behavioral Risk Factor Surveillance System – Physical Activity, Years post-dx = years since diagnosis, Years post-tx = years since treatment, CSPro-S = Symptom Burden Domain, CSPro-F = Function Domain, CSPro-HB = Health Behavior Domain, CSPro-HS = Health Service Domain

POST-HOC ANALYSES

Several post-hoc analyses were conducted to determine the power of the models to detect an effect size given this particular dataset and to determine whether an empirically pruned predictive model would yield more accuracy in predictions.

Power Analysis

Post hoc power analyses were conducted using G*Power (43). Effect sizes (f^2) were determined post hoc using the R-square (R^2) of the full linear regression models for each dependent variable to determine Cohen's effect size for an F-test (29; 104). When effect sizes are measured using the Cohen f^2 statistic, values of .02 are considered small, .15 are medium, and .35 are considered large (30). The effect size for the regression model predicting CES-D was large at 1.89, and the effect size for the regression model predicting BRFSS was medium at a value of .27. These effect sizes were then used to conduct the *post hoc* G*Power analysis of the two regression models. Power for the model predicting CES-D was sufficient at 1.00, as was the calculated power for the model predicting BRFSS at .99. Unfortunately, there are no statistical procedures to determine an *a priori* or *post hoc* power analysis for a neural network model (12); although many researchers advocate for large sample sizes in neural network analysis (50; 73).

Hierarchical Regression Model

A hierarchical regression analysis was conducted to evaluate the ability of the clinical predictor variables (i.e., CSPro domains) to predict scores of depression (CES-D) and physical activity (BRFSS), after controlling for the demographic and medical

predictor variables. Hierarchical analysis is not possible with the SPSS Neural Network program; therefore, this analysis was not conducted with a neural network model in the present study.

For the regression predicting depression scores (Table 9), all demographic variables (age, race, education, partner status, employment, income) were entered at Step 1. Demographic variables in Step 1 explained a significant amount of the variance (R^2 = .16) in depression scores. The addition of the medical variables (stage at diagnosis, time since diagnosis, treatment received, adjuvant treatment, time since treatment, menopausal status) in Step 2 resulted in a non-significant increase in R^2 of .01. In the final block, Step 3, the clinical variables were added. The addition of clinical variables (symptom burden, function, health behavior, health service needs) demonstrated a substantial and statistically significant increase in R^2 of .48 ($p < .001$) and brought the total variance accounted for by this model as a whole to 65%, F (16, 177) = 20.95, $p < .001$. The statistically significant findings of this hierarchical model indicated that the clinical variables accounted for 48% of the variance in depression scores, over and above the influence of demographic and medical variables, *F change* (4, 177) = 61.76, $p < .001$. In the final model, only the CSPro-Symptom Burden (*beta* = .54, $p < .001$) and CSPro-Function (*beta* = .27, $p = .001$) domains were statistically significant.

The hierarchical regression predicting physical activity scores (Table 10) followed the same procedure outlined above with demographic variables entered at Step 1. Demographic variables (age, race, education, partner status, employment, income) accounted for a non-significant amount of the variance (R^2 = .03) in physical activity scores. The medical variables (stage at diagnosis, time since diagnosis, treatment

received, adjuvant treatment, time since treatment, menopausal status) entered at Step 2 represented a non-significant increase in R^2 of .01. In Step 3, the clinical variables (symptom burden, function, health behavior, health service needs) were added and demonstrated a large and statistically significant increase in R^2 of .17 ($p < .001$). This model as a whole accounted for 21% total variance in physical activity scores, F (16, 175) = 2.95, $p < .001$. The statistically significant findings of this hierarchical model demonstrated that the clinical variables accounted for 17% of the variance in physical activity scores, over and above the influence of demographic and medical variables, F *change* (4, 175) = 9.59, $p < .001$. In the final model, only the CSPro-Health Behavior domain was statistically significant (*beta* = -.37, $p < .001$).

Table 9. Hierarchical Regression Predicting Depression Scores (CES-D)

Hierarchical Regression Model predicting CES-D (N = 194)			
	R	R^2	R^2 *Change*
Step 1	.40	.16**	--
Demographic Variables *Age* *Race* *Education* *Partnered* *Employment* *Income*			
Step 2	.42	.17**	.01
Demographic Variables Medical Variables *Stage* *Years post-diagnosis* *Treatment* *Adjuvant* *Years post-treatment* *Menopausal*			
Step 3	.81	.65**	.48**
Demographic Variables Medical Variables Clinical Variables *CSPro-Symptom Burden*** *CSPro-Function*** *CSPro-Health Behavior* *CSPro- Health Service*			

*p = .001, **p < .001; CES-D = Center for Epidemiological Studies – Depression Scale

Table 10. Hierarchical Regression Predicting Physical Activity Scores (BRFSS)

Hierarchical Regression Model predicting BRFSS (N = 192)			
	R	R^2	R^2 *Change*
Step 1	.18	.03	--
Demographic Variables *Age* *Race* *Education* *Partnered* *Employment* *Income*			
Step 2	.20	.04	.01
Demographic Variables Medical Variables *Stage* *Years post-diagnosis* *Treatment* *Adjuvant* *Years post-treatment* *Menopausal*			
Step 3	.46	.21**	.17**
Demographic Variables Medical Variables Clinical Variables *CSPro-Symptom Burden* *CSPro-Function* *CSPro-Health Behavior** *CSPro- Health Service*			

*p = .001, **p < .001; BRFSS = Behavioral Risk Factor Surveillance System – Physical Activity

Model Comparisons of Significant Independent Variables

Meyer and colleagues (73) suggest that, rather than compare neural network and regression models, regression models should provide the researcher with an empirical approach to selecting appropriate predictor variables for the neural network model(50; 73). In this regard, linear regression may be seen as a necessary first step in determining the subsequent predictors of a neural network. Using this approach, only the statistically significant variables identified in the hierarchical regression analysis were used to evaluate the predictive abilities of the two models, linear regression and neural network; resulting in a pruned predictive model. Specifically, only CSPro-Symptom Burden and CSPro-Function were simultaneously entered as predictors in both the pruned linear regression and pruned neural network models predicting depression scores (CES-D). The pruned neural network model predicting depression scores resulted in 2 hidden nodes (plus the bias node). Similarly, only CSPro-Health Behavior was entered as a predictor in both the pruned linear regression and pruned neural network models predicting physical activity scores (BRFSS). This pruned neural network model yielded 1 hidden node (plus the bias). Weights for the neural network models are presented in Table 11 and Table 12. Diagrams for these models are provided in Figure 6 and Figure 7.

Table 11. Weights of Pruned Neural Network Model Predicting Depression Scores

Pruned NN Model predicting CES-D (N = 194)		
Input Layer	**Hidden Layers**	
	H(1:1)	H(1:2)
Bias	-.417	.261
CSPro-S	.065	-.145
CSPro-F	-.046	-.109

CES-D = Center for Epidemiological Studies – Depression Scale, CSPro-S = Symptom Burden Domain, CSPro-F = Function Domain

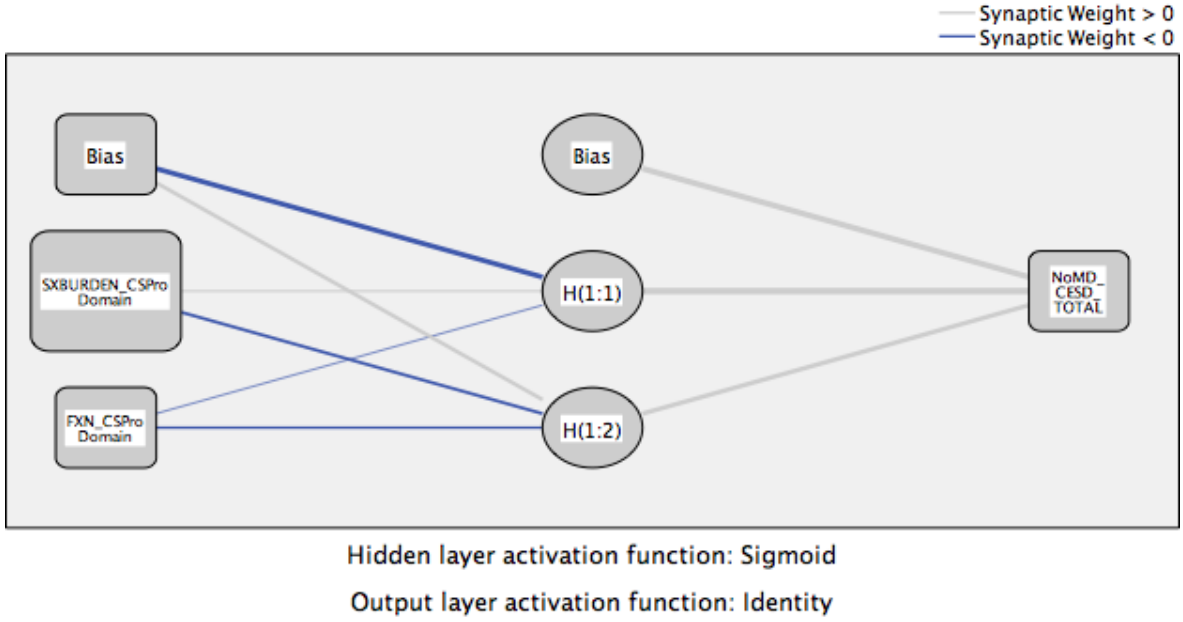

Figure 6. Diagram of Pruned Neural Network Model Predicting Depression Scores
SXBURDEN_CSPro Domain = CSPro Symptom Burden Domain; FXN_CSPro Domain = CSPro Function Domain; NoMD_CESD_TOTAL = CES-D Depression Scores
Note: The size of the rectangle provides a pictorial representation of the contribution of that independent variable to the prediction of depression scores (Table 8 illustrates the numerical importance of each independent variable in the predictive model)

Table 12. Weights of Pruned Neural Network Model Predicting Physical Activity

Pruned NN Model predicting BRFSS (N = 192)	
Input Layer	**Hidden Layers**
	H(1:1)
Bias	2.051
CSPro-HB	-.015

BRFSS = Behavioral Risk Factor Surveillance System – Physical Activity, CSPro-HB = Health Behavior Domain

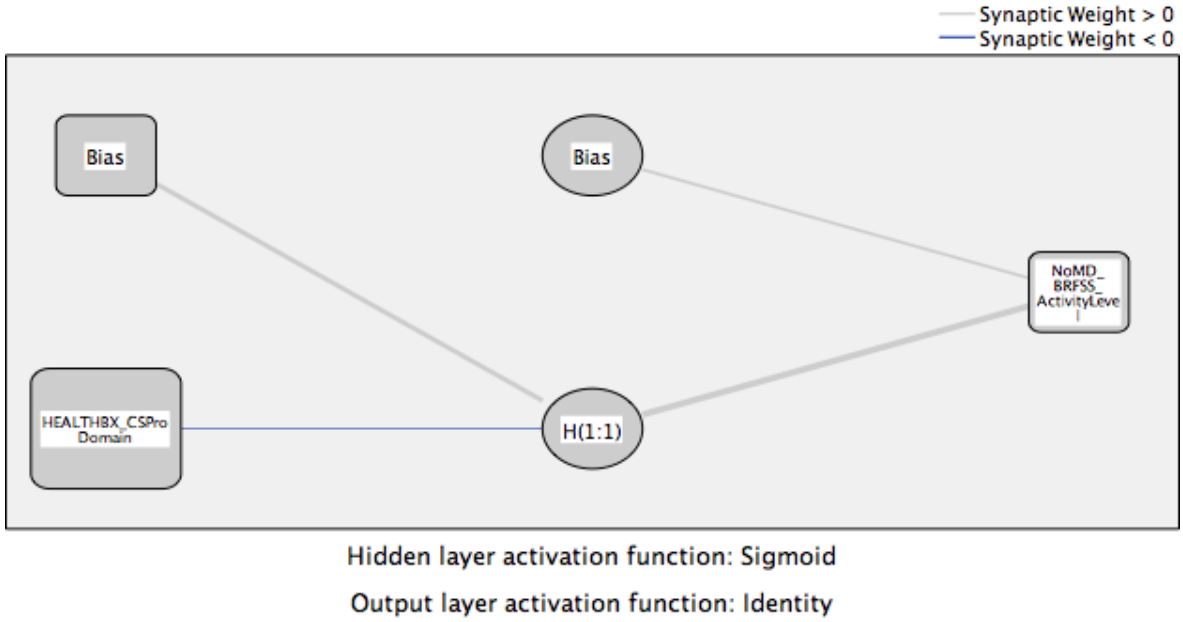

Figure 7. Diagram of Pruned Neural Network Model Predicting Physical Activity Scores
HEALTHBX_CSPro Domain = CSPro Health Behavior Domain;
NoMD_BRFSS_ActivityLevel = BRFSS Physical Activity Scores
Note: The size of the rectangle provides a pictorial representation of the contribution of that independent variable to the prediction of physical activity scores (Table 8 illustrates the numerical importance of each independent variable in the predictive model)

The comparative results of these analyses are presented in Table 13. In this case, statistical pruning resulted in a performance degradation for the models predicting depression scores (CES-D). This decreased performance was marginal in the pruned linear model of depression scores, yielding a slightly higher MSE and MAPE as compared to the same values in the original model (see Table 7 for original model statistics). However, the performance degradation was marked for the pruned neural network model of depression scores, demonstrating notable increases in the MSE, MAPE, and MBE as compared to these values in the original model (see Table 7 for original model statistics). The larger MBE in this case suggested that the pruned neural network model tended to over predict the scores of depression. Statistical pruning also resulted in a decreased model performance for the pruned linear model predicting physical activity scores (BRFSS). Again, the degradation was negligible but produced a higher MSE and MAPE than the original linear model (see Table 7 for original model statistics). However, predictive accuracy was slightly improved for the pruned neural network model predicting physical activity scores. Specifically, the pruned neural network model demonstrated a slightly lower MSE and MAPE in predicting physical activity as compared to these same values in the original model (see Table 7 for original model statistics).

Table 13. Pruned Predictive Models Performance Statistics

Models predicting CES-D (N = 194)			**Models predicting BRFSS** (N = 192)		
O = 35.42 s_o = 12.59 $Range_o$ = 20.00 to 74.00			O = 2.78 s_o = 1.12 $Range_o$ = 1.00 to 4.00		
	Linear Regression	**Neural Network**		**Linear Regression**	**Neural Network**
P	35.42	33.35	P	2.78	2.77
s_p	9.96	1.46	s_p	0.45	0.38
$Range_p$	14.94 to 61.50	27.37 to 35.05	$Range_p$	1.07 to 3.86	1.72 to 3.70
MBE	0.00	2.07	MBE	0.00	0.01
SSE	11430.95	14020.49	SSE	202.45	101.67
MSE	59.85	73.41	MSE	1.07	0.54
RMSE	7.74	8.57	RMSE	1.03	0.73
MAE	5.97	9.27	MAE	0.87	0.88
MAPE	596.92%	927.46%	MAPE	87.35%	88.37%
R^2	.63**	n/a	R^2	.16**	n/a

**$p < .001$; CES-D = Center for Epidemiological Studies – Depression Scale; BRFSS = Behavioral Risk Factor Surveillance System – Physical Activity; O = average of the observed values of the dependent variable; s_o = standard deviation of the observed values of the dependent variables; $Range_o$ = range of the observed values of the dependent variable; P = average of the predicted values of the dependent variable; s_p = standard deviation of the predicted values of the dependent variable; $Range_p$ = range of the predicted values of the dependent variable MBE = mean bias error (difference between the average observed and average predicted values); SSE = sum of squares error; MSE = mean square error; RMSE = root of mean square error; MAE = mean absolute error; MAPE = mean absolute percent error; R^2 = proportion of variance explained by the model

CHAPTER 5: Discussion

This study investigated whether artificial neural network modeling demonstrated better accuracy (as defined by less predictive error) than traditional linear regression in predicting depressive symptoms and physical activity levels in a sample of post-treatment breast cancer survivors. The two predictive models were compared on measures of goodness of fit, predictive accuracy, and independent variable importance. The results of the present study generally did not support the *a priori* hypotheses that neural networks would outperform linear regression models on these measures and there are a number of possible reasons for these results.

This study does indicate several important clinical findings. The results from the linear regression provide new evidence of the importance of the clinical domains of the CSPro as correlates of mental and physical functioning in this sample of post-treatment breast cancer survivors. Additionally, both the linear regression and neural network analysis, two very different statistical approaches, with different underlying assumptions of the relationships among independent and dependent variables produced similar findings with regard to specific CSPro domains. The neural network approach also identified additional variables that may be of clinical importance and may have a non-linear relationship with the dependent variables.

STRENGTHS AND CLINICAL IMPLICATIONS

Relevant clinical implications are suggested from these findings. Of the performance metrics used in the present study, mean square error (MSE) may be the most meaningful measure to determine whether a particular statistical model is performing well; however, the clinical value of these statistical models is best determined by the

independent variable importance analysis. In the present study, the independent variable importance analysis identified the important correlates of the outcomes of interest for both statistical models. With regard to these findings, the neural network model not only confirmed the findings of the linear regression, but also suggested potentially important non-linear relationships among age and years' post-diagnosis with the outcome of interest. These findings suggest that the neural network model may indeed be capturing more complexity in the relationships among these variables that the linear regression did not detect, and suggest that additional predictor variables (age and years' post-diagnosis) may have clinical relevance with regard to mental and physical health status in this post-treatment sample of breast cancer survivors.

The *post-hoc* hierarchical regression analysis revealed a statistically significant relationship for both the CSPro Symptom Burden domain and the CSPro Function Domain related to depressive symptoms on the CES-D measure (Table 9). Greater difficulties with symptoms and functioning were positively correlated with higher scores of depression. While causality cannot be determined, these associations highlight the importance of managing symptom burden, function, and depressive mood. Additionally, the significant findings of the hierarchical regression showed that the statistical significance of the clinical variables (which are modifiable) was over and above the effects of the demographic and medical variables, many of which are non-modifiable.

Modifiable variables identified as important by both the neural network and linear regression models in predicting depressive scores include the CSPro Symptom Burden and CSPro Function. These findings suggest that interventions designed to reduce symptoms and improve function could have an appreciable, positive impact on

decreasing depressive symptoms. The CSPro Symptom Burden domain encompasses areas such as fatigue, depressive symptoms, anxiety, pain, fear of recurrence, body image, and fertility distress. The Function domain of the CSPro involves social relationships, work, sexual function, cognitive function, and sleep disturbance. Specific interventions aimed at reducing problems in both symptom burden and functional areas may include psychoeducation, various forms of counseling (individual, couples, group, web- or telephone-based), and behavioral strategies such as exercise and stress management techniques (23; 44; 70; 71; 92; 98; 105; 121). While symptom burden and function were also identified using the neural network approach, this technique identified two additional survivor variables including age and challenges in ability to obtain health care (Health Service Needs Domain of the CSPro) (Table 8). These findings suggest that the neural network model may be taking more factors into account and possibly identifying more complexity among relationships. Specifically, age and health service needs may have an important non-linear relationship with mental functioning. This represents a relevant clinical finding suggesting that age and health service needs may have a marked impact on mental functioning; however, the actual shape of these non-linear relationships is unclear and should be further defined to better aid clinical decision-making.

Regarding predictors of physical activity (BRFSS), both the neural network model and the hierarchical regression model identified the CSPro Health Behavior domain as an important predictor (Tables 8 and 10). The significance of clinical predictors in the hierarchical regression model was also above and beyond the effects of the demographic and medical variables. Higher scores on the CSPro Health Behavior

domain were associated with lower scores on the BRFSS, suggesting that poor health behaviors (poor diet and exercise) were correlated with lower levels of physical activity. Here again, these results are promising because health behaviors have the ability to be modified through various forms of psychoeducation, behavioral strategies, and behavioral programs, ultimately improving physical activity and possibly quality of life (39; 61; 63; 71; 88; 92; 116). In addition to health behavior, the neural network model also identified time since diagnosis, symptom burden, and age as important predictors of physical activity on the BRFSS (Table 8), suggesting again that perhaps the neural network model may be identifying the complexity in the relationships among the predictor variables and physical activity scores. This suggests that time since diagnosis, symptom burden, and age may have important non-linear relationships with physical functioning. These factors are important clinically with regard to impacts on physical functioning; but, the actual shape of these non-linear relationships is not known and should also be further defined to assist clinical decision-making regarding physical functioning.

MODEL PERFORMANCE

Although the linear regression model produced a slightly lower overall error than the neural network model, the differences were negligible and neither model performed particularly well on our selected metrics of interest. This is most evident regarding the MAPE findings, none of which was below the threshold criterion of 50% (above which suggests markedly low predictive accuracy). It is unknown whether the sample size was adequate for neural network analysis, but this explanation does not account for the poor performance of the regression model since the post hoc analysis suggested adequate power to detect an effect size. Another possibility, as stated previously, lies in the non-

normal distributions of the dependent variables. However, both parametric tests and neural network models are quite robust with regard to non-normal data (48; 72), and data resulting from psychological research is quite often non-normally distributed (90). An alternative possibility is that, although the selection of independent variables was based on theoretical assumptions and experience, there may be different predictor variables that could be included to increase the overall accuracy of the models. Although the present study did not support the original hypotheses, the predictive models explored should not be abandoned on the basis of these metrics alone as the results suggest important clinical findings.

Both statistical approaches include general strengths and weaknesses which were observed in this study. Linear regression has the benefit of being simple to use, simple to understand, and easy to interpret; however, linear regressions cannot model non-linear relationships and therefore may not be suitable to model more complex relationships among predictor and outcome variables. Neural network models do have the capability to identify non-linear relationships and may be better able to capture complex relationships among variables; but, this approach is much more difficult to interpret and the relationships among the variables are not easily understood. Because of these strengths and weaknesses, researchers studying these statistical approaches have suggested that a complementary use of the two models (linear regression and neural network) may be the most optimal approach (73; 118). Because neural networks do not allow researchers to see a direct relationship between predictors and the outcome of interest, these models alone may not be sufficient in aiding researchers to develop targeted interventions for identified outcomes, such as mental and physical functioning.

Conversely, traditional statistical models do provide information regarding relationships among variables, but may not capture more complex, nonlinear relationships inherent in clinical samples. Despite the findings in the present study using fewer predictor variables in the pruned models (Tables 11-13), linear regression may be a useful method to reduce the number of variables before entering them in a neural network model analysis. In this way, linear regressions can interpret specific relationships that lead researchers to targeted interventions while neural network models can further clarify the overall relationships identified by the regression model.

LIMITATIONS

Although a *post hoc* power analysis demonstrated moderate to large effect sizes in the dataset and substantial power to detect these effects using a linear regression, our sample size may have been too small for a neural network model. There are no *a priori* methods to determine sufficient sample size for neural network models (12). Although neural networks can be used with small datasets, small sample sizes can decrease the generalizability of the results and may make the analysis more susceptible to multicollinearity and overfitting the data (12; 73; 96). Previous neural network research with similar design parameters to the current study and a relatively small sample size has demonstrated acceptable generalizability of model results to a validation sample. Specifically, Baxt (13) conducted a neural network analysis with 20 independent (input) variables to determine the occurrence of myocardial infarction in 351 patients who presented with chest pain. The results of this analysis showed good generalization to a validation sample of over 300 patients. However, data in the present study were not found to be multicollinear, and the results suggested that underfitting (rather than

overfitting) was a significant problem. Therefore, neural network models may be less stable with smaller sample sizes. In fact, Warner and Misra (118) propose that traditional statistical approaches may actually be preferred over neural network modeling for small sample sizes, citing that regression models perform better when theory or experience suggests the underlying relationship between factors studied; whereas, neural network models are more useful at uncovering a previously unknown functional relationship among factors. They argue that this feature makes neural networks data dependent and therefore better able to perform as the sample size increases.

Conversely, overfitting is most likely to occur in neural networks when the sample size is too large (95). When a neural network overfits the data on which it is trained, the generalizability of the model can be significantly degraded (52). There are measures in place to reduce the likelihood of overfitting, such as early stopping rules (a measure employed in this study) and train-test-validation sets; however, there are no such measures to account for problems associated with small data sets in neural network modeling. When the data is known to the researcher, such problems may be detected by a careful investigation of the model's behavior as compared to the actual data, as was done in this investigation. However, a better solution would be the development of an *a priori* power analysis for various neural network architectures, such as a best practice rule-of-thumb calculation or an empirically derived formulation such as that provided by G*Power for traditional statistical modeling.

Another possible reason for the unexpected poor performance of neural network models in this study may lie in the characteristics of the data. Specifically, if the relationship among the independent variables and dependent variables is truly linear, then

a linear regression would naturally be a more appropriate model to determine these relationships. True linearity is not always known but may be expected when most of the predictor variables in a model are dichotomous because this suggests that their contribution to the overall model is on a linear scale (118). However, in the present research, only two of the predictor variables were binary; therefore, if the true relationship among the variables is linear, it is likely not an artifact of the variable scale.

The neural network software application turned out to be somewhat limited for the current study. Specifically, the SPSS Neural Network Add-on program did not allow the planned analysis for Specific Aim 3 (global sensitivity analysis) to be conducted for the neural network model because the software did not allow the connection weights in the model to be held constant for follow-up comparisons. As a result, global sensitivity analysis could only be carried out on the linear regression model which precluded a direct comparison of this analysis with the neural network model. This required an alternative sensitivity analysis (independent variable importance) be conducted to evaluate Specific Aim 3.

Finally, this study was a cross-sectional analysis and cannot provide causal predictions or information on changes that occur in cancer survivor health status over time.

FUTURE RESEARCH

This study demonstrated clinically relevant findings with regard to the importance of the clinical domains on the CSPro as related to mental and physical functioning in this post-treatment sample of breast cancer survivors. However, no analysis was conducted to evaluate which subscales of the global clinical domains were significant correlates of

mental and physical functioning. For example, subscales of the Symptom Burden Domain include anxiety, pain, fear of recurrence, body image, fatigue, and depression. It would be useful to identify which specific subscales contribute to significant changes in mental and physical functioning outcomes to develop more targeted interventions.

The potential clinical significance of identifying unique variables in the neural network model should not be underestimated. In addition to the clinical domain variables (CSPro domains) identified by both statistical approaches, age (demographic variable) and time since diagnosis (medical variable) were also identified in the neural network as potentially important predictors. These findings suggest that the neural network model is highlighting important non-linear relationships among these predictor variables and the dependent variables. The shape or nature of this relationship is not known. Understanding the shape of these relationships could provide additional clinical utility for clinicians and patients in understanding the trajectory of their mental and physical health status. Future research should clarify the exact shape of these non-linear relationships (e.g., oscillating function, exponential function, etc.)

Future research in this area should also include larger sample sizes to compare and contrast neural network models to traditional statistical models in predicting psychosocial factors in cancer survivors to decrease any possible confound of small sample size in neural network analysis. If recruiting a large number of participants is unrealistic, a resampling method such as bootstrapping may be useful. Bootstrapping involves a computer-generated, repeated random sampling-with-replacement from the full set of known cases to produce random samples for analysis that characteristically differ from the original sample. This resampling method allows the same sample to be

repeatedly used for statistical analysis in an effort to offset the drawbacks of a small dataset.

Given the unexpected problems encountered in this project with regard to sensitivity analysis, careful consideration should be given to the particular software application used. The SPSS Neural Network Add-on (60) may best used in project that requires only a basic application of the neural network model. *STATISTICA* is neural network software that has been used by other researchers to evaluate the same specific aims outlined in this project, including global sensitivity analysis (99; 114). Other programs that have this capability include *R: neuralnet* (51) and *MATLAB* (108). However, aside from SPSS, these software packages require varying levels of familiarity with programming code to run more advanced neural network analysis.

The present study is cross-sectional in nature and, therefore, does not provide information on changes that can occur in cancer survivor health status over time. As a result, the research design does not allow the investigators to examine the differential performance of the predictive statistical models with multiple measures over time (i.e., traditional statistical models compared to neural network models). A prospective follow-up study could examine the trajectory of breast cancer survivors' mental and physical health status over time by evaluating these factors immediately after treatment and then again at 1- and 5-years later. The comparison and performance of predictive statistical models with this prospective data may also be informative.

Because this study focuses on the comparison of two statistical models, no conclusion can be made about the outcome modifying each independent variable would have on cancer survivor functioning. In the future, an intervention study would be

needed to determine the impact of specific interventions suggested by both analytic approaches on depression and physical activity.

CONCLUSIONS

Neural network models did not outperform linear regression analysis in predicting mental and physical functioning in this sample of post-treatment breast cancer survivors. However, neural network models may still be useful in modeling cancer survivors' mental and physical functioning. Both linear regression and neural network modeling identified modifiable variables (clinical domains of the CSPro) as important correlates of post-treatment mental and physical functioning. The neural network model also added to the results by identifying additional variables (age, time since diagnosis) that have some type of non-linear relationship with mental and physical functioning. These findings may promote a better understanding of post-treatment health status.

APPENDICES

APPENDIX 1: STUDIES USING PREDICTIVE STATISTICAL MODELS TO EVALUATE MENTAL COMPONENT SUMMARY (MCS) AND PHYSICAL COMPONENT SUMMARY (PCS) OF THE SF-36

Author/Year	Cancer Survivor Sample	Design	Predictive Statistical Model	Significant Predictors/Findings
Soares et al. (103)	Breast, 1 year post-treatment (n = 70)	Cross-sectional	Linear Regression	Compared to survivors living with a partner, being single, separated, or widowed was a significant predictor of MCS (estimated $\beta = -5.77$, $p < .02$)
Thong et al. (109)	Rectal, up to 10 years post-diagnosis (n = 340)	Cross-sectional	Linear Regression	Comorbidity ($\beta = -7.9$, $p < .0001$), tumor grade ($\beta = -5.0$, $p < .05$), years since diagnosis ($\beta = .50$, $p < .05$), and age ($\beta = -.14$, $p < .05$) were significant predictors of PCS
Aarts et al. (1)	Prostate, 5 to 10 years post-diagnosis (n = 584)	Cross-sectional	Linear Regression	Survivors with a low socioeconomic status (SES) demonstrated a significantly lower MCS than those in the high ($p <.001$) or intermediate ($p <.01$) SES categories Survivors in the high SES category showed a higher PCS than those in the intermediate category ($p < .05$)
Andersen et al. (8)	Breast, 2 to 10 years post-diagnosis	Cross-sectional	Linear Regression	Age was a significant predictor of MCS ($\beta = .24$, $p < .001$) and PCS ($\beta = -.24$, $p < .001$) Income was also a significant predictor of MCS ($\beta = .12$, $p < .05$) and PCS ($\beta = .22$, $p < .001$)
Bowen et al. (17)	Breast, 6-months and 35-months post-diagnosis (n = 804)	Prospective	Linear Regression	Significant predictors of MCS were: Hispanic race ($\beta = -2.02$, $p = .05$) Cognitive status/mood ($\beta = -3.84$, $p < .01$) Social/emotional status ($\beta = 2.10$, $p < .01$) Fear of recurrence ($\beta = -.42$, $p < .01$) Fatigue ($\beta = -2.63$ to -6.00, $p < .01$)

				Significant predictors of PCS were: African American race (β = -3.42, $p < .01$) Other race (β = -3.75, $p = .05$)) Unemployment (β = -5.35, $p < .01$) Not working outside the home/retired/disabled (β = -4.80, $p < .01$) Urinary incontinence (β = -.70, $p = .04$) Caregiving/financial status (β = 2.45, $p = .01$) Social/emotional status (β = -1.71, $p = .03$) Exercise/diet (β = 2.11, $p < .01$) Fear of recurrence (β = -.16, $p = .04$) Fatigue (β = -3.66 to -6.99, $p < .01$) Current lymphedema (β = -3.14, $p < .01$) The full multiple regression models, including baseline and follow-up measures, accounted for 41% of the variance in MCS and 38% of the variance in PCS.
Mols et al. (75)	Mixed (prostate, non-Hodgkin's lymphoma, and endometrial), 5 to 15 years post-diagnosis (n = 1112)	Cross-sectional	Linear Regression	For survivors younger than age 70, occupation was a significant predictor of MCS (β = .12, $p < .05$) and comorbidity was a significant predictor of PCS (β = -.31, $p < .001$) For survivors aged 70 or older, comorbidity was a significant predictor of MCS (β = -.14, $p < .01$); and, comorbidity (β = -.15, $p < .01$), age (β = -.20, $p < .001$), and occupation (β = .12, $p < .01$) were significant predictors of PCS

Conde et al. (33)	Breast, 6-months post-treatment (n = 75)	Cross-sectional	Linear Regression	Significant predictors of MCS were: Being married (estimated β = -.63, p = .02) Insomnia (estimated β = -.52, p < .01) Significant predictors of PCS were: Dizziness (estimated β = -.46, p < .01) Postmenopausal status (estimated β = -.42, p < .01) Radiation therapy (estimated β = .30, p < .01) Breast-conserving therapy (estimated β = -.24, p < .01)
Bloom et al. (16)	Breast, at diagnosis and 5 years post-diagnosis (n = 160)	Prospective	Linear Regression	Significant predictors of change in MCS were: Number of chronic conditions (β = -1.66, p = .05) Baseline MCS score (β = -.60, p < .01) Change in emotional support (β = .38, p = .03) Significant predictors of change in PCS were: Children under age 18 in the home (β = -4.77, p < .01) Chemotherapy (β = 3.88, p = .03) Employed at least part-time (β = 3.24, p = .04) Number of chronic conditions (β = -2.60, p < .01) Baseline PCS score (β = -.63, p < .01) The adjusted multiple regression models, including baseline measures of MCS and PCS, accounted for 36% of the variance in MCS and 46% of the variance in PCS.
Casso et al. (24)	Breast, 5-10 years post-diagnosis (n = 216)	Cross-sectional	Logistic Regression	Low MCS scores* were predicted by: Reporting breast-related symptoms (OR = 2.3, 95% CI: 1.2-4.6)

				An annual income of >$35,000 (OR = 0.4-1.2, 95% CI: 0.5-2.8) Low PCS scores* were predicted by: Reporting breast-related symptoms (OR = 3.7, 95% CI: 1.6-8.2) An annual income of >$35,000 (OR = 0.2-0.3, 95% CI: 0.1-.08) Receipt of chemotherapy (OR = 2.4, 95% CI: 1.0-5.7) Having undergone mastectomy (as compared to women who received breast conserving therapy) (OR = 2.6, 95% CI: 1.1-6.1) *Scores were categorized as low if they fell in the bottom tertile of the MCS and PCS (i.e., $\leq$ 40)

[a]Higher MCS and PCS scores indicate better mental and physical functioning, respectively.

APPENDIX 2: DEMOGRAPHIC AND MEDICAL SURVEY

Please complete the following questions.

What is your date of birth?

_____

What is your age?

_____

What is your highest level of education?

1. Less than high school
2. High school
3. Some college
4. Associate's degree
5. Bachelor's degree
6. Some graduate school
7. Graduate degree

What is your marital status?

1. Single
2. Single, cohabitating
3. Married
4. Divorced
5. Widowed

What is your race?

1. Asian
2. Black or African American
3. Caucasian
4. Hispanic or Latino
5. Native American/Alaska Native
6. Native Hawaiian or Pacific Islander
7. Other

What is your employment status?

1. Unemployed (by choice)
2. Unemployed (not by choice)
3. Work full-time
4. Work part-time

If you work, what is your job title?

_____

What is your estimated household income?

1. Less than $10,000
2. $10,000 - $19,000
3. $20,000 - $39,000
4. $40,000 - $59,000
5. $60,000 - $79,000
6. $80,000 - $99,000
7. $100,000 or more

What stage of cancer were you diagnosed with?

1. Stage I
2. Stage II
3. Stage III

Were you treated with surgery for cancer?

1. Yes
2. No

Were you treated with chemotherapy for cancer?

1. Yes
2. No

Were you treated with radiation for cancer?

1. Yes
2. No

Did you receive any adjuvant treatment for cancer?

1. Yes
2. No

Did you receive other treatment for cancer?

1. Yes
2. No

What was the date you were diagnosed with cancer?
Month: _____
Day: _____
Year: _____

What was the date that all primary treatment (surgery, chemotherapy, radiation) was completed?
Month: _____
Day: _____
Year: _____

What is your menopausal status?

1. Pre-menopausal prior to cancer, post-menopausal after treatment
2. Pre-menopausal prior to treatment, pre-menopausal after treatment
3. Post-menopausal before diagnosis or treatment

APPENDIX 3: CANCER SURVIVOR PROFILE (CSPRO)

(112)

Given your life as it is now, how do you feel about having had cancer?
Mark the box that best describes how much you agree or disagree with each statement.

1. Having had cancer makes me feel uncertain about my health.
   1 = Strongly disagree
   2 = Disagree
   3 = Neutral
   4 = Agree
   5 = Strongly agree
2. I worry about the future.
   1 = Strongly disagree
   2 = Disagree
   3 = Neutral
   4 = Agree
   5 = Strongly agree
3. Having had cancer makes me feel unsure about the future.
   1 = Strongly disagree
   2 = Disagree
   3 = Neutral
   4 = Agree
   5 = Strongly agree
4. I worry about cancer coming back.
   1 = Strongly disagree
   2 = Disagree
   3 = Neutral
   4 = Agree
   5 = Strongly agree
5. New symptoms make me worry about the cancer coming back.
   1 = Strongly disagree
   2 = Disagree
   3 = Neutral
   4 = Agree
   5 = Strongly agree
6. I worry about my health.
   1 = Strongly disagree
   2 = Disagree
   3 = Neutral
   4 = Agree
   5 = Strongly agree
7. I feel disfigured.
   1 = Strongly disagree
   2 = Disagree

3 = Neutral
4 = Agree
5 = Strongly agree

8. I sometimes wear clothing to cover parts of my body.
   1 = Strongly disagree
   2 = Disagree
   3 = Neutral
   4 = Agree
   5 = Strongly agree
9. I worry about how my body looks.
   1 = Strongly disagree
   2 = Disagree
   3 = Neutral
   4 = Agree
   5 = Strongly agree

The following questions are about having a family.
Mark the box whether you agree or disagree with each statement.

10. Before being diagnosed with cancer, had you wanted to have a child (or another child)?
    1 = Yes
    2 = No
11. Since having had cancer, have you wanted to have a child (or another child)?
    1= Yes
    2= No
12. When I see families with children I feel left out.
    1 = Strongly disagree
    2 = Disagree
    3 = Neutral
    4 = Agree
    5 = Strongly agree
13. I can't help comparing myself with friends who have children.
    1 = Strongly disagree
    2 = Disagree
    3 = Neutral
    4 = Agree
    5 = Strongly agree
14. I will do just about anything to have a child (or another child).
    1 = Strongly disagree
    2 = Disagree
    3 = Neutral
    4 = Agree
    5 = Strongly agree
15. Having a child (or another child) is not necessary for my happiness.

1 = Strongly disagree
2 = Disagree
3 = Neutral
4 = Agree
5 = Strongly agree

16. I could visualize a happy life together, without a child (or another child).
    1 = Strongly disagree
    2 = Disagree
    3 = Neutral
    4 = Agree
    5 = Strongly agree
    6 = Not applicable
17. We could have a long, happy relationship without a child (or another child).
    1 = Strongly disagree
    2 = Disagree
    3 = Neutral
    4 = Agree
    5 = Strongly agree
    6 = Not applicable

The next set of questions relate to how you view your health.
Mark the box that best describes how much you agree or disagree with the statement.

18. No matter how hard I try, my health just doesn't turn out the way I would like.
    1 = Strongly disagree
    2 = Disagree
    3 = Neutral
    4 = Agree
    5 = Strongly agree
19. It is difficult for me to find effective solutions to the health problems that come my way.
    1 = Strongly disagree
    2 = Disagree
    3 = Neutral
    4 = Agree
    5 = Strongly agree
20. I succeed in the projects I undertake to improve my health.
    1 = Strongly disagree
    2 = Disagree
    3 = Neutral
    4 = Agree
    5 = Strongly agree
21. I'm generally able to accomplish my goals with respect to my health.
    1 = Strongly disagree

2 = Disagree
3 = Neutral
4 = Agree
5 = Strongly agree

22. I find my efforts to change things I don't like about my health are ineffective.
    1 = Strongly disagree
    2 = Disagree
    3 = Neutral
    4 = Agree
    5 = Strongly agree
23. Typically, my plans for my health don't work out well.
    1 = Strongly disagree
    2 = Disagree
    3 = Neutral
    4 = Agree
    5 = Strongly agree

The next set of questions ask about how confident you are in your ability to interact with your doctor.
Mark the box about how confident you are in your ability:

24. How confident are you in your ability to ask a doctor questions about your chief health concern?
    1 = Not at all
    2 = A little bit
    3 = Somewhat
    4 = Quite a bit
    5 = Very much
25. How confident are you in your ability to get a doctor to answer all your questions?
    1 = Not at all
    2 = A little bit
    3 = Somewhat
    4 = Quite a bit
    5 = Very much
26. How confident are you in your ability to explain your chief health concern to a doctor?
    1 = Not at all
    2 = A little bit
    3 = Somewhat
    4 = Quite a bit
    5 = Very much
27. How confident are you in your ability to get a doctor to take your chief health concern seriously?
    1 = Not at all

2 = A little bit
3 = Somewhat
4 = Quite a bit
5 = Very much

28. How confident are you in your ability to get a doctor to do something about your chief health concern?
    1 = Not at all
    2 = A little bit
    3 = Somewhat
    4 = Quite a bit
    5 = Very much
29. How confident are you in your ability to ask a doctor for more information if you don't understand what he or she said?
    1 = Not at all
    2 = A little bit
    3 = Somewhat
    4 = Quite a bit
    5 = Very much

The next set of questions is about your relationship with others since the end of primary treatment (e.g., chemotherapy, radiation, surgery).
Mark the box that best describes how you feel about each statement.

30. I feel people avoid talking to me.
    1 = Never
    2 = Rarely
    3 = Sometimes
    4 = Usually
    5 = Always
31. I feel isolated from others.
    1 = Never
    2 = Rarely
    3 = Sometimes
    4 = Usually
    5 = Always
32. I have someone who will listen to me when I need to talk.
    1 = Never
    2 = Rarely
    3 = Sometimes
    4 = Usually
    5 = Always
33. I have someone who understands my problems.
    1 = Never
    2 = Rarely
    3 = Sometimes

4 = Usually
5 = Always

34. I can get helpful advice from others when dealing with a problem.
    1 = Never
    2 = Rarely
    3 = Sometimes
    4 = Often
    5 = Always
35. Is someone available to help you if you need it?
    1 = Never
    2 = Rarely
    3 = Sometimes
    4 = Usually
    5 = Always

The following questions ask about your ability to perform at work.
Mark the box that best describes how you feel about each statement.

36. Are you currently employed?
    1 = Yes
    2 = No
37. Current work ability compared to your highest work ability ever:
    How many points would you give your current work ability?
    0 means that you cannot currently work and 5 is your work ability at its best.

0	1	2	3	4	5
completely unable to work					work ability at its best

38. Work ability in its relation to the demands of the job.
    How do you rate your current work ability with respect to the **physical** demands of your work?
    1 = Very good
    2 = Rather good
    3 = Moderate
    4 = Rather poor
    5 = Very poor
39. Work ability in its relation to the demands of the job.
    How do you rate your current work ability with respect to the **mental** demands of your work?
    1 = Very good
    2 = Rather good
    3 = Moderate
    4 = Rather poor

5 = Very poor

The next questions are about your height and weight.

40. About how much do you weigh without shoes? _____
41. About how tall are you without shoes? _____

The next set of questions is about challenges you may have had in the <u>past 7 days</u>.
Mark the box that best describes how you feel about each statement.
In the <u>past 7 days</u>:

42. How much did pain interfere with your day-to-day activities?
    1 = Not at all
    2 = A little bit
    3 = Somewhat
    4 = Quite a bit
    5 = Very much
43. How severe was your pain?
    1 = Not at all
    2 = A little bit
    3 = Somewhat
    4 = Quite a bit
    5 = Very much
44. How severe was your joint pain?
    1 = Not at all
    2 = A little bit
    3 = Somewhat
    4 = Quite a bit
    5 = Very much
45. How much did pain (e.g., back pain, arm pain, hand pain, hip pain, bone pain, muscle pain) affect your daily activities?
    1 = Not at all
    2 = A little bit
    3 = Somewhat
    4 = Quite a bit
    5 = Very much
46. How much did you experience burning and/or sharp pain?
    1 = Not at all
    2 = A little bit
    3 = Somewhat
    4 = Quite a bit
    5 = Very much

The next set of questions is about challenges you may have had in the past 7 days.
Mark the box that best describes how you feel about each statement.
In the past 7 days:

47. I was satisfied with my sleep.
    1 = Not at all
    2 = A little bit
    3 = Somewhat
    4 = Quite a bit
    5 = Very much
48. I had difficulty falling asleep.
    1 = Not at all
    2 = A little bit
    3 = Somewhat
    4 = Quite a bit
    5 = Very much
49. My sleep was restless.
    1 = Not at all
    2 = A little bit
    3 = Somewhat
    4 = Quite a bit
    5 = Very much
50. I had a problem with my sleep.
    1 = Not at all
    2 = A little bit
    3 = Somewhat
    4 = Quite a bit
    5 = Very much
51. I felt tired.
    1 = Not at all
    2 = A little bit
    3 = Somewhat
    4 = Quite a bit
    5 = Very much
52. My sleep quality was.
    1 = Very good
    2 = Good
    3 = Fair
    4 = Poor
    5 = Very poor

The next set of questions is about challenges you may have had in the past 7 days.
Mark the box that best describes how you feel about each statement.
In the past 7 days:

53. How run-down did you feel on average?
    1 = Not at all
    2 = A little bit
    3 = Somewhat
    4 = Quite a bit
    5 = Very much
54. How fatigued were you on average?
    1 = Not at all
    2 = A little bit
    3 = Somewhat
    4 = Quite a bit
    5 = Very much
55. To what degree did you feel that you had no energy?
    1 = Not at all
    2 = A little bit
    3 = Somewhat
    4 = Quite a bit
    5 = Very much
56. How often did you need to rest during the day?
    1 = Not at all
    2 = A little bit
    3 = Somewhat
    4 = Quite a bit
    5 = Very much
57. How often did you experience fatigue?
    1 = Not at all
    2 = A little bit
    3 = Somewhat
    4 = Quite a bit
    5 = Very much
58. How often did your fatigue come on suddenly?
    1 = Not at all
    2 = A little bit
    3 = Somewhat
    4 = Quite a bit
    5 = Very much

The next set of questions is about challenges you may have had in the <u>past 7 days</u>.
Mark the box that best describes how you feel about each statement.
In the <u>past 7 days</u>:

59. I felt like nothing could cheer me up.
    1 = Never
    2 = Rarely
    3 = Sometimes

4 = Often
5 = Always

60. I felt unhappy.
    1 = Never
    2 = Rarely
    3 = Sometimes
    4 = Often
    5 = Always
61. I felt depressed.
    1 = Never
    2 = Rarely
    3 = Sometimes
    4 = Often
    5 = Always
62. I felt that I had nothing to look forward to.
    1 = Never
    2 = Rarely
    3 = Sometimes
    4 = Often
    5 = Always
63. I felt very emotional.
    1 = Never
    2 = Rarely
    3 = Sometimes
    4 = Often
    5 = Always
64. I felt tearful or like crying.
    1 = Never
    2 = Rarely
    3 = Sometimes
    4 = Often
    5 = Always

The next set of questions is about challenges you may have had in the <u>past 7 days</u>.
Mark the box that best describes how you feel about each statement.
In the <u>past 7 days</u>:

65. I felt anxious.
    1 = Never
    2 = Rarely
    3 = Sometimes
    4 = Often
    5 = Always
66. I felt fearful.
    1 = Never

2 = Rarely
3 = Sometimes
4 = Often
5 = Always

67. I felt tense.
    1 = Never
    2 = Rarely
    3 = Sometimes
    4 = Often
    5 = Always
68. My worries overwhelmed me.
    1 = Never
    2 = Rarely
    3 = Sometimes
    4 = Often
    5 = Always
69. I felt irritable.
    1 = Never
    2 = Rarely
    3 = Sometimes
    4 = Often
    5 = Always
70. I felt worried about my health.
    1 = Never
    2 = Rarely
    3 = Sometimes
    4 = Often
    5 = Always

The next set of questions is about challenges you may have had in the <u>past 7 days</u>.
Mark the box that best describes how you feel about each statement.
In the <u>past 7 days</u>:

71. My thinking has been slow.
    1 = Never
    2 = Rarely (Once)
    3 = Sometimes (Two or three times)
    4 = Often (About once a day)
    5 = Very often (Several times a day)
72. I have had trouble shifting back and forth between different activities that require thinking.
    1 = Never
    2 = Rarely (Once)
    3 = Sometimes (Two or three times)
    4 = Often (About once a day)

5 = Very often (Several times a day)

73. My problems with memory, concentration, or making mental mistakes have interfered with the quality of my life.
    1 = Never
    2 = Rarely (Once)
    3 = Sometimes (Two or three times)
    4 = Often (About once a day)
    5 = Very often (Several times a day)
74. I have had trouble concentrating.
    1 = Never
    2 = Rarely (Once)
    3 = Sometimes (Two or three times)
    4 = Often (About once a day)
    5 = Very often (Several times a day)
75. My brain was in a fog.
    1 = Never
    2 = Rarely (Once)
    3 = Sometimes (Two or three times)
    4 = Often (About once a day)
    5 = Very often (Several times a day)
76. I have had trouble finding words when talking to someone.
    1 = Never
    2 = Rarely (Once)
    3 = Sometimes (Two or three times)
    4 = Often (About once a day)
    5 = Very often (Several times a day)

The next set of questions is about challenges you may have had in the <u>past 30 days</u>.
Mark the box that best describes how you feel about each statement.
In the <u>past 30 days</u>:

77. How interested have you been in sexual activity?
    1 = Not at all
    2 = A little bit
    3 = Somewhat
    4 = Quite a bit
    5 = Very much
78. How often have you felt like you wanted to have sex?
    1 = Never
    2 = Rarely
    3 = Sometimes
    4 = Often
    5 = Always
79. How satisfied have you been with your sex life?
    1 = Not at all

2 = A little bit
3 = Somewhat
4 = Quite a bit
5 = Very much

80. How much have scars from surgery affected your satisfaction with your sex life?
1 = Not at all
2 = A little bit
3 = Somewhat
4 = Quite a bit
5 = Very much

The next set of questions are about financial matters related to cancer.
Indicate how often each of these statements has been true for you in the <u>past 30 days</u>.

81. You had financial problems because of the cost of cancer surgery or treatment.
1 = Never
2 = Rarely
3 = Sometimes
4 = Often
5 = Always

83. You had problems with insurance because of cancer.
1 = Never
2 = Rarely
3 = Sometimes
4 = Often
5 = Always

84. You had money problems that arose because you had cancer.
1 = Never
2 = Rarely
3 = Sometimes
4 = Often
5 = Always

85. You had financial problems due to a loss of income as a result of cancer.
1 = Never
2 = Rarely
3 = Sometimes
4 = Often
5 = Always

The next set of questions is about challenges you may have had in the <u>past 30 days</u>.
Mark the box that best describes how you feel about each statement.
In the <u>past 30 days</u>:

86. Did you drink any type of alcoholic beverage?
    1 = Yes
    2 = No
87. I took risks when I drank.
    1 = Never
    2 = Rarely
    3 = Sometimes
    4 = Often
    5 = Almost always
88. Drinking created problems between me and others.
    1 = Never
    2 = Rarely
    3 = Sometimes
    4 = Often
    5 = Almost always
89. I had trouble getting things done after I drank.
    1 = Never
    2 = Rarely
    3 = Sometimes
    4 = Often
    5 = Almost always

Please think about what you usually ate or drank during the past month, that is, the <u>past 30 days</u>. Please read each question and report how many times per day, week, or month you ate each food.

90. How many times per **day**, **week**, or **month** did you **usually** eat **bacon** or **sausage**, not including low fat, light, or turkey varieties?
    1 = Never
    2 = 1-3 times last month
    3 = 1-2 times per week
    4 = 3-4 times per week
    5 = 5-6 times per week
    6 = 1 time per day
    7 = 2 times per day
    8 = 3 times per day
    9 = 4 or more times per day
91. How often did you eat **hot dogs** made of beef or pork?
    1 = Never
    2 = 1-3 times last month
    3 = 1-2 times per week
    4 = 3-4 times per week
    5 = 5-6 times per week
    6 = 1 time per day
    7 = 2 times per day

8 = 3 times per day
9 = 4 or more times per day

92. How often did you use **regular fat salad dressing or mayonnaise**, including on salad and sandwiches? Do **not** include low-fat, light, or diet dressings.

1 = Never
2 = 1-3 times last month
3 = 1-2 times per week
4 = 3-4 times per week
5 = 5-6 times per week
6 = 1 time per day
7 = 2 times per day
8 = 3 times per day
9 = 4 or more times per day

93. How often did you eat **French fries, home fries,** or **hash brown potatoes**?

1 = Never
2 = 1-3 times last month
3 = 1-2 times per week
4 = 3-4 times per week
5 = 5-6 times per week
6 = 1 time per day
7 = 2 times per day
8 = 3 times per day
9 = 4 or more times per day

94. How often did you eat **peanuts, walnuts, seeds,** or **other nuts**? Do **not** include peanut butter.

1 = Never
2 = 1-3 times last month
3 = 1-2 times per week
4 = 3-4 times per week
5 = 5-6 times per week
6 = 1 time per day
7 = 2 times per day
8 = 3 times per day
9 = 4 or more times per day

95. How often did you eat **regular fat potato chips, tortilla chips, or corn chips**? Do **not** include low-fat chips.

1 = Never
2 = 1-3 times last month
3 = 1-2 times per week
4 = 3-4 times per week
5 = 5-6 times per week
6 = 1 time per day
7 = 2 times per day
8 = 3 times per day
9 = 4 or more times per day

Below are questions about needs that you may have experienced as a result of having cancer. Mark the box that best describes whether you have needed help with these needs in the last 30 days. There are 5 possible answers to choose from:

No Need	**1 Not applicable-** This was not a problem for me as a result of cancer.
	2 Satisfied- I did need help with this, but my need for help was satisfied at the time.
Some Need	**3 Low need-** This item caused me concern or discomfort. I had little need for additional help.
	4 Moderate need- This item caused me concern or discomfort. I had some need for additional help.
	5 High need- This item caused me concern or discomfort. I had a strong need for additional help.

96. Being given written information about important aspects of your care.
    1 = Not applicable
    2 = Satisfied
    3 = Low need
    4 = Moderate need
    5 = High need
97. Being given explanations of those tests for which you would like explanations.
    1 = Not applicable
    2 = Satisfied
    3 = Low need
    4 = Moderate need
    5 = High need
98. Being adequately informed about the benefits and side-effects of treatments before you choose to have them.
    1 = Not applicable
    2 = Satisfied
    3 = Low need
    4 = Moderate need
    5 = High need
99. Being informed about your test results as soon as feasible.
    1 = Not applicable
    2 = Satisfied
    3 = Low need
    4 = Moderate need
    5 = High need
100. Being informed about things you can do to help yourself get well.
    1 = Not applicable
    2 = Satisfied
    3 = Low need
    4 = Moderate need
    5 = High need

101. Being able to judge the quality of cancer related information provided on the Internet.

1 = Not applicable
2 = Satisfied
3 = Low need
4 = Moderate need
5 = High need

For the next set of questions, use the following as a guide to describe your activity level:

1. **Physical Inactivity**: The inactive person spends most waking hours sitting or standing quietly. Activities include working at a desk, reading, watching television, or other quiet pursuits. Usually does not walk more than a few minutes.

2. **Light Physical Inactivity**: This person usually walks more than 10 minutes at a time each day, leisurely rides a bicycle, fishes, bowls, golfs, or engages in light carpentry, light gardening, light industrial work, teaching, or light housework on a regular basis.

3. **Moderate Physical Activity:** This person participates in such activities as brisk walking, recreation or doubles tennis, or swimming; or works in such occupations as mail carrier, telephone repair, light building, and construction; or engages in housework and home repairs or moderate gardening.

4. **Heavy Physical Activity:** This person performs vigorous activity on a regular basis, including jogging, singles tennis, paddleball, or high-intensity aerobics; or engages in heavy activities, such as carrying heavy weights (20 lb or more), strenuous farm work, or strenuous gardening.

102. Thinking about the things you usually did at **work** during the **last 12 months,** how would you describe the kind of physical activity you performed?

1 = Inactive
2 = Light
3 = Moderate
4 = Heavy

103. Thinking about the things you usually did at **home** during the **last 12 months,** how would you describe the kind of physical activity you performed?

1 = Inactive
2 = Light
3 = Moderate
4 = Heavy

104. Thinking about the things you usually did in your **leisure time** during the **last 12 months,** how would you describe the kind of physical activity you performed?

1 = Inactive
2 = Light
3 = Moderate
4 = Heavy

The next set of questions is about cigarette smoking.
Mark the box that best describes your experience with each statement.

105. Have you smoked at least 100 cigarettes in your entire life?
Note: 5 packs = 100 cigarettes
1 = Yes
2 = No
3 = Don't know / Not sure
106. Do you smoke cigarettes every day, some days, or not at all?
1 = Every day
2 = Some days
3 = Not at all
4 = Don't know / Not sure
107. During the past 12 months, have you stopped smoking for one day or longer because you were trying to quit smoking?
1 = Yes
2 = No
3 = Don't know / Not sure
108. How long has it been since you last smoked a cigarette, even one or two puffs?
1 = Within the past month (less than 1 month ago)
2 = Within the past 3 months (1 month but less than 3 months ago)
3 = Within the past 6 months (3 months but less than 6 months ago)
4 = Within the past year (6 months but less than 1 year ago)
5 = Within the past 5 years (1 year but less than 5 years ago)
6 = Within the past 10 years (5 years but less than 10 years ago)
7 = 10 years or more
8 = Don't know / Not sure

APPENDIX 4: CENTER FOR EPIDEMIOLOGICAL STUDIES - DEPRESSION SCALE (CES-D)

Available in the public domain http://www.ncbi.nlm.nih.gov/books/NBK64056/ (25)

Below is a list of some of the ways you may have felt or behaved. Please indicate how often you have felt this way *during the past week*.

1. I was bothered by things that usually don't bother me.
   1 = Rarely or none of the time (less than 1 day)
   2 = Some or a little of the time (1-2 days)
   3 = Occasionally or a moderate amount of the time (3-4 days)
   4 = Most or all of the time (5-7 days)

2. I did not feel like eating; my appetite was poor.
   1 = Rarely or none of the time (less than 1 day)
   2 = Some or a little of the time (1-2 days)
   3 = Occasionally or a moderate amount of the time (3-4 days)
   4 = Most or all of the time (5-7 days)

3. I felt that I could not shake off the blues even with help from my family or friends.
   1 = Rarely or none of the time (less than 1 day)
   2 = Some or a little of the time (1-2 days)
   3 = Occasionally or a moderate amount of the time (3-4 days)
   4 = Most or all of the time (5-7 days)

4. I felt that I was just as good as other people.
   1 = Rarely or none of the time (less than 1 day)
   2 = Some or a little of the time (1-2 days)
   3 = Occasionally or a moderate amount of the time (3-4 days)
   4 = Most or all of the time (5-7 days)

5. I had trouble keeping my mind on what I was doing.
   1 = Rarely or none of the time (less than 1 day)
   2 = Some or a little of the time (1-2 days)
   3 = Occasionally or a moderate amount of the time (3-4 days)
   4 = Most or all of the time (5-7 days)

6. I felt depressed.
   1 = Rarely or none of the time (less than 1 day)
   2 = Some or a little of the time (1-2 days)
   3 = Occasionally or a moderate amount of the time (3-4 days)
   4 = Most or all of the time (5-7 days)

7. I felt that everything I did was an effort.
    1 = Rarely or none of the time (less than 1 day)
    2 = Some or a little of the time (1-2 days)
    3 = Occasionally or a moderate amount of the time (3-4 days)
    4 = Most or all of the time (5-7 days)

8. I felt hopeful about the future.
    1 = Rarely or none of the time (less than 1 day)
    2 = Some or a little of the time (1-2 days)
    3 = Occasionally or a moderate amount of the time (3-4 days)
    4 = Most or all of the time (5-7 days)

9. I thought my life had been a failure.
    1 = Rarely or none of the time (less than 1 day)
    2 = Some or a little of the time (1-2 days)
    3 = Occasionally or a moderate amount of the time (3-4 days)
    4 = Most or all of the time (5-7 days)

10. I felt fearful.
    1 = Rarely or none of the time (less than 1 day)
    2 = Some or a little of the time (1-2 days)
    3 = Occasionally or a moderate amount of the time (3-4 days)
    4 = Most or all of the time (5-7 days)

11. My sleep was restless.
    1 = Rarely or none of the time (less than 1 day)
    2 = Some or a little of the time (1-2 days)
    3 = Occasionally or a moderate amount of the time (3-4 days)
    4 = Most or all of the time (5-7 days)

12. I was happy.
    1 = Rarely or none of the time (less than 1 day)
    2 = Some or a little of the time (1-2 days)
    3 = Occasionally or a moderate amount of the time (3-4 days)
    4 = Most or all of the time (5-7 days)

13. I talked less than usual.
    1 = Rarely or none of the time (less than 1 day)
    2 = Some or a little of the time (1-2 days)
    3 = Occasionally or a moderate amount of the time (3-4 days)
    4 = Most or all of the time (5-7 days)

14. I felt lonely.
    1 = Rarely or none of the time (less than 1 day)
    2 = Some or a little of the time (1-2 days)
    3 = Occasionally or a moderate amount of the time (3-4 days)

4 = Most or all of the time (5-7 days)

15. People were unfriendly.
    1 = Rarely or none of the time (less than 1 day)
    2 = Some or a little of the time (1-2 days)
    3 = Occasionally or a moderate amount of the time (3-4 days)
    4 = Most or all of the time (5-7 days)

16. I enjoyed life.
    1 = Rarely or none of the time (less than 1 day)
    2 = Some or a little of the time (1-2 days)
    3 = Occasionally or a moderate amount of the time (3-4 days)
    4 = Most or all of the time (5-7 days)

17. I had crying spells.
    1 = Rarely or none of the time (less than 1 day)
    2 = Some or a little of the time (1-2 days)
    3 = Occasionally or a moderate amount of the time (3-4 days)
    4 = Most or all of the time (5-7 days)

18. I felt sad.
    1 = Rarely or none of the time (less than 1 day)
    2 = Some or a little of the time (1-2 days)
    3 = Occasionally or a moderate amount of the time (3-4 days)
    4 = Most or all of the time (5-7 days)

19. I felt that people disliked me.
    1 = Rarely or none of the time (less than 1 day)
    2 = Some or a little of the time (1-2 days)
    3 = Occasionally or a moderate amount of the time (3-4 days)
    4 = Most or all of the time (5-7 days)

20. I could not get “going.”
    1 = Rarely or none of the time (less than 1 day)
    2 = Some or a little of the time (1-2 days)
    3 = Occasionally or a moderate amount of the time (3-4 days)
    4 = Most or all of the time (5-7 days)

APPENDIX 5: BEHAVIORAL RISK FACTOR SURVEILLANCE SYSTEM (BRFSS) - PHYSICAL ACTIVITY

Available in the public domain http://www.cdc.gov/brfss/questionnaires/index.htm (27)

1. During the past month, other than your regular job, did you participate in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise?

1 = Yes
2 = No
3 = Don't know / Not sure

2. What type of physical activity or exercise did you spend the most time doing during the past month?

1 = Active gaming devices (Wii Fit, Dance Dance Revolution)
2 = Aerobics video or classes
3 = Backpacking
4 = Badminton
5 = Basketball
6 = Bicycling machine exercise
7 = Bicycling
8 = Boating (canoeing, rowing, kayaking, sailing for pleasure)
9 = Bowling
10 = Boxing
11 = Calisthenics
12 = Canoeing / rowing in competition
13 = Carpentry
14 = Dancing (ballet, ballroom, Latin, hip hop, etc.)
15 = Elliptical / EFX machine exercise
16 = Fishing from a river bank or boat
17 = Frisbee
18 = Gardening (spading, weeding, digging, filling)
19 = Golf (with motorized cart)
20 = Golf (without motorized cart)
21 = Handball
22 = Hiking cross-country
23 = Hockey
24 = Horseback riding
25 = Hunting large game such as deer or elk
26 = Hunting small game such as quail
27 = Inline skating
28 = Jogging
29 = Lacrosse
30 = Mountain climbing

31 = Mowing lawn
32 = Paddleball
33 = Painting / papering house
34 = Pilates
35 = Racquetball
36 = Raking lawn
37 = Running
38 = Rock climbing
39 = Rope skipping
40 = Rowing machine exercise
41 = Rugby
42 = Scuba diving
43 = Skateboarding
44 = Skating, ice or roller
45 = Sledding, tobogganing
46 = Snorkeling
47 = Snow blowing
48 = Snow shoveling by hand
49 = Snow skiing
50 = Snowshoeing
51 = Soccer
52 = Softball / baseball
53 = Squash
54 = Stair climbing / stair master
55 = Stream fishing in waders
56 = Surfing
57 = Swimming
58 = Swimming in laps
59 = Table tennis
60 = Tai Chi
61 = Tennis
62 = Touch football
63 = Volleyball
64 = Walking
66 = Waterskiing
67 = Weight lifting
68 = Wrestling
69 = Yoga
70 = Other activity
71 = Don't know / not sure

3. How many times per week did you take part in this activity during the past month?
   1 = 1
   2 = 2
   3 = 3

4 = 4
5 = 5
6 = 6
7 = 7
8 = 8
9 = 9
10 = 10
11 = 11
12 = 12
13 = 13
14 = 14
15 = 15
16 = 16
17 = 17
18 = 18
19 = 19
20 = 20
21 = 21
22 = 22
23 = 23
24 = 24
25 = 25
26 = 26
27 = 27
28 = 28
29 = 29
30 = 30

4. And when you took part in this activity, for how many minutes did you usually keep at it?

_____ (answer provided in minutes)

5. What other type of physical activity gave you the next most exercise during the past month?

1 = Active gaming devices (Wii Fit, Dance Dance Revolution)
2 = Aerobics video or classes
3 = Backpacking
4 = Badminton
5 = Basketball
6 = Bicycling machine exercise
7 = Bicycling
8 = Boating (canoeing, rowing, kayaking, sailing for pleasure)
9 = Bowling

10 = Boxing
11 = Calisthenics
12 = Canoeing / rowing in competition
13 = Carpentry
14 = Dancing (ballet, ballroom, Latin, hip hop, etc.)
15 = Elliptical / EFX machine exercise
16 = Fishing from a river bank or boat
17 = Frisbee
18 = Gardening (spading, weeding, digging, filling)
19 = Golf (with motorized cart)
20 = Golf (without motorized cart)
21 = Handball
22 = Hiking cross-country
23 = Hockey
24 = Horseback riding
25 = Hunting large game such as deer or elk
26 = Hunting small game such as quail
27 = Inline skating
28 = Jogging
29 = Lacrosse
30 = Mountain climbing
31 = Mowing lawn
32 = Paddleball
33 = Painting / papering house
34 = Pilates
35 = Racquetball
36 = Raking lawn
37 = Running
38 = Rock climbing
39 = Rope skipping
40 = Rowing machine exercise
41 = Rugby
42 = Scuba diving
43 = Skateboarding
44 = Skating, ice or roller
45 = Sledding, tobogganing
46 = Snorkeling
47 = Snow blowing
48 = Snow shoveling by hand
49 = Snow skiing
50 = Snowshoeing
51 = Soccer
52 = Softball / baseball
53 = Squash
54 = Stair climbing / stair master
55 = Stream fishing in waders

56 = Surfing
57 = Swimming
58 = Swimming in laps
59 = Table tennis
60 = Tai Chi
61 = Tennis
62 = Touch football
63 = Volleyball
64 = Walking
66 = Waterskiing
67 = Weight lifting
68 = Wrestling
69 = Yoga
70 = Other activity
71 = Don't know / not sure

6. How many times per week did you take part in this activity during the past month?
   1 = 1
   2 = 2
   3 = 3
   4 = 4
   5 = 5
   6 = 6
   7 = 7
   8 = 8
   9 = 9
   10 = 10
   11 = 11
   12 = 12
   13 = 13
   14 = 14
   15 = 15
   16 = 16
   17 = 17
   18 = 18
   19 = 19
   20 = 20
   21 = 21
   22 = 22
   23 = 23
   24 = 24
   25 = 25
   26 = 26
   27 = 27
   28 = 28

29 = 29
30 = 30

7. And when you took part in this activity, for how many minutes did you usually keep at it?

_____

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