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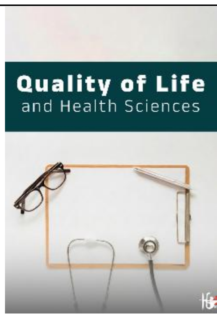

Support Vector Machine Classification of Low Quality of Life Among Breast Cancer Survivors Using Fatigue, Depression, and Social Support Indicators

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A B S T R A C T

Objective: This study aimed to classify low quality of life among breast cancer survivors using a support vector machine model based on fatigue, depression, and perceived social support indicators.
Methods and Materials: This cross-sectional predictive study was conducted among 312 female breast cancer survivors receiving follow-up care in oncology clinics and survivorship units in Tehran, Iran. Quality of life was assessed using the EORTC QLQ-C30, and participants with global health status/quality-of-life scores below 50 were classified as having low quality of life. Fatigue was measured using the Functional Assessment of Chronic Illness Therapy–Fatigue scale, depression using the Beck Depression Inventory-II, and perceived social support using the Multidimensional Scale of Perceived Social Support. After data screening and standardization, the dataset was divided into stratified training and testing subsets using an 80:20 ratio. A support vector machine classifier with a radial basis function kernel was developed, and model hyperparameters were optimized through grid search and cross-validation.
Findings: Participants with low quality of life had significantly higher depression scores, greater fatigue burden, and lower total perceived social support compared with survivors without low quality of life. Significant differences were also observed in family support, friend support, and significant-other support. The support vector machine model achieved strong classification performance, with cross-validation accuracy of 0.85 and independent test accuracy of 0.84. In the independent test set, sensitivity was 0.79, specificity was 0.87, precision was 0.79, F1-score was 0.79, balanced accuracy was 0.83, and the area under the receiver operating characteristic curve was 0.90. Permutation-based importance analysis showed that fatigue was the most influential predictor, followed by depression, total perceived social support, and family support.
Conclusion: The support vector machine model classified low quality of life among breast cancer survivors with high accuracy, indicating that fatigue, depression, and perceived social support are clinically meaningful indicators for identifying survivors at risk of poor quality of life.
Keywords: *Breast cancer survivors; quality of life; support vector machine; fatigue; depression; social support; machine learning; survivorship.*

1. Introduction

Breast cancer survivorship has become a major focus of oncology, psycho-oncology, rehabilitation, and public health because improvements in detection and treatment have increased survival while also revealing persistent post-treatment burdens that may continue long after completion of primary therapy. For many survivors, the end of active treatment does not represent a simple return to pre-diagnosis functioning; rather, survivorship is often accompanied by fatigue, emotional distress, sleep disturbance, body-image concerns, physical limitations, fear of recurrence, social role disruption, and uncertainty about long-term health. Quality of life is therefore a central outcome in breast cancer survivorship because it reflects not only disease status or treatment completion, but also the survivor's physical, psychological, social, and functional adaptation to life after cancer. Prior survivorship research has consistently emphasized that quality of life among breast cancer survivors is multidimensional and shaped by symptoms, emotional adjustment, lifestyle, social resources, treatment-related sequelae, and contextual factors (Boivin et al., 2021; Culbertson et al., 2020; Davis & Snyder, 2024). This multidimensionality makes low quality of life a clinically important but analytically complex outcome, particularly when the aim is to identify survivors who may require additional psychosocial, rehabilitative, or supportive care.

The importance of assessing quality of life among breast cancer survivors is further supported by evidence showing that survivorship experiences vary considerably across populations, cultures, treatment stages, and healthcare contexts. Studies from different regions have shown that quality of life in breast cancer survivors is associated with both clinical and psychosocial variables, including symptom burden, physical functioning, emotional well-being, lifestyle behaviors, and access to care (Azam et al., 2021; D'Souza, 2021; Rauf et al., 2024). In post-treatment cancer survivors, quality of life is not determined solely by cancer history; it is also influenced by psychological health, health behaviors, social circumstances, and survivorship support systems (Kim et al., 2023). Among breast cancer survivors specifically, quality of life trajectories may change over time after treatment, indicating that a survivor's needs are dynamic rather than fixed (Park et al., 2023). Therefore, identifying low quality of life at a given point in survivorship is not merely descriptive; it can support risk stratification, timely referral, and individualized intervention planning.

Fatigue is one of the most prevalent and disabling symptoms experienced by breast cancer survivors and is frequently described as a core determinant of reduced quality of life. Cancer-related fatigue differs from ordinary tiredness because it may be persistent, disproportionate to activity, and insufficiently relieved by rest. It can interfere with daily functioning, occupational performance, physical activity, emotional regulation, and social participation. Evidence from studies on prolonged symptoms in breast cancer survivorship shows that fatigue may remain present after treatment and may cluster with other persistent symptoms that compromise quality of life (Jang et al., 2020). Fatigue is also closely linked with treatment-related complications such as lymphedema, particularly among survivors who have undergone axillary lymph node dissection, further intensifying functional limitations and reducing well-being (Özşaker, 2025). Psychosocial consequences of breast cancer-related lymphedema, including distress, altered body perception, and reduced participation, further demonstrate how physical complications may extend into emotional and social dimensions of survivorship (Eaton et al., 2020). Because fatigue is both a symptom and a functional constraint, it is a highly relevant predictor for classifying low quality of life in breast cancer survivors.

Depression is another major determinant of quality of life among cancer survivors. Depressive symptoms may emerge in response to diagnosis, treatment burden, fear of recurrence, body-image changes, sexual concerns, social role changes, and perceived loss of control. Persistent depressive symptoms can reduce motivation, impair self-care, disrupt sleep, increase perceived symptom burden, and weaken engagement in health-promoting behaviors. Longitudinal evidence indicates that breast cancer survivors with persistent depressive symptoms experience poorer quality of life compared with those without such symptoms, highlighting depression as a clinically meaningful indicator of survivorship vulnerability (Ribeiro et al., 2023). More broadly, psychosocial determinants of quality of life in breast cancer survivors include emotional distress, coping resources, social support, and psychological adaptation (Culbertson et al., 2020). Research on predictors of quality of life and life satisfaction among young breast cancer survivors also emphasizes the relevance of psychological factors in survivorship adjustment (Martens et al., 2021). Although cognitive impairment research is not limited to breast cancer, cancer-related self-reported cognitive problems have also been associated with reduced quality of life, reinforcing the broader principle that subjective psychological and neurocognitive symptoms can meaningfully affect cancer survivors' daily functioning and well-being (Ferguson et al., 2022).

Social support is a protective factor that may buffer the negative impact of fatigue, depression, and treatment-related burden on quality of life. Perceived support from family, friends, and significant others can enhance emotional security, treatment adherence, coping capacity, and confidence in managing survivorship challenges. In many cultural contexts, family support may be particularly important because family members often provide practical assistance, emotional reassurance, and decision-making support throughout cancer treatment and recovery. Studies examining determinants of quality of life immediately after completion of primary breast cancer treatment have shown that psychosocial and interpersonal factors are central to survivors' well-being (Park et al., 2021). Similarly, research on factors affecting quality of life among breast cancer patients highlights the need to consider social and contextual determinants, not only clinical indicators (Maharani et al., 2023). Community-based and culturally tailored interventions, including programs designed for Latina breast cancer survivors, further demonstrate the importance of engagement, cultural responsiveness, and social context in survivorship care (AuBuchon et al., 2025). Therefore, perceived social support is not only a descriptive psychosocial variable but also a plausible predictor of whether survivors experience low quality of life.

Lifestyle and physical activity represent another major domain in breast cancer survivorship research. Physical activity has been repeatedly examined as a modifiable factor associated with better quality of life, reduced fatigue, improved psychological health, and greater functional recovery. Reviews of physical activity in cancer care have emphasized its role as part of comprehensive survivorship management (Misiąg et al., 2022). Among breast cancer survivors, physical activity has been directly associated with quality of life, supporting the relevance of active living as a survivorship resource (Agussalim et al., 2024). Lifestyle considerations are especially important among early-stage breast cancer patients receiving adjuvant endocrine therapy, for whom symptoms and treatment-related side effects may influence daily functioning and long-term well-being (Meglio et al., 2021). During periods of social restriction, such as the COVID-19 pandemic, changes in physical activity were also related to physical and mental health among breast cancer survivors, indicating that behavioral routines and environmental constraints may affect survivorship outcomes (Tamai et al., 2024). Interventions using wearable activity tracking have also been evaluated, reflecting increasing interest in objective monitoring and behavior-support technologies for breast cancer survivors (Pan et al., 2024). Although the present study focuses on fatigue, depression, and social support indicators, this broader literature demonstrates that quality of life is embedded in modifiable behavioral and psychosocial systems.

Non-pharmacological interventions have been increasingly investigated to improve quality of life and related psychological outcomes among breast cancer survivors. Movement-based interventions such as Tai Chi Chuan have shown potential benefits for breast cancer patients, suggesting that structured mind-body activity may support physical and psychological recovery (Luo et al., 2020). Dance interventions have also been examined, with systematic review and meta-analytic evidence indicating improvements in quality of life and related psychological factors among breast cancer survivors (Chen et al., 2026). Specific dance-based programs such as Argentine tango have been investigated for their effects on cancer-associated fatigue and quality of life, with both randomized and sustainability-oriented studies highlighting the relevance of embodied, social, and enjoyable activity formats in survivorship care (Oei et al., 2023; Schad et al., 2023). Peer-led physical activity programs have additionally shown relevance for psychosocial outcomes, suggesting that supportive group-based activity may combine behavioral activation with social reinforcement (Pinto et al., 2024). Forest-environment and living-lab approaches have also been explored as potential strategies to improve psychological health among cancer survivors, reflecting growing interest in restorative environments and ecological models of survivorship well-being (Kim et al., 2024).

Digital health and technology-supported survivorship care have become increasingly important because many survivors require long-term support beyond hospital-based treatment settings. Information and communication technology-based telehealth approaches have been reviewed in relation to occupational therapy interventions for cancer survivors, highlighting the potential for remote rehabilitation and supportive care delivery (Hwang et al., 2020). Connected health interventions have shown effects on psychological well-being and quality of life among patients with cancer, suggesting that technology can extend supportive care access and monitoring (Gitonga et al., 2022). Mobile applications have also been systematically reviewed in relation to quality of life among breast cancer patients and survivors, reflecting the growing role of app-based tools in symptom tracking, self-management, and survivorship education (Saevarsdottir & Guðmundsdóttir, 2023). Evidence-based digital health interventions for breast cancer survivor care have been synthesized in umbrella review research, further showing that digital modalities are now a major component of survivorship research and practice (Jiménez-Díaz et al., 2025). Patient-centered survivorship care plans supported by big data and artificial intelligence technologies also indicate a shift toward data-driven survivorship models capable of integrating multiple patient indicators for individualized care (Mlakar et al., 2021).

Psychological interventions are also central to improving survivorship outcomes. Cognitive behavioral therapy integrated with activity pacing has been proposed for fatigued breast cancer patients undergoing chemotherapy, indicating that fatigue management may benefit from structured psychological and behavioral regulation strategies (Chen et al., 2021). Mindfulness-based interventions in oncology have also been reviewed as approaches with relevance for emotional distress, coping, symptom burden, and quality-of-life outcomes (Chen et al., 2025). Sleep problems represent another important survivorship-related concern because sleep disturbance can worsen fatigue, depression, cognitive functioning, and quality of life; conceptual work on sleep disorder among patients with breast cancer underscores its clinical significance and its interconnection with broader symptom experiences (Aini et al., 2022). These intervention and symptom literatures collectively suggest that fatigue, depression, sleep, physical functioning, and psychosocial resources are not isolated domains but interacting components of survivorship health.

Despite extensive evidence on factors associated with quality of life, many studies in breast cancer survivorship rely on traditional statistical approaches that estimate average associations between predictors and outcomes. While such approaches are valuable, they may be less suited to classification tasks where the clinical objective is to identify individuals who are likely to belong to a low-quality-of-life group. Machine learning methods, including support vector machine classification, offer an alternative analytic framework for modeling complex, potentially nonlinear relationships among predictors and for producing individual-level classifications. This is especially relevant when quality of life is shaped by the joint influence of fatigue, depression, perceived social support, and clinical characteristics. The distinction between disease-specific and generic quality-of-life instruments also demonstrates that measurement choices influence interpretation and prediction, reinforcing the need for analytic models that are aligned with the specific outcome being classified (Jang et al., 2022). In this context, support vector machine classification may be useful because it can separate outcome groups using multidimensional predictor patterns rather than relying solely on linear assumptions.

The need for classification models is particularly important in clinical settings where resources for psychosocial assessment and intervention may be limited. If survivors at risk for low quality of life can be identified using brief indicators such as fatigue, depression, and social support, healthcare providers may be better able to prioritize referrals, supportive counseling, rehabilitation, fatigue management, and social support enhancement. Prior research has already established that quality of life among breast cancer survivors is influenced by prolonged symptoms, psychological distress, physical activity, lifestyle, digital support, and social context, but fewer studies have translated these indicators into a predictive classification framework that directly distinguishes survivors with low quality of life from those with more favorable adjustment. A support vector machine model using fatigue, depression, and social support indicators can therefore contribute to survivorship research by combining clinically meaningful psychosocial variables with a predictive analytic approach suitable for individualized risk identification.

The aim of this study was to classify low quality of life among breast cancer survivors in Tehran using a support vector machine model based on fatigue, depression, and perceived social support indicators.

2. Methods and Materials

2.1. Study Design and Participants

This study was conducted using a cross-sectional predictive design to classify low quality of life among breast cancer survivors based on fatigue, depression, and perceived social support indicators. The study population consisted of female breast cancer survivors receiving follow-up care in oncology clinics and cancer survivorship units in Tehran, Iran. A total of 312 breast cancer survivors were included in the final analysis. Participants were selected through convenience sampling from eligible patients who attended routine post-treatment follow-up visits. Eligibility criteria included being 18 years of age or older, having a confirmed medical diagnosis of breast cancer, having completed the main phase of treatment including surgery, chemotherapy, and/or radiotherapy at least six months before participation, and being able to read and complete the study questionnaires independently. Participants were excluded if they had documented metastatic disease, active recurrence, a diagnosis of another major cancer, severe cognitive impairment, or incomplete questionnaire data that prevented inclusion in the machine learning analysis. Before data collection, the purpose and procedures of the study were explained to all participants, and written informed consent was obtained. Participation was voluntary, and participants were assured that their information would remain confidential and would be analyzed anonymously.

2.2. Measures

Data were collected using a demographic and clinical information checklist and standardized self-report instruments measuring quality of life, fatigue, depression, and perceived social support. The demographic and clinical checklist included age, marital status, educational level, employment status, time since diagnosis, type of treatment received, cancer stage at diagnosis, current medication use, and history of psychological support. These variables were used to describe the sample and to provide clinical context for the interpretation of the classification model.

Quality of life was assessed using the European Organization for Research and Treatment of Cancer Quality of Life Questionnaire Core 30, version 3.0. This instrument is widely used among patients with cancer and cancer survivors and evaluates global health status and quality of life, functional status, and cancer-related symptoms. In the present study, the global health status and quality of life scale was used as the outcome variable for classification. Scores were transformed to a 0 to 100 scale according to the standard scoring procedure, with higher scores indicating better quality of life. For the purpose of support vector machine classification, participants with a global health status and quality of life score below 50 were classified as having low quality of life, whereas participants with scores of 50 or higher were classified as not having low quality of life. The validity and reliability of this instrument have been confirmed in previous cancer-related studies, including studies involving breast cancer populations.

Fatigue was measured using the Functional Assessment of Chronic Illness Therapy–Fatigue scale. This instrument assesses the intensity and impact of fatigue on daily functioning during the previous week. It contains items related to physical tiredness, weakness, lack of energy, difficulty initiating or maintaining activities, and the interference of fatigue with social and functional roles. Responses are scored on a Likert-type scale, and the total score reflects the level of fatigue-related impairment. In this study, fatigue scores were used as one of the main predictor variables in the classification model. The scale has demonstrated acceptable psychometric properties in oncology populations, and its validity and reliability have been confirmed in previous studies.

Depression was assessed using the Beck Depression Inventory-II. This questionnaire measures depressive symptoms including sadness, pessimism, loss of pleasure, self-critical thoughts, sleep disturbance, fatigue, appetite change, concentration problems, and loss of interest. The instrument consists of 21 items rated according to symptom severity, and higher total scores indicate more severe depressive symptoms. In the present study, the total depression score was entered into the predictive model as an indicator of psychological distress. The Beck Depression Inventory-II is a standard instrument in psychological and clinical research, and its validity and reliability have been confirmed in previous studies with both clinical and non-clinical populations.

Perceived social support was measured using the Multidimensional Scale of Perceived Social Support. This scale assesses perceived support from family, friends, and significant others. It includes 12 items scored on a Likert-type response format, with higher scores indicating greater perceived social support. The total score and subscale scores were considered as indicators of the survivor’s perceived interpersonal and emotional resources. In this study, perceived social support was used as a psychosocial predictor of quality of life classification. The scale has been widely used in health psychology and cancer survivorship research, and previous studies have confirmed its validity and reliability.

2.3. Data Analysis

Data analysis was performed in two main stages: preliminary statistical analysis and machine learning classification. First, the dataset was screened for missing values, outliers, and distributional characteristics. Cases with substantial missing data were excluded, while minor missing values were handled using appropriate statistical imputation based on the pattern and proportion of missingness. Descriptive statistics including mean, standard deviation, frequency, and percentage were used to summarize demographic, clinical, and psychological characteristics of the participants. The internal consistency of the study instruments was evaluated using Cronbach's alpha coefficients. Before model development, all continuous predictor variables were standardized using z-score normalization to ensure that variables measured on different scales contributed appropriately to the support vector machine model.

The target variable was low quality of life, defined according to the transformed global health status and quality of life score of the EORTC QLQ-C30. Participants with scores below 50 were coded as the low-quality-of-life group, and those with scores of 50 or higher were coded as the comparison group. Predictor variables included fatigue, depression, perceived social support, and selected demographic and clinical variables that were theoretically relevant to quality of life among breast cancer survivors. The dataset was divided into training and testing subsets using a stratified 80:20 split to preserve the proportion of participants with and without low quality of life in both subsets. Accordingly, 250 participants were used for model training and 62 participants were reserved for final model testing.

A support vector machine classifier was developed to classify participants according to low quality of life status. Because the relationship between psychological and behavioral indicators and quality of life may be nonlinear, the radial basis function kernel was used as the main kernel function. Model hyperparameters, including the regularization parameter and kernel coefficient, were optimized using grid search with cross-validation within the training dataset. Cross-validation was applied to reduce overfitting and improve the generalizability of the model. The best-performing model was then evaluated on the independent test dataset. Model performance was assessed using accuracy, sensitivity, specificity, precision, F1-score, and the area under the receiver operating characteristic curve. The confusion matrix was used to examine the number of correctly and incorrectly classified cases in each quality-of-life group. In addition, permutation-based feature importance analysis was conducted to determine the relative contribution of fatigue, depression, social support, and clinical variables to the classification of low quality of life. All analyses were conducted with appropriate statistical and machine learning software, and the level of statistical significance for inferential comparisons was set at $p < 0.05$.

3. Findings and Results

A total of 312 breast cancer survivors from Tehran were included in the final analysis. The participants had a mean age of 49.63 years with a standard deviation of 8.74 years, indicating that the sample mainly represented middle-aged adult survivors. The mean time since breast cancer diagnosis was 32.41 months with a standard deviation of 18.76 months. Most participants were married, with 214 survivors representing 68.59% of the sample, while 98 participants, equal to 31.41%, were single, widowed, divorced, or separated. Regarding education, 137 participants, equal to 43.91%, had a university-level education, while the remaining participants had diploma or lower educational attainment. In terms of employment status, 96 participants, representing 30.77% of the sample, were employed, and 216 participants, representing 69.23%, were unemployed, homemakers, retired, or on medical leave. With respect to clinical characteristics, 78 participants, equal to 25.00%, had been diagnosed at stage I, 148 participants, equal to 47.44%, at stage II, and 86 participants, equal to 27.56%, at stage III. Most participants had received more than one treatment modality; 296 participants had undergone surgery, 248 had received chemotherapy, 221 had received radiotherapy, and 196 were receiving or had received hormone therapy. Based on the predefined classification criterion using the EORTC QLQ-C30 global health status and quality of life score, 118 participants, equal to 37.82% of the sample, were classified as having low quality of life, whereas 194 participants, equal to 62.18%, were classified as not having low quality of life.

Table 1

Psychological and Quality-of-Life Indicators According to Low Quality of Life Status

Variable	Total Sample Mean ± SD	Low Quality of Life Mean ± SD	Non-Low Quality of Life Mean ± SD	Test Statistic	p-value	Effect Size
Global health status/quality of life	58.34 ± 21.06	34.78 ± 9.82	72.66 ± 13.25	t = -26.91	< 0.001	d = 3.14
Fatigue score	33.37 ± 9.41	25.43 ± 7.36	38.21 ± 7.52	t = -14.68	< 0.001	d = 1.71

Depression score	17.26 ± 9.83	24.86 ± 8.72	12.64 ± 7.04	t = 13.56	< 0.001	d = 1.58
Total perceived social support	55.48 ± 14.36	45.62 ± 12.73	61.48 ± 11.68	t = -11.23	< 0.001	d = 1.31
Family support	19.14 ± 5.67	15.83 ± 5.23	21.15 ± 4.78	t = -9.14	< 0.001	d = 1.06
Friend support	17.28 ± 5.81	13.91 ± 5.14	19.33 ± 5.12	t = -9.06	< 0.001	d = 1.06
Significant-other support	19.06 ± 5.74	15.88 ± 5.36	20.99 ± 4.91	t = -8.58	< 0.001	d = 1.00
Time since diagnosis in months	32.41 ± 18.76	31.09 ± 17.83	33.22 ± 19.29	t = -0.97	0.333	d = 0.11

As shown in Table 1, breast cancer survivors classified as having low quality of life demonstrated a clearly different psychological profile compared with survivors who were not classified in the low-quality-of-life group. The largest difference was observed in the global health status and quality of life score, which was expected because this variable was used to define the classification outcome. Participants in the low-quality-of-life group had a substantially lower mean quality-of-life score than participants in the comparison group. The two groups also differed significantly in fatigue, depression, and perceived social support. Survivors with low quality of life reported markedly lower fatigue scale scores, indicating greater fatigue burden and more severe fatigue-related impairment. They also reported considerably higher depressive symptom scores, suggesting that psychological distress was strongly associated with reduced quality of life among breast cancer survivors. In contrast, perceived social support was significantly lower among survivors with low quality of life across the total scale and all three subdomains, including family support, friend support, and significant-other support. The magnitude of the group differences was large for fatigue, depression, and perceived social support, indicating that these variables were not only statistically significant but also clinically meaningful. Time since diagnosis did not differ significantly between the two groups, suggesting that low quality of life in this sample was more strongly related to current fatigue, depressive symptoms, and perceived interpersonal resources than to the amount of time that had passed since diagnosis.

Table 2

Support Vector Machine Classification Performance for Low Quality of Life

Performance Indicator	Training Cross-Validation Mean ± SD	Independent Test Set
Accuracy	0.85 ± 0.04	0.84
Sensitivity	0.80 ± 0.06	0.79
Specificity	0.88 ± 0.05	0.87
Precision	0.81 ± 0.06	0.79
F1-score	0.80 ± 0.05	0.79
Balanced accuracy	0.84 ± 0.04	0.83
Area under the ROC curve	0.90 ± 0.03	0.90

Table 2 presents the performance of the support vector machine classifier in identifying breast cancer survivors with low quality of life. The model demonstrated strong classification performance during cross-validation and maintained a similar level of performance when applied to the independent test set, suggesting that the classifier was not merely fitted to the training data but retained acceptable generalizability. In the independent test set, the model achieved an accuracy of 0.84, meaning that 84% of participants were correctly classified as either having or not having low quality of life. The sensitivity value of 0.79 indicated that the model correctly identified 79% of survivors who truly belonged to the low-quality-of-life group. This is particularly important because false negative classifications may lead to overlooking survivors who require psychosocial or supportive care. The specificity value of 0.87 showed that the model also performed well in correctly identifying survivors who did not have low quality of life. The precision and F1-score values were both 0.79, indicating a balanced relationship between correct identification of low-quality-of-life cases and control of false positive predictions. The area under the receiver operating characteristic curve was 0.90 in the independent test set, reflecting excellent discrimination between survivors with low and non-low quality of life. Overall, the findings suggest that an SVM model using fatigue, depression, social support, and selected clinical indicators can classify low quality of life among breast cancer survivors with a high level of predictive accuracy.

Table 3

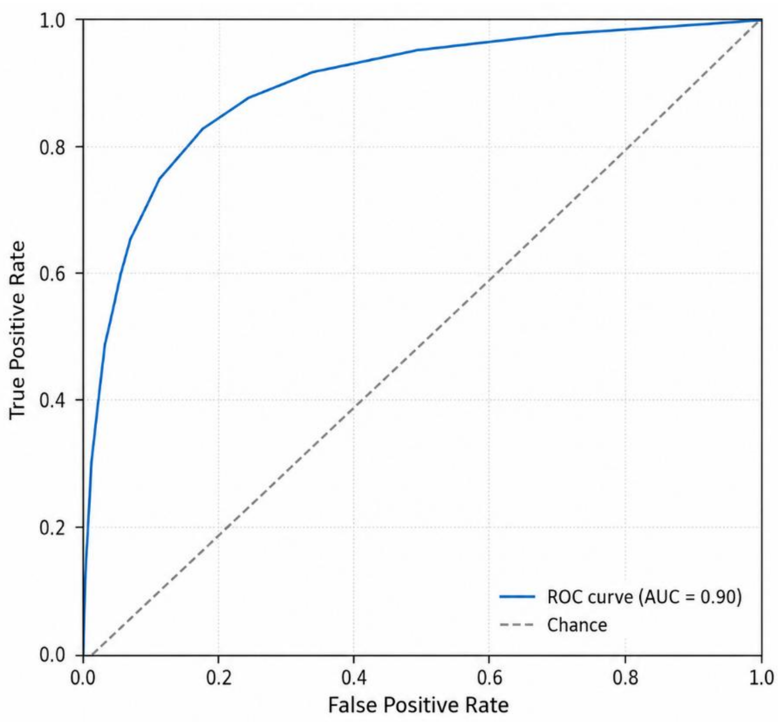
Confusion Matrix and Classification Distribution in the Independent Test Set

Actual Group	Predicted Low Quality of Life	Predicted Non-Low Quality of Life	Total
Low quality of life	19	5	24
Non-low quality of life	5	33	38
Total	24	38	62

As displayed in Table 3, the independent test set included 62 participants, of whom 24 were actual low-quality-of-life cases and 38 were actual non-low-quality-of-life cases. The support vector machine model correctly classified 19 of the 24 survivors with low quality of life and misclassified 5 survivors in this group as not having low quality of life. This indicates that the model was able to detect the majority of survivors at risk, although a small proportion of vulnerable participants were missed. Among the 38 participants who did not have low quality of life, the model correctly classified 33 and misclassified 5 as having low quality of life. These findings show that the model had a balanced classification pattern, with the same number of false positive and false negative classifications in the test set. The confusion matrix also indicates that the classifier did not obtain its performance by overpredicting one group, but rather preserved meaningful discrimination between both outcome categories. This pattern supports the practical usefulness of the model as a screening-oriented predictive tool, particularly in clinical settings where identifying survivors at risk of poor quality of life is important for referral to psychological, rehabilitation, and social support services.

Figure 1

Receiver Operating Characteristic Curve of the Support Vector Machine Model for Classifying Low Quality of Life Among Breast Cancer Survivors



The receiver operating characteristic curve demonstrated that the support vector machine model had strong discriminatory capacity across different classification thresholds. The area under the curve was 0.90 in the independent test set, indicating that the model had a high probability of assigning a greater risk score to a survivor with low quality of life than to a survivor without low quality of life. The curve showed favorable separation from the diagonal reference line, confirming that the model performed substantially better than random classification. This result supports the adequacy of the radial basis function support vector machine model for capturing nonlinear patterns among fatigue, depression, perceived social support, and quality of life status. The ROC findings further confirm that the classification model was not limited to a single decision threshold and had stable predictive value across a range of sensitivity and specificity trade-offs.

Table 4

Permutation-Based Importance of Predictors in the Final Support Vector Machine Model

Predictor Variable	Mean Decrease in Accuracy	Relative Importance Rank
Fatigue score	0.164	1
Depression score	0.139	2
Total perceived social support	0.117	3
Family support	0.071	4
Time since diagnosis	0.034	5
Cancer stage at diagnosis	0.029	6
Age	0.024	7
Type of treatment received	0.018	8

Table 4 reports the permutation-based importance of the predictors included in the final support vector machine model. Fatigue emerged as the most important predictor of low quality of life, producing the largest decrease in classification accuracy when its values were permuted. This finding indicates that fatigue was the strongest contributor to the model's ability to distinguish survivors with low quality of life from those with better quality of life. Depression was the second most important predictor, confirming the central role of depressive symptoms in the classification of reduced quality of life among breast cancer survivors. Total perceived social support ranked third, showing that social and interpersonal resources provided meaningful predictive information beyond symptom burden and psychological distress. Among the social support dimensions, family support had the highest contribution, suggesting that perceived support from family may be particularly relevant in the survivorship context. Clinical and demographic variables, including time since diagnosis, cancer stage at diagnosis, age, and treatment type, had lower relative importance compared with the psychosocial variables. These findings suggest that current subjective and psychological conditions, especially fatigue, depression, and perceived support, were more informative for classifying low quality of life than basic clinical background variables alone. Therefore, the final model supports a biopsychosocial interpretation of quality of life among breast cancer survivors, in which symptom burden, emotional distress, and perceived relational support jointly contribute to the identification of survivors at greater risk for poor quality of life.

4. Discussion

The present study aimed to classify low quality of life among breast cancer survivors in Tehran using a support vector machine model based on fatigue, depression, and perceived social support indicators. The findings showed that 37.82% of the participants were classified as having low quality of life according to the predefined EORTC QLQ-C30 global health status and quality-of-life cut-off. This proportion indicates that a considerable subgroup of breast cancer survivors continued to experience compromised well-being after the main phase of treatment, despite being in the survivorship period. This result is consistent with the broader survivorship literature, which emphasizes that breast cancer survival does not necessarily imply full restoration of physical, psychological, and social functioning. Previous studies have shown that quality of life among breast cancer survivors is affected by prolonged symptoms, psychosocial distress, treatment-related complications, lifestyle factors, and survivorship care resources (Culbertson et al., 2020; Davis & Snyder, 2024). The finding also aligns with longitudinal evidence showing that quality of life after breast cancer treatment follows heterogeneous trajectories, meaning that some survivors recover relatively well while others remain vulnerable to persistent reductions in well-being (Boivin et al., 2021; Park et al., 2023). Therefore, the identification of a sizeable low-quality-of-life subgroup in the current study supports the need for systematic screening after treatment completion rather than assuming that survivorship is uniformly associated with recovery.

The descriptive and comparative findings showed that survivors with low quality of life had significantly greater fatigue burden, higher depression scores, and lower perceived social support than survivors who were not classified as having low quality of life. Among these variables, fatigue demonstrated one of the strongest group differences and later emerged as the most important predictor in the support vector machine model. This finding is highly consistent with prior evidence identifying cancer-related fatigue as one of the most persistent and disabling symptoms among breast cancer survivors. Jang and colleagues reported that prolonged symptoms among Korean breast cancer survivors were closely related to quality-of-life impairment, supporting the view that symptom persistence is a major determinant of survivorship well-being (Jang et al., 2020). The importance of fatigue is also supported by studies linking fatigue with treatment-related complications such as lymphedema, particularly after axillary lymph node dissection, where fatigue and physical burden may jointly reduce quality of life (Özşaker, 2025). In the same direction, literature on breast cancer-related lymphedema has emphasized that physical complications can produce psychosocial consequences, including reduced activity, distress, altered body image, and impaired participation (Eaton et al., 2020). The current result therefore suggests that fatigue should not be interpreted merely as a secondary symptom, but as a central clinical marker for identifying survivors at risk for poor quality of life.

Depression was also significantly higher among survivors with low quality of life and ranked as the second most important feature in the support vector machine model. This finding confirms the central role of psychological distress in breast cancer survivorship. Depression can influence quality of life directly through sadness, hopelessness, anhedonia, negative self-perception, and reduced motivation, and indirectly through sleep disturbance, reduced physical activity, impaired social interaction, and poorer self-management. The current result is strongly aligned with the 12-month follow-up study by Ribeiro and colleagues, which showed that breast cancer survivors with persistent depressive symptoms had poorer quality of life than those without persistent depressive symptoms (Ribeiro et al., 2023). It is also consistent with scoping evidence indicating that psychosocial determinants, including emotional distress and coping resources, are essential components of quality of life among breast cancer survivors (Culbertson et al., 2020). Research on young breast cancer survivors has similarly shown that psychological factors are important predictors of quality of life and life satisfaction, reinforcing the relevance of depression for survivorship adjustment (Martens et al., 2021). Although Ferguson and colleagues examined self-reported cognitive impairments in another cancer population, their findings support the broader oncology principle that subjective psychological and cognitive burdens are closely tied to reduced quality of life (Ferguson et al., 2022). Thus, the present findings support the integration of depression screening into breast cancer survivorship care, particularly for survivors reporting fatigue and diminished functioning.

Perceived social support was significantly lower among survivors with low quality of life, and the model showed that total perceived social support had meaningful predictive value beyond fatigue and depression. This finding supports the biopsychosocial interpretation of quality of life in cancer survivorship. Social support may protect quality of life by improving emotional regulation, reducing loneliness, strengthening coping, supporting treatment adherence, and facilitating practical assistance in daily life. In the current study, family support also contributed to classification, suggesting that family-based resources may be particularly relevant in the Iranian context, where family involvement often plays an important role in illness management and emotional support. This result is consistent with evidence showing that quality of life after breast cancer treatment is influenced by interpersonal, psychosocial, and contextual determinants (Maharani et al., 2023; Park et al., 2021). It also aligns with research emphasizing that culturally responsive, community-based interventions can engage breast cancer survivors and support survivorship outcomes, particularly when programs are adapted to survivors' social and cultural contexts (AuBuchon et al., 2025). More broadly, studies from South Asia and other non-Western contexts have shown that quality of life among cancer survivors is shaped by social, cultural, and healthcare-related factors, supporting the importance of contextualized models of survivorship care (Azam et al., 2021; D'Souza, 2021; Rauf et al., 2024).

The support vector machine classifier demonstrated strong predictive performance, with an independent test accuracy of 0.84 and an area under the receiver operating characteristic curve of 0.90. Sensitivity was 0.79 and specificity was 0.87, indicating that the model was able to identify most survivors with low quality of life while also maintaining good discrimination among survivors without low quality of life. This result is important because clinical prediction in survivorship care requires more than identifying average associations; it requires distinguishing individuals who are likely to need additional assessment or intervention. The high AUC value suggests that the combined pattern of fatigue, depression, social support, and selected clinical indicators provided strong separation between low and non-low quality-of-life groups. This supports the increasing relevance of data-driven and technology-supported approaches in cancer survivorship. The PERSIST study protocol, for example, reflects growing interest in patient-centered survivorship care plans supported by big data and artificial intelligence technologies (Mlakar et al., 2021). Similarly, reviews of connected health interventions, telehealth approaches, mobile applications, and evidence-based digital health interventions indicate that survivorship care is moving toward more scalable, personalized, and technology-enabled models (Gitonga et al., 2022; Hwang et al., 2020; Jiménez-Díaz et al., 2025; Saevarsdottir & Guðmundsdóttir, 2023). The present study contributes to this direction by demonstrating that a machine learning classifier can use clinically meaningful psychosocial indicators to identify breast cancer survivors at risk for low quality of life.

The feature-importance findings further showed that fatigue, depression, and social support were more influential than basic demographic and clinical variables such as age, cancer stage, treatment type, and time since diagnosis. This does not mean that clinical factors are irrelevant; rather, it suggests that current subjective symptom burden and psychosocial resources may be more proximal indicators of quality of life than static clinical background variables. This interpretation is compatible with prior work showing that lifestyle, physical activity, emotional status, sleep, and psychosocial functioning are strongly related to survivorship outcomes (Agussalim et al., 2024; Meglio et al., 2021; Misiąg et al., 2022). The relatively lower importance of time since diagnosis in the present model also corresponds with the idea that survivorship quality of life is not determined only by chronological time after treatment but by the survivor's ongoing symptom and psychosocial profile. Park and colleagues demonstrated that quality of life during the first year after treatment may follow different patterns, indicating that time alone is insufficient to characterize survivorship recovery (Park et al., 2023). The present findings therefore suggest that clinicians should prioritize current fatigue, mood, and support indicators when attempting to identify survivors with low quality of life.

The results also correspond with intervention studies showing that quality of life among breast cancer survivors can be improved through approaches that target physical activity, fatigue, emotional distress, and psychosocial engagement. Exercise and movement-based interventions, including Tai Chi Chuan, dance interventions, and Argentine tango, have been associated with improvements in quality of life, fatigue, and psychological factors among breast cancer survivors (Chen et al., 2026; Luo et al., 2020; Oei et al., 2023; Schad et al., 2023). Peer-led physical activity programs and wearable activity tracking interventions further suggest that behavioral activation and self-monitoring may improve psychosocial outcomes and support healthier survivorship patterns (Pan et al., 2024; Pinto et al., 2024). During the COVID-19 pandemic, changes in physical activity were associated with physical and mental health among breast cancer survivors, reinforcing the role of daily activity patterns in maintaining quality of life (Tamai et al., 2024). The finding that fatigue was the strongest predictor in the present model supports the clinical relevance of such interventions, particularly those that combine activity regulation, gradual movement, and fatigue management.

Psychological and supportive interventions are also relevant to the interpretation of the present results. Cognitive behavioral therapy integrated with activity pacing has been proposed for fatigued breast cancer patients, supporting the idea that fatigue and psychological distress should be addressed together rather than separately (Chen et al., 2021). Mindfulness-based interventions in oncology have also been reviewed as strategies for improving psychological outcomes and quality of life, particularly by targeting distress regulation, acceptance, attention, and coping (Chen et al., 2025). Sleep disturbance is another important factor because it can intensify both fatigue and depression; conceptual work on sleep disorder among breast cancer patients supports the interconnectedness of sleep, symptoms, and quality of life (Aini et al., 2022). Restorative and nature-based models, such as forest-environment living lab approaches, also suggest that psychological health among cancer survivors may benefit from interventions that address environmental and experiential dimensions of recovery (Kim et al., 2024). These studies collectively support the current model’s emphasis on psychosocial and symptom indicators as key components of low-quality-of-life classification.

5. Conclusion

The findings highlight the importance of measurement and model design in survivorship research. Jang and colleagues emphasized that disease-specific and generic instruments may capture different aspects of quality of life among breast cancer survivors, making instrument selection critical when studying survivorship outcomes (Jang et al., 2022). In the current study, the classification outcome was defined using the global health status and quality-of-life score, which provided a clinically interpretable distinction between survivors with low and non-low quality of life. However, the strong performance of the support vector machine model suggests that brief psychosocial indicators may be useful for screening even when comprehensive quality-of-life assessment is not feasible. Prior research on posttreatment cancer survivors has also shown that quality of life is associated with multiple demographic, clinical, and psychosocial factors, indicating that multidimensional models are needed to capture survivor vulnerability (Kim et al., 2023). Therefore, the present study supports a predictive survivorship framework in which fatigue, depression, and social support are not only outcomes of interest but also practical indicators for risk classification.

6. Limitations & Suggestions

The main limitation of this study was its cross-sectional design, which prevents causal interpretation of the relationships among fatigue, depression, social support, and low quality of life. Although the support vector machine model classified low quality of life with strong accuracy, the findings cannot determine whether fatigue and depression caused low quality of life, whether low quality of life intensified symptom perception, or whether reciprocal relationships existed among the variables. The use of convenience sampling from Tehran also limits the generalizability of the findings to breast cancer survivors in other cities, rural areas, healthcare systems, or cultural contexts. In addition, the study relied on self-report instruments, which may be influenced by recall bias, response style, emotional state at the time of assessment, or social desirability. The classification cut-off used to define low quality of life was clinically interpretable, but different cut-off points or quality-of-life instruments may produce different group distributions and model performance. Finally, although the test-set results were promising, external validation in an independent sample was not performed.

Future studies should use longitudinal designs to examine whether fatigue, depression, and perceived social support predict future changes in quality of life among breast cancer survivors. Repeated assessment across multiple survivorship phases would help clarify whether machine learning models can detect early risk patterns before quality of life declines. Future research should also validate the current model in larger, multicenter samples from different regions and healthcare settings to evaluate its generalizability. Incorporating additional predictors such as sleep quality, pain, fear of recurrence, cognitive complaints, physical activity, lymphedema severity, endocrine therapy side effects, socioeconomic status, and healthcare access may improve predictive accuracy and clinical interpretability. Comparative studies should also test support vector machine models against other algorithms, such as random forest, gradient boosting, logistic regression, and neural networks, to determine the most accurate and explainable approach. Further research should also examine whether explainable machine learning techniques can make predictive models more transparent and acceptable for clinical decision-making.

In practice, the findings suggest that breast cancer survivorship care should include routine screening for fatigue, depressive symptoms, and perceived social support. Survivors identified as being at risk for low quality of life should receive timely referral to psychological counseling, fatigue management programs, rehabilitation services, physical activity interventions, and family-centered support resources. Oncology nurses, psychologists, rehabilitation specialists, and physicians can use brief psychosocial assessment tools to identify survivors who may appear clinically stable but continue to experience substantial impairment in daily life. The results also support the development of digital or clinic-based screening systems that automatically flag survivors with high fatigue, high depression, and low social support for further evaluation. In settings with limited resources, such predictive screening may help prioritize supportive care for survivors most likely to benefit from intervention, thereby improving the efficiency and patient-centeredness of survivorship services.

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Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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Authors' Contributions

All authors equally contributed to this article.

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