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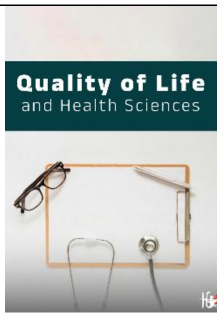

Machine Learning Classification of Quality of Life Risk Profiles Among Stroke Survivors Using Support Vector Machine and Decision Tree Algorithms

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ABSTRACT

Objective: This study aimed to classify quality of life risk profiles among stroke survivors in Armenia using Support Vector Machine and Decision Tree algorithms and to identify the most influential clinical, functional, psychological, and sleep-related predictors of high-risk quality of life status.

Methods and Materials: This cross-sectional predictive modeling study was conducted on 426 stroke survivors recruited from neurological, rehabilitation, and post-stroke care centers in Armenia. Data were collected using a demographic and clinical information form, the Stroke-Specific Quality of Life Scale, Barthel Index, Modified Rankin Scale, National Institutes of Health Stroke Scale, Patient Health Questionnaire-9, Generalized Anxiety Disorder-7, and Pittsburgh Sleep Quality Index. Participants were classified into high-risk, moderate-risk, and low-risk quality of life profiles. The dataset was divided into training and testing sets using stratified sampling. Support Vector Machine and Decision Tree models were trained, optimized through cross-validation, and evaluated using accuracy, precision, recall, F1-score, area under the curve, and confusion matrix indices.

Findings: Significant differences were observed among the three quality of life risk profiles in neurological severity, disability, functional independence, depressive symptoms, anxiety symptoms, sleep quality, and total quality of life scores ($p < 0.001$). The Support Vector Machine model showed superior cross-validation performance compared with the Decision Tree model, with higher accuracy, macro F1-score, and macro AUC. In the testing set, the Support Vector Machine achieved a macro precision of 0.82, macro recall of 0.82, macro F1-score of 0.82, and macro AUC of 0.90. The Decision Tree achieved a macro precision of 0.73, macro recall of 0.74, macro F1-score of 0.74, and macro AUC of 0.81. Functional independence, global disability, depressive symptoms, sleep quality, neurological severity, and anxiety symptoms were the most important predictors.

Conclusion: Machine learning models, particularly Support Vector Machine, can effectively classify quality of life risk profiles among stroke survivors and may support individualized rehabilitation planning by identifying patients at greater risk for poor post-stroke quality of life.

Keywords: *Stroke Survivors; Quality of Life; Machine Learning; Support Vector Machine; Decision Tree; Functional Independence; Post-Stroke Depression*

1. Introduction

Stroke remains one of the most consequential neurological conditions worldwide because its effects extend far beyond the acute cerebrovascular event and frequently lead to long-term physical, psychological, cognitive, social, and occupational limitations. Although advances in emergency care, vascular risk management, rehabilitation, and secondary prevention have improved survival, many stroke survivors continue to experience persistent impairment in everyday functioning and reduced health-related quality of life. Quality of life after stroke is a multidimensional construct that reflects not only neurological recovery but also functional independence, emotional adjustment, cognitive ability, social participation, perceived control, family support, and the capacity to resume meaningful life roles. For this reason, contemporary stroke outcome assessment has increasingly moved beyond mortality and impairment-based indices toward patient-centered indicators that capture how survivors live with and adapt to post-stroke consequences (Chen et al., 2023; Kariyawasam & Pathirana, 2020; Lalu, 2021).

Health-related quality of life among stroke survivors is shaped by a complex interaction of clinical and non-clinical determinants. Functional disability is consistently identified as one of the strongest predictors of quality of life, because reduced independence in activities of daily living limits autonomy, increases dependence on caregivers, and restricts participation in family and community roles. Studies conducted in different contexts have shown that lower functional independence, greater post-stroke disability, and reduced physical activity are associated with poorer quality of life outcomes among stroke survivors (Ana Railka de Souza et al., 2023; Ellepola et al., 2022; Ogwumike et al., 2021). Similarly, research on changes in functional independence after ischemic stroke has emphasized that recovery trajectories are heterogeneous and that patients with slower or incomplete functional improvement may remain vulnerable to reduced long-term well-being (Yun et al., 2020). These findings suggest that functional status should be considered a central feature in classifying quality of life risk profiles after stroke.

However, quality of life after stroke cannot be fully explained by physical disability alone. Depression, anxiety, fatigue, perceived stress, sleep disturbance, and reduced psychological resilience are common after stroke and may independently reduce quality of life even when physical recovery is relatively favorable. Post-stroke depression has been widely reported as a major determinant of poorer adjustment, lower motivation for rehabilitation, decreased treatment adherence, and reduced participation in daily life (Kuma et al., 2025; Selvaraj et al., 2021). Anxiety is also a clinically relevant post-stroke outcome, and one-year follow-up evidence indicates that post-stroke anxiety can persist after rehabilitation and contribute to continuing emotional burden (Kuptniratsaikul et al., 2022). Studies among young adults and broader stroke populations further show that depression and anxiety are strongly associated with health-related quality of life, indicating that psychological symptoms should not be treated as secondary complications but as core components of post-stroke outcome assessment (Chaudhury & Rohatgi, 2024; Ignacio et al., 2023).

The psychosocial context of stroke recovery is equally important. Stroke affects not only the survivor but also caregivers, spouses, and family systems. Caregiver burden, caregiver depression, and psychosocial strain may influence the survivor's adjustment, cognitive outcomes, treatment engagement, and overall quality of life. Evidence from caregiver-focused studies indicates that the quality of life of stroke survivors and informal caregivers is interconnected, particularly when dependency levels are high and psychological distress is present (Khan et al., 2024; Moura et al., 2021). Dyadic research has further shown that disability, depression, social support, and quality of life interact within couples affected by stroke, highlighting the relational nature of post-stroke adaptation (Liu et al., 2025). Similarly, caregiver psychosocial factors have been linked to cognitive outcomes among stroke survivors, suggesting that quality of life risk may emerge from a broader social and caregiving ecology rather than from individual clinical factors alone (Blake et al., 2025). These findings justify the inclusion of social support, caregiver-related variables, and participation indicators in predictive models of post-stroke quality of life.

Social participation and role reintegration represent another important domain of quality of life after stroke. Stroke survivors often experience restrictions in mobility, employment, interpersonal relations, leisure participation, and community engagement. Participation restriction is strongly connected to perceived social support and health-related quality of life, and narrative evidence has emphasized that survivors who experience reduced social participation may report lower well-being even when basic physical functioning has improved (Darmadi et al., 2023). Return to work is one particularly meaningful indicator of social and functional reintegration. Qualitative evidence among stroke survivors has shown that contextual health conditions and social barriers may influence the possibility of returning to work and maintaining social identity after stroke (Naidoo et al., 2025). Therefore, quality of life risk profiles should be understood as reflecting the interaction of impairment, activity limitations, participation restriction, and psychosocial reintegration.

Existing evidence also indicates that the determinants of post-stroke quality of life may differ by age group, stroke subtype, time since stroke, and cultural or healthcare context. Young adult stroke survivors may face unique challenges related to employment, family responsibilities, identity disruption, and long-term participation expectations (Gurková et al., 2023). Patients with mild residual deficits may still experience reduced health-related quality of life because subtle impairments, emotional distress, and reduced participation can remain clinically meaningful despite apparently favorable neurological recovery (Gurková et al., 2022). In addition, studies from diverse countries and healthcare systems demonstrate that the relationship between stroke-related impairment and quality of life is influenced by rehabilitation access, social support, economic conditions, and cultural expectations of care (Kumar et al., 2021; Lourenço et al., 2021; Rosa et al., 2023). These findings are important because they suggest that predictive modeling should not assume a single universal pathway to poor quality of life but should identify empirically derived risk patterns within specific populations.

Longitudinal and follow-up studies further show that quality of life after stroke remains dynamic over time. Survivors may experience improvement as functional recovery progresses, but they may also face delayed psychological distress, persistent fatigue, cognitive difficulties, recurrent medical problems, and social disengagement. Five-year follow-up evidence has shown that health-related quality of life can remain impaired long after the initial event, indicating that post-stroke care should include long-term monitoring rather than short-term discharge-based assessment only (Segerdahl et al., 2023). Cognitive impairment also plays a significant role in quality of life and caregiver outcomes, as post-stroke cognition is associated with both survivor well-being and caregiver burden (Stolwyk et al., 2024). Evidence from studies of subarachnoid hemorrhage and intracerebral hemorrhage survivors similarly underscores the need to assess broader quality of life outcomes across different cerebrovascular conditions, not only ischemic stroke (Banjar et al., 2023; Harvey et al., 2025). Together, these studies support a multidimensional approach to post-stroke risk classification that includes physical, cognitive, psychological, and social variables.

Measurement of quality of life after stroke requires instruments that are sensitive to stroke-specific functional and psychosocial consequences. The development and validation of stroke-specific quality of life measures have contributed to more precise assessment of survivors' needs and outcomes. The construction and validation of the 17-item Stroke-Specific Quality of Life Scale illustrates the effort to produce comprehensive but efficient measures that capture functional, psychosocial, and therapeutic dimensions of life after stroke (Sakr et al., 2022b). Related research on post-stroke pharmacotherapy adherence also shows that treatment-related behavior may be connected with clinical outcomes and quality of life, reinforcing the importance of integrating behavioral and therapeutic factors into post-stroke assessment (Sakr et al., 2022a). These measurement advances provide a foundation for predictive models that classify patients into meaningful risk profiles rather than relying only on global clinical impressions.

Systematic reviews and meta-analyses have synthesized the predictors and modifiable determinants of post-stroke quality of life. A systematic review with meta-analysis identified several predictors of health-related quality of life one year after stroke, emphasizing the importance of functional status, emotional symptoms, and other clinical characteristics (Silva et al., 2024). Evidence on non-pharmacological interventions indicates that rehabilitation, psychosocial support, exercise-based programs, and other non-drug interventions can improve quality of life among stroke survivors, suggesting that risk classification may have direct implications for intervention targeting (Gao et al., 2024). Multicomponent exercise interventions have also been associated with improvements in quality of life, depression, and anxiety, further showing that functional and psychological outcomes are interrelated and potentially modifiable (Song et al., 2023). These findings support the clinical value of identifying survivors who are at high risk for poor quality of life, because early classification may guide individualized rehabilitation planning, psychological screening, and integrated post-stroke care.

Despite the growing evidence base, traditional statistical approaches have several limitations when applied to quality of life prediction after stroke. Many studies use linear models that estimate the independent contribution of selected predictors, but quality of life is often determined by nonlinear, interactive, and threshold-based relationships among multiple variables. For example, the effect of depression on quality of life may differ according to disability level, social support, physical capability, or perceived control. Recent evidence has shown that the association between physical capability and quality of life may involve both mediation and moderation mechanisms, indicating that simple direct-effect models may not fully represent the complexity of post-stroke well-being (Yang et al., 2025). Similarly, cross-sectional evidence has emphasized associations among health-related quality of life, emotional disturbances, physical functionality, and perceived control, reinforcing the need for analytical approaches capable of handling multivariable and interactive patterns (Ghazali et al., 2025). This complexity creates a strong rationale for the use of machine learning methods in post-stroke quality of life research.

Machine learning offers a flexible framework for classifying stroke survivors into risk profiles based on multidimensional predictor sets. Unlike conventional models that focus primarily on estimating average associations, supervised machine learning algorithms can learn patterns from clinical, functional, psychological, demographic, and social variables and use those patterns to classify individuals into clinically meaningful outcome groups. Support Vector Machine algorithms are particularly useful when the boundary between outcome classes is complex, because they can model nonlinear separations through kernel-based transformations. Decision Tree algorithms, although sometimes less accurate than more complex models, provide transparent classification rules that may be easier for clinicians to interpret. The application of machine learning to predict quality of life subtypes among disabled stroke survivors has already shown that data-driven methods can identify meaningful quality of life categories and support more individualized post-stroke care (Xu et al., 2023). This emerging evidence indicates that machine learning can contribute to precision rehabilitation by identifying which survivors are most likely to belong to high-risk, moderate-risk, or low-risk quality of life profiles.

The use of machine learning is also consistent with the broader movement toward personalized and patient-centered stroke care. Personalized medicine frameworks emphasize that prevention, treatment, and rehabilitation should be tailored to patient-specific risk factors, preferences, and expected outcomes (Harvey et al., 2025). In stroke rehabilitation, this means that two survivors with similar neurological diagnoses may require different care pathways depending on functional independence, emotional symptoms, caregiver context, sleep quality, participation restriction, and social resources. Broader quality of life research among serious illness survivors also suggests that multidimensional post-acute outcomes require integrated risk assessment rather than reliance on single indicators (Лихванцев et al., 2022). Therefore, machine learning classification may provide a practical bridge between multidimensional assessment and individualized clinical decision-making.

Although international research has increasingly examined post-stroke quality of life and its predictors, evidence from Armenia and similar regional contexts remains limited. Health systems, rehabilitation availability, family caregiving patterns, socioeconomic conditions, and cultural expectations may influence both the experience of stroke recovery and the predictors of poor quality of life. Consequently, models developed in one country may not generalize directly to another population without local validation. Investigating quality of life risk profiles among Armenian stroke survivors can provide context-specific evidence for rehabilitation planning and may contribute to the international literature by extending machine learning approaches to an underrepresented setting. By comparing Support Vector Machine and Decision Tree algorithms, the present study also addresses both predictive performance and interpretability, which are essential for translating machine learning findings into clinical practice.

The aim of this study was to classify quality of life risk profiles among stroke survivors in Armenia using Support Vector Machine and Decision Tree algorithms and to identify the clinical, functional, psychological, sleep-related, and demographic predictors most strongly associated with high-risk quality of life status.

2. Methods and Materials

2.1. Study Design and Participants

This study was designed as a cross-sectional predictive modeling study aimed at classifying health-related quality of life risk profiles among stroke survivors using supervised machine learning algorithms. The study population consisted of adult stroke survivors receiving outpatient neurological follow-up, rehabilitation services, or post-stroke care in selected medical and rehabilitation centers in Armenia. Participants were recruited from neurology clinics, rehabilitation departments, and community-based stroke follow-up services in Yerevan and other urban regions of

Armenia. The final sample included 426 stroke survivors who met the eligibility criteria and completed the required assessments. Inclusion criteria were age 18 years or older, confirmed diagnosis of ischemic or hemorrhagic stroke based on medical records, at least three months having passed since the most recent stroke event, ability to communicate sufficiently to complete the questionnaires either independently or with researcher assistance, and willingness to participate in the study. Participants were excluded if they had severe cognitive impairment that prevented valid questionnaire completion, recurrent acute neurological instability, severe aphasia without reliable caregiver-assisted reporting, diagnosed major psychiatric or neurodegenerative disorders unrelated to stroke, or incomplete data on the main quality of life outcome. All participants were informed about the purpose of the study, confidentiality of their responses, and voluntary nature of participation before providing written informed consent. The study was conducted in accordance with ethical principles for human research, and all data were anonymized before statistical and machine learning analyses.

2.2. Measures

Data were collected using a structured demographic and clinical information form, standardized stroke-related assessment measures, and validated psychological and quality of life instruments. The demographic and clinical form was developed by the research team to record age, sex, marital status, educational level, employment status, place of residence, type of stroke, time since stroke onset, number of previous stroke events, affected side of the body, comorbid medical conditions, medication use, rehabilitation history, smoking status, and level of social support. Clinical information was verified, when available, through medical records and rehabilitation files. These variables were included as potential predictors in the machine learning models because post-stroke quality of life is influenced by demographic, neurological, functional, behavioral, and psychosocial factors.

Health-related quality of life was measured using the Stroke-Specific Quality of Life Scale. This instrument evaluates quality of life domains that are particularly relevant to stroke survivors, including energy, family roles, language, mobility, mood, personality, self-care, social roles, thinking, upper-extremity function, vision, and work/productivity. Items are rated on a five-point scale, with higher scores indicating better quality of life. For the purpose of machine learning classification, the total quality of life score was used to derive quality of life risk profiles. Participants were classified into low-risk, moderate-risk, and high-risk quality of life profiles according to the distribution of total scores and clinically meaningful impairment patterns. Lower scores represented greater risk for poor quality of life, whereas higher scores represented more favorable post-stroke adjustment and functioning. The scale was selected because it captures both physical and psychosocial dimensions of life after stroke and provides a comprehensive outcome measure for predictive classification.

Functional independence was assessed using the Barthel Index, which measures the participant's ability to perform basic activities of daily living, including feeding, bathing, grooming, dressing, bowel control, bladder control, toilet use, transfers, mobility, and stair climbing. Higher scores indicate greater independence in daily functioning. Stroke-related disability was assessed using the Modified Rankin Scale, which evaluates global disability and dependence after stroke. Neurological severity was recorded using the National Institutes of Health Stroke Scale when available in clinical records or through trained clinical assessment. These functional and neurological indicators were included as predictor variables because limitations in mobility, self-care, and neurological functioning are central determinants of post-stroke quality of life.

Psychological symptoms were measured using the Patient Health Questionnaire-9 for depressive symptoms and the Generalized Anxiety Disorder-7 scale for anxiety symptoms. The Patient Health Questionnaire-9 includes nine items assessing the frequency of depressive symptoms over the previous two weeks, with higher scores indicating greater depressive symptom severity. The Generalized Anxiety Disorder-7 scale includes seven items evaluating anxiety-related symptoms, also with higher scores indicating greater severity. Sleep quality was assessed using the Pittsburgh Sleep Quality Index, which measures subjective sleep quality, sleep latency, sleep duration, sleep efficiency, sleep disturbance, use of sleep medication, and daytime dysfunction. These psychological and sleep-related variables were included because emotional distress and sleep disturbance are common after stroke and may substantially increase the risk of impaired quality of life.

2.3. Data Analysis

Data analysis was conducted in two main stages: conventional descriptive analysis and supervised machine learning classification. First, the dataset was inspected for accuracy, missing values, outliers, and distributional characteristics. Missing data were evaluated at the item and scale levels. Cases with missing values on the primary quality of life outcome were excluded, while missing predictor values were handled using appropriate imputation procedures based on the type and distribution of the variable. Continuous variables were summarized using means and standard deviations, and categorical variables were summarized using frequencies and percentages. Before model development, categorical predictors were encoded, continuous predictors were standardized where required, and all preprocessing steps were applied within the training data to prevent data leakage.

The target variable for machine learning analysis was the quality of life risk profile, categorized into low-risk, moderate-risk, and high-risk groups based on Stroke-Specific Quality of Life Scale scores. The full dataset of 426 participants was divided into training and testing subsets using stratified sampling to preserve the proportional distribution of the three quality of life risk classes. Seventy percent of the sample was allocated to the training set and thirty percent to the testing set. The training set included 298 participants and was used for model development, hyperparameter tuning, and internal validation, while the testing set included 128 participants and was used only for final model evaluation.

Two supervised machine learning algorithms were developed and compared: Support Vector Machine and Decision Tree. The Support Vector Machine model was trained using both linear and radial basis function kernel options, and the final kernel was selected based on cross-validation performance. Hyperparameters, including the regularization parameter and kernel coefficient, were optimized through grid search using repeated k-fold cross-validation within the training set. Because Support Vector Machine models are sensitive to feature scaling, all continuous predictor variables were standardized before model fitting. The Decision Tree classifier was developed as an interpretable comparison model, with tuning of maximum tree depth, minimum samples per split, minimum samples per leaf, and splitting criterion to reduce overfitting and improve generalizability. Pruning procedures and cross-validation were used to identify the most stable tree structure.

Model performance was evaluated using accuracy, precision, recall, F1-score, and confusion matrix values for each quality of life risk class. Because the identification of participants at high risk for poor quality of life was clinically important, recall and F1-score for the high-risk class were given particular attention in model interpretation. Macro-averaged and weighted-averaged performance indices were calculated to assess classification performance across all classes. Receiver operating characteristic analysis and area under the curve values were computed using a one-vs-rest approach for multiclass classification. Feature importance was examined for the Decision Tree model, while permutation-based importance was used to estimate the relative contribution of predictors in the Support Vector Machine model. The final interpretation focused on the comparative classification performance of the two algorithms and on identifying the demographic, clinical, functional, psychological, and sleep-related predictors most strongly associated with poor quality of life risk profiles among Armenian stroke survivors.

3. Findings and Results

A total of 426 stroke survivors from Armenia were included in the final analysis. The mean age of the participants was 62.84 years with a standard deviation of 10.91 years, and the age range was 34 to 86 years. Of the total sample, 233 participants were male, representing 54.69% of the sample, and 193 participants were female, representing 45.31%. Most participants were married, with 281 individuals reporting married status, while 145 participants were single, widowed, divorced, or separated. Regarding educational status, 97 participants had primary or lower-secondary education, 162 had completed secondary education, and 167 had university-level education. In terms of occupational status, 108 participants were employed, 120 were unemployed or unable to work because of post-stroke limitations, and 198 were retired. Most participants lived in urban areas, particularly Yerevan and surrounding urban regions, while a smaller proportion came from semi-urban or rural areas. Ischemic stroke was the most common stroke type, reported in 331 participants, whereas 95 participants had experienced hemorrhagic stroke. The mean time since the most recent stroke event was 14.72 months with a standard deviation of 9.38 months. Most participants had experienced a first-ever stroke, while a smaller group reported recurrent stroke. Right-sided motor involvement was reported by 183 participants, left-sided involvement by 166 participants, and bilateral or non-lateralized neurological involvement by 77 participants. A total of 309 participants had received at least one form of rehabilitation service after stroke, whereas 117 had not received regular rehabilitation. Hypertension was the most frequently reported comorbidity, followed by dyslipidemia, cardiovascular disease, and diabetes mellitus. Based on the Stroke-Specific Quality of Life Scale classification used in the present study, 133 participants were classified as having a high-risk quality of life profile, 169 participants as having a moderate-risk profile, and 124 participants as having a low-risk profile.

Table 1

Clinical, functional, psychological, sleep-related, and quality of life characteristics according to quality of life risk profile

Variable	High-risk profile (n = 133) Mean ± SD	Moderate-risk profile (n = 169) Mean ± SD	Low-risk profile (n = 124) Mean ± SD	F	p-value
Time since stroke, months	18.21 ± 10.36	14.58 ± 8.91	11.18 ± 7.64	18.47	<0.001
NIHSS score	8.49 ± 3.26	5.71 ± 2.64	3.28 ± 1.91	124.62	<0.001
Modified Rankin Scale score	3.21 ± 0.75	2.35 ± 0.68	1.52 ± 0.61	214.39	<0.001
Barthel Index score	52.43 ± 15.88	68.95 ± 14.26	84.37 ± 10.94	176.58	<0.001
PHQ-9 depression score	14.87 ± 5.11	9.56 ± 4.37	5.21 ± 3.08	168.73	<0.001
GAD-7 anxiety score	11.36 ± 4.42	7.88 ± 3.71	4.62 ± 2.86	111.24	<0.001
Pittsburgh Sleep Quality Index score	10.24 ± 3.52	7.34 ± 3.05	5.19 ± 2.43	93.81	<0.001
Stroke-Specific Quality of Life total score	126.35 ± 22.41	167.82 ± 18.96	211.45 ± 20.17	628.46	<0.001
Physical domain score	58.74 ± 13.65	77.91 ± 12.48	99.36 ± 13.14	361.28	<0.001
Psychosocial domain score	67.61 ± 14.29	89.91 ± 13.21	112.09 ± 12.83	398.72	<0.001

Table 1 shows clear and statistically significant differences among the three quality of life risk profiles across all clinical, functional, psychological, sleep-related, and quality of life indicators. Participants in the high-risk profile had the longest time since stroke, the highest neurological severity scores, the highest disability levels, and the lowest functional independence scores. The mean NIHSS score was 8.49 in the high-risk group compared with 5.71 in the moderate-risk group and 3.28 in the low-risk group, indicating that greater neurological impairment was associated with poorer quality of life classification. Similarly, the Modified Rankin Scale score was highest in the high-risk group, whereas the Barthel Index score was lowest in this group, showing that higher disability and lower independence in activities of daily living were strongly related to high-risk quality of life status. Psychological distress also differed substantially across the three profiles. Participants in the high-risk group reported the highest levels of depressive symptoms, anxiety symptoms, and poor sleep quality, whereas participants in the low-risk group reported the most favorable psychological and sleep-related scores. The Stroke-Specific Quality of Life total score showed the largest between-group difference, with the high-risk group having a mean score of 126.35, the moderate-risk group having a mean score of 167.82, and the low-risk group having a mean score of 211.45. Both the physical and psychosocial quality of life domain scores followed the same pattern, confirming that the classification reflected meaningful differences in both functional and emotional-social aspects of post-stroke adjustment.

Table 2

Distribution of quality of life risk profiles in the total sample, training set, and testing set

Quality of life risk profile	Total sample (N = 426) n (%)	Training set (n = 298) n (%)	Testing set (n = 128) n (%)
High-risk profile	133 (31.22)	93 (31.21)	40 (31.25)
Moderate-risk profile	169 (39.67)	118 (39.60)	51 (39.84)
Low-risk profile	124 (29.11)	87 (29.19)	37 (28.91)
Total	426 (100.00)	298 (100.00)	128 (100.00)

Table 2 presents the distribution of the three quality of life risk profiles in the full dataset and after stratified division into training and testing sets. The moderate-risk profile was the largest class, including 169 participants, equivalent to 39.67% of the total sample. The high-risk profile included 133 participants, representing 31.22% of the sample, and the low-risk profile included 124 participants, representing 29.11%. The stratified sampling procedure preserved the proportional distribution of the outcome classes in both the training and testing subsets. In the training set, 93 participants were classified as high risk, 118 as moderate risk, and 87 as low risk. In the testing set, 40 participants were classified as high risk, 51 as moderate risk, and 37 as low risk. This proportional balance was important because it reduced the possibility that model performance would be influenced by unequal class representation between model development and final evaluation. The distribution also indicated that the classification task was clinically meaningful, as nearly one-third of stroke survivors belonged to the high-risk profile and therefore represented a group requiring special attention in post-stroke care planning.

Table 3

Cross-validation results and optimized hyperparameters for the Support Vector Machine and Decision Tree models

Model	Optimized hyperparameters	Cross-validation accuracy Mean ± SD	Macro precision	Macro recall	Macro F1-score	Macro AUC
Support Vector Machine	Radial basis function kernel; C = 10; gamma = 0.01	0.797 ± 0.041	0.789	0.781	0.783	0.884
Decision Tree	Gini criterion; maximum depth = 5; minimum samples split = 12; minimum samples leaf = 6	0.719 ± 0.052	0.706	0.691	0.696	0.791

Table 3 summarizes the internal validation results obtained during model training and hyperparameter optimization. The Support Vector Machine model with a radial basis function kernel demonstrated stronger cross-validation performance than the Decision Tree model across all evaluated indices. The optimized Support Vector Machine model achieved a mean cross-validation accuracy of 0.797, with a macro precision of 0.789, macro recall of 0.781, macro F1-score of 0.783, and macro area under the curve of 0.884. These values indicate that the model showed stable discrimination across the three quality of life risk categories and was not limited to predicting only the largest class. The Decision Tree model achieved a mean cross-validation accuracy of 0.719, with a macro precision of 0.706, macro recall of 0.691, macro F1-score of 0.696, and macro area under the curve of 0.791. Although the Decision Tree model had lower predictive performance, it remained clinically useful because of its interpretability and ability to show decision pathways based on functional disability, depressive symptoms, sleep quality, and neurological severity. Overall, the cross-validation results indicated that the Support Vector Machine algorithm was better able to capture the nonlinear relationships among post-stroke clinical, functional, psychological, and sleep-related variables in predicting quality of life risk profiles.

Table 4

Final testing performance of the Support Vector Machine and Decision Tree models

Model	Risk profile	Precision	Recall	F1-score	AUC
Support Vector Machine	High-risk profile	0.83	0.85	0.84	0.91
Support Vector Machine	Moderate-risk profile	0.78	0.76	0.77	0.86
Support Vector Machine	Low-risk profile	0.84	0.86	0.85	0.92
Support Vector Machine	Macro average	0.82	0.82	0.82	0.90
Support Vector Machine	Weighted average	0.81	0.81	0.81	0.89
Decision Tree	High-risk profile	0.76	0.78	0.77	0.83
Decision Tree	Moderate-risk profile	0.70	0.67	0.68	0.77
Decision Tree	Low-risk profile	0.74	0.78	0.76	0.82
Decision Tree	Macro average	0.73	0.74	0.74	0.81
Decision Tree	Weighted average	0.73	0.73	0.73	0.80

Table 4 presents the final performance of both machine learning models in the independent testing set. The Support Vector Machine model achieved the strongest overall classification performance, with macro-averaged precision, recall, and F1-score values of 0.82 and a macro AUC of 0.90. The model performed particularly well in identifying participants in the high-risk and low-risk quality of life profiles. For the high-risk profile, which was the most clinically important group, the Support Vector Machine model achieved a precision of 0.83, recall of 0.85, F1-score of 0.84, and AUC of 0.91. This indicates that the model was able to correctly identify most stroke survivors with poor quality of life while maintaining a relatively low rate of false high-risk classifications. The low-risk profile was also classified with strong performance, with a precision of 0.84, recall of 0.86, F1-score of 0.85, and AUC of 0.92. The moderate-risk profile showed slightly lower performance, with a precision of 0.78, recall of 0.76, and F1-score of 0.77, suggesting that some participants in the intermediate category shared characteristics with either the high-risk or low-risk groups. The Decision Tree model showed acceptable but weaker performance. Its macro F1-score was 0.74, and its macro AUC was 0.81. The Decision Tree model classified the high-risk profile with a recall of 0.78 and F1-score of 0.77, indicating useful but less accurate detection of clinically vulnerable participants compared with the Support Vector Machine model. These results demonstrate that both algorithms were capable of classifying quality of life risk profiles among stroke survivors, but the Support Vector Machine model provided superior generalization and discrimination in the testing set.

Table 5

Confusion matrix for the final Support Vector Machine and Decision Tree models in the testing set

Model	Actual risk profile	Predicted high-risk	Predicted moderate-risk	Predicted low-risk	Total
Support Vector Machine	High-risk profile	34	5	1	40
Support Vector Machine	Moderate-risk profile	6	39	6	51
Support Vector Machine	Low-risk profile	1	4	32	37
Decision Tree	High-risk profile	31	7	2	40
Decision Tree	Moderate-risk profile	8	34	9	51
Decision Tree	Low-risk profile	2	6	29	37

Table 5 shows the classification patterns of the two models in the independent testing set. The Support Vector Machine model correctly classified 34 of 40 participants in the high-risk group, 39 of 51 participants in the moderate-risk group, and 32 of 37 participants in the low-risk group. The highest number of misclassifications occurred in the moderate-risk group, where six participants were classified as high risk and six as low risk. This pattern suggests that the moderate-risk group contained participants with overlapping clinical and psychological characteristics, making it more difficult to classify than the more clearly differentiated high-risk and low-risk groups. The Support Vector Machine model produced only one direct misclassification from high risk to low risk and one from low risk to high risk, indicating that severe classification errors between the most clinically distinct groups were rare. The Decision Tree model correctly classified 31 of 40 high-risk participants, 34 of 51 moderate-risk participants, and 29 of 37 low-risk participants. Compared with the Support Vector Machine model, the Decision Tree model produced more moderate-risk misclassifications and showed weaker separation between adjacent categories. Nevertheless, its classification structure remained clinically interpretable and showed that decision-based models can still provide meaningful screening support, especially when transparency is prioritized.

Figure 1

Relative importance of clinical, functional, psychological, and sleep-related predictors in the classification of quality of life risk profiles among stroke survivors

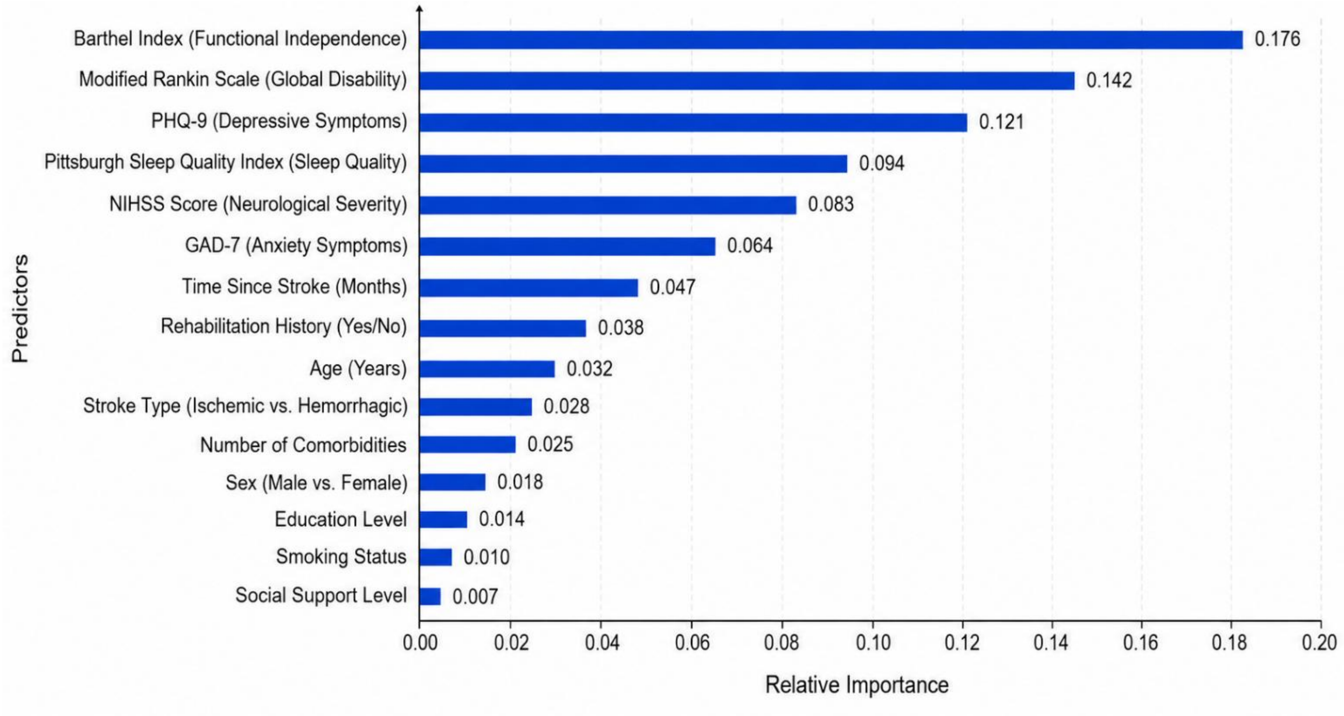

Figure 1 shows the relative contribution of the main predictors to the classification of quality of life risk profiles. Functional independence, measured by the Barthel Index, emerged as the strongest predictor of quality of life risk classification, indicating that limitations in daily activities were central to distinguishing high-risk from moderate- and low-risk stroke survivors. Global disability, measured by the Modified Rankin Scale, was the second most influential predictor, followed by depressive symptoms, sleep quality, neurological severity, and anxiety symptoms. These findings indicate that quality of life risk after stroke was not determined by neurological impairment alone but reflected the combined influence of disability, emotional distress, sleep disturbance, and reduced functional autonomy. Time since stroke, rehabilitation history, age, stroke type, and comorbid medical conditions contributed to model performance but had lower relative importance than functional and psychological indicators. The overall pattern of predictor importance supports a multidimensional interpretation of post-stroke quality of life, in which high-risk profiles are most likely to appear among individuals with greater functional dependence, higher disability, more depressive symptoms, poorer sleep quality, and more severe neurological impairment. Therefore, the results suggest that machine learning classification can be used not only to assign stroke survivors to risk profiles but also to identify clinically actionable factors that may guide rehabilitation planning and psychosocial intervention.

4. Discussion

The present study aimed to classify quality of life risk profiles among stroke survivors in Armenia using Support Vector Machine and Decision Tree algorithms and to identify the most influential predictors associated with high-risk quality of life status. The findings demonstrated that stroke survivors differed substantially across high-risk, moderate-risk, and low-risk quality of life profiles in terms of functional independence, disability, neurological severity, depressive symptoms, anxiety symptoms, sleep quality, and stroke-specific quality of life domains. Participants in the high-risk profile had lower Barthel Index scores, higher Modified Rankin Scale scores, higher NIHSS scores, greater depressive and anxiety symptoms, poorer sleep quality, and markedly lower physical and psychosocial quality of life scores. These results confirm that post-stroke quality of life is not a single-domain outcome determined only by neurological impairment but a multidimensional construct shaped by the interaction of physical functioning, emotional status, sleep, disability, and participation-related factors.

This interpretation is consistent with previous evidence showing that health-related quality of life after stroke is influenced by functional independence, physical capacity, psychological distress, social support, and contextual factors (Ghazali et al., 2025; Kariyawasam & Pathirana, 2020; Lourenço et al., 2021).

One of the most important findings was that functional independence emerged as the strongest predictor of quality of life risk classification. Participants in the high-risk group showed the lowest level of independence in activities of daily living, while those in the low-risk group had the highest Barthel Index scores. This finding is strongly supported by prior studies showing that independence in daily functioning is one of the most consistent determinants of quality of life among stroke survivors. Ellepola et al. reported that physical activities of daily living were closely related to quality of life after stroke, while Ogwumike et al. found that functional independence, fatigue, and exercise self-efficacy were significantly associated with quality of life in stroke survivors (Ellepola et al., 2022; Ogwumike et al., 2021). Similarly, studies in Brazil and Sri Lanka indicated that functionality and post-stroke disability were central predictors of quality of life outcomes, emphasizing that patients with greater difficulty in self-care, mobility, and daily activities experience more severe quality of life impairment (Ana Railka de Souza et al., 2023; Kariyawasam & Pathirana, 2020). The present findings therefore reinforce the clinical importance of functional independence as a primary indicator of post-stroke well-being.

The strong contribution of global disability and neurological severity to quality of life risk classification also aligns with earlier stroke outcome research. In this study, the high-risk group had the highest Modified Rankin Scale and NIHSS scores, suggesting that greater neurological impairment and dependence increased the probability of belonging to a poor quality of life profile. This is consistent with evidence showing that stroke survivors with higher disability levels, more severe residual deficits, and lower physical capability are more vulnerable to poor health-related quality of life (Silva et al., 2024; Yang et al., 2025). Yun et al. emphasized that changes in functional independence after ischemic stroke are critical to recovery trajectories, and Gurková et al. showed that even patients with mild residual deficits may report impaired quality of life when functional and psychosocial difficulties persist (Gurková et al., 2022; Yun et al., 2020). These findings suggest that disability should not be interpreted only as a motor or neurological outcome but as a broader determinant of autonomy, social participation, and subjective well-being.

Psychological distress was another central component of the quality of life risk profiles. In the present study, depressive symptoms and anxiety symptoms were substantially higher in the high-risk group than in the moderate- and low-risk groups, and depression was among the most important predictors in the machine learning models. This result is consistent with previous studies showing that post-stroke depression and anxiety have a strong negative effect on quality of life. Studies among young Filipino adults demonstrated that post-stroke depression and anxiety were associated with reduced health-related quality of life, while research from Ethiopia and India highlighted the high prevalence and clinical importance of depressive symptoms after stroke (Chaudhury & Rohatgi, 2024; Ignacio et al., 2023; Kuma et al., 2025). Kuptniratsaikul et al. also showed that post-stroke anxiety may remain present one year after rehabilitation, indicating that emotional symptoms can persist beyond the acute and subacute phases of recovery (Kuptniratsaikul et al., 2022). The present findings extend this evidence by showing that depressive and anxiety symptoms are not merely associated with quality of life in conventional statistical terms but also contribute meaningfully to machine learning classification of risk profiles.

Sleep quality also played an important role in differentiating quality of life risk profiles. Stroke survivors in the high-risk group had poorer sleep quality compared with those in the moderate- and low-risk groups, and the Pittsburgh Sleep Quality Index was among the most influential variables in the classification model. Poor sleep can intensify fatigue, reduce motivation for rehabilitation, worsen mood symptoms, impair cognitive functioning, and decrease participation in daily activities. Although many stroke quality of life studies focus primarily on physical disability and emotional distress, the present findings suggest that sleep disturbance should be considered an important clinical marker of poor post-stroke adaptation. This interpretation is consistent with broader evidence showing that quality of life after stroke is shaped by multiple interacting physical, psychological, and behavioral determinants rather than by a single impairment domain (Gao et al., 2024; Ghazali et al., 2025; Song et al., 2023). Therefore, the inclusion of sleep quality in predictive models may improve the identification of survivors who require more comprehensive rehabilitation and psychosocial support.

The classification results demonstrated that the Support Vector Machine model outperformed the Decision Tree model across cross-validation and independent testing indices. In the testing set, the Support Vector Machine achieved stronger macro precision, macro recall, macro F1-score, and macro AUC than the Decision Tree. The model was particularly effective in identifying high-risk and low-risk quality of life profiles, while the moderate-risk profile was more difficult to classify. This pattern is clinically understandable because moderate-risk survivors may share features with both high-risk and low-risk groups. For example, a survivor may have relatively preserved physical functioning but high depressive symptoms, or moderate disability but strong social support and perceived control. Such mixed profiles create overlapping boundaries that are better captured by flexible algorithms such as Support Vector Machine. This finding is consistent with the machine learning study by Xu et al., which demonstrated the usefulness of machine learning for predicting quality of life subtypes among disabled stroke survivors (Xu et al., 2023). The superiority of Support Vector Machine in the present study suggests that nonlinear classification methods may be particularly appropriate for modeling quality of life outcomes when predictors interact in complex ways.

Although the Decision Tree model had lower predictive performance, it remained clinically meaningful because of its interpretability. Decision Tree algorithms can provide transparent decision rules that help clinicians understand how combinations of disability, functional independence, depression, sleep quality, and neurological severity may lead to different quality of life risk classifications. This is important because clinical implementation of machine learning requires not only accuracy but also interpretability, acceptability, and practical relevance. The findings support the idea that Support Vector Machine may be preferable when the goal is maximum classification performance, whereas Decision Tree models may be useful when the goal is to provide simple, interpretable decision pathways for clinical screening. This balance between predictive accuracy and interpretability is consistent with the broader movement toward personalized, patient-centered stroke care, in which multidimensional assessment is used to guide individualized rehabilitation decisions (Harvey et al., 2025; Sakr et al., 2022b).

The importance of psychosocial and social-contextual factors should also be emphasized. Although functional independence and disability were the strongest predictors, the results showed that emotional symptoms and sleep-related problems contributed substantially to risk classification. Prior research has shown that social support, participation restriction, caregiver distress, and dyadic adjustment can influence quality of life after stroke (Darmadi et al., 2023; Liu et al., 2025). Studies of caregiver quality of life and caregiver depression further indicate that stroke recovery occurs within a family and caregiving system, not only within the individual survivor (Aldabbour et al., 2024; Khan et al., 2024; Moura et al., 2021). Blake et al. also reported that caregiver psychosocial factors were associated with stroke survivor cognitive outcomes, highlighting the interdependence between survivor and caregiver well-being (Blake et al., 2025). Therefore, quality of life risk classification should be used not only to identify individual impairment but also to detect survivors who may benefit from family-centered education, caregiver support, and social participation interventions.

The present findings are also consistent with evidence that post-stroke quality of life varies across time, age groups, and cerebrovascular conditions. Segerdahl et al. showed that health-related quality of life remains an important outcome years after stroke, supporting the need for long-term follow-up rather than short-term assessment only (Segerdahl et al., 2023). Gurková et al. emphasized that young adult stroke survivors face distinctive quality of life challenges, including social role disruption, employment concerns, and long-term participation limitations (Gurková et al., 2023). Research on subarachnoid hemorrhage and other cerebrovascular conditions also shows that quality of life impairment is relevant across different forms of stroke and vascular brain injury (Banjar et al., 2023). The inclusion of stroke survivors from Armenia contributes to this international evidence by examining quality of life risk classification in a setting where data remain limited. Studies from Portugal, Brazil, Malaysia, India, Nigeria, and other contexts show that quality of life after stroke is shaped by local healthcare access, rehabilitation resources, caregiver structures, and socioeconomic factors (Kumar et al., 2021; Lalu, 2021; Naidoo et al., 2025; Rosa et al., 2023). Therefore, locally developed predictive models may provide more relevant evidence for clinical decision-making than models transferred directly from other healthcare systems.

The findings also support the value of early and continuous screening for emotional, cognitive, and functional risk indicators. Stolwyk et al. showed that post-stroke cognition is associated with survivor quality of life and caregiver outcomes, indicating that cognitive status should be incorporated into comprehensive post-stroke assessment (Stolwyk et al., 2024). Selvaraj et al. emphasized the importance of early screening for post-stroke depression because depression may affect functional outcomes, quality of life, and mortality (Selvaraj et al., 2021). Pharmacotherapy adherence and therapeutic engagement may also influence long-term recovery and should be considered in quality of life assessment frameworks (Sakr et al., 2022a). In addition, evidence from non-pharmacological intervention reviews indicates that exercise-based, rehabilitation, and multicomponent interventions can improve quality of life, depression, and anxiety among stroke survivors (Gao et al., 2024; Song et al., 2023). These findings suggest that machine learning classification has practical value only if it is connected to targeted intervention pathways. Identifying a survivor as high risk should lead to more intensive rehabilitation, psychological assessment, sleep evaluation, caregiver involvement, and structured follow-up.

5. Conclusion

Finally, the present study contributes to the growing literature that views quality of life as a central outcome in neurological and post-acute care. Bibliometric evidence shows increasing research attention to stroke and quality of life, reflecting recognition that survival alone is insufficient as an outcome indicator (Chen et al., 2023). Similar concerns have emerged in broader critical illness and post-intensive care populations, where long-term quality of life has become a major endpoint of recovery research (Лихванцев et al., 2022). In stroke care, this perspective is especially important because survivors may live for many years with disability, emotional distress, participation restrictions, and dependence. The present study demonstrates that machine learning can help classify these multidimensional risks and identify clinically meaningful patterns that may not be fully captured by conventional single-predictor approaches.

6. Limitations & Suggestions

This study had several limitations that should be considered when interpreting the findings. First, the cross-sectional design prevented causal conclusions about the relationships among functional independence, disability, psychological symptoms, sleep quality, and quality of life risk profiles. Although the machine learning models identified important predictors of classification, they could not determine whether these variables caused poor quality of life or were consequences of it. Second, the study relied partly on self-report instruments, which may be affected by recall bias, emotional state, fatigue, cognitive limitations, or social desirability. Third, although the sample size was adequate for the selected algorithms, larger datasets would allow more robust model training, external validation, and subgroup analyses. Fourth, the study was conducted among stroke survivors in Armenia, and the findings may not be directly generalizable to other countries or healthcare systems with different rehabilitation structures, socioeconomic conditions, and post-stroke care pathways. Fifth, the study compared only Support Vector Machine and Decision Tree algorithms, while other machine learning approaches such as Random Forest, Gradient Boosting, neural networks, and ensemble models may produce different performance patterns.

Future research should use longitudinal designs to examine how quality of life risk profiles change from the acute and subacute phases of stroke recovery to long-term follow-up. Such designs would help clarify whether improvements in functional independence, emotional status, sleep quality, and social participation lead to movement from high-risk to moderate- or low-risk profiles over time. Future studies should also validate the present models in larger and more diverse samples, including rural populations, younger stroke survivors, older adults with multiple comorbidities, and patients with different stroke subtypes. External validation in other countries would be especially valuable to determine whether the model structure is culturally and clinically transferable. Researchers should also compare a broader range of machine learning algorithms and examine whether ensemble models improve classification accuracy without sacrificing interpretability. In addition, future studies should include caregiver variables, cognitive performance, fatigue, rehabilitation intensity, medication adherence, socioeconomic status, and health service access to develop more comprehensive prediction models.

The findings suggest that post-stroke care should include systematic screening for quality of life risk rather than focusing only on neurological impairment or physical recovery. Clinicians should pay particular attention to survivors with low functional independence, high disability, depressive symptoms, anxiety symptoms, poor sleep quality, and greater neurological severity, as these individuals are more likely to belong to a high-risk quality of life profile. Machine learning tools can support clinical decision-making by identifying patients who may require more intensive rehabilitation, psychological assessment, sleep management, caregiver education, and long-term follow-up. However, such tools should be used as decision-support systems rather than replacements for clinical judgment. In rehabilitation settings, interpretable models may help clinicians explain risk patterns to patients and families, while more accurate models may help allocate services more efficiently. Integrating quality of life risk classification into routine stroke follow-up could improve individualized care planning and support more comprehensive, patient-centered recovery.

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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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