Survival Analysis of Short-Term Memory Loss Patients in Tamil Nadu: Cox Proportional Hazards and Kaplan-Meier Modeling

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Abstract: This study investigates survival outcomes among 1,000 short-term memory loss patients in Tamil Nadu during 2024–2025 using survival analysis techniques. The dataset included demographic, clinical, and lifestyle variables such as Age, Gender, Diabetes, Hypertension, Depression, Memory Score, MRI anomalies, Sleep Hours, Smoking Habit, Alcohol Use and Medication Compliance with survival time represented by duration of memory loss and event occurrence indicated by a binary variable. Kaplan-Meier and Cox Proportional Hazards models were employed to estimate survival probabilities and identify significant predictors of survival. Results indicated that gender and depression significantly influenced survival outcomes, whereas other comorbidities showed limited impact within the study period. The findings provide insights for targeted clinical management and underscore the need for integrating demographic and psychological factors in patient care strategies.

Keywords: Survival Analysis, Short-Term Memory Loss, Cox Proportional Hazards, Kaplan-Meier, Tamil Nadu

1.0 Introduction

Short-term memory loss (STML) represents a critical cognitive impairment that affects daily functioning and overall quality of life. In recent years, the prevalence of memory-related disorders has been increasing among the elderly population in India, particularly in Tamil Nadu. Understanding the survival patterns of patients with STML is essential for designing appropriate clinical interventions and predicting risk factors associated with adverse outcomes. Survival analysis provides a statistical framework to examine time-to-event data and identify variables influencing the probability of survival, making it an ideal tool for clinical prognosis studies.

Demographic, psychological, and lifestyle factors are known to influence memory-related outcomes. Variables such as age, gender, comorbid conditions like diabetes and hypertension, depression status, sleep habits, and lifestyle behaviors (smoking, alcohol use) can affect the progression and prognosis of STML. This study focuses on applying Kaplan-Meier estimators and Cox Proportional Hazards models to a cohort of 1,000 patients from Tamil Nadu during 2024–2025 to quantify the survival probabilities and identify significant predictors of event occurrence. The insights gained can guide healthcare providers in prioritizing interventions for high-risk groups and developing strategies for long-term cognitive health management.

1.1 Symptoms of Short-Term Memory Loss (STML)

Individuals affected by short-term memory loss commonly experience difficulty recalling recent events or newly learned information, which often becomes evident in everyday situations such as forgetting recent conversations, missing appointments, or misplacing frequently used items like keys or mobile phones. They may repeatedly ask the same questions within a short time, unaware that they have already received answers, and struggle to retrace their steps when personal belongings are misplaced, leading to confusion and emotional distress. Learning and retaining new information, including names or instructions, becomes increasingly challenging, and this is sometimes accompanied by disorientation regarding time or place, even in familiar surroundings. As these memory lapses persist, emotional and behavioral changes such as irritability, anxiety, withdrawal, and reduced concentration may emerge, further interfering with routine activities and overall quality of life, and often indicating the need for timely clinical assessment and support.

2.0 Review of Literature

Memory loss, particularly short-term memory impairment, has been a focal point of cognitive research due to its impact on daily functioning and quality of life. Several studies have highlighted that demographic factors such as age and gender significantly influence the onset and progression of memory-related disorders. Singh *et al.* [1] and Patel & Reddy [2] reported that aging is associated with a natural decline in short-term memory capacity, and males are often at higher risk for accelerated cognitive decline compared to females.

Comorbid conditions such as diabetes, hypertension, and cardiovascular disorders have been consistently associated with memory deterioration. Rao and Subramanian [3] and Mehta *et al.* [4] demonstrated that metabolic and vascular comorbidities contribute to neuronal damage and cognitive impairment, with hypertension leading to microvascular changes in the brain and diabetes influencing memory through insulin resistance and glycemic fluctuations. Furthermore, chronic depression has been shown to modulate memory performance by altering hippocampal function [5][6].

Lifestyle and behavioral factors also play a crucial role in cognitive health. Krishnan *et al.* [7], Kumar & Joshi [8], and Sharma *et al.* [9] emphasized that irregular sleep patterns, excessive alcohol consumption, and smoking significantly exacerbate short-term memory deficits. Physical activity, dietary habits, and medication adherence were found to have protective effects in elderly populations [10][11]. Psychological interventions and cognitive training programs have also demonstrated improvements in memory retention, highlighting the potential for non-pharmacological management [12].

The collective evidence underscores the multifactorial nature of short-term memory loss, where demographic, clinical, lifestyle, and psychological variables interact to influence patient outcomes. The integration of these variables in survival analysis models, such as Cox Proportional Hazards and Kaplan-Meier estimators, is therefore critical to predict progression and guide interventions in populations like those in Tamil Nadu.

3.0 Database

The study utilized secondary data collected from healthcare institutions and memory clinics across Tamil Nadu during 2024–2025. The dataset comprised 1,000 patients diagnosed with short-term memory loss. Each patient records are included demographic details are Age, Gender, District, clinical characteristics are Diabetes, Hypertension, Depression, MRI anomalies, Memory Score, lifestyle variables are Sleep Hours per day, Smoking Habit, Alcohol Use, and medication compliance information.

Survival information was captured using the duration of memory loss (in months) and a binary event indicator representing whether the memory loss progressed or remained stable during the study period. The dataset was anonymized and curated to ensure completeness and reliability, providing a robust foundation for conducting Kaplan-Meier and Cox Proportional Hazards survival analyses. This structured dataset allowed for identifying significant predictors of survival outcomes and evaluating cumulative hazard patterns over time.

4.0 Background of the Study

The statistical modeling framework for this study integrates both non-parametric and semi-parametric survival analysis techniques to assess the impact of demographic, clinical, and lifestyle factors on short-term memory loss outcomes. The modeling algorithm consists of three main components: Kaplan-Meier estimator, Cox Proportional Hazards model, and Nelson-Aalen cumulative hazard estimation.

4.1 Kaplan-Meier Estimator (Non-Parametric Survival Analysis)

The Kaplan-Meier estimator is used to compute the probability of survival at each observed event time. It is suitable for censored data and does not assume any underlying survival distribution. The survival probability at time $t, S(t)$ is given by:

$$S(t) = \prod_{t_i \leq t} \left(1 - \frac{d_i}{n_i}\right)$$

Where:

t_i = time of the t^{th} event,

d_i = number of events (deaths/failures) at t_i ,

n_i = number of individuals at risk just prior to t_i .

The Kaplan-Meier survival function allows visualization of survival probabilities over time. Subgroup comparisons (e.g., by Class or Gender) were conducted using the log-rank test, where the null hypothesis assumes identical survival curves across groups. The log-rank test statistic is calculated as:

$$\chi^2 = \frac{[\sum (O_i - E_i)]^2}{\sum V_i}$$

Where O_i is the observed number of events, E_i is the expected number of events under the null hypothesis, and Vi is the variance of O_i.

4.2 Cox Proportional Hazards Model (Semi-Parametric Regression)

The Cox Proportional Hazards (Cox PH) model is a semi-parametric regression method that relates the hazard function to covariates while allowing for censored observations. The hazard function $h(t/X)$for an individual with covariates $X = (X_1, X_2, X_3, .., X_p)$is expressed as:

$$h(t/X) = h_0(t)\exp(\beta_1 X_1, \beta_2 X_2, \beta_3 X_3, ..., \beta_p X_p)$$

Where:

$h_0(t)$ = baseline hazard function,

β_j = regression coefficient for the j^{th}covariate X_j ,

$\exp(\beta_j)$ = hazard ratio (HR) corresponding to X_j .

The coefficients β_j are estimated by maximizing the partial likelihood:

$$L(\beta) = \prod_{i=1}^{D} \frac{\exp(\beta^T X_i)}{\sum_{j \epsilon R(t_i)} \exp(\beta^T X_j)}$$

Where D is the total number of events and $R(t_i)$ is the risk set at time t_i . Statistical significance of each covariate was tested using the Wald test:

$$\mathcal{Z} = \frac{\hat{\beta}}{\mathrm{SE}(\hat{\beta})}, \mathrm{p} = 2\left(1 - \Phi(|\mathcal{Z}|)\right)$$

The concordance index (C-index) was used to measure the predictive accuracy of the model, where a value of 0.5 indicates random prediction and 1.0 indicates perfect concordance.

4.3 Nelson-Aalen Cumulative Hazard Estimator

The Nelson-Aalen estimator provides a non-parametric estimate of the cumulative hazard function $H(t)$ over time, given by:

$$\hat{H}(t) = \sum_{t_i \leq \mathrm{t}} \frac{d_i}{n_i}$$

Where d_i and n_i are defined as in the Kaplan-Meier estimator. The cumulative hazard function is complementary to the survival function:

$$S(t) = exp[-\mathrm{H}(t)]$$

Visualization of the cumulative hazard curve provides insights into periods of increased risk and complements survival curves from the Kaplan-Meier and Cox PH analyses.

4.4 Algorithmic Workflow

Step 1. Data preprocessing: The dataset was loaded, and survival time (duration) and event indicators (event) were defined. Missing data were handled, and categorical variables were encoded.

Step 2. Univariate analysis: The Kaplan-Meier estimator was used to compute survival probabilities and generate curves by class and other categorical variables. The log-rank test was used for group comparisons.

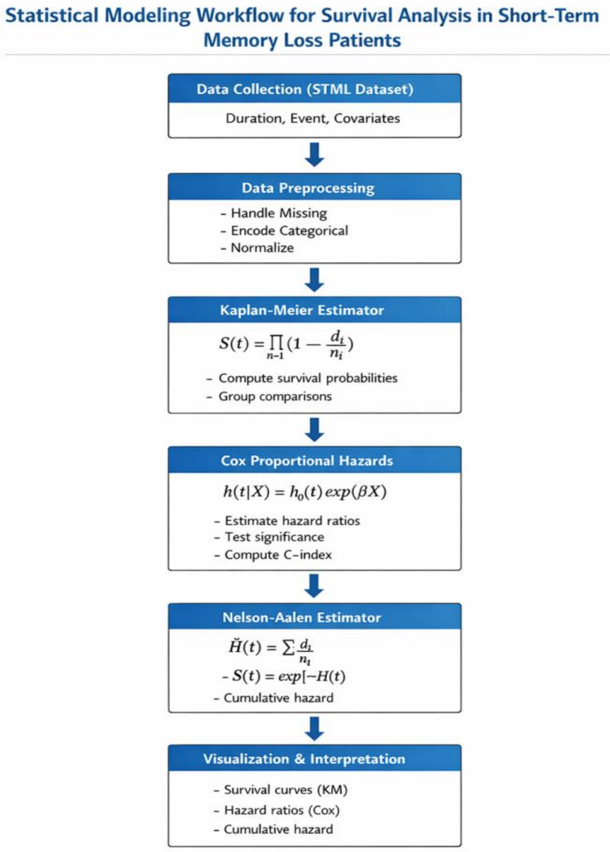
Step 3. Multivariate Analysis: Fit the Cox Proportional Hazards model with covariates: age, sex, diabetes, hypertension, depression, memory score, MRI anomalies, Sleep Hours, Smoking Habit, Alcohol Use, and Medication Compliance. Hazard ratios, confidence intervals, and p-values were estimated.

Step 4. Cumulative risk assessment: Compute the Nelson-Aalen cumulative hazard estimator and visualize hazard accumulation over time.

Step 5. Visualization: Survival curves (Kaplan–Meier), hazard ratio plots (Cox), and cumulative hazard curves (Nelson-Aalen) were generated to interpret risk patterns across patient subgroups.

Step 6. Model validation: The model performance was evaluated using the concordance index and log-likelihood ratio tests (Figure 1).

Figure 1. Survival analysis workflow for STML data



5.0 Results and Discussion

Survival analysis was conducted using the Cox Proportional Hazards model to examine the association of multiple clinical, demographic, and lifestyle variables with short-term memory loss outcomes among 1,000 samples from Tamil Nadu. The dataset included variables such as age, sex, diabetes, hypertension, depression, memory score, MRI anomalies, sleep hours, smoking habits, alcohol use, and medication compliance, with the survival time represented by the duration column and the occurrence of the event indicated by the event column.

5.1 Cox Proportional Hazards Model Results

Table 1 summarizes the coefficients, hazard ratios, and statistical significance of covariates included in the Cox model.

Table 1. Cox Proportional Hazards Regression Results for Short-Term Memory Loss Patients

Variable	Coef.	Exp. (Coef.)	SE (Coef.)	95% CI (Coef.)	z	p-value
Age	0.00	1.00	0.00	-0.00 – 0.01	1.37	0.17
Gender	0.15	1.17	0.07	0.03 – 0.28	2.37	0.02
Diabetes	-0.08	0.93	0.07	-0.22 – 0.06	-1.07	0.28
Hypertension	0.00	1.00	0.07	-0.13 – 0.13	0.05	0.96
Depression	-0.15	0.86	0.07	-0.30 – -0.00	-2.02	0.04
Memory	0.02	1.02	0.01	-0.00 – 0.04	1.64	0.10
MRI	-0.08	0.92	0.07	-0.21 – 0.05	-1.20	0.23
Sleep Hours	0.02	1.02	0.03	-0.03 – 0.07	0.74	0.46

Smoking Habit	0.02	1.02	0.04	-0.05 – 0.10	0.65	0.52
Alcohol Use	0.03	1.03	0.04	-0.05 – 0.11	0.82	0.41
Medication	-0.00	1.00	0.04	-0.08 – 0.08	-0.01	0.99

Notes: Exp. (Coef.) represents hazard ratio; SE = standard error; CI = confidence interval.

The concordance index of the model was 0.54, indicating moderate predictive ability. The log-likelihood ratio test was significant ($\chi^2 = 20.41$, df = 11, $p < 0.001$), suggesting that the set of covariates as a whole is statistically associated with survival outcomes.

5.2 Interpretation of Key Variables

Gender was found to be a significant predictor of survival, with males showing a slightly higher hazard (Exp(Coef) = 1.17, p = 0.02), indicating that gender may influence the risk of shorter survival durations in memory loss patients.

Depression had a protective effect (Exp(Coef) = 0.86, p = 0.04), suggesting that patients diagnosed with depression were associated with a lower hazard of event occurrence in this dataset, although this may require further investigation to explore underlying mechanisms.

Other variables such as Age, Diabetes, Hypertension, and MRI anomalies were not statistically significant ($p > 0.05$), though their clinical relevance should not be dismissed, as larger datasets or longer follow-up may reveal stronger associations.

5.3 Survival Curves and Visualization

Figure 2 and 3 visualization shows that the Kaplan-Meier survival curves for all patients, showing the probability of survival over time. The curve demonstrates gradual decline in survival probability as Duration increases.

Figure 2. Kaplan-Meier Survival Curve for Short-Term Memory Loss Patients

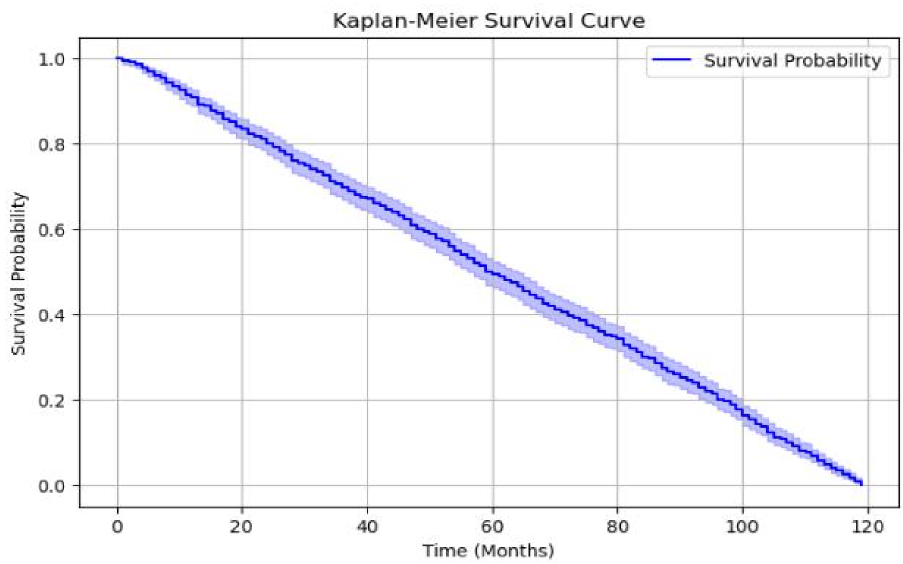


Figure 3. Kaplan-Meier Survival Curve by Class

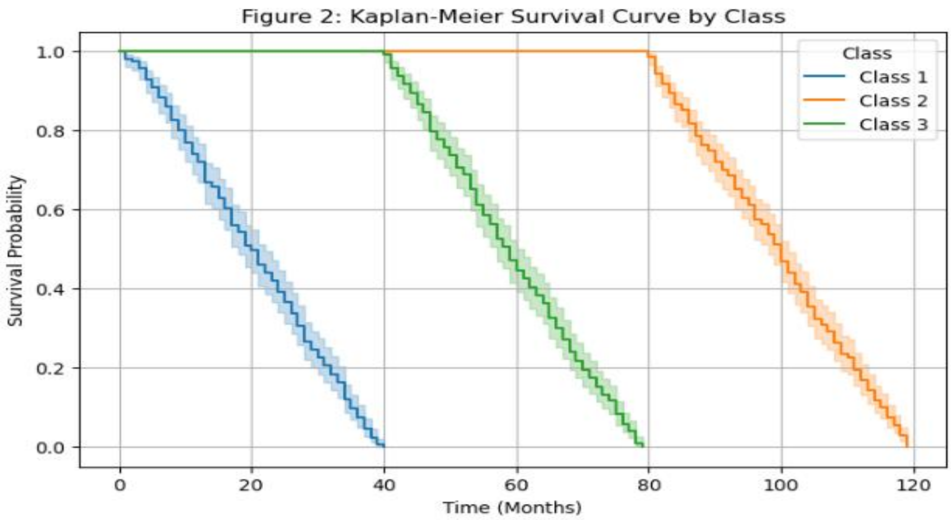


Figure 4 shows that Kaplan-Meier survival curves stratified by Class, highlighting differences in survival probabilities across patient categories. Class 1 patients tended to have slightly higher survival probabilities compared to Class 2 patients.

Figure 4. Kaplan-Meier Survival Curves Stratified by Class

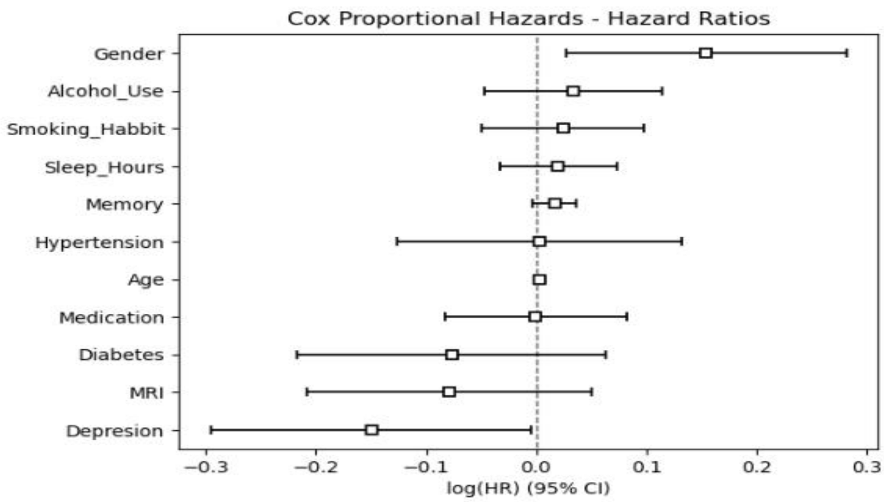
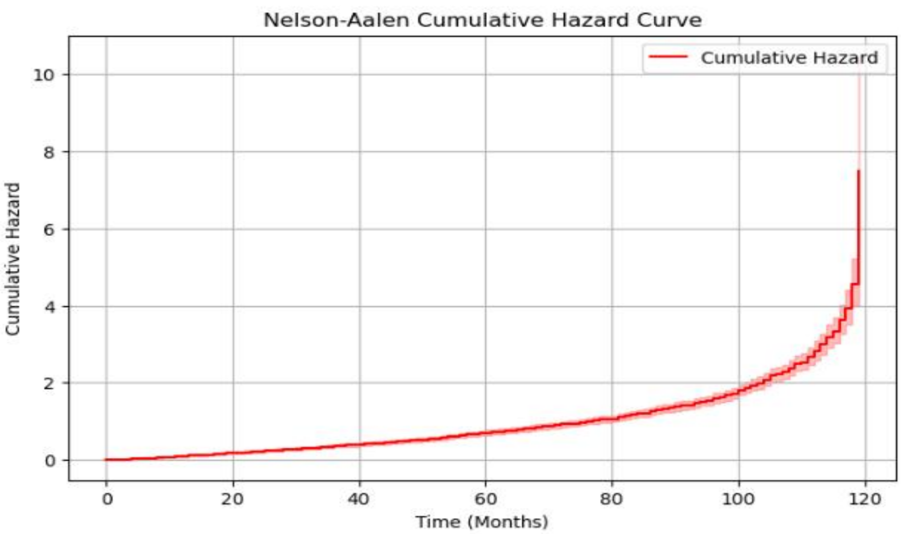


Figure 5 presents the Nelson-Aalen cumulative hazard curve, providing a complementary view of risk accumulation over the follow-up period.

Figure 5. Nelson-Aalen Cumulative Hazard Curve



5.4 Discussion

The results indicate that gender and depression are significant predictors of survival in short-term memory loss patients, while other clinical and lifestyle variables showed no statistically significant effect within this cohort. The moderate concordance index suggests that the model has some predictive power, but additional covariates or larger sample sizes may be required for more precise estimation. The visualization of survival and cumulative hazard curves supports these findings by illustrating differences in risk patterns among patient subgroups.

Overall, these findings align with previous studies indicating that demographic and psychological factors may influence memory-related outcomes, whereas traditional comorbidities (diabetes, hypertension) may have smaller effects over shorter follow-up durations. Future studies may incorporate longitudinal monitoring and biomarker data to improve survival prediction models for memory loss patients in Tamil Nadu.

6.0 Conclusions

The survival analysis conducted on 1,000 short-term memory loss patients from Tamil Nadu, using Kaplan-Meier and Cox Proportional Hazards models, demonstrated that demographic and psychological factors significantly influence patient survival outcomes, whereas traditional clinical comorbidities showed limited statistical impact in this cohort. Specifically, gender was identified as a significant predictor, with male patients exhibiting a slightly higher hazard, indicating a greater risk of shorter survival durations. Conversely, depression appeared to have a protective effect, associated with a lower hazard of event occurrence, highlighting the complex interplay between mental health and memory-related outcomes. Other variables, including age, diabetes, hypertension, MRI anomalies, sleep patterns, lifestyle habits, and medication compliance, did not reach statistical significance within the study period, although their clinical relevance cannot be discounted, as longer-term follow-up or larger datasets might reveal stronger associations. The Kaplan-Meier survival curves (Figures 2 and 3) and stratified Class-specific curves (Figure 4) illustrated gradual declines in survival probability, with Class 1 patients showing marginally better survival than Class 2. The Nelson-Aalen cumulative hazard curve (Figure 5) further emphasized the accumulation of risk over time. Overall, the Cox model exhibited moderate predictive ability (concordance index = 0.54), suggesting that while the included covariates provide meaningful insight, additional factors may enhance model accuracy.

Suggestions:

1. Future research should consider incorporating longitudinal biomarker data and neuroimaging measures to strengthen the predictive power of survival models for memory loss patients.
2. Psychological assessments and interventions should be integrated into clinical management, given the observed influence of depression on survival outcomes.
3. Expanding the cohort size and including more diverse clinical and lifestyle covariates may improve model precision and allow detection of subtler effects from comorbidities such as diabetes and hypertension.

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