International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V71I8P231

Volume 71 Issue 8, 356-366, August 2023


*Original Article*

# Deep Learning Based Time-to-Event Prediction of MCI Transition Leveraging Sensor-captured Daily Activities Data

Rajaram Narasimhan[1], Muthukumaran Gopalan[2], Mathangi Damal Chandrasekhar[3]

[1,2]*Centre for Sensors and Process Control, Hindustan Institute of Technology and Science, Chennai, India.*
[3]*Sri Ramachandra Institute of Higher Education and Research, Porur, Chennai, India.*

[1]*Corresponding Author : nrr76_2000@yahoo.com*

Received: 10 May 2023 Revised: 29 July 2023 Accepted: 05 August 2023 Published: 15 August 2023

***Abstract*** *- Mild Cognitive Impairment (MCI) is known to be a condition in older adults presenting cognitive impairment symptoms in the absence of functional impairment. This could be a transitional stage to developing Alzheimer's disease (AD), but it does not always lead to AD. Early detection of MCI symptoms is vital in determining personalized interventions to slow down the MCI progression. This study proposes a survival analysis approach based on deep learning techniques to predict the probability of an individual transitioning from a cognitively healthy stage to MCI at a given time point by utilizing activity data captured through unobtrusive sensors by continuously monitoring the older adults' daily routines. The performance of the proposed models, Neural Multi-Task Logistic Regression and Non-Linear Cox, in predicting the probability of time-to-transition are examined and compared against the Standard Cox PH model. The two well-known metrics, Concordance Index (CI) and Integrated Brier Score (IBS), are used to evaluate the model performance. Additionally, the features are ranked based on the model-learned weights and results are interpreted. Deep learning-based models perform better than the standard Cox PH model, with the best average CI of 0.714 and IBS of 0.119. The results suggest that the proposed models can accommodate the nonlinear elements from the data and account for the fact that the rate of progression of two individuals will vary with time. Feature ranking reveals the age and years of education to be in the top 5, in addition to features from sleep and mobility domains which are clinically meaningful. This study demonstrates that a practical, less expensive, and non-invasive way of observing older adults' activity routines coupled with computing advancements such as deep learning techniques offer phenomenal opportunities for early detection of MCI transition.*

***Keywords*** *- Activities of daily living, Alzheimer's disease, Deep learning, Mild cognitive impairment, Time-to-event prediction, Unobtrusive sensor.*

## 1. Introduction

Mild cognitive impairment (MCI) is known to be a condition in older adults presenting the symptoms of cognitive impairment in the absence of functional impairment. MCI could be a transitional stage to developing Alzheimer's disease (AD), but it does not always lead to the AD stage. Besides impacting the physical and psychological health of individuals, the AD condition has a profound impact on the social/economic aspects of not just the individuals with this condition but society at large. Therefore, detecting the symptoms of the MCI condition, a prodromal stage is important as early as possible. Several studies [1, 2] reported the association between this cognitive decline and activities of daily living (ADLs)/daily routines. Conventional assessment methods/tools (e.g., self-reporting, informant reporting questionnaires) are not designed to observe the subtle intra-individual changes known to occur over time when older adults perform cognitively mediated activities.[3] This informs the need for a mechanism that is more practical, less expensive and non-invasive to continuously observe daily routines and provide reliable indications for subtle yet meaningful changes. Technology advancements such as wireless sensors and data analytics can now be adopted in continuous monitoring and realize an ecologically valid assessment mechanism for their real-world cognitive/functional changes.[4]

Since AD is degenerative in nature, it is important to understand the disease trajectory associated with this degeneration through disease progression modeling methods and plan for individualized interventions. The 'time-to-event' modeling with survival analysis is one such disease progression modeling approach which predicts the probability

that an event of interest happens at a particular time. Early detection of the transition to the MCI stage (the event of interest in the context of this study) is crucial in older adults, and time-to-event modeling can be adopted to understand this transition process and estimate the probability of transition occurring at a given time.[5]

Two well-known classical models are the Kaplan-Meier model (KM) and Cox proportional hazard model (Cox PH). KM is a popular univariate method and computes the survival probability at the population level, not at the individual subject level. The Cox PH model computes the survival probability at the individual subject level while describing a linear relationship between survival distribution and the subject's covariates/risk factors.[6] The main drawback of this method is the assumption that the rate at which the event of interest occurs for any two subjects must be constant over time.

Therefore, modeling the individualized progression to MCI does not find KM and Cox PH methods a good fit and rather requires methods that can accommodate the nonlinear elements from the data and account for the fact that the rate of progression of two individuals will vary with time. The state-of-the-art deep learning techniques are found to address these requirements.

## 2. Related Works – "Deep Learning-Based Survival Analysis" to Model AD Progression

Sharma et al. [7] simulated the disease progression based on patient profiles through deep neural networks-based survival methods while utilizing the National Alzheimer's Coordinating Center (NACC) supplied dataset. Nakagawa et al. [8] examined if it was feasible with deep survival analysis to predict the transition of cognitively normal subjects and MCI subjects to the AD stage by leveraging brain magnetic resonance imaging (MRI) data found in the Alzheimer's Disease Neuroimaging Initiative (ADNI) database.

Mirabnahrazam et al. [9] also utilized the ADNI dataset and examined the influence of numerous features/factors derived from multiple data modalities (e.g., MRI, genetic assessments, Cerebrospinal Fluid) on the disease progression. Wu et al. [10] devised an approach using deep learning techniques to estimate the probabilities of time to conversion by leveraging multiple visit details obtained from the NACC database. All these studies demonstrated that the survival analysis based on state-of-the-art deep learning could outperform the standard Cox PH method. However, each of these studies utilized the dataset corresponding to point-in-time assessments/ evaluations comprising of either of the below or a combination:

- Subject demographics, medical history, cognitive/behavioral/functional scores etc., were collected through self-reporting, informant reporting questionnaires and clinical assessments (e.g., NACC dataset).
- Neuroimaging, genetics, other biomarkers etc. (e.g., ADNI dataset).

There are certain shortcomings observed with the above-said datasets. Firstly, point-in-time assessments consume lots of time and may not necessarily observe intra-individual changes effectively. Secondly, the questionnaire-based assessments could not produce objective results. Thirdly, datasets of imaging and biospecimen modalities involve high costs and are invasive in nature. To address these shortcomings, there is a continued need to identify daily activities-based markers that are "*clinically relevant, non-invasive, cost-effective, and scalable"* to reach the growing population of older adults. [11]

## 3. Research Questions and Contributions

In exploring to address the above-mentioned problem, this study seeks answers to the following questions:

- How well do the activity measures computed from non-wearable sensors aid in predicting the probability of time-to-transition (from cognitively healthy stage to MCI)?
- Can a deep learning-based survival analysis approach consider nonlinear elements in the complex activity patterns for the predictions?
- How well is the individualized distribution of survival probability over time estimated using the activity measures as risk variables?

### *3.1. Hypothesis*

The activity data captured through continuous monitoring of older adults' daily activities via non-wearable sensors (gathered from a longitudinal study) provide sufficient information to detect the probability of time-to-transition.

### *3.2. Key Contributions from this Study can be Described as follows:*

- Leveraging activity data captured via unobtrusive sensors in survival modeling for MCI transition/progression.
- Non-linear dependencies among the features – modelled effectively through deep learning techniques and demonstrated improved prediction performance over the traditional linear modeling techniques.

In this study, the survival models based on two deep learning techniques, namely Neural Multi-Task Logistic Regression (N-MTLR), Non-Linear Cox (NL Cox), were developed and compared against the traditional survival Cox PH in predicting the probability of time-to-conversion from cognitively healthy stage to MCI.

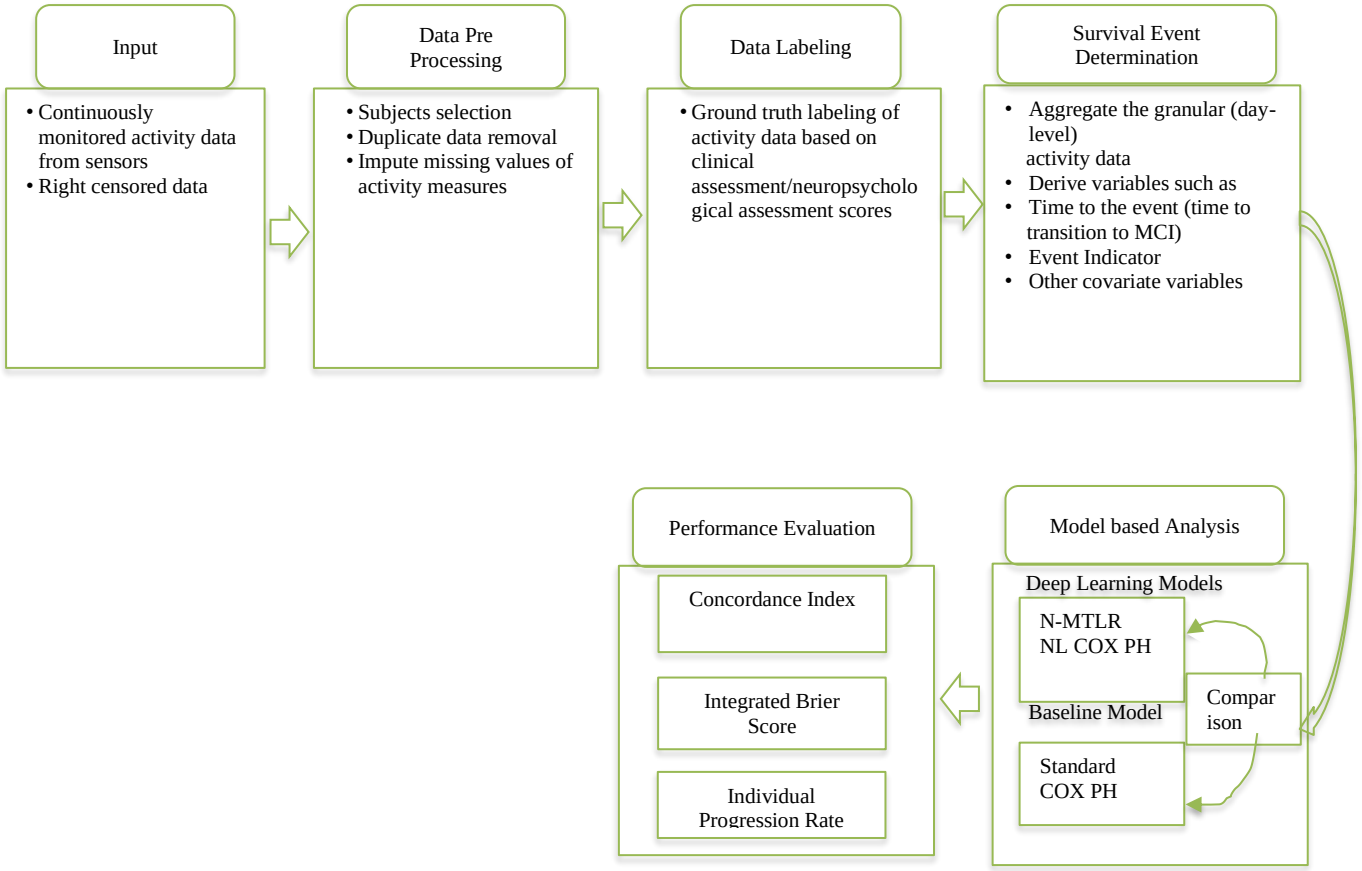


**Fig. 1 Schematic of the complete survival analysis workflow adopted in this study**

**Table 1. Demographic details of subjects in study**

| Demographic Variable | Male; Count =11 | Female; Count =46 |
|---|---|---|
| Baseline Age - years, mean (SD) | 83.35 (7.5) | 82.5 (8.0) |
| Years of Schooling, mean (SD) | 16.8 (2.1) | 15.3 (2.28) |
| Mean elapsed duration of sensor monitoring – months | 32.8 | 30.1 |
| MMSE Score at the start, mean (SD) | 28.72 (1.42) | 29.17(0.95) |

## 4. Materials and Methods

This study examines the use of older adults' activity patterns/trends observed via longitudinal monitoring in predicting the stage at which the disease has progressed, specifically, transition to MCI by leveraging survival modeling techniques. Observations from the intra-individual functional/ behavioral changes (including the minute changes) occurring over time provide invaluable information regarding the transition points that older adults might be approaching. Figure 1 depicts the schematic of the survival analysis workflow, which includes cleaning activity data derived from sensor raw data, assigning appropriate cognitive stage labels, event variables and activity features consolidation, modeling, and evaluation.

### *4.1. Data Collection, Analysis & Pre-processing*

The "Oregon Center for Aging and Technology" ("ORCATECH") is a research institute, part of "Oregon Health & Science University" (OHSU), USA [4], that supplied the dataset required for this study. As part of a "longitudinal community cohort study", ORCATECH deployed a home-based activity assessment platform at hundreds of senior homes, and this platform included several non-wearable sensors to monitor and capture daily activity patterns continuously.

Passive infrared (PIR) motion sensors, Wireless contact switches, and Sleep mats were those non-wearable sensors, to name a few. Activity data captured typically correspond to physical mobility, sleep, room transitions, out-of-home visits etc. All subjects gave written informed consent prior to participating in study activities.

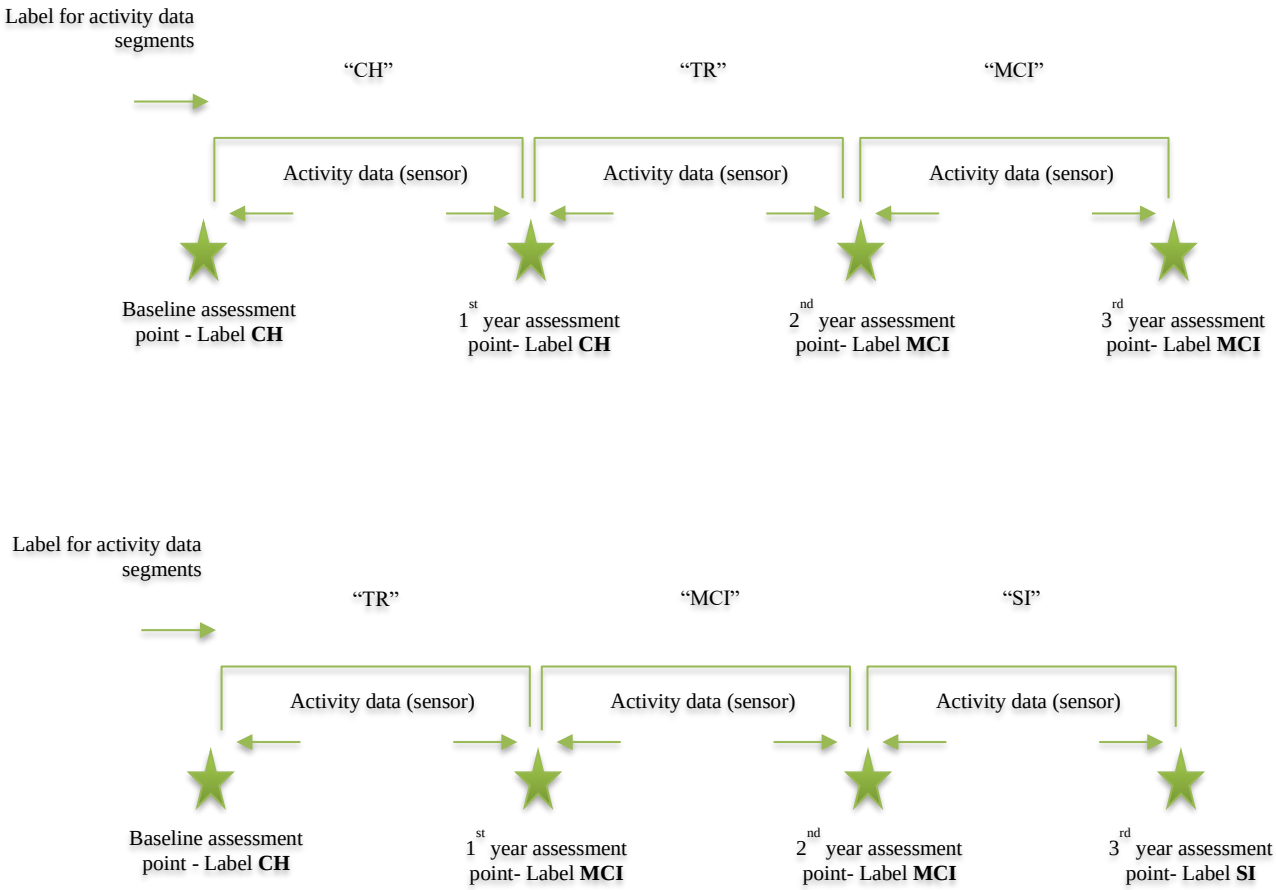


**Fig. 2 Labeling the cognitive stages throughout the subject's activity timeline**

The OHSU's Institutional Review Board (IRB #2353) had approved the necessary research protocol followed in ORCATECH' study.

Besides sensor-based monitoring, annual clinical assessments of study subjects were done by qualified health professionals. Annual clinical assessment data typically included demographics, functional assessments, health assessments, and neuropsychological test scores. Inclusion criteria for the study subjects were the age being 70 years and above (at the time of onboarding), cognitively healthy (indicated by "Clinical Dementia Rating – CDR" less than 0.5; Score of "Mini-Mental State Examination – MSME" more than 24) and health condition relevant to age. For further details on in-home sensor arrangements, participants' recruitment criteria and clinical assessments, readers can refer to [4].

Activity data supplied by ORCATECH contained the daily activity measures (per subject) derived from raw sensor signals. ORCATECH applied various proprietary algorithms on raw sensor signals data and derived these measures (e.g., walking speed, number of walks, sleep duration). Out of the total 125,119 records of day-level sensor data supplied, 51,505 number of records were finalized after pre-processing (e.g., linking sensor data to clinical assessment data and removing duplicate/invalid records). This final dataset taken for analysis corresponds to a total of 57 subjects, and Table 1 shows the demographics of these subjects.

### *4.2. Data Labeling for Cognitive Stage Shift*

This study leveraged the neuropsychological test scores to assign labels to activity data. These labels indicate the subject's 'cognitive stage' at a particular time. Petersen criteria [12] were adopted for diagnostic labeling to derive point-in-time labels in every subject's activity timeline, such as, 'CH' ("Cognitively Healthy"), 'MCI' ("Mild Cognitive Impairment") and 'SI' ("Severely Impaired"). Since the transition to MCI is not a sudden event but rather a gradual process, this study introduced a label/stage called 'Transitioning' (TR) and assigned it to all activity data that fall between stages 'CH' and 'MCI' when a subject experienced this transition.

Figure 2 illustrates the example scenarios in this labeling approach. For further granular details of data labeling, refer to the previous work. [13]

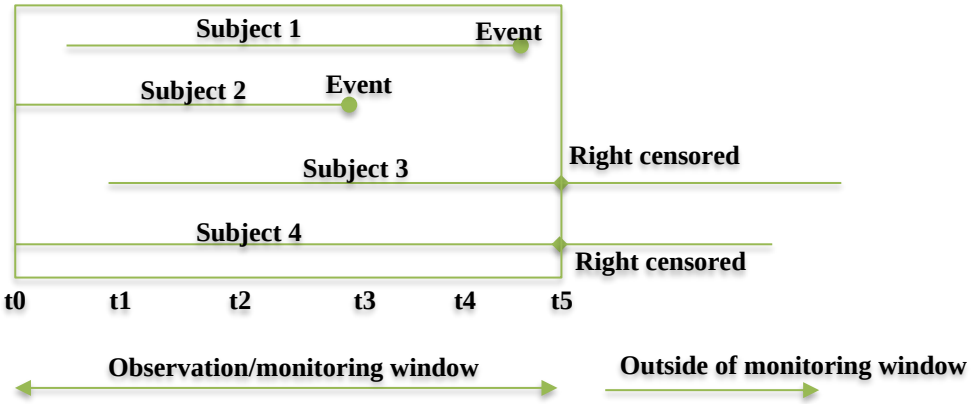


**Fig. 3 Events and censorship in survival data**

**Table 2. Input data construct for survival modeling**

| $X_1$ | $X_2$ | … | $X_n$ | Event indicator | Event Duration (months) |
|---|---|---|---|---|---|
| 34 | 80 | … | 0 | 1 | 800 |
| … | … | … | … | … | … |
| 67 | 120 | … | 1 | 0 | 1400 |

### *4.3. Methodology to Determine Event Occurrence, Event Duration and Model Input Dataset*

For this survival analysis, the focus would be on the event of some subject getting into the 'TR' stage (the pre-cursor to MCI). Two variables, 'Event Indicator' (Boolean) and 'Event Duration', were introduced to facilitate the survival analysis. Event indicator = 1 if the subject transitioned; otherwise, event indicator = 0. Event duration is calculated as the elapsed duration between the start date of the activity monitoring and the date when the subject transitioned (CH to TR). For right-censored subjects (remained at CH; event indicator =0), event duration is the elapsed duration between the start of the monitoring and the last day of monitoring, as found in the dataset supplied. Figure 3 illustrates the events and censorship in survival data.

Day-level activity measures or observations ($X_i$) data for the identified subjects were aggregated to arrive at one record per subject, and this would serve as the input for modeling. Table 2 depicts the input data construct (derived based on the approach described above) used for survival analysis and modeling in this study.

### *4.4. Model Training and Evaluation Approach*

As mentioned previously, this study adopted two deep learning-based models, N-MTLR and NL Cox and compared them against the standard Cox PH model. NL Cox method, popularized by Katzman et al. [14], is an extension of the Std Cox PH technique, whereas N-MTLR, developed by Fotso [5], uses a deep learning framework via a multi-layer perceptron (MLP) and does not rely on any Cox PH assumptions.

#### *4.4.1. Features used in Modeling*

In addition to the subjects' gender and years of education, several activity measures (derived from raw data streams obtained from continuous in-home monitoring) were used as features for training the survival analysis models (Table 3).

**Table 3. List of features used in this study, along with the cognitive/behavioral domain**

| Cognitive/ Behavioral Domain | Features used in modeling |
|---|---|
| Demographics | • Age (at baseline/start of the monitoring)<br>• Gender<br>• Years of education |
| Physical Mobility | • Dwell time in bathroom area in seconds<br>• Dwell time in bedroom area in seconds<br>• Dwell time in living room area in seconds |
| Social Engagement / Time Out of Home | • Out of home number of instances<br>• Out of home total time seconds |
| Sleep Night Time Behavior | • Sleep in living room in seconds<br>• Number of trips out of the bedroom (sleep time)<br>• Sleep time total in seconds<br>• Wake after sleep onset (WASO) in seconds |
| Physical Mobility | • Walking speed variability<br>• Walking speed (cm/second)<br>• Number of captured walks |
| Event Variables | • Event Indicator<br>• Event Duration |

**Table 4. Hyperparameters configuration for deep learning neural networks**

| Parameter | N-MTLR | NL Cox PH |
|---|---|---|
| Hidden layers | 4 | 4 |
| Neurons (units) in each layer | 100 | 100 |
| Activation function | ReLU | ReLU |
| Optimizer function | adam | adam |
| Learning Rate | 0.002 | 0.002 |
| Epoch count | 1000 | 1000 |
| Dropout rate in each layer | 0.2 | 0.2 |

*4.4.2. Modeling Scenarios and Machine Learning Set Up*

Several models were built based on various feature combinations and hyperparameters, evaluated, and compared against each other's performance. Table 4 provides the hyperparameter details of neural networks (N-MTLR & NL Cox) adopted in the experiments.

For the standard Cox PH model, the setting up of the parameters included the learning rate of 0.002, maximum iterations of 1000, 0.95 as the confidence level (alpha) and 0.001 as tolerance for stopping criteria.

This study selected three feature combination scenarios and built models for each of these scenarios leveraging the three survival techniques described above.

- All features scenario (all the features listed in Table 3).
- Walk features only (Walking related + age, gender, and years of education).
- Sleep features only (Sleep-related + age, gender, and years of education)

To implement the models for all three techniques, this study utilized the open-source Python package "PySurvival." [15]

*4.4.3. Model Training & Testing Approach*

A random split of 0.8:0.2 ratio was applied to create training and test data. In the experiments, while training and testing each model, the study performed 10 different random splits of data and repeated the runs for 5 times. The average over these repeated runs was computed, and results were reported. To account for uncertainties, 95% confidence intervals for each model performance metric were computed with a few hundred bootstrapped samples.

*4.4.4. Model Performance Metrics*

This study leveraged two standard metrics to assess the performance of the 'Cognitively healthy' stage to 'MCI' stage transition prediction:

- Concordance Index (CI) [16] is the commonly used discriminative index to assess the survival models' predictive power, assuming that a subject who did not experience the event should have received a lower risk score than subjects who experienced the event. The value of CI lies between 0 and 1; A larger CI value indicates a better performance of the survival prediction model.
- Integrated Brier Score (IBS) [17] is an extension of the Brier score. Brier score provides the accuracy of predicted survival probability with respect to actual survival status at a given time point. IBS is the calculation of accuracy/performance at all available times. A smaller value of IBS indicates a better performance.

To determine the differences in predictions obtained from various models are statistically significant, Wilcoxon Signed-Rank Test was adopted. (Statistical significance was set at $p < 0.05$).

## 5. Results and Discussion

This study developed deep learning-based non-linear survival models, and the survival probability predictions obtained from these models provide insights into the individual's rate of degeneration, in other words, transition to the MCI stage.

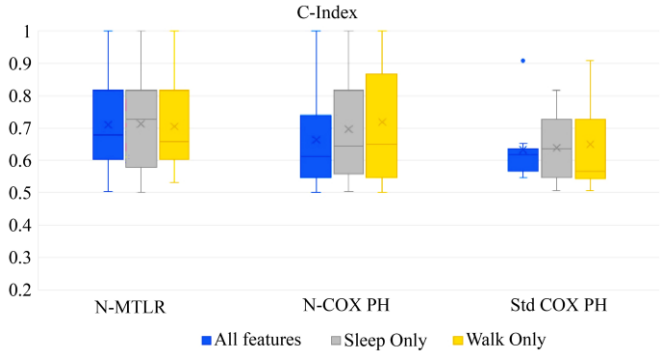


**Fig. 4 CI results distribution for various modeling scenarios**

**Table 5. C-index as the performance evaluation metric. Within parenthesis are the 95% bootstrapped confidence intervals.**

| Model Scenario | N-MTLR | NL-Cox PH | Std. Cox PH |
|---|---|---|---|
| All Features *(Sleep, Walk, Out of Home, Dwell)* | **0.693**[a] (0.5-0.85) | 0.662 (0.5-0.88) | 0.640 (0.51 - 0.88) |
| Sleep alone | **0.714**[a] (0.5-0.82) | 0.667 (0.5-0.80) | 0.625 (0.5-0.86) |
| Walk alone | **0.701**[a] (0.5-0.92) | 0.692[a] (0.51-0.76) | 0.661 (0.5-0.83) |

*Average value from 5 repeated runs of 10 different random splits; bold values indicate the best performance.*

[a] *Statistically significant performance improvement as compared to baseline technique - Std. Cox (Wilcoxon test, $p < 0.05$)*

Prediction performances in terms of CI of various models are presented in Table 5. The distribution of CI metrics from various runs is shown in Figure 4. The models built using deep learning techniques performed better than the baseline Cox PH method and showed a good improvement in predicting the probability of transition to MCI within a given period. Specifically, the N-MTLR model, when it included sleep

features alone, outperformed and resulted in a CI value of 0.714 (the best average value). Overall, all the model scenarios built on the N-MTLR technique demonstrated the best prediction performance compared to other techniques in terms of CI.

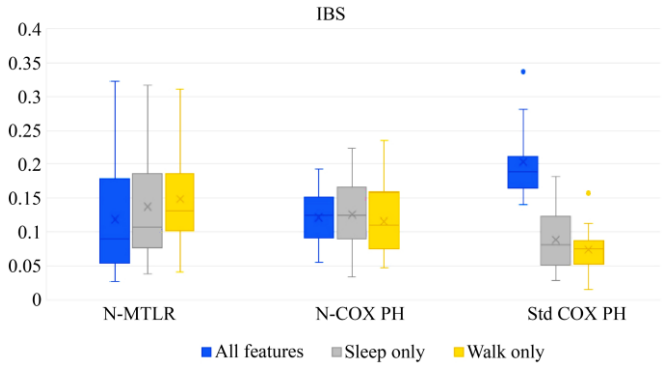


**Fig 5 IBS results distribution for various modeling**

**Table 6. IBS as the performance evaluation metric. within parenthesis are the 95% bootstrapped confidence intervals**

| Model Scenario | N-MTLR | NL-Cox PH | Std. Cox PH |
|---|---|---|---|
| All Features *(Sleep, Walk, Out of Home, Dwell)* | **0.119**[a] (0.08-0.23) | 0.122[a] (0.06-0.26) | 0.203 (0.1-0.42) |
| Sleep alone | 0.138[a] (0.08-0.28) | 0.126[a] (0.05-0.24) | **0.088** (0.04-0.28) |
| Walk alone | 0.150[a] (0.1-0.3) | 0.116[a] (0.04-0.23) | **0.075** (0.05-0.24) |

*Average value from 5 repeated runs of 10 different random splits; bold values indicate the best performance.*
*[a] Statistically significant performance improvement as compared to baseline technique - Std. Cox (Wilcoxon test, $p < 0.05$)*

The relatively poor performance of the standard Cox PH method can be attributed to its drawback of the proportional hazard assumption, which specifies that the rate at which an event of interest occurs for any subject must be constant over time. In reality, it is known that not only the rate of decline varies from one individual to another (inter-individual) but also the rate of decline for an individual (intra-individual) can also vary over time. The CI results from this study suggest that the deep learning models had learnt these nuances from the activity pattern data while estimating the risk scores and were able to overcome the above-said drawback of the standard Cox PH method. In general, it is known that the complex nature of older adults' activity/ daily routines does not appear to exhibit a straightforward/linear relation to their cognitive changes over time but rather a non-linear association. Therefore, these results suggest that the proposed deep learning models are able to capture the nonlinear elements in the activity patterns, learn their nuances and provide a better prediction for time-to-transition.

As discussed previously, CI measures the quality of the risk prediction model, and these CI results suggest that the proposed N-MTLR approach can produce a high number of concordant pairs indicating that the predicted higher risks correspond to an effectively shorter transition time compared to lower risks.

From the results of IBS (Table 6 and Figure 5), the baseline method might appear to perform slightly better than the deep learning-based models (because of lower values). The underlying calculation of the Brier score is associated with the probability estimation of the event occurrence. The disease prevalence among the population under study (the a priori probability) has, in fact, an influence on the Brier score calculation. [18]

In the study dataset, since most subjects did not experience the event (i.e., the lower prevalence of the MCI transition cases), the brier scores from the baseline technique could appear more specific than sensitive, resulting in comparatively lower values. Typically, as the harms of missing to detect the MCI transition far outweigh the harms of unnecessary interventions, one would favour the test with a higher sensitivity. Nevertheless, it is quite important to validate and understand the performance of the proposed deep learning-based survival techniques in a cohort with a higher prevalence of MCI transitions.

To facilitate the interpretation of prediction results obtained from the proposed deep learning models, the study did the ranking of features used by the model. The learned weight matrix by deep learning techniques was leveraged, and the L2 norms of this matrix were computed. Based on L2 norms, this study scored the important features and determined the top 5 features in each scenario, as shown in Table 7.

Results from the feature ranking aid in making the following observations and interpretations:

- Overall, across most scenarios, "Age" (age of the subjects at the baseline) is the top most ranked feature. Age is a well-known key risk factor for cognitive decline, and this ranking result is consistent with several findings reported in the literature. [19, 20]
- Another most frequently occurred demographic feature is "Years of education". In the understanding of cognitive health, "cognitive reserve" (CR) is a crucial aspect, and this refers to the brain or mind's resiliency to continue to function as usual, even in the presence of any brain damage. Several studies suggest that CR play a big role in protecting against age-related cognitive decline and identify the individual's education as one of the key determinants for imparting this reserve. [21, 22]

- Surprisingly, the feature 'gender' did not appear as a top predictor common across all scenarios. Since most subjects were female in the study dataset, the models could not find this feature helpful in predicting the risk of event occurrence.
- As seen in Table 5, the performance of the N-MTLR technique is statistically superior to the baseline model for all modeling scenarios, especially the scenario with sleep features alone. Associating this finding with the results in Table 7, one could observe that the sleep features, specifically total sleep time, are the most occurred predictor. This is in alignment with findings from several studies that the quality of sleep has a profound association with the development of cognitive decline. [24, 30]
- Nonetheless, several studies have found that activity measures based on the three domains- sleep, mobility and social engagement- strongly associate with subsequent cognitive decline.
  - Blackwell et al. [25] reported that reduced sleep efficiency, greater nighttime wakefulness, and a greater number of long wake episodes (LWEPs) were associated with subsequent cognitive decline.
  - From the physical mobility perspective, Kaye et al. [26] and Dodge et al. [27] found walking speed and associated measures to be strong factors for predicting cognitive/functional well-being in older adults.
  - Total time/count of instances – out of home indicates the individual's willingness to leave home and have social engagement. These features have been linked with numerous health outcomes, including cognitive decline, low emotional state etc. Petersen et al. [28] and Suzuki et al. [29] found an association between the amount of time spent outside the home and cognitive function.

One of the key goals of this study is to understand the rate of progression towards MCI at an individual level rather than a population level. Towards this goal, the survival probability curves estimated by the proposed deep learning-based approaches were plotted and visually verified. These survival probability curves indicate the probability of an individual staying at the 'cognitively healthy' stage (i.e., rate of progression towards MCI). Figure 6 depicts the estimated survival probability curves in various modeling scenarios and the actual time of the event per chosen subject. As seen in this figure, both techniques produced good predictions in the 'All Features' scenario. NL Cox technique appears relatively consistent (perhaps, robust) in probability predictions across all scenarios.

In summing up all the above observations, this study finds the proposed deep learning-based survival analysis approach is very promising in leveraging older adults' activity patterns/trends and predicting the probabilistic time-to-MCI transition personalized at the individual level. Feature ranking of these proposed approaches could help explain the prediction results very well. Age being the top most predictor/feature is inconsistent with findings by several studies. Besides age, Other top-ranked features from this study have been proven to be clinically and functionally meaningful in understanding older adults' cognitive health, specifically cognitive decline.

**Table 7. Feature ranking: Based on the learned weight matrix by N-MTLR and Non-Linear Cox techniques, the Top 5 ranking of features was done based on L2 norms calculated for the first layer weight matrix, and this ranking would help interpret the prediction results**

| Model Scenario | N-MTLR | NL Cox PH |
|---|---|---|
| All Features *(Sleep, Walk, Out of Home, Dwell)* | • Sleep time total<br>• Walking speed variability<br>• Out of home number of instances<br>• Years of education<br>• Age | • Out of home total time<br>• Sleep-wake after sleep onset<br>• Number of trips out of the bedroom (sleep time)<br>• Dwell time bathroom area<br>• Dwell time bedroom area |
| Sleep alone | • Sleep time total<br>• Sleep time in the living room<br>• Number of trips out of the bedroom (sleep time)<br>• Years of education<br>• Age | • Sleep time in the living room<br>• Number of trips out of the bedroom (sleep time)<br>• Sleep-wake after sleep onset<br>• Sleep time total<br>• Age |
| Walk alone | • Walking speed Number of captured walks<br>• Walking speed variability<br>• Gender<br>• Age | • Walking speed variability<br>• Walking speed<br>• Number of captured walks<br>• Years of education<br>• Age |

### *5.1. Limitations*

There are certain known limitations associated with the dataset utilized for this study and described below:

- There has been a bit of imbalance in the dataset in terms of the number of study participants who experienced the event/transition, and the ratio is approximately 0.82:0.18 (non-event vs event cases).

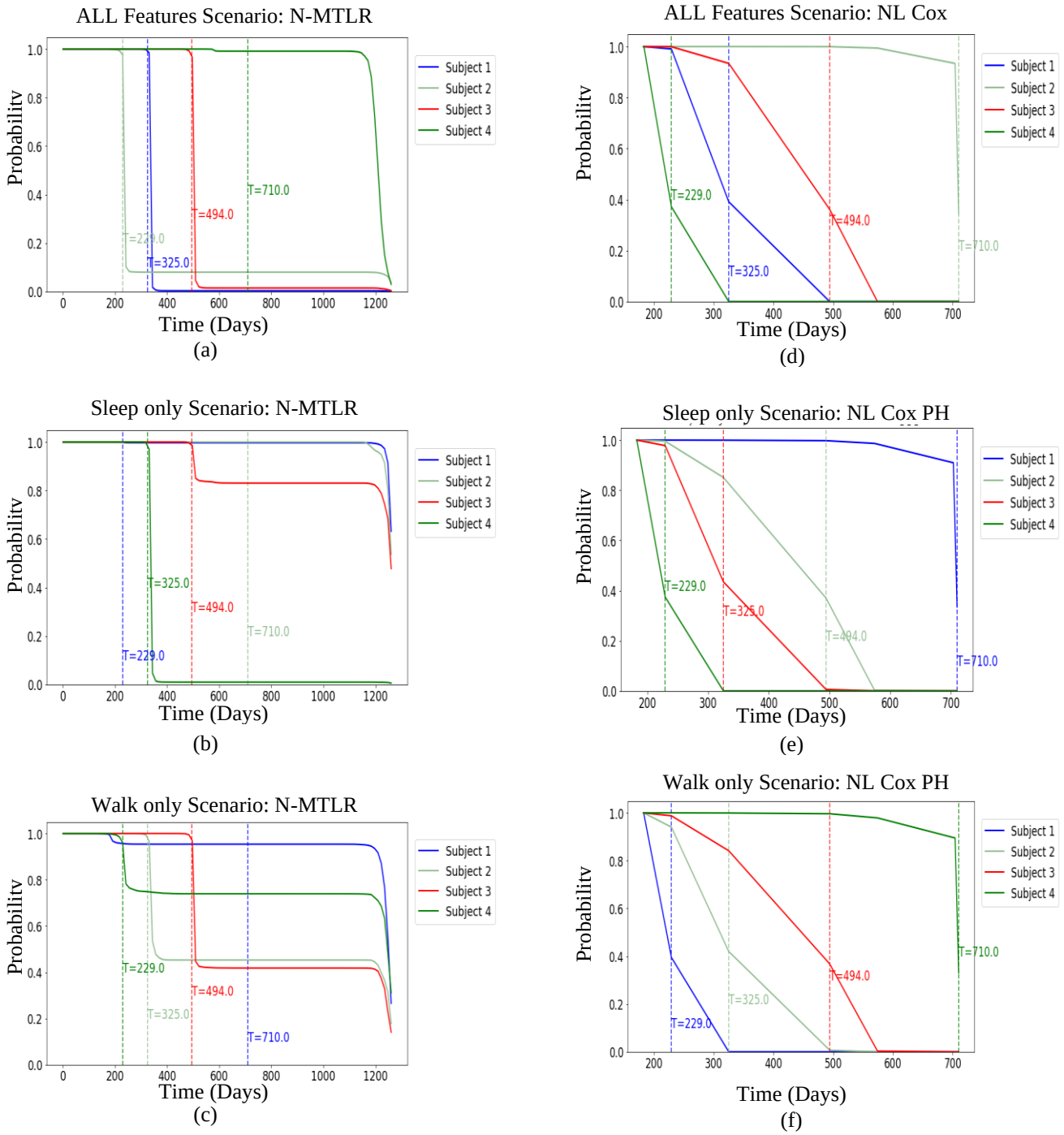


**Fig. 6 Visualization of Survival Plots for 4 randomly chosen subjects in various modeling scenarios. X-axis indicates the time in days (baseline time is the origin). Y-axis indicates the probability of remaining intact in the Cognitively Healthy stage. The actual time of the transition event is shown as vertical dotted lines.**

- In the cohort considered for this study, the majority of the participants were female, and this dataset could exhibit an imbalanced gender mix.
- Approximately 80% of the study cohort had years of education of 14 and above. This could indicate a highly educated cohort and might have had an implication on an individual's cognitive abilities.

To some extent, these limitations reduce the generalizability of the study findings to a more diverse

population. Hence, future studies need to focus on a larger dataset representing heterogeneity among the subjects in terms of demographic, socioeconomic, and MCI incidence parameters.

## 6. Conclusion

This study leveraged the activity data captured through in-home, continuous monitoring of older adults' daily activities via non-wearable sensors. As opposed to conventional point-in-time assessments, activity measures derived from this continuously obtained data stream help identify subtle intra-individual functional changes over time and improve the prediction for cognitive stage shift. This study demonstrates that state-of-the-art deep learning techniques combined with a survival analysis approach can predict individualized trajectories associated with this cognitive shift. This is crucial for healthcare professionals in determining personalized interventions well in advance, delaying the progression and thus ensuring older adults' independence and quality of life.

## Acknowledgments

The dataset used in this study was provided by ORCATECH. The authors would like to acknowledge and thank ORCATECH for their support. ORCATECH's research studies that collected this dataset include – "ADC Clinical Core" ("PI: J.Kaye; eIRB 725; funding support by the NIH P30 AG008017") and "ORCATECH; PI: J.Kaye; eIRB 2765; funding support by the NIH P30 AG024978".

## References

[1] D. Galasko et al., "Detailed Assessment of Activities of Daily Living in Moderate to Severe Alzheimer's Disease," *Journal of the International Neuropsychological Society*, vol. 11, no. 4, pp. 446–453, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[2] Prafulla Nath Dawadi, Diane Joyce Cook, and Maureen Schmitter-Edgecombe, "Automated Cognitive Health Assessment from Smart Home-Based Behavior Data," *IEEE Journal of Biomedical and Health Informatics*, vol. 20, no. 4, pp. 1188–1194, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[3] Rajaram Narasimhan, G. Muthukumaran, and Charles McGlade "Current State of Non-Wearable Sensor Technologies for Monitoring Activity Patterns to Detect Symptoms of Mild Cognitive Impairment to Alzheimer's Disease," *International Journal of Alzheimer's Disease*, vol. 2021, pp. 1–18, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[4] Jeffrey A. Kaye et al., "Intelligent Systems for Assessing Aging Changes: Home-Based, Unobtrusive, and Continuous Assessment of Aging," *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, vol. 66B, no. 1, pp. i180–i190, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[5] Stephane Fotso, "Deep Neural Networks for Survival Analysis Based on A Multi-Task Framework," *Machine Learning, arXiv*, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[6] D. R. Cox, "Regression Models and Life-Tables," *Journal of the Royal Statistical Society: Series B (Methodological)*, vol. 34, no. 2, pp. 187–202, 1972. [CrossRef] [Google Scholar] [Publisher Link]

[7] Rahul Sharma et al., "Time-to-Event Prediction using Survival Analysis Methods for Alzheimer'sDisease Progression," *Alzheimer's & Dementia: Translational Research & Clinical Interventions*, vol. 7, no. 1, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[8] Tomonori Nakagawa et al., "Prediction of Conversion to Alzheimer's Disease Using Deep Survival Analysis of MRI Images," *Brain Communications*, vol. 2, no. 1, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[9] Ghazal Mirabnahrazamet al., "Predicting Time-To-Conversion for Dementia of Alzheimer's Type Using Multi-Modal Deep Survival Analysis," *Neurobiology of Aging*, vol. 121, pp. 139-156, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[10] Xinxing Wu et al., "Machine Learning Approach Predicts Probability of Time to Stage-Specific Conversion of Alzheimer's Disease," *Journal of Alzheimer's Disease*, vol. 90, no. 2, pp. 891–903, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[11] Adriana Seelye et al., "Weekly Observations of Online Survey Metadata Obtained Through Home Computer Use Allow for Detection of Changes in Everyday Cognition Before Transition to Mild Cognitive Impairment," *Alzheimer's & Dementia*, vol. 14, no. 2, pp. 187–194, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[12] R. C. Petersen, "Mild Cognitive Impairment as a Diagnostic Entity," *Journal of Internal Medicine*, vol. 256, no. 3, pp. 183–194, 2004. [CrossRef] [Google Scholar] [Publisher Link]

[13] Rajaram Narasimhan et al., "Recurrent Neural Network based Prediction of Transition to Mild Cognitive Impairment Using Unobtrusive Sensor Data," *IEEE International Conference on Data Science and Information System (ICDSIS)*, pp. 1-6, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[14] Jared L. Katzman et al., "DeepSurv: Personalized Treatment Recommender System using a Cox Proportional Hazards Deep Neural Network," *BMC Medical Research Methodology*, vol. 18, no. 24, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[15] S. Fotso, Square/Pysurvival: Open Source Package for Survival Analysis Modeling, GitHub, 2019. [Online]. Available: https://github.com/square/pysurvival/

[16] Hajime Uno et al., "On the C-statistics for Evaluating Overall Adequacy of Risk Prediction Procedures with Censored Survival Data," *Statistics in Medicine*, vol. 30, no. 10, pp. 1105–1117, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[17] Thomas A. Gerds, and Martin Schumacher, "Consistent Estimation of the Expected Brier Score in General Survival Models with Right-Censored Event Times," *Biometrical Journal*, vol. 48, no. 6, pp. 1029–1040, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[18] Yun-Chun Wu, and Wen-Chung Lee, "Alternative Performance Measures for Prediction Models," *PLoS ONE*, vol. 9, no. 3, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[19] Lotte G. M. Cremers et al., "Predicting Global Cognitive Decline in the General Population Using the Disease State Index," *Frontiers in Aging Neuroscience*, vol. 11, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[20] V. Solfrizzi et al., "Vascular Risk Factors, Incidence of MCI, and Rates of Progression to Dementia," *Neurology*, vol. 63, no. 10, pp. 1882–1891, 2004. [CrossRef] [Google Scholar] [Publisher Link]

[21] Yaakov Stern, "Cognitive Reserve in Ageing and Alzheimer's Disease," *The Lancet Neurology*, vol. 11, no. 11, pp. 1006–1012, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[22] Christine Sattler et al., "Cognitive Activity, Education and Socioeconomic Status as Preventive Factors for Mild Cognitive Impairment and Alzheimer's Disease," *Psychiatry Research*, vol. 196, no. 1, pp. 90–95, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[23] Srinivasan Suresh, "Prediction of Roadway Crashes Using Logistic Regression in SAS," *SSRG International Journal of Computer Science and Engineering*, vol. 7, no. 10, pp. 13-17, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[24] Shelley S. Tworoger et al., "The Association of Self-Reported Sleep Duration, Difficulty Sleeping, and Snoring with Cognitive Function in Older Women," *Alzheimer Disease & Associated Disorders*, vol. 20, no. 1, pp. 41–48, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[25] Terri Blackwell et al., "Poor Sleep is Associated with Impaired Cognitive Function in Older Women: The Study of Osteoporotic Fractures," *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, vol. 61, no. 4, pp. 405–410, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[26] Jeffrey Kaye et al., "One Walk a Year to 1000 within a Year: Continuous in-Home Unobtrusive Gait Assessment of Older Adults," *Gait & Posture*, vol. 35, no. 2, pp. 197–202, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[27] H. H. Dodge et al., "In-Home Walking Speeds and Variability Trajectories Associated with Mild Cognitive Impairment," *Neurology*, vol. 78, no. 24, pp. 1946–1952, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[28] Johanna Petersen et al., "Time Out-Of-Home and Cognitive, Physical, and Emotional Wellbeing of Older Adults: A Longitudinal Mixed Effects Model," *PLOS ONE*, vol. 10, no. 10, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[29] T. Suzuki and S. Murase, "Influence of Outdoor Activity and Indoor Activity on Cognition Decline: Use of an Infrared Sensor to Measure Activity," *Telemedicine and e-Health*, vol. 16, no. 6, pp. 686–690, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[30] Tamara L. Hayes et al., "Estimation of Rest-Activity Patterns Using Motion Sensors," *Annual International Conference of the IEEE Engineering in Medicine and Biology*, pp. 2147-2150, 2010. [CrossRef] [Google Scholar] [Publisher Link]